# **Relationship between Stock Market Index and Macroeconomic Indices: Empirical Evidence from Bangladesh**



## Dissertation submitted to the University of Dhaka for the degree of Doctor of Philosophy in Business Administration

By

### **Md. Rafiqul Matin**

Registration Number – 186/ 2012-2013

Institute of Business Administration University of Dhaka January 2018

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### **DECLARATION BY SUPERVISOR**

This thesis has been submitted for the degree of Doctor of Philosophy of the University of Dhaka with my approval as the supervisor.

**Dr. Md. Jawadur Rahim Zahid**, Professor, Institute of Business Administration

Signature .. Date ..................................

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### **Abstract**

*Stock market is often believed to be a predictor of the economy in which it operates. We try to find empirical evidence defining the relationship between stock market index and macroeconomic indices of Bangladesh. Specifically, we investigate to see if there exists any relationship between Dhaka Stock Exchange General Index (DSEGEN) and some important macroeconomic variables which represent the economy of Bangladesh. Based on the objectives, following six specific research questions are investigated: (1) Does any significant long-run association exist between DSEGEN and six macroeconomic variables viz.; industrial production index, interest rate, inflation, exchange rate, money supply and gold price? (2) Is there any short-term relationship between DSEGEN and the macroeconomic variables? (3) Is there any causal relationship between DSEGEN and the macroeconomic variables? (4) Are the relationships same between DSEGEN and the macroeconomic variables in bubble, meltdown and recovery periods of the stock market? (5) Does any relationship exist between DSEGEN volatility and the macroeconomic volatility? (6) What is the relationship between DSEGEN and the real economy of Bangladesh?*

*This study has used the macroeconomic version of the semi strong EMH and macro variable model of the APT to investigate the aforesaid research questions using sophisticated econometric tools such as Vector Autoregression, Granger Causality, Johansen and Juselius Cointegration, Autoregressive Distributed Lag (ARDL), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The investigations on 25 years data, from January 1991 to December 2015, have revealed that there exists a long-run equilibrium relationship and a short-run disequilibrium between the stock market and the macroeconomic variables in Bangladesh. Also, the stock market has Granger caused only two macroeconomic variables - industrial production and exchange rate, but the opposite is not true.* 

*Among the catastrophes of 1996 and 2010, structural instability is found around 1996. The findings have also indicated that the exchange rate and the interest rate are at least partially responsible for the bubble creation and bubble crash of 1996. The explanatory power of the macroeconomic variables to explain the stock market return varies across bubble, meltdown and recovery periods of 1996 indicating that the stock prices are sometimes partially driven by fad and fashions, which are not related to the economic factors. Furthermore, no leverage effect is seen in the stock market volatility, although a shock has persisted over many future periods. The market volatility has showed instability throughout the period revealing that the volatility of the market is a problem in Bangladesh. Moreover, the outcome of the study has also revealed that despite numerous reform measures and the automation initiatives being implemented since 1998, stock market in Bangladesh is not yet that much developed to play its due role in influencing the real economy.* 

## **Declaration**

I hereby declare that this thesis, and the research underpinning it, is entirely my own work and that this thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree.

Singed: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ Dated: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

 **Md. Rafiqul Matin**

*To the memory of my mother, who was constant source of inspiration of my life; my father, who is consistently supporting all my endeavors; and my wife, my son and daughter, who have encouraged me all the way.*

#### **Acknowledgement**

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My profound thanks and gratitude to my father; his prayers and support enabled me to complete my studies over the period. Special thanks go to my wife Munia who contributed in numerous ways to the success of this project. Without her assistance and encouragement my success would have been hampered. I would like to thank my son Prottoy and daughter Tamanna, who provided me support, patience and understanding during my study.

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Finally, I thank all the people who are directly and indirectly involved in helping me to write this thesis.

## **List of Abbreviation**

- ADF Augmented Dickey-Fuller
- APM Arbitrage Pricing Model
- APT Arbitrage Pricing Model
- AR Autoregressive
- ARCH Autoregressive Conditional Heteroscedastic
- ARDL Autoregressive Distributed Lag
- AR-GARCH Autoregressive- Generalised Autoregressive Conditional Heteroscedastic
- ARIMA Autoregressive Integrated Moving Average
- BDT Bangladeshi Taka
- BSE Bombay Stock Exchange
- CAPM Capital Assets Pricing Model
- CCH Chan, Chen, and Hsieh
- CMDP Capital Market Development Program
- CPI Consumer Price Index
- CRR Chen, Roll and Ross
- CUSUM Cumulative Sum
- CUSUMSQ Cumulative Sum Squares
- DDM Dividend Discount Model
- DMB Deposit Money Bank
- DSE Dhaka Stock Exchange
- DSEGEN Dhaka Stock Exchange General Index
- ECM Error Correction Model
- EGARCH Exponential Generalised Autoregressive Conditional Heteroscedastic
- EMH Efficient Market Hypothesis
- FSRP Financial Sector Reform Project
- FTSE Financial Times Stock Exchange
- GARCH Generalised Autoregressive Conditional Heteroscedastic
- GDP Gross Domestic Product
- ICAPM Intertemporal Capital Asset Pricing Model
- IPI Industrial Production Index
- ISE Istanbul Stock Exchange
- JJA Johansen and Juselius Approach
- KLCI Kuala Lumpur Composite Index
- KPSS Kwiatkowski, Phillips, Schmidt, and Shin
- LAN Local Area Network
- LA-VAR Lag-augmented Vector Autoregression
- LM Lagrange Multiplier
- NPV Net Present Value
- NSE Nigerian Stock Exchange
- NYSE New York Stock Exchange
- OLS Ordinary Least Squares
- PBR Price to Book Value Ratio
- P/E Price Earning
- PP Phillips and Perron
- RWM Random Walk Model
- S&P Standard & Poor
- SENSEX Sensitivity Index
- SES Stock Exchange of Singapore
- TSE Tokyo Stock Exchange
- UK United Kingdom
- US United States
- USD United States Dollar
- VAR Vector Autoregression
- VEC Vector Error Correction
- VECM Vector Error Correction Model
- WAN Wide Area Network

Chapter 1 1

### **Chapter 1**

#### **Scheme of the Research**

#### **1.1 Introduction**

A stock market is often seen as an indicator or predictor of the economy in which it operates. Many believe that large current decreases in stock prices are reflections of a future recession, whereas large current increases in stock prices suggest future economic growth (Comincioli, 1996). The traditional "valuation model of stocks" and the "wealth effect" include the theoretical reasons for why stock prices might predict future state of economy.

The traditional valuation model of stock suggests that the determinants of a stock price are the expected cash flows from the stock and the required rate of return commensurate with the cash flows' riskiness. As investors' expectations about future cash flows and the required rate of return depend on investors' expectations about the future prospect of the economy, so stock prices should rise (or fall) before the actual rise (or fall) of general economic activity. Besides, Chen et al. (1986) have demonstrated that economic state variables, through their effect on future dividends and discount rate, exert systematic influence on stock returns.

The wealth effect suggests that with the rise in stock prices investors become wealthier and their propensity to consume more results in expansion of economy. On the other hand, if stock prices decline, investors become less wealthy and they spend less; this results in slower economic growth. Pearce (1983) has supported the claim of stock market's ability to predict the future state of economy arguing that as fluctuations in stock prices have a direct effect on aggregate spending, so the economy can be predicted from the stock market.

Stock market as an indicator or predictor of movements of the economy, however, does not go without controversies. Critics have pointed to several reasons for not trusting the stock market as an indicator of future state of economy. Many believe that economy is not just about a bunch of public companies; economy is about all the companies - public and private; it is, in fact, about every citizen who is in the nation. So, stock market constitutes only a tiny fraction of the whole economy, which is not enough to make a measurable impact on the overall economic performance of the country (Mishra and Pan, 2016). However, the argument does not hold the ground as a tiny mirror can reflect a huge banyan tree. In fact, a miniscule retina can reflect all planets and stars in the sky.

Pearce (1983) has mentioned that stock market has previously generated false signals about economy, and therefore, should not be relied on as an economic indicator. Also, skeptics have pointed to the strong economic growth in US followed by 1987 stock market crash in New York Stock Exchange as a reason to doubt the stock market's predictive ability. Moreover, investors' expectations about future prospect of the economy are subject to human error, because investors could not always anticipate it correctly. Thus, stock prices sometimes increase before the economy enters recession and decrease before the economy expands. Hence the stock market often misleads the direction of the economy (Comincioli, 1996).

Despite all these controversies, stock markets are commonly believed to react sensitively to economic news. Our experiences also support the truth that individual stock prices are influenced by a wide variety of unanticipated events and some of these events are more pervasive than others (Chen et al., 1986). Although a single stock can be affected by influences that are not systematic or pervasive to economy, but returns on stock market mainly be influenced by systematic risk because idiosyncratic risk on individual stocks are cancelled out through the process of diversification.

#### **1.2 Objective of the Research**

It is revealed from the foregoing discussion that stock prices react sensitively to economic news and there is a general belief among economists and market participants that the stock market return and economy are closely correlated. On the other hand, macroeconomic variables are indicators or main signposts signaling the trends in the economy (Siamwalla et al. 1999). So, macroeconomic variables are the economic state variables which affect the economy and thereby affect the returns on stock market.

Considering this, the broad objective of this research is to find empirical evidence defining relationship between stock market and overall economy. More specifically, our objective is to find relationship between Dhaka Stock Exchange (DSE) and some important economic state variables which are considered important from the perspective of the economy and the stock market of Bangladesh.

#### **1.3 Research Questions**

Based on the objective of the research, the study will focus on the following specific research questions:

1. Does any significant long-run equilibrium relationship exist between the stock market, represented by Dhaka Stock Exchange General Index (DSEGEN), and six macroeconomic variables - namely Industrial Production Index, Interest Rate, Inflation, Exchange Rate, Money Supply and Gold Price?

- 2. Is there any short-term equilibrium relationship between DSEGEN and the macroeconomic variables?
- 3. Is there any causal relationship between DSEGEN and the macroeconomic variables?
- 4. Are the relationships same between DSEGEN and the macroeconomic variables in different periods, viz.; bubble, meltdown and recovery periods?
- 5. Is there any relationship between DSEGEN volatility and the macroeconomic variables' volatilities?
- 6. What is the relationship between DSEGEN and the real economy of Bangladesh?

#### **1.4 Scope, Limitations and Assumptions of the Research**

In this study, the relationship between the aggregate stock market, represented by DSE General Index, and the macroeconomic variables have been investigated for the period from January 1991 to December 2015. Hence the outcomes of this study are not applicable, in terms of generalizability, to individual stocks listed on the Dhaka Stock Exchange (DSE) and to any other period. Moreover, the DSE General Index tracks the performance of category A, B, G and N companies. Therefore, the findings are also limited to only aggregate stock market returns comprising those categories of stocks. Additionally, the stock market returns have been calculated based on the market index considering the capital gains component of stock returns and excluded the dividend aspect of the returns, thus limiting the full impact of actual returns.

In our empirical analysis, we have used monthly data of industrial production index of medium to large-scale manufacturing industries as a proxy of Gross Domestic Product (GDP), because data on the former is available on monthly basis but the latter is not. Tainer (1993) is of the view that the industrial production index is procyclical; that is, it rises

during economic expansion and falls during a recession. It is typically used as a proxy for the level of real economic activity, that is, a rise in industrial production would signal economic growth. In many studies (for example Adrangi et al., 1999; Ibrahim and Aziz, 2003), GDP is represented by industrial production index. However, among the fifteen sectors of GDP, Bangladesh economy is dominated by the services sector which accounted for 56.3% of GDP in FY2015, followed by broad industry sector (28.1%). The broad industry sector includes following four sectors: (1) construction; (2) mining and quarrying; (3) manufacturing; and (4) electricity, gas and water supply. Out of these four sectors, the contribution of the manufacturing sector is the highest  $(17.6%)$  in GDP.<sup>1</sup> In this perspective, the small contribution of the manufacturing sector to GDP may create question whether the industrial production index remains as an acceptable proxy for GDP in Bangladesh.

Apart from macroeconomic variables, this study has not considered the impact of many other factors such as the effectiveness of legal institutions, corruption due to insider trading, and political instability consequences, just to mention a few, on the stock market returns. The non-inclusion of such factors may also be considered as a limitation of the study. Furthermore, this study has focused on six macroeconomic variable which may not represent completely the macroeconomic condition of Bangladesh.

The underlying theories and prior empirical works have relied on the validity of various assumptions and to that extent, this study is not an exception. Like the previous studies, on relationship between stock market and macroeconomic variables, this study is also

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<sup>&</sup>lt;sup>1</sup> Source: Bangladesh Bureau of Statistics

based on following two fundamental assumptions: (1) financial markets are informationally efficient; and (2) market participants are rational.

#### **1.5 Rationale of the Research**

The current literature does not provide specific direction as to which macroeconomic variables affect stock market returns and to what extent (Chen et al., 1986). There are also unresolved theoretical and methodological issues. It is expected that a common set of macroeconomic risk factors will be identified from the empirical studies. But the existing literatures, coming from a wide range of different time periods and countries, fail to identify the common set of economic factors. So, there is a need for continuing research in this area.

In this context, this study has aimed to tackle this complex challenge of examining the relationship between stock market and macroeconomic indices in Bangladesh. By doing this, we have tried to identify the significant macroeconomic factors that affect Bangladesh stock market. Apart from identifying the significant macroeconomic factors, the research has also examined the relationship between stock market and macroeconomic indices of Bangladesh from different perspectives.

Firstly, a long-term equilibrium approach has been applied to address the question as to how some important macroeconomic variables are related with the stock market index in the long-run. The motivation behind this is that most of the institutional investors - like insurance companies or pension funds, have long-term investment horizons of several years or even decades. So, these investors are more interested in the long-term expected returns from stock market, rather than short-term fluctuations based on business cycles or investors' sentiment.

Secondly, even though there exists a significant long-run equilibrium relationship, there might be disequilibrium in the short-run. So, the study has also investigated the significance of short-run relationship along with the presence of error correction process which will adjust the short-term disequilibrium between the stock market and the macroeconomic variables to bring about a stable long-run equilibrium relationship.

Thirdly, the causal relationships between the selected macroeconomic variables and the stock market have been investigated to determine whether one series is useful for forecasting another. This is very crucial to the investors as well as to the policy makers. If the macroeconomic condition can be used as a reliable indicator for the stock market, then the macroeconomy can help investors in managing their investment portfolios. On the other hand, from the macroeconomic point of view, if stock market leads economy, then the policymakers could use stock market as a leading indicator to predict future economy.

Fourthly, this study has investigated the relationships between the stock market and the macroeconomic factors in different periods. These investigations have helped us describe the relationships in bubble, meltdown and recovery periods of the stock market. The relationships in these periods have been be assessed separately to compare the influences of the priced factors across the different periods. The study has also tried to identify the macroeconomic factors which have played the key role in bubble creation as well as in bubble crush.

Fifthly, considering two irrational fluctuations of stock prices in Bangladesh within one and a half decades, one in 1996 and other in 2010, and the size of their effects on households, banks and finally on overall economy, the knowledge on the nexus between the stock market volatility and the macroeconomic variables' volatilities has become very important to the investors and to the policy makers. So, the study has also focused on the relationship between the macroeconomic volatility and the stock market volatility using non-linear models.

Finally, stock market in Bangladesh and its economy has been going through numerous liberalization and deregulation processes since 1991, which has significantly increased the size of the economy as well as the stock market. In addition, Dhaka Stock Exchange (DSE) has been striving for continuous up-gradation of its trading platform since August 1998 to set the foundation for sustainable market development and to build up state-of-the-art market surveillance system to increase the transparency of market transactions to increase the investors' confidence. These initiatives are expected to enhance the interrelation between stock market and real economy of Bangladesh. In view of this, the study has aimed to examine the relationships between the stock market and the real economy during different market conditions. Moreover, the investigation has been extended further to examine whether the stock market's ability to predict the real economy has increased following the aforesaid initiatives or the stock is still not in a position to influence the real sector and hence further development is required.

#### **1.6 Research Methodology**

The study has aimed to examine the long- and short-run dynamic relationships along with the direction of causality between stock market and some important macroeconomic variables of Bangladesh. Towards this effort, different models have been formulated, using the secondary data of stock market and macroeconomic variables of different time span, according to the need of the study. Nelson and Plosser (1982) have argued that most macroeconomic series are nonstationary, meaning that these time series data evolve over time such that their mean and variance are not constant. They have showed that linear regression of such nonstationary time series data may lead macroeconomists to wrongly conclude that the variables are related when, in reality, they are not. This phenomenon is well known as spurious regression in the literature.

Later, it is thought that the typical method to analyze a nonstationary process is either to detrend or difference the data depending on the type of trend to make it stationary. Although these methods may provide stationary variables for the regression, but they can cause a serious loss of significant long-run information and omitted variables bias. In this context, Granger and Newbold (1974) have showed that de-trending does not work to eliminate the problem of spurious regression, and that the superior alternative is the use of cointegration approach.

There are different cointegration approaches available in the literature to investigate the long-run equilibrium relationship among variables based on the idea of Granger (1981). The most popular are the Engle and Granger (1987) and the Johansen and Juselius (1990) cointegration approaches. Later, the cointegration technique proposed by Pesaran et al. (2001), known as Auto Regressive Distributed Lag (ARDL), provides some econometric and estimation advantages over both Engle and Granger (1987) and Johansen and Juselius (1990) cointegration techniques.

In this study, both Johansen and Juselius (1990) and Auto Regressive Distributed Lag (ARDL) cointegration approaches have been used. These two approaches have been used to examine the long-run relationship among the variables and to check the robustness of the findings. However, tests for stationarity and deterministic trend of the time series are essential for the cointegration test. So, the empirical analysis of the study has begun with

testing the stationarity of the variables by applying different unit root tests. Then to check the trend specification of each variable, we have used loglikelihood ratio test.

To examine the short-run relationships among the variables and the speed of adjustment towards the long-run equilibrium relationship the Error Correction Models (ECM) have been used. Granger causality test has been applied to determine the direction of causality between macroeconomic variables and the stock market returns. Finally, different diagnostic and stability tests of the residuals have been employed to check the viability of the model and the stability of the long-run coefficients respectively.

This study has also examined the asymmetric relationship and the link between stock market volatility and macroeconomic variables' volatilities in Bangladesh using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models. Later, the GARCH family models have been used to estimate the conditional variance of each variable being studied, and then these conditional variances have been used to examine the cointegration relationship and the causality between the stock market volatility and the macroeconomic volatility.

#### **1.7 Organization of the Thesis**

The thesis is organized in seven chapters. Chapter 1 introduces the subject matter of the thesis. The chapter has described the background for studying relationship between stock market and macroeconomic indices. It also has articulated the objectives of the research, research questions, scope, limitation and assumptions of the dissertation, rationale of the study and the research methodologies.

The relevant literatures are reviewed, and research gap is established in Chapter 2. The relevant studies on different countries as well as on Dhaka Stock Exchange have been reviewed to oversee the findings on the relationship between macroeconomic variables and stock markets in different economies. More specifically, the literatures on relationship in line with our research questions have been reviewed and arranged separately to identify the gaps on various aspects of the relationships.

The theoretical framework is described in chapters 3. The chapter has outlined the economics of the stock market and has presented the economic theories relevant to this study. The theories related to the valuation of stocks from the perspective of portfolio theory, efficient market hypothesis, and rational expectations hypothesis are investigated. In addition, the basis of portfolio theory, the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT) are discussed in detail. The details of these theories along with empirical evidences and other relevant questions are covered in this chapter.

Chapter 4 is the first empirical investigation chapter of the thesis. In this chapter, we have investigated the long-run, short-run and causal relationships between the stock market and the macroeconomic variables using data over a period of twenty-five years (from January 1991 to December 2015). At the beginning, we have discussed the motivation of selecting the macroeconomic variables for the empirical analysis. After that, the methodologies to be used in the analysis have been described in detail. Finally, the findings of the empirical investigations are reported.

Chapter 5 has outlined the results of the statistical analyses on relationships between the stock market and the selected macroeconomic variables in the bubble, meltdown and recovery periods of the stock market. The relationships in these periods have been assessed separately to compare the influences of the priced factors across different conditions of the stock market. In this chapter, further investigations have been carried out to identify the macroeconomic factors which have played the key role in bubble creation as well as in bubble crush.

Chapter 6 has reported the findings of the investigations on the asymmetric relationship and the nexus between stock market volatility and macroeconomic volatility in Bangladesh. Moreover, the long- and short-term relationships between stock market and macroeconomic conditional volatilities are investigated in this chapter. The causal relationships between the stock market volatility and the macroeconomic variables' volatilities have also been examined.

In chapter 7, the relationship between the stock market and the real economy has been investigated. Explaining such a relationship involves assessing the direction of causality, hence the causal relationship between stock market and the real economy has also been investigated using Granger causality test. Furthermore, considering the crash of 1996 and subsequent capital market development initiatives, the study has been extended further to examine the relationship during different periods, viz., bubble, meltdown and recovery periods. The study has also examined whether capital market development initiatives have improved the efficiency of the stock market.

Finally, in the last Chapter (Chapter 8) a summary of the empirical evidence and findings obtained to answer the research questions has been presented. This chapter has also discussed the contributions of the research along with the policy implications of the study. The shortcomings which have emerged over the course of the research have been pointed out to outline the areas where further research could be done to address these issues.
# **Chapter 2**

# **Literature Review**

# **2.1 Introduction**

Perceiving the importance of influences of economic forces on stock market returns, many studies have been conducted on relationship between stock market and the macroeconomic forces for both developed and developing countries. Initially, studies on the determinants of stock returns have concentrated on developed markets. Later, the academics have turned their attention to developing countries, especially emerging economies, with the rapid development of capital markets in these countries. However, it is also valuable to review the previous studies on developed markets before exploring the existing literature on emerging markets.

In addition, the number of crashes in the stock markets and the size of their effects on households, banks and finally on economy have increased the interest of practitioners, regulators and researchers towards the study of the volatility of the stock market. Since stock market at aggregate level depends on the state of economy, so it is likely that an uncertainty about future macroeconomic conditions would introduce a change in stock market volatility. In view of this, the relationship between macroeconomic volatility and stock market volatility has received a considerable attention in the recent days. However, most of the researchers have studied the volatility of stock market in the context of developed economies, even though the risk return behavior analysis of stock market in the developing countries is of immense importance. Because these stock markets are smaller in size and relatively illiquid, which result in higher risk compared to the developed markets. This higher risk compels the risk averse investors to demand higher risk premium that results in higher cost of capital on investments, which slows down the economic growth of the country (Mala and Reddy, 2007).

In this perspective, literature review has been conducted on relevant previous and existing studies on different countries as well as on Dhaka Stock Exchange to examine the findings on the relationship between macroeconomic variables and stock market in different economies from the two aforesaid perceptions and in line with our research questions. It is essential to review the relevant empirical literatures, because this will assist us to choose the appropriate models, methodologies and important macroeconomic indices from the viewpoint of economy and stock market of Bangladesh.

Based on the research questions, the reviews are arranged in five sections. The first section describes literatures on long-term relationship and short-term dynamics between stock market and macroeconomic indices. Second section portrays the empirical works which have examined the causal relationships between different macroeconomic variables and stock market to examine whether one variable is useful for forecasting another. Literatures on the relationships in different periods, viz., bubble, meltdown and recovery periods, are reported in the third section. Fourth section describes the studies on relationship between macroeconomic indices and stock market volatilities. Fifth section focuses on studies on relationship between stock market and real economy. Finally, based on the literature review, the research gap has been identified in the conclusion.

## **2.2 Long-term Relationship and Short-term Dynamics**

Most of the empirical studies have examined the relationship between macroeconomic variables and stock market utilizing Arbitrage Pricing Theory (APT). However, different econometric models and methodologies have been used for this purpose. Most of the early studies are based on different regression techniques, while recent studies are using more sophisticated models - such as Vector Autoregression (VAR), cointegration techniques along with error correction model, and Autoregressive Integrated Moving Average (ARIMA). In this section, the early studies based on regression analysis will be discussed first and then the studies which have used more sophisticated methodologies will be described. Finally, the studies on Bangladesh stock market will be reviewed.

#### **2.2.1 Based on Regression Analysis**

Many of the early studies on relationship between economic forces and stock market were conducted pioneering the studies of Chan et al. (1985) and Chen et al. (1986) which have been conducted using US data. Most of the earlier studies have tried to examine the validity of these two studies in their countries.

The study of Chan et al. (1985), hereafter denoted as CCH, used Fama-MacBeth (1973) regression technique, which is a two-stage regression technique. The first set of regressions estimated the portfolios' exposures to pricing factors (betas) and the second set of regressions estimated the market prices for the beta values obtained from the first set of regressions. The result of this two-stage regression methodology was used to generate a time series of estimated premium for each risk factor. The time series of risk premium were then tested to see if these were significantly different from zero.

They tried to examine whether the returns on 20 size-ranked portfolios were related to the market portfolio and a few macroeconomic variables. They used data for the period 1953- 1977. For each test year from 1958 to 1977, the previous five-year intervals were considered as an estimation period (i.e., 1953-1957 was the estimation period for 1958,

1954-1958 was the estimation period for 1959, etc.). The sample of the study consisted of New York Stock Exchange (NYSE) firms that existed at the beginning of the estimation period and had price data up to the end of the estimation period. Firm size was defined as the market capitalization of the firm's equity at the end of the estimation period. Each firm was ranked by firm size and assigned to one of twenty portfolios.

They found that the risk premium for the equally weighted market portfolio was positive in each sub-period but not statistically significant. Over the entire period, they found significant premium for the industrial production, the expected and unexpected inflation, and the low-grade bond spread. The study highlighted that the difference in raw return between the smallest and the largest stocks was 11.5% per annum; however, the yearly risk-adjusted return difference was only 1.5%. They mentioned that almost half of this difference in raw returns could be explained by the spread between low-grade and government bonds, which was regarded as a measure of risk premia due to the change in risk exposure of the largest and smallest stocks. So, they argued that the firm size effect disappeared when the macroeconomic factors were considered. Hence, they concluded that the macroeconomic variables essentially captured the size effect.

Similarly, Chen et al. (1986), hereafter denoted as CCR, explored the impacts of a set of economic state variables on stock market using security-pricing model following APT. They used the Fama-MacBeth (1973) technique like CCH, but unlike CCH, the crosssectional regressions were run simultaneously with the time series regressions. That is, the time periods used to get estimates of betas by the time series regressions was the same time periods as those were used for the cross-sectional regressions. CRR used US data for the period 1958 to 1984. To reduce the noise of individual asset returns, 20 equally weighted portfolios based on firm size were formed.

They divided the whole study period into four sub-periods (1958-84, 1958-67, 1968-77 and 1978-84) and by employing seven macroeconomic variables, they found that the financial market did not price per capita consumption and oil prices. However, industrial production, changes in risk premium and twists in the yield curve were found significant in explaining stock returns. On the other hand, measures of unanticipated inflation and changes in expected inflation had some influence as well, but only when these variables were highly volatile.

They claimed that the study did not develop a theoretical foundation for signs of the state variables, but the results revealed that stock returns had positive relations with industrial production and changes in risk premium, while negative relations with twist in yield curve, changes in unexpected and expected inflation. Consistent with the study of CCH, they also reported that the value-weighted New York Stock Exchange Index, although explaining a significant portion of time series variability of stock returns, had an insignificant influence on stock pricing when macroeconomic factors were also considered. They argued that the variability of the stock market returns was included into the different macroeconomic variables used in the study. Further, they mentioned that the size effect, which was expected to be strongly related with the average return, did not create any bias to the results of the study.

Like CRR, Hamao (1988) employed Fama-MacBeth (1973) approach to present an empirical investigation of the Arbitrage Pricing Theory (APT) in the Japanese equity market using Japanese macroeconomic factors. Factors considered were industrial production, inflation, default risk premium, interest rate, foreign exchange, and oil prices. He argued that these variables were chosen in view of a simple financial theory of asset pricing. He tried to examine the international robustness of the CRR study and also to find out the risk premium for different priced and non-price factors in the context of Japanese economy.

The study used data for the period from January 1975 to December 1984. Out of a total of 1066 companies, some were excluded because of missing observations. In order to average out individual eccentricities in the data, stocks are grouped into 20 equally weighted portfolios with an approximately equal number of securities sorted by size. Like CRR, the cross-sectional regressions were run with the same time periods as time series regressions. He found that changes in expected inflation, unanticipated changes in default risk premium and unanticipated changes in the slope of term structure had a significant effect on the Japanese stock market, but the study documented weaker evidence of a risk premium against changes in monthly industrial production.

The study highlighted that signs of the risk premia were consistent throughout the analysis but opposite for expected and unexpected inflation compared to the results of CRR. The positive sign for inflation risk premia in this study indicated that stocks were more valuable with more inflation, other things being equal. On the other hand, Hamao included two additional macroeconomic factors - namely oil price and foreign exchange, but found both were not priced in the stock market. He opined that this was surprising considering the importance of international trade in the Japanese economy. Like CRR, he found that equally weighted market indices neither had statistically significant risk premium nor they captured extra systematic risk missed by other macroeconomic state variables. Finally, Hamao concluded that the risk premium on several factors showed the robustness of the approach of CRR in different but parallel economy like Japan.

Poon and Taylor (1991) used the data of the London Stock Exchange and considered the

same macroeconomic variables as CRR for the period from 1965 to 1984 to see whether the CRR study was applicable to UK stock market. But the results showed that the variables did not affect stock prices in UK in the manner described in CRR. They argued that there could be other macroeconomic factors for UK market, or the methodology in CRR was inadequate for detecting such pricing relationship or possibly both explanations were applicable.

Their study had pointed two cons of CRR study to explain why CRR study could not be replicated in UK. Firstly, they pointed that the study of CRR had mentioned that size could provide the desired dispersion without biasing the results of the economic variables. But Poon and Taylor argued that this might be valid for US but not for other countries, because the "size effect" could be a determining factor for most of the countries. They added that the validity of this argument was further strengthened from the findings of Hamao, who stated that some of his findings were opposite to the findings of CRR and mentioned these results as surprising considering the economy of Japan.

Secondly, Poon and Taylor (1991) argued that the time periods used in the first set of regressions to estimate the betas and using these betas to predict returns for the same periods using second set of regressions might create bias towards producing significant results and this also be contradictory to the spirit of the ex-ante orientation of the Fama-MacBeth method.

Clare and Thomas (1994) presented empirical evidence of the pricing of macroeconomic factors in the UK stock market using two different portfolio-ordering techniques. The month end returns (adjusted for stock splits, dividends, etc.) on 840 UK stocks were chosen randomly for the period from January 1978 to December 1990. They used the variant of Fama-MacBeth (1973) technique. First, the securities were grouped into 56 portfolios each comprised of 15 equally weighted stocks, and the excess returns were regressed on the macro surprises for the period from January1978 to December 1982, yielding 56 estimates for each beta. These betas were then used as independent variables in cross-section (for the period 1983 to 1990) regressions to provide estimates of risk premium associated with each macro variables.

The portfolios were ordered in two ordering methods in an attempt to assess the robustness of results to portfolio ordering. Firstly, they ranked the individual securities by their market betas, so the first portfolio consisted of those 15 stocks with the lowest betas, while the last portfolio consisted of those 15 stocks with the highest betas. Secondly, the stocks were ordered from small to large based on the market value of each firm as on 1st January 1978. Then 56 portfolios were formed based on size, so that portfolio 1 containing the smallest 15 firms and portfolio 56 containing the largest 15 firms.

For beta sorted portfolios, the study highlighted significant positive risk premium attached to the default risk, which was consistent with CRR finding, but in contrast with CRR, they found that shocks in inflation carry a positive risk premium. Also, they found negative risk premium for oil prices and they explained that this reflected the fact that the UK was a net exporter of oil. They included existing account balance in the list, which showed positive relation with risk premium. Finally, they documented a positive risk premium for the shocks in the amount of UK bank lending to the private sector, which reflected investors' dislike for expansions in bank credit. However, when market value ('size') sorted portfolios were used then default risk and the retail price index were priced. Most interestingly, they noted that the firm size ordering did not provide evidence for the "small firm effect" (as explained by Banz, 1981).

The foregoing studies has revealed that the studies of CRR and CCH have been considered as pioneer of many studies for exploring the relationship between the economic variables and the stock market. Unlike the three studies conducted by CRR, CCH and Hamao, the study of Clare and Thomas (1994) has used two portfolio ordering methods - based on size and betas. Their findings have revealed that beta sorted portfolio has provided more consistent results compared to the more conventional size sorted portfolio. This has indicated that the macro factors are sensitive to the ordering method chosen.

Nevertheless, Clare and Thomas (1994) have reported that larger firms' returns have outperformed smaller firms' returns, which is inconsistent with the study of Banz (1981). Reinganum (1982) has examined the differential return between small and large stocks between 1926 and 1989 to test their cyclical behavior. The study has revealed that the small capitalization portfolios outperformed the large capitalization portfolios, but this return behavior is volatile and tends to reverse itself. Similarly, Bhardwaj and Brooks (1993) have examined the size effect in bull and bear stock markets during 1926-1988 and have claimed that in bear market small firm stocks underperform large firm stocks, which is contrary to the evidence widely reported in prior studies. So, these studies suggest that firms' size could have varying impacts on returns depending on the stage of the market.

Buyuksalvarci (2010) analyzed the impact of macroeconomic variables on the Turkish Stock Market using the Arbitrage Pricing Theory (APT) framework. The study considered monthly data from January 2003 to March 2010 and used multiple regression models with stock market return represented by Istanbul Stock Exchange-100 Index as dependent variable and seven macroeconomic variables - namely consumer price index, money market interest rate, gold price, industrial production index, international crude oil price, foreign exchange rate and money supply, as independent variables.

The results of this study indicated that the Turkish stock market was negatively influenced by interest rate, industrial production index, oil price, and foreign exchange rate, while the impact of money supply was positive. Interestingly, he found consumer price index and gold price did not influence stock return. He argued that the market had evaluated inflation figures correctly before the announcement and to justify this argument, it was mentioned that the price stability was one of the macroeconomic policy objectives of the Turkish government. Considering gold as an alternative investment tool, a negative relation was expected. But the study found insignificant relationship, which was not explained.

However, the negative relations between stock returns and exchange rate was explained stating that a depreciation of the Turkish currency in terms of US dollars had not attracted foreign investments in stock market. Conversely, it had increased the cost of production. The study found relation between industrial production and ISE-100 index but with a wrong sign. The result of negative relation between oil price and stock market return was explained considering oil as a key factor in determining the production cost of the firms.

Singh et al. (2011) used GDP, employment rate, exchange rate, inflation and money supply as macroeconomic variables to determine the cause and effect relationship with stock return in Taiwan. The analysis was based on stock portfolios rather than single stock. In portfolio construction, four criteria were used: market capitalization, price to earnings ratio (P/E ratio), price to book value ratio (PBR) and yield. First, all the companies listed in Taiwan Stock Exchange were grouped into big, medium, and small companies based on market capitalization. Then from each of these groups, three sub-portfolios were formed based on P/E ratio, PBR, and yield.

They used data from 2003 to 2008 and considered the macroeconomic variables as the

independent variables and the individual portfolio return as the dependent variable and applied regression to calculate the impact of macroeconomic variables on stock market. The results showed that employment rate, inflation and money supply had negative relationships with stock returns, while GDP and exchange rate had positive relationships with stock returns for all the six portfolios of big and medium companies.

They argued that the findings regarding inflation rate and GDP were consistent with the bulk of empirical evidences. They explained the positive relation between exchange rate and the portfolios index returns mentioning that one of the probable reasons for this might be continuous expansion of foreign trade, with a pronounced increase in Taiwan's Trade Surplus. They highlighted the continuing loose monetary policy in Taiwan before 2006 along with the Central Bank's continued interest rate hikes as a reason for the negative relationship between money supply and portfolio index returns. However, for small size companies the results were slightly different - for P/E ratio portfolio, only exchange rate had positive relationship with stock returns; for yield portfolio, employment rate and exchange rate had positive relationship; while for PBR portfolio, exchange rate and inflation had positive relationships with stock returns.

Diacogiannis (1986) used data of London Stock Exchange for the period from January 1972 to December 1983 to verify whether the security return generating model utilizing Arbitrage Pricing Theory (APT) remained the same across security groups and across various time periods. The study was made with two objectives: firstly, it aimed to verify whether the number of factors affecting the security returns was related to the size of the group been factored. Secondly, the study examined whether the number of factors that influenced the security returns remained unchanged across various time periods for security groups having the same size.

In the study, 200 securities were listed in ascending order of size and five master groups, each consisting of forty securities, had drawn from these 200 securities. Further, seven subgroups were formed from each of the master group of samples containing 5, 10, 15, 20, 25, 30 and 35 securities respectively. The findings indicated that the number of factors changed as group size was changed and the number of factors also changed across various time periods for the same as well as for the different groups of securities.

Diacogiannis (1986) argued that the security return-generating model of Arbitrage Pricing Theory (APT) was not a unique one. He suggested that since APT did not specify the number and nature of the underlying factors that influenced the security returns, so there existed an identification problem. He also pointed that for specified group size, the security return-generating model produced by factor analysis did not represent a unique generating model of APT and this generating model could not necessarily test the validity of APT.

The finding of Diacogiannis (1986) has indicated that the security-pricing model of APT is dependent on group size and on time of the study. These two major findings can be explained with the existing financial theories and the behavior of the stock market. Firstly, although individual stock returns can be affected by influences that are systematic as well as nonsystematic to the economy but returns on large portfolios are mainly influenced by systematic risk because idiosyncratic risk on individual stocks are cancelled out through the process of diversification. But the benefit of diversification depends on the number of securities in the portfolio or group. This may be the reason of getting different results for different portfolio compositions by Diacogiannis (1986). Secondly, the diverse results across the periods have revealed the fact that investors have the tendency to react differently to the same type of news during different conditions of the stock market. For example, during a crisis in stock market, a slight fall in expected industrial production could initiate panic among investors and they hastily try to close their position causing an increase in stock market volatility, which may not happen in a long bull market.

The findings of the early literatures are summarized in Table 2.1. The summary reveals that the findings are diverse - different studies have found different relationships, even a single study has found varied relationships in different periods and different portfolio formations. This divergence of findings discloses the fact that the response of stock market to changes in economy, represented by macroeconomic variables, cannot be determined in advance as it varies across countries as well as across time within the same country.

The empirical studies have also disclosed that firm size is an important factor and size effect is dependent on stages of the stock market; in good economic condition, small firms usually grow faster than large and mature firms; but in the bad time, small firms tend to perform poorly (some even enter into bankruptcy). Different studies have provided the empirical evidence of the cyclical behavior of size effect. These studies have also depicted that the formation of portfolio on different criterion creates divergence in results.

Moreover, Clare and Thomas (1994) pointed that neither CCH nor CRR were concerned with econometric model to derive innovations in the series, rather they considered the changes in the growth of the variables as surprises. Although CRR suggested that a VAR model might be more appropriate and believed that single equation could be more robust, but they argued that since monthly returns were nearly serially uncorrelated, these could be employed as innovations without alteration. But Clare and Thomas (1994) mentioned that it was evident from the autocorrelation properties of the 'surprises' of CRR that highly significant lagged information was omitted from the generation of the innovations and this was clearly not consistent with the interpretation of these variables as 'surprises'.



#### **Table 2.1: Summary of the Findings of Early Studies on Relationship between Stock Market and Macroeconomic Variables**

\* For all 6 portfolios based on P/E ratio, Yield and PBR of big and medium capitalization firms \*\* For portfolio based on P/E ratio of small firms \*\*\* For portfolio based on Yield of small firms \*\*\*\* For portfolio based on PBR of small firms

In this context, with the availability of sophisticated econometric tools, such as Vector Autoregression (VAR), the cointegration and the ARIMA, recent studies have used these tools to investigate the relationship between stock market and macroeconomic variables. The VAR model can examine the lead-lag relationships among the variables and can also be considered as a means of conducting causality tests. Furthermore, Johansen and Juselius (1990) have proposed a testing procedure that can capture the short-term dynamics and long-term relationship among variables. However, the Johansen and Juselius (1990) approach can only be applied if the variables are integrated of order 1, *I(1)*.

Later, Pesaran et al. (2001) have developed a new approach to cointegration testing which is applicable irrespective of whether the variables are *I(0)* or *I(1).* The test is based on a single Autoregressive Distributed Lag (ARDL) equation, rather than a VAR in Johansen and Juselius approach, thus reducing the number of parameters to be estimated. Moreover, a dynamic error correction model (ECM) can be derived from ARDL through a simple linear transformation (Banerjee et al., 1993). The ECM integrates the short-run dynamics with the long-run equilibrium, without losing long-run information. Finally, the ARDL approach provides robust results for a smaller sample size. In the next section, we will focus on the literatures which have used these latest methodologies.

### **2.2.2 Based on Sophisticated Econometric Tools**

Mukherjee and Naka (1995) employed Johansen's (1991) Vector Error Correction Model (VECM) to examine the relationship between Tokyo Stock Exchange (TSE) index and six Japanese macroeconomic variables - namely the exchange rate, money supply, inflation, industrial production, long-term government bond rate, and call money rate. The sample period for this study spanned from January 1971 to December 1990, consisting of 240 monthly observations for each variable.

The study found positive relationship between TSE index and three macroeconomic variables, these were exchange rates, money supply and industrial production. The relation between TSE index and inflation was negative. But interestingly, the findings of the study showed a mixed relationship between TSE index and interest rates. While the relation between the TSE index and long-term government bond rates was negative, the opposite seemed to hold between the TSE index and call money rates. They argued that possibly in Japan the long-term government bond rate had served as better representative for the nominal risk-free component of the discount rate in the stock valuation model than the short-term call money rates.

To check the robustness of the results to the selection of macroeconomic variables, they took six possible combinations of five microeconomic variables chosen from the original set of six. For each of these five combinations of microeconomic variables, the study explored the relations in six-dimension systems (the TSE index and five macroeconomic variables). The study found at least one cointegrating relation in each system. To examine the equilibrium relations over sub-periods the sample data was divided into two subperiods having equal numbers of observations (from January 1971 to December 1980 and from January 1981 to December 1990). The result indicated three possible cointegrating relations for the first sub-period and two for the second sub-period. In this context, they argued that their findings are robust to the selection of microeconomic variables and the sub-periods.

Adrangi et al. (1999) conducted empirical tests within Fama's proxy hypothesis framework, which stated: (1) a negative relationship between inflation and real activity; and (2) a positive relationship between the real stock returns and real activity. They selected Korea and Mexico for their study and argued that these two countries were selected because these two countries were at dissimilar stages of implementing market economy; Korea was one of the first emerging market economies to introduce economic reforms in the mid-1980s, while Mexican economy was mired in chaos during 1980s. However, they added that in the early 1990s the Mexican economy was relatively healthy. They argued that these two economies might represent two emerging economies at dissimilar stages of development.

The period of this study covered from January 1978 to March 1996 for Korea and from August 1985 to December1995 for Mexico and the index of industrial production was selected as a proxy for the real economic activity in both the markets. To derive the expected and unexpected components of inflation rate, they employed two commonly used statistical approaches, Hodrick-Prescott filter (HP) and ARIMA. They mentioned that these two approaches had been adopted as the series for expected inflation rate were unavailable in developing economies.

Their findings revealed that the expected inflation was negatively related to stock market and significant for Korea but positively related and insignificant for Mexico. On the other hand, unexpected inflation in both markets were negatively related to real stock returns but it was significant for Korea only. So, they argued that these results did not unequivocally validate the proxy hypothesis. They stated that the negative relationship between inflation rates and real stock returns in both markets seemed to stem from the unexpected component of the inflation rate.

The negative relationship between the real stock returns and inflation rate for Korea persisted even after the negative relationship between inflation and real activity were purged. To explain these, they stated that the real stock returns might be adversely affected by inflation because (1) inflationary pressures had threaten future corporate profits; and (2) nominal discount rates rose under inflationary pressures, reducing current value of future profits, and thus, stock returns. The study also found that real returns are positively related to real economic activity for both Korea and Mexico.

They also applied Johansen and Juselius (1990) cointegration approach to examine the long-run equilibrium relationship among price level, industrial production, and stock prices in each of the two countries. The results showed some evidence of a long-run equilibrium relationship among stock prices, inflation, and industrial production in both economies consistent with the proxy effect hypothesis. So, they argued that the proxy effect hypothesis might be valid in the long-run and yet not in the short-run.

Ibrahim and Aziz (2003) considered the interactions between the Malaysian equity market and four macroeconomic variables – namely real output, price level, money supply and exchange rate. The study used monthly data for the period from January 1977 to August 1998. They employed Johansen and Juselius cointegration approach and vector autoregression techniques. To measure stock market returns, they used end-of-the-month values of the Kuala Lumpur Composite Index (KLCI). They represented real output by real industrial production index (IPI), the aggregate price level by the consumer price index (CPI), money supply by broad money M2, and bilateral Ringgit exchange rate vis-a-vis US dollar as a measure of the exchange rates.

They found that the stock prices had long-run positive relationships with industrial production index and CPI. They explained that the positive relation between CPI and stock return was consistent with the finding of Khil and Lee (2000), where Malaysia was found as only country out of ten Pacific-rim countries which exhibited a positive association between CPI and stock return.

They found a negative long-run association between stock prices and money supply M2. They argued that theoretically the relation between these two variables could be positive or negative. Because the expansionary effect of money supply on real economic activity might create a positive relation (Mukherjee and Naka, 1995). However, if the increase in money supply initiated inflation as well as created inflationary uncertainty, then it might exert a negative influence on the stock prices. They added that the increase in money supply might have generated inflationary uncertainty causing equity prices to fall (Cornell, 1983). They argued that their negative long-run coefficient seemed to indicate the dominance of these negative channels.

A surprising aspect of the results was that they found money supply was negatively related to stock prices, while consumer price index was positively related to stock prices. They explained this dissimilarity by mentioning that the expansionary effect of money supply had affected the stock prices through two channels: (1) by creating inflationary pressures; and (2) by creating expectation of contractionary monetary policy in near future. The first channel had created positive impact on stock prices due to the positive relation of inflation with stock prices, while the second channel had created negative impact on stock prices as the expected contraction had generated higher risk premium for investing stocks. Finally, they concluded that the dominance of the second channel had resulted the negative relationship between money supply and stock prices.

The negative association between stock prices and the exchange rate was explained by mentioning that Malaysian economy was highly dependent on international trade, i.e. on exports and imports of capital and intermediate goods, while currency depreciation had encouraged exports, conversely, it increased costs of production through increasing domestic prices of imported capital and intermediate goods. The latter effect of currency depreciation on expected cash flows of the firms seemed to be more dominant.

Maysami et al. (2004) highlighted a void in the literature related to examining the cointegration between macroeconomic variables and stock market's sectoral indices rather than the composite index. Their study built upon and extended the literature to examine the long-run equilibrium relationship between selected macroeconomic variables and the Singapore stock market index, as well as with three sectoral indices, which were the finance index, the property index, and the hotel index.

The study considered six macroeconomic variables - namely short- and long-term interest rates, industrial production, inflation, exchange rate and money supply. The results showed that the aggregate stock market was significantly positively related to industrial production and money supply, while negatively related to exchange rates and long-term interest rates. On the other hand, the finance sector was significantly positively affected by inflation and short-term interest rates, while negatively affected by exchange rates and long-term interest rates. The impact of changes in money supply to the finance sector was weaker as compared to the aggregate stock market. The results for property sector were similar to the aggregate stock market with an exception that short-term interest rates were significant; they pointed that this supported the findings of Wang and Liow (1999) who reported a strong co-movement of the returns of property stocks and the general market.

The results of hotel sector were curious because except for real economic activity, all other relations were opposite of those observed for the aggregate stock market. The results highlighted short- and long-term interest rates as well as the money supply did not have significant effects on the Singapore Hotel Index. Their finding of significant positive relation between the Hotel sector and the exchange rate was explained with the argument that the depreciation of the currency was deemed favorable for the Singapore tourism industry as the hotel rates had become relatively cheaper in terms of foreign currencies and hence had increased the demand. The finding of negative relation between inflation and hotel sector was explained with the justification that controlling inflation had ensured the competitiveness of the tourism sector of the country.

Humpe and Macmillan (2007) examined whether a number of macroeconomic variables influence stock prices in the US and Japan. A cointegration analysis was applied to model the long-term relationships between industrial production, the consumer price index, money supply, long-term interest rates and stock prices in the US and Japan. They used monthly data over the period from January 1965 to June 2005 to analyze the impact of the macroeconomic factors on both stock markets.

Using US data, they found a single cointegrating vector between stock prices, industrial production, inflation and the long-term interest rate. They pointed that the coefficients of long-run equation suggested that US stock prices were influenced, as expected, positively by industrial production and negatively by inflation and the long-term interest rate. However, they found that the money supply had an insignificant influence over the stock prices in US. They pointed that money supply was likely to influence share prices through at least three mechanisms: firstly, changed in the money supply might be related to unanticipated increases in inflation and future inflation uncertainty and hence negatively related to the share price, secondly, changes in the money supply might positively influence the share price through its expansionary impact on economic activity, thirdly, portfolio theory also suggested a positive relationship, since an increase in money supply

might create a shift from interest bearing money to equities. Their findings of insignificant impact of money supply were explained suggesting that the various influences of the money supply on the stock price might 'cancel out' each other.

In Japan, their findings were less straightforward. They found two cointegrating vectors. The first cointegration vector, normalized on the stock prices, provided evidence that stock prices were positively related to industrial production but negatively related to money supply. The second cointegrating vector, normalized on industrial production, indicated that the industrial production were negatively influenced by the consumer price index. So, the finding suggested that the influence of inflation on stock prices was negative but indirectly, via industrial production. They pointed that this result was surprising and different from that of Mukherjee and Naka (1995), who found a negative coefficient on inflation for a cointegrating vector normalized on the stock prices.

They argued that one reason for this difference might be the longer sample period; while Mukherjee and Naka used data from the period 1971 to 1990, which corresponded to a period of relatively high inflation in Japan (after the impact of the 1973 oil price shock) and stable growth in industrial production. On the other hand, their study considered sample from January 1965 until June 2005 which included the period of strong disinflation (in the late 90s) and falling stock price (the downturn of Japanese stock market in the early 90s) with stagnant but volatile industrial production.

They also found that the discount rate was insignificant, and they explained this unexpected result arguing that this might also be, at least partly, due to the difficulties faced by the Japanese economy since 1990. Finally, they mentioned that their results on Japan were consistent with an increasing money supply, falling interest rate that were unable to pull Japanese economy out of its slump, or prevented stock prices from falling.

Mohammad et al. (2009) studied the impact of macroeconomic variables on stock prices in Pakistan. For this purpose, the quarterly data were obtained for the period 1986-2008. The macroeconomic variables considered were exchange rate, foreign exchange reserve, gross fixed capital formation, broad money M2, Call Money Rate (proxy of interest), Industrial Production Index (IPI) and whole sales price index (proxy of inflation). They used Autoregressive Integrated Moving Average (ARIMA) model for testing.

The result showed that the exchange rate, foreign exchange reserve and inflation had positive significant effects on the stock prices, while interest rate and money supply had significant negative effect on stock prices. However, the other variables like industrial production index and gross fixed capital formation did not affect stock prices. They explained that the positive relation between exchange rate and stock return revealing the fact that depreciation of domestic currency had increased the foreign investments in the stock market, which had increased the demand of stocks and thus the value. This increased in foreign investment had increased the foreign exchange reserve showing a positive relation between the foreign exchange return and stock prices.

Chia and Lim (2015) investigated the response of the Malaysian stock market on selected macroeconomic variables - namely industrial production, inflation, money supply, interest rate and exchange rate, using the Autoregressive Distributed Lag (ARDL) Bounds test. The results indicated that share prices were cointegrated with the selected macroeconomic variables. Moreover, the long-run coefficients suggested that Malaysian share prices were influenced positively by money supply and interest rate and negatively by inflation. On the other hand, the results from the error correction mechanism revealed that real share returns were Granger caused by real money growth and real interest rate growth. When exchange rate was included in the estimation, the results indicated that exchange rate fluctuations could also cause movement in stock prices. They concluded that domestic macroeconomic activities had influenced the Malaysian stock market.

Joshi and Giri (2015) examined the dynamic long- and short-run relationship between stock prices and a set of macroeconomic variables for Indian economy with monthly data from April 2004 to July 2014 using the ARDL Bounds testing approach. The Bounds test confirmed that there existed a long-run cointegrating relationship between different macroeconomic variables and stock prices in India. The long-run estimates of ARDL test showed that industrial production, inflation and exchange rate influenced stock prices positively and the influences were significant, while gold price had significant negative influence on stock price. Thus, they concluded that industrial production, exchange rate, inflation and gold prices seemed to be suitable targets for the government to focus on to stabilize the stock market and to encourage more capital flows into the capital market. The error correction model of ARDL approach revealed that the adjustment process from the short-run deviation was slow. More precisely, error correction term confirmed that the derivation from the long-run equilibrium path was corrected 22% per year.

The findings of the studies, which have used sophisticated models, are summarized in Table 2.2. The summary has revealed that the findings are diverse  $-$  i.e., different studies have found different relationships in different countries as well as across different sectors in the same country. Also, a single study has found varied relationships for different countries. This divergence of findings has disclosed the fact that the response of stock market to macroeconomic variables cannot be determined in advance as it varies across countries. So, there is a need for continuing research in this area.



**Table 2.2: Summary of the Findings of Studies on Relationship between Stock Market and Macroeconomic Variables using Sophisticated Econometric Tools** 

 $K$  For Korea  $M$  For Mexico  $U$  For US <sup>A</sup>For Aggregate Market <sup>F</sup> For Finance Sector  $P$  For Property Sector  $H$  For Hotel Sector

 $\frac{U}{P}$  For Japan<br><sup>P</sup> For Property Sector



### **Table 2.2: Summary of the Findings of Studies on Relationship between Stock Market and Macroeconomic Variables using Sophisticated Econometric Tools (Cont'd)**

 $K$  For Korea  $M$  For Mexico  $U$  For US  $A$  For Aggregate Market F For Finance Sector P For Property Sector  $A$  For Hotel Sector

 $\frac{U}{P}$  For Japan<br>
P For Property Sector

#### **2.2.3 Based on Bangladesh**

Quadir (2012) examined whether the return of Dhaka Stock Exchange (DSE), represented by stock market indices, could be explained by two macroeconomic variables -namely interest rates and industrial production. The study considered monthly averages of respective stock market indices, T-bill rate and industrial production from January 2000 to February 2007. The Autoregressive Integrated Moving Average (ARIMA) time series process was applied to determine the relationship between the dependent variable (stock market return) and independent variables (industrial production and interest rate). The study hypothesized a positive relationship between the industrial growth and stock return and a negative relation between stock return and T-bill rate. But they found that the stock market returns had statistically insignificant relationships with T-bill rate and industrial production. This inconsistency of the result with the existing literature was explained with stating that many of the macroeconomic variables, such as inflation rate, exchange rate, money supply, balance of trade and consumer price index, which were influential in determining the value of stocks, were not considered in the study.

Khan and Yousuf (2013) investigated the long-term relationship between macroeconomic variables and the Dhaka stock market prices using Johansen multivariate cointegration analysis and Vector Error Correction Model. They used data from January 1992 to June 2011 and macroeconomic forces were represented by interest rates, exchange rates, consumer price index, crude oil prices and money supply, while the Dhaka Stock Exchange All-Share Price Index was used to represent the Dhaka stock market prices.

The main finding of the study indicated a long-term relationship between the stock prices and macroeconomic variables. The long-run equilibrium equation disclosed that interest rate was positively related with the stock prices, which was unexpected as higher interest rates, theoretically, shift investors away from stocks and vice versa. They argued that this converse result was not uncommon in the literature; Mukherjee and Naka (1995), Maysami and Koh (2000), and Bulmash and Trivoli (1991) found a positive relation between shortterm interest rates and stock prices, and a negative relation between long-term interest rates and stock prices. They opined that the increase in short-term interest rates might give the signal to fall in the future, which instigated the investors to buy more stocks now since fall in interest rate in near future would increase the stock prices.

The study showed that the exchange rate was negatively related with the stock price, which was unexpected. They hypothesized that the depreciation of Bangladesh currency (BDT) against US dollar should result in increasing foreign investment in the stock market, and would increase the stock prices. To explain this converse relationship, they pointed to the findings of some literatures, where the negative relationship between the exchange rate and stock prices was described with the argument that depreciation of currency resulted in increased imported raw materials and capital goods cost and thereby had increased the cost of production of the forms.

The impact of consumer price index was found negative, but insignificant. They argued that large inflation in Bangladesh might render this insignificant relationship. The relationship between crude oil prices and stock prices was found positive and significant. They opined that this was consistent with some recent studies, although inconsistent with theory. The positive relation of money supply with the stock prices was explained by the expansionary effect of the money supply. They found that the relationships of stock prices with interest rates, exchange rates and consumer price index were robust, while with money supply and oil price were sensitive to lag length. The short-term results of VECM revealed that the stock return and macroeconomic variables were insignificant at most lags. Ahmed and Imam (2007) investigated long-term equilibrium relationship as well as shortrun dynamic adjustment of such relationship between a group of macroeconomic variables and stock market of Bangladesh. They used monthly data for the period from July 1997 to June 2005. The stock market was represented by market index and the macroeconomic variables were represented by the industrial production index, broad money supply, interest rate, T-bill rate and GDP.

They found no cointegration between stock market prices with industrial production index, money supply and GDP. However, when one additional variable - interest rate was added with the previous model, a significant long-run relationship was observed. Furthermore, industrial production index, GDP and interest rate were positively related with stock index, however, relation was statistically insignificant for industrial production index. On the other hand, money supply (M2) was positively and significantly related with stock market index. Similarly, instead of interest rate when T-bill rate was considered, the model provided almost same results with only one exception that T-bill had negative relation with stock market index. The results of the Vector Error Correction model showed no convincing argument in favor of the short-run adjustments. The Granger causality test provided a unidirectional causality from interest rate change to stock market return.

Ali (2011) investigated the long-run equilibrium, short-run dynamic adjustment as well as causal relationship between the all share price index of Dhaka Stock Exchange (DSE) and the macroeconomic variables including consumer price index (CPI), Gross Domestic Product (GDP), foreign remittances, and import payment. He employed Johansen and Juselius (1990) cointegration approach to examine long-run equilibrium relationship and Vector Error Correction Model (VECM) to test short-run dynamic adjustment towards equilibrium among the variables.

Finally, Granger (1988) causality test was performed to identify the causal relationships among the variables. The data used for this investigation included monthly data series for the period from January 1987 to December 2010. He pointed that due to unexpected abnormal behavior of stock prices at Dhaka Stock Exchange (DSE) during the period from January 1996 to June 1997 (total 18 months), these monthly observations were excluded from the analysis.

The results of the study indicated that there existed one cointegrating equation among the variables at 5 percent significance level. The long-run equation showed that the stock market prices were influenced positively by consumer price index (CPI) and foreign remittances (REMIT). Conversely, gross domestic product measured at current market price (GDPMP) and import payment (IMPMT) affected the stock market prices negatively. The Vector Error Correction Model (VECM) showed a short-run dynamic adjustment rate of 5.98 percent per month indicating a slower adjustment towards long-term equilibrium, thus revealing weak form of efficiency in Dhaka Stock Exchange.

From the summary of the findings of different studies (see Table 2.3) on Bangladesh, we can conclude that the results are also diverse for Bangladesh. Furthermore, most of the studies have employed Johansen and Juselius (1990) cointegration approach to examine long-run equilibrium relationship and Vector Error Correction Model (VECM) to test short-run dynamic adjustment towards equilibrium among the variables. We have not found any study on relationship between macroeconomic variables and stock market on Bangladesh which has used the ARDL approach. This study has used ARDL cointegration approach along with Johansen Juselius test. Use of ARDL has assisted not only to check the robustness of the results but also has helped to examine the cointegration when the variables are not integrated in the same order.

### **Table 2.3: Summary of the Findings of Studies on Relationship between Stock Market and Macroeconomic Variables on Bangladesh**



## **2.3 Causal Relationships**

There are evidences that stock prices are driven by macroeconomic variables, the so-called "fundamentals" of the economy. Furthermore, another issue in the interpretation of this relationship is very important, which is whether the relationship is a contemporaneous or lead-lag relationship. Many studies on the relationship between stock market return and macroeconomic variables has also examined whether macroeconomic variables can be used to predict future stock market movement or stock market can be used to predict future macroeconomic conditions.

Gunasekarage et al. (2004) examined the influence of macroeconomic variables on equity values in Sri Lanka. They used the Colombo All Share Price Index to represent the stock market and the macroeconomic variables were represented by money supply, treasury bill rate (as a measure of interest rates), consumer price index (as a measure of inflation), and exchange rate. With monthly data from January 1985 to December 2001 and using unit root test, cointegration, and Vector Error Correction Model (VECM), they examined both long- and short-run relationships between the stock market index and the macroeconomic variables.

The results of study indicated that at least one cointegrating relationship existed among these variables. Therefore, the causal relationship between the market index and macroeconomic variables was examined using the VECM specification. The results provided some support for the argument that the lagged values of changes in macroeconomic variables Granger caused variations in the share price index for Sri Lanka. They found statistically significant negative influence of inflation at lag 3, positive influence of growth on money supply at lag 1, and consistent negative influence of interest rate on the stock prices. Surprisingly, the result indicated that the exchange rate did not have any influence on stock prices. They argued that though the devaluation of the local currency throughout the sample period provided attractive investment opportunities in the stock market to foreign investors, but practically the limited participation of foreign investors in share trading activities of the Colombo Stock Exchange might be the reason for the absence of any relationship.

The study revealed that in case of reverse causality from the market index to economic variables, the market index did not exert any lagged influence on macroeconomic variables except interest rate. They opined that the negative bilateral relationship between the Treasury bill rate and the stock index might indicate that the local investors employed a market timing strategy and shifted their funds between the risk-free asset and risky securities using their predictions about the movements of the returns on these two assets. The results of the variance decomposition analysis indicated that a major proportion of the variability in the market index was explained by its own innovations, while only a minority was explained by macroeconomic variables. They pointed that this might be for the subset of the total macroeconomic variables used in this study.

Ali (2011) investigated the long-run equilibrium, short-run dynamic adjustment as well as causal relationships between the all share price index of Dhaka stock Exchange (DSE) and the macroeconomic variables including consumer price index (CPI), Gross Domestic Product (GDP), foreign remittances, and import payment. The Granger (1988) causality test was performed to identify the causal relationships among the variables. The data used for this investigation included monthly data series for the period from January 1987 to December 2010. The results of the Granger causality provided unidirectional causal relationships from CPI and foreign remittance to DSE Index, bi-directional causality between import payment and stock index, and no casual relation between GDP and stock index. He pointed that the no causal relation between GDP and stock index was consistent with the test performed by Ahmed and Imam (2007).

Joshi and Giri (2013) investigated the relationship between stock prices and macroeconomic variables in India. They employed multivariate cointegration test and the Granger causality test to examine the relation between the Bombay Stock Exchange (BSE) Sensitivity Index (SENSEX) and the macroeconomic variables. The macroeconomic variables selected were 91 days T-bill rate, Foreign Institutional Investors, Reserve Money, Money Supply (Narrow Money-M1, Broad Money-M3), Gold Prices, Crude Oil Prices, Index of Industrial production, Foreign Exchange Reserve, and Real Effective Exchange Rate.

The findings from Granger causality based on the Vector Autoregression (VAR) Framework indicated that Foreign Exchange Reserve and 91 day T-Bill Granger caused stock price but stock price did not Granger cause either of the two so the causations were unidirectional, and there were no causal relationships between Real Effective Exchange Rate, Foreign Institutional Investors, Index of Industrial Production, Crude Oil Prices, Gold Price, Money Supply (Narrow Money-M1, Broad Money-M3), and Reserve Money to BSE Sensitivity Index. So, they concluded that the stock market could not be used as a leading or lagging indicator for the selected macroeconomic variables.

Tangjitprom (2012a) examined the relationship between stock market return and macroeconomic variables in Thailand. He used four macroeconomic variables, which were unemployment rate, interest rate, inflation and exchange rate. He used normal regression model to find the relationship between the stock market return and the macroeconomic variables. The Vector Autoregression (VAR) model was used to examine the lag structure of the above regression model. Also, Granger causality tests were conducted to reexamine the lead-lag relationships among the variables. Finally, the variance decomposition was used to examine the impacts of innovations of each of the macroeconomic factors to the overall stock market and sectoral level.

He used monthly data of the variables for the period from January 2001 to December 2010. Due to unavailability of monthly GDP data in Thailand, the monthly unemployment rate was used to represent the general business condition and business cycle factor, while interest rate, inflation and exchange rate were represented by a five-year government bond yield, monthly consumer price index, and the nominal exchange rate between Baht and US Dollar respectively.

The results of the regression showed, as expected, two macroeconomic variables - interest rate and exchange rate, were significantly related with stock market return. While unemployment rate and inflation were not significant. He pointed that though both unemployment rate and inflation normally should carry valuable information about general business condition and cyclical factor but surprisingly these variables were not found significant to explain the stock market performance. He explained that it happened due to timing gap problem of the available data. He pointed that data about stock market, interest rate and exchange rate were available day-to-day, but that of unemployment rate and consumer price index were not available immediately.

So, he re-estimated the regression using two-month lagged of unemployment rate and inflation. The results revealed that unemployment rate slightly Granger-caused the stock market return, but the opposite was not true indicating that the change in unemployment rate could be used to predict the future stock market return, but the stock return could not help to predict the future unemployment rate. On the other hand, interest rate Granger caused the stock market return and stock market return also Granger caused the interest rate. However, both inflation rate and exchange rate did not Granger cause stock market return but stock market return Granger-caused both inflation and exchange rate. Therefore, the results highlighted that stock market return Granger caused most of the macroeconomic variables. So, they concluded that the performance of stock market was a good indicator to explain the future macroeconomic situation. He mentioned that this result was consistent with the report of Bank of Thailand, where stock market index was used as the leading economic indicator.

For sectorial index, he found that the sensitivity of each industry to macroeconomic variables was different from other industries. He pointed that because of the requirement of high capital investment, the importance of interest rate was very high for some industries like Automobile, Petrochemical, Household Products and Transportation. On the other hand, he found that some industries like Personal Care were more sensitive to unemployment rate, and some industries were less sensitive to any of the macroeconomic variables.

It is revealed from the literature review that the informational efficiency of major stock markets has been extensively examined through the study of causal relationships between stock market indices and macroeconomic aggregates. The findings of these studies are important since informational inefficiency in stock market implies on the one hand, that market participants can develop profitable trading rules and thereby can consistently earn more than average returns, and on the other hand, that the stock market is not likely to play
an effective role in channeling financial resources to the most productive sectors of the economy.

In an efficient capital market security prices adjust rapidly to all available information and, therefore, the current prices of securities reflect all information about the security. Moreover, economic theory suggests that stock prices should reflect expectations about future corporate profits and corporate profits generally depend on future prospect of the economy. Therefore, it can be concluded that, in an informationally efficient market, past (current) information about the economic activities are not useful in predicting current (future) stock prices. However, the causality from lagged values of stock prices to economic activities does not violate informational efficiency, this finding is equivalent to the existence of causality from current values of stock prices to future levels of the economic variable. This would suggest that stock prices lead the economic activities and that the stock market makes rational forecasts of the economy.

If, however, lagged changes in one economic variable cause current variations in stock prices and past fluctuations in stock price also cause current variations in the economic variable, then a bi-directional causality is implied between these two series. This behavior indicates stock market inefficiency. In contrast, if changes in the economic variable neither influence nor are influenced by stock price fluctuations, then the two series are considered as independent of each other and the market is termed as informationally efficient.

In this study, literature on causal relationships are reviewed and summary of the results is reported in Table 2.4. From the summary, it is evident that the findings on causal relationship between stock market and macroeconomic variables are mixed. So, there is a need for continuing research in this area.



### **Table 2.4: Summary of the Findings on Causal Relationship between Stock Market and Macroeconomic Variables**

### **2.4 Relationships during Bubble, Meltdown and Recovery Periods**

Critics argue that stock market does not always accurately reflect the underlying fundamentals of the economy, especially, when speculative bubbles and subsequent crashes emerge in the market (Binswanger, 1999). The author has argued that under such situations, prices of stock are no longer driven by macroeconomic fundamentals rather they tend towards irrational behavior. So, explaining the price pattern becomes a challenge during the crisis of the stock market. Yet extreme price movements - at odds with any reasonable economic explanation, are observed throughout history. Considering the adverse effect of these extreme price movements on economy, may studies have explored the reasons behind these irrational fluctuations.

Kazuo (1995) mentioned that since the 1950s, Japan's stock market has gone into bubbles every ten years or so (early 50s, early 60s, and early 70s). However, the bubble of 1980s was very strong and went on for several years (late 1982 to the end of 1989). He tried to investigate the causes of this strong bubble using quarterly data for the period from 1981 to 1994. The study examined the stock-price formation in Japan in the 1980s and the early 1990s. He applied the fundamental equation to decompose the changes in stock prices due to the changes in the earnings of the stocks, interest rates, and stock price appreciation expectations.

The study revealed that the key factor was the nominal interest rate which continued to decline until the late 1980s due to the extremely relaxed monetary policy pursued by the Bank of Japan. In addition, investors' stock price expectations added to the effect of low interest rates. In fact, the expectations factor played the leading role in the beginning and end of the bubble period, as well as in the post-bubble period, while more blame must be given to the interest factor during the bubble period.

He argued that in the 1980s, the Japanese economy faced a macroeconomic contradiction - a low rate of goods inflation and a high rate of asset inflation. He explained this apparent contradiction mentioning that the double-digit rate of money growth did not lend itself to goods inflation. Instead, it gave rise to asset inflation, both in stock price and in land price.

The study of Azeez and Yonezawa (2006) tried to examine the effect of macroeconomic factors on stock returns under pre-bubble, bubble and post-bubble conditions. They used McElroy and Buremeister (1985) framework to explore whether macroeconomic factors were priced source of risk using monthly data for the period 1973-1998. They argued that the study had considered data over a relatively longer period compared to other studies on the Japanese stock returns. Particularly, they pointed that the bubble economy of Japan in the late 1980s was well known and its impact continued even during the time of the study not only on the financial market but also on the whole economy. This motivated them to investigate the causes of asset-price fluctuations during that period.

To identify systematic influences on stock returns under the bubble period, they used 10 years data from January 1980 to December 1989. The rest of the periods were considered as pre-bubble period (1973–1979) and post-bubble period (1990–1998), and separately assessed to compare the priced factors of these periods with bubble period. The dependent variables were monthly returns expressed in excess of risk-free rate on 28 industry portfolios (as per the classification of the Tokyo Stock Exchange). The industry portfolio returns are fully adjusted for dividends. The macroeconomic factors considered were unanticipated shocks to money supply, inflation, industrial production, term structure of interest, and exchange rate.

They found negative risk premium for inflation and exchange rates, while positive risk

premium for industrial production, money supply, and term structure of interest rate in all sample periods. However, money supply, inflation, exchange rate, and industrial production had significant influence on stock returns in all sample periods. On the other hand, the term structure of interest rates was significantly priced over the bubble period and insignificantly priced both in pre-bubble and post-bubble periods.

Although the number of priced factors and the signs of risk premiums were approximately stable across each period, but the magnitudes of risk premiums in absolute values increased during the bubble and post-bubble periods compared to pre-bubble period. Meanwhile, the variances of macroeconomic factors were not increased in the bubble period. They pointed that the higher risk premiums during the bubble and post-bubble periods could be due to the increase of bubble crash risk.

Finally, they pointed that over the bubble period during the 1980s, factors that were pervasive and carried a reward for systematic risk were those that were likely to be directly affected by monetary policy, specifically the money supply factors. Because in the loose monetary policy, money supply grew at a double-digit rate, but interest rates were kept at low level. They argued that these results were consistent with Kazuo (1995), who argued that the most important single factor for raising Japan's stock prices was Japan's low interest rate.

Asekome and Agbonkhese (2015) examined the macroeconomic variables that contributed the market's bubble, burst, and its gradual recovery. The study covered a period of 24 years from 1990 to 2013 during which the Nigeria stock market witnessed a remarkable market bubble and eventual melt down when the market capitalization of 12.6 trillion Nigerian Naira during the month of March 2008, dropped to 6.96 trillion Nigerian Naira in the month of December and crashed to 4.48 trillion Nigerian Naira in the month of March 2009. However, as at the end of December 2013, the market recovered gradually with market capitalization increased to well over 13.6 trillion Nigerian Naira.

They used Nigerian Stock Exchange (NSE) value index as the dependent variable, while gross domestic product, money supply (M2), exchange rate, capacity utilization and inflation were used as independent macroeconomic variables. The results indicated that the coefficients of gross domestic product and exchange rate had the correct signs and in conformity with the theoretical expectations. However, money supply (M2) and capacity utilization had negative signs instead of a positive, while inflation had a positive sign instead of a negative sign. Nevertheless, the coefficients of GDP and money supply (M2) were statistically significant, while exchange rate, capacity utilization and inflation were not significant. The result further showed that regressors could explain about 97 percent of the systemic variations of all share index (ASI) during the period.

They argued that the negative sign exhibited by the money supply might be due to the fact that a reasonable portion of the total deposit mobilized by the deposit money banks (DMBs) did not translate to the domestic economy of Nigeria by way of credit creation. They added that the negative sign of capacity utilization was an indication of poor performance of the manufacturing sector which could be explained by low capacity utilization, poor effective demand for final products, exchange rate misalignment, and input procurement constraint; while the positive sign of inflation might not be unconnected with conspicuous consumption of Nigerians.

It is revealed from the literature review that a bubble is a well-known empirical phenomenon in stock markets, but there is no consensus about the mechanisms behind it. When a pricing bubble appears, prices rise rapidly, making the listed stocks substantially overvalued. Generally, a bubble is followed by a crash. As the impact of a large crash on the stock market is considerable, hence bubbles and crashes are of profound importance to risk management of investment portfolios. Bangladesh stock market has experienced inefficient and irrational fluctuations twice since its inception, one in 1996 and the other one is in 2010. But no empirical study on Bangladesh has been found which has examined the reasons for the stock market bubble and its demise? Is it, as is commonly alleged, investors' speculative zeal? Or are there more mundane factors such as mismanaged monetary policy or some other macroeconomic factors behind this?

This research has aimed to examine the relationships between the selected macroeconomic factors and the stock market in Bangladesh during bubble and crash of 1996, as this is more prominent than that of 2010, and to find out which factors have played the key role in the bubble creation and subsequent crash. Also, the analysis has been extended to the recovery period. The relationships between the stock market and the macroeconomic variables in these periods have been separately assessed to compare the influences of the priced factors across the different periods. This new dimension has contributed to the void in the literature related to Bangladesh in this area.

# **2.5 Relation between Stock Market and Macroeconomic Volatilities**

Theoretically, the fundamental value of a corporate stock equals the present value of expected dividends. On the other hand, the future dividends ultimately depend on future corporate profits, and corporate profits, in turn, depend on future economic activities. So, if available information is taken into account, there would be a close relationship between stock prices and expected future economic activities. Similarly, as the prices of stocks at the aggregate level depend on the state of economic activities, so it is likely that any change in the level of uncertainty of future macroeconomic conditions would cause a change in stock return volatility. In other words, stock markets may be volatile simply because real economic activities fluctuate (Zukarnain and Sofian, 2012).

In this context, the impacts of macroeconomic volatility on stock market volatility received a considerable attention among academics, economists and financial analysts. One of the earliest attempts to examine the impact of macroeconomic variables' volatilities on stock market return volatility has been made by Schwert (1989). His study has mentioned three important reasons as to why stock market volatility and the macroeconomic volatility are interrelated. Firstly, he has found a positive linkage between macroeconomic volatility and stock market volatility, with the direction of causality being stronger from the stock market volatility to the macroeconomic volatility. Secondly, he has argued that the evidence of stock market uncertainty being higher during recessions than expansions. These results have been explained through an operating leverage effect, i.e. profits tend to fall more rapidly than revenues during recessions if fixed costs are large. Thirdly, he has found that the level of macroeconomic volatility can explain less than half of the volatility of stock market returns.

Liljeblom and Stenius (1997) examined the relationship between conditional stock market volatility and macroeconomic volatility using monthly data of Finland for the period from 1920 to 1991. Conditional monthly volatility was measured as simple weighted moving averages which was obtained from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) estimations. The results of the study indicated that the stock market conditional volatility was a predictor of macroeconomic volatility, as well as the converse. Tests of the joint and simultaneous explanatory power of the macroeconomic volatilities indicated that one-sixth to more than two-thirds of the changes in aggregate stock market conditional volatility might be related to macroeconomic volatility.

Morelli (2002) attempted to determine the relationship between conditional stock market volatility and conditional macroeconomic volatility using monthly UK data for the period from January 1967 to December 1995. Conditional volatilities were estimated using the well-known Autoregressive Conditional Heteroscedasticity (ARCH) and Generalised ARCH (GARCH) models. The macroeconomic variables used were industrial production, real retail sales, money supply, inflation, and exchange rate. The results of the study confirmed that conditional macroeconomic variables' volatilities did not explain the conditional stock market volatility.

Beltratti and Morana (2006) investigated the relationship between macroeconomic volatility and stock market volatility using S&P500 data for the period 1970-2001. They found evidence of both long memory and structural change in volatility and a twofold linkage between stock market and macroeconomic volatility. In terms of the break processes, their results showed that there were frequent cases where the break in the volatility of stock returns was associated within few months with breaks in the volatility of the Federal funds rate and M1 growth. After accounting for the structural breaks, there remained interesting relations among the break free series.

Using fractional cointegration analysis, the study found the existence of three long-run relationships linking stock market, money growth, inflation, the Federal funds rate, and output growth volatility, and two common long memory factors which were mainly associated with output and inflation volatility. The study showed that stock market volatility dynamics, both persistent and non-persistent, were associated in a causal way with macroeconomic volatility shocks, particularly to output growth volatility. The stock market idiosyncratic shock, which accounted for the bulk of the overall dynamics, also had influenced macroeconomic volatility. Yet the evidence suggested that the causality direction was stronger from macroeconomic to stock market volatility than the other way around.

Chowdhury et al. (2006) examined how the macroeconomic risk associated with industrial production, inflation, and exchange rate was reflected to the stock market return in the context of Bangladesh capital market. They used monthly data for the period from January 1990 to December 2004. Since many macroeconomic variables and stock returns were believed to follow GARCH (Generalized Autoregressive Conditional Heteroskedasticity) process, this technique was used to find predicted volatility series for the variables considered in the study.

Finally, VAR (Vector Autoregression) was employed to investigate the relation between the variables. The results showed significant unidirectional causality running from industrial production volatility to stock market volatility and from stock market volatility to inflation volatility. The latter being consistent considering the theory. They concluded that there was relation between stock market volatility and macroeconomic volatility, but it was not that strong as suggested by standard finance theory. They recommended for further study.

Chinzara (2010) examined how the time-varying macroeconomic risk associated with industrial production, inflation and exchange rates were related to time-varying volatility in the South African stock market. The study focused on both aggregate stock market indices and sectorial indices to investigate whether the response to macroeconomic volatility varied across sectors. Furthermore, the study also distinguished between the different stages of the economy, i.e. times of tranquility and times of crisis. He used augmented autoregressive GARCH (AR-GARCH) and Vector Autoregression models. The findings showed although the volatilities in inflation, gold price and oil price played a role, but volatility in short-term interest rates and exchange rates were most important, suggesting that South African domestic financial markets are increasingly becoming interdependent. The results also revealed that the financial crises had increased the volatility in the stock market and in most macroeconomic variables and, by doing so, strengthened the effects of changes in macroeconomic variables on the stock market.

Kadir et al. (2011) examined the predictability power of exchange rate and interest rate volatilities on stock market volatility and return using monthly Kuala Lumpur Composite Index (KLCI) returns, 3 months Malaysia Treasury bond and monthly exchange rate of Ringgit per US Dollar for the period from January 1997 to November 2009. The study adopted two models based on GARCH (1,1), model 1 (model 2) without (with) interest rate and exchange rate. Mean equations of model 1 and model 2 suggested that lagged KLCI returns had insignificant impact on contemporaneous KLCI returns, but the relationships between interest rate and exchange rate with KLCI returns were found negative, but significant for exchange rate and insignificant for interest rate. The results suggested that the conditional volatility of the stock market return was quite persistent in both models.

On the other hand, variance equations of the models showed that the volatility of KLCI was negatively related to interest rate volatility and positively related to exchange rate volatility. However, both relationships were not significant. They opined that exchange rates and interest rates could not be used to predict the volatility of the market.

Wang (2011) examined the relationship between stock market volatility and macroeconomic volatility for China using exponential generalized autoregressive conditional heteroskedasticity (EGARCH) and lag-augmented VAR (LA-VAR) models. They found evidence that there was a bilateral relationship between inflation and stock prices, while a unidirectional relationship existed between the interest rate and stock prices, with the direction from stock prices to the interest rate. However, the relationship between stock prices and real GDP was not significant. They argued that the results suggesting that the stock market was likely to be less efficient than those of the US and other developed countries and was somehow separated from the real economy of China.

The study of Adeniji (2015) pursued analysis on the relationship between stock market volatility and macroeconomic volatility in a developing country, Nigeria. He used GARCH (1,1) models with monthly data for a period from January 1990 to December 2014. To examine the relationship between stock market volatility and macroeconomic volatility, the study used cointegration, bi-variate and multivariate VAR, Granger causality tests as well as regression analysis. The cointegration test confirmed a long-run relationship among the volatilities of the variables.

The results of GARCH (1,1) model showed that three out of the five macroeconomic variables chosen had significant relationships with stock market prices volatility. At the same time GARCH results confirmed that stock market volatility was influenced by its own ARCH and GARCH factors, meaning that the stock market volatility was influenced by its own past volatilities as well as the new innovations. However, the results of Granger causality revealed that the volatility in GDP, inflation and money supply did not Grangercause stock market volatility, but the volatility in interest rate and exchange rate did Granger-cause stock market return volatility.

On the other hand, ordinary least squares (OLS) regression analysis showed that interest rate and exchange rate volatilities were significantly related to stock market volatility. Also, OLS results disclosed that the coefficient of volatility of exchange rate was relatively large compared to other coefficients, which indicated that exchange rate volatility was a key factor in determining the volatility in stock market returns in Nigeria. However, pointing to the low explanatory power of the regression analysis, the researcher argued that the volatilities of the macroeconomic variables used in regression played very minor role in explaining the stock market volatility in Nigeria. He added that this finding was admissible in the case of developing countries with the supremacy of non-institutional investors and the existence of information asymmetry problem among investors.

From the foregoing literature review, it is revealed that stock market volatility has profound importance to policy makers, financial managers, firms, investors and other stakeholders to understand the causes and determinants of this volatility. Alongside, macroeconomic variables have been considered as the powerful tool to forecast the volatility of stock market all over the globe. In this backdrop, enormous studies have been conducted to investigate the relationship between stock market variability and macroeconomic variability. However, a very few studies on Bangladesh have focused on this topic and it is very important to find out the factors causing the irrational fluctuations in the stock market of Bangladesh.

# **2.6 Relation between Stock Market and Real Economy**

A stock market is seen as a general measure of the state of the economy of the country where it operates. An increase in stock prices provides a stimulus to the confidence of households and firms and reduces the uncertainty they have about their future economic situation. So, the equity risk premium provides an insight into the degree of risk aversion in the economy which, in turn, can affect the real economy. This channel works through the perceived riskiness of equity and the risk compensation desired by investors.

Men and Li (2006) examined the relationship between the stock market index and the national economy of China using cointegration and Granger causality tests. This study used Gross Domestic Product (GDP) to represent the economy and two stock market indices - namely Shanghai Securities Exchange Composite Index and Shenzhen Securities Exchange Composite Index, as the representatives of Chinese stock markets. The study period was from1995 to 2005 and the number of the observations was 132 in total.

The results of empirical study showed that both Shanghai Securities Exchange Composite Index and Shenzhen Securities Exchange Composite Index were not cointegrated with Chinese GDP. Moreover, for both markets they did not find any causal relationship between stock markets' return and GDP growth rate. They argued that there could be many possible reasons to explain the seemingly abnormal relationship between Chinese stock index and the national economy.

Firstly, although the private sector played a key role in contributing to the GDP growth in China, but 90.5% of the capital of private sector financing were based on self-financing, 4% was supported by bank loan, and even less financing was acquired from stock market. Therefore, the stock did not show the actual situation of the GDP.

Secondly, most of Chinese financing was supported by commercial bank loans and the total capital raised from stock market accounted for only 0.57% of the volume of bank loan in 2004. So, the dominant commercial banking industry weakened the role played by the stock market. Hence, the unbalanced financial structure could explain at least partly why Chinese stock market was not playing an important role in the development of the national economy.

Antonios (2010) investigated the causal relationship between stock market development and economic growth using Granger causality test. The study also examined the long-run relationship between these variables applying the Johansen cointegration analysis. The sample used in this study consisted of annual observations for Germany for the period from 1965 to 2007. The variable of economic growth was measured by the rate of change of real GDP, while the general stock market index was used as a proxy for the stock market development.

The empirical analysis suggested that there existed a cointegration relationship among the variables. Then the short-run dynamics of the model was studied using Vector Error Correction Model (VECM). The results of the VECM indicted that the speed of adjustment forced the long-run behavior of the endogenous variables to converge to their equilibrium relationship. Finally, the Granger causality test showed that there was a unidirectional causality between stock market development and economic growth with direction from stock market development to economic growth.

Husain (2006) examined the causal relationships between stock prices and the variables in Pakistan. The variables representing the real sector of the economy were real GDP, real consumption expenditures, and real investment spending. Annual data for the period from 1959-60 to 2004-05 were used in the study. He considered the expected shift in the data due to the start of the economic liberalization program in the early 1990s, which resulted in significant improvements in the size and depth of the Pakistani stock market. To take care of that economic liberalization program the sample was further classified into two sub-samples. Sample I, from 1959-60 to 1990-91 which covered the period prior to the liberalization program, while Sample II, from 1991-92 to 2004-05 represented the postliberalization period. Similarly, in regression analysis he included a dummy from 1991-92 onwards to take care of the possible shift in relations between variables due to economic liberalization program.

The results showed that in the pre-reform period, the correlations are almost zero. However, the post-reform period showed a significant increase in correlation coefficients, indicating the beginning of association of stock prices with real variables following liberalization measures. In particular, the correlation between stock prices and GDP was very high. On the other hand, the results of the Engle-Granger cointegration tests indicated that in all cases there existed significant long-run relationships between stock prices and real variables.

The findings of Error Correction Models indicated a unidirectional causality running from the real sector variables to the stock prices in the long-run. But the lagged variables as well as the F-values were not significant in all the cases suggesting that in the short-run these variables were independent of each other. Hence, he concluded that the stock market in Pakistan was not that developed to influence the real sector and therefore could not be considered as the leading indicator of the economy.

In addition, to take care of the shifts in variables representing the stock market as well as the real sector due to the liberalization measures, a dummy variable was added in the analysis that took the value of one from 1991-92 onwards. The results showed that the dummy variable was not significant implying that the relations of stock prices with the variables representing real sector were not affected by the liberalization measures. Nevertheless, the results of error correction model were similar to those obtained without taking care of the shifts. So, he concluded that despite significant developments the stock market in Pakistan was still not in a position to influence the real sector.

Krchniva (2013) investigated the relationships between stock markets and the economic growth of seven countries – namely United States, Japan, Germany, Poland, Hungary, the Czech Republic and the euro area. She used seasonally adjusted quarterly time series data of those seven countries for the period from first quarter of 2000 to the second quarter of 2012. The stock markets were represented by stock market indices and the economic growths of the selected countries were represented by Gross Domestic Product (GDP) at constant prices.

The hypothesis of the study was whether the stock markets had an ability to predict the economic development. This was tested by correlation analysis and the Granger causality test. The results exhibited unique correlation between the stock market and the economy in five of the seven countries. In addition, Granger causality test showed in most cases the stock market led economic development by one quarter. However, for US the relationship between the stock market and economy reversed, while for Hungary the relationship was bi-directional.

The results revealed that for German, Japan, Czech, Polish and the euro area the stock markets led economic development by one quarter. She mentioned that these results were consistent with the study of Estrella and Mishkin (1996). On the other hand, in the case of US the opposite unilateral relation seemed to exist between the stock market and the economy, which corresponded to the conclusion of the study of Goktas and Hepsag (2011), where it was showed that the performance of stock markets was overtaken by economic

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development.

Finally, she concluded that the findings of the study were in contradiction with the conclusions of some studies but on the other hand, in accordance with many others. This could be due to the maturity or size of the economy and its stock market. However, at the end, she supported the view that stock indices could be used as an important leading indicator of economic development.

From the foregoing literature review, it is revealed that the relationship between the stock market and the real economy depends on the size and maturity of the economy and its stock market. The stock market in Bangladesh and its economy are passing through numerous liberalization and deregulation processes. As a result, size of the economy as well as the stock market have increased significantly during our study period. So, it would be interesting to examine whether this has increased the stock market's ability to reflect the real economy as per the theory.

Moreover, Bangladesh stock market has experienced two major bubbles within a decade and a half, one in 1996 and other in 2010. However, the catastrophe of 1996 is more prominent compared to that of 2010. This has motivated us to examine the relationships between the stock market and the real economy of Bangladesh around the catastrophe of 1996 - that is during the bubble and meltdown periods of 1996. In fact, these investigations have been conducted to describe the relationships between the stock market and the real economy during the crisis times of the stock market.

On the other hand, following the crash of 1996, several capital market development programs have been initiated through a strong partnership between the government of Bangladesh and the Asian Development Bank to broaden the market capacity and develop a fair, transparent, and efficient domestic capital market. The main objective of these programs has been set forth to restore investors' confidence, which has significantly damaged after the market crash of 1996, because of excessive speculations, allegedly aggravated by widespread irregular activities. Also, the stock market has been striving for continuous upgradation of its trading platform since August 1998 to fulfill the dream of transforming Dhaka Stock Exchange (DSE) into modern world class exchange. In these perspectives, this study has also examined whether these initiatives have increased the response of stock market to real economy of Bangladesh.

# **2.7 Conclusion**

In last three decades, numerous studies have tried to investigate empirically the relationship between macroeconomic variables and stock market. The results of these studies reveal that the relationship cannot be determined in advance since it varies across countries and within a country it varies across times because of different legal and institutional structures that affect the link between stock prices and macroeconomic variables vary from country to country and within the country that vary across times.

Although most of the researchers have documented evidence that fundamental economic activities in developed countries are strongly linked to stock market returns, it is unclear whether such a relationship exists in emerging stock markets in less developed countries. Because compared to their developed market counterparts, these stock markets are smaller in size and relatively illiquid. The economies of these countries are influenced to a far greater extent by global economic factors rather than domestic economic measures. Furthermore, the growing influence of foreign investors in these markets may weaken any link between national economic variables and stock market returns.

The literature review has revealed that early studies have used multi-factor asset pricing models based on the assumption that stock market returns are affected by different macroeconomic factors. However, to forecast the stock returns variation and its relationship to macroeconomic factors need modern econometric techniques and models. The selection of an appropriate model for the investigation of relationship is still a contentious issue due to distinctive features and parameters of different models.

The literature review has indicted that most of the studies have used a single model to examine the relationship between macroeconomic variables and stock market. However, this study has employed multiple models to check the robustness of the results on the relationship. Furthermore, we have found that none of the studies on Bangladesh has used most recent ARDL cointegration approach to examine the relationship between stock market and macroeconomic variables. This study has attempted to fill this gap by exploring the relation between stock market and macroeconomic variables in Bangladesh applying the ARDL approach.

Many studies on the relationship between stock market and macroeconomic variables have also examined stock market predictability to examine whether stock market is a leading indicator of the future economic activities or other way around. The findings of the existing literature on this implication are also mixed. Moreover, most of the works, if not all, on Bangladesh has hitherto concentrated primarily on contemporaneous relationship leaving gap in causal relationship. This study has attempted to examine the casual relationships between stock market and macroeconomic variables to address the void in the literature.

On the other hand, a bubble is a well-known empirical phenomenon in stock markets, but there is no consensus about the mechanisms behind it. A bubble is followed by a crash. As the impact of a large crash on the stock market is considerable, hence bubbles and crashes are of profound importance to risk management of investment portfolios. Alongside, Bangladesh stock market has experienced inefficient and irrational fluctuationstwice since its inception. However, we have found that no study on Bangladesh has concentrated on this implication, leaving a serious gap in the literature.

This study has examined the relationships between stock market and macroeconomic variables during bubble and meltdown periods of stock market. In addition, this study has aimed to identify the factors responsible for creating bubble and bubble crash. Moreover, the analysis has been extended to the recovery period to compare the influences of the priced factors across different periods. This will add a new dimension in the literature on Bangladesh.

The impact of a large market crash on households, banks and finally on overall economy has increased the interest of regulators, researchers and investors towards the relationship between stock market volatility and macroeconomic volatility. Additionally, the risk return behavior analysis of stock market is more important in developing countries because these markets are very volatile. The degrees of volatility in these stock markets compel the investors to demand higher risk premium, which creates higher cost of capital and slows down the economic development (Mala and Reddy, 2007). The stock market volatility in Bangladesh is mostly influenced by trade syndication or the decisions of other regulatory bodies like Bangladesh Bank (Siddikee and Begum, 2016). In this perspective, this study has examined the stock market volatility and macroeconomic volatility in Bangladesh.

Furthermore, stock market is seen as a general measure of the state of economy through which stock prices affect the real economy via a confidence channel. An increase in stock prices provides a stimulus to the confidence of households and firms and reduces the uncertainty about future economic situation. However, empirically the predictive content of stock prices for economic growth is less clear-cut and it depends on size of the economy as well as the stock market (Krchniva, 2013).

Bangladesh stock markets have grown significantly during the last decade due to the steps taken to strengthen the stock market following the crash of 1996. Still, the size of the market is relatively small compared to other Asian Markets. However, Bangladesh stock market is continuously passing through upgradation of its trading platform to set the foundation for sustainable market development and to build up state-of-the-art market surveillance system to increase the transparency of market transactions and contribute significantly to enhanced investor confidence.

In this backdrop, it important to know the relationship of stock market with the dynamics of real economic activities of Bangladesh. It is also important to investigate whether the reforms and the automation initiatives have improved the ability of the stock market to predict the real economy. But none of the study is found which has addressed these issues. This study has focused on these issues to fill up the void in the literature on Bangladesh.

The major drawbacks of our stock market are the lack of information transparency and investors have lack of knowledge (fundamental and technical). Moreover, DSE has very short histories of organized share trading system and the perception of investors may be different from those in developed markets. Therefore, the behavior of the market prices may not be tied to economic fundamentals; rather the stock prices may be driven by the speculative activities of irrational investors.

Hassan et al. (1999) have found that DSE returns show positive skewness, excess kurtosis

and deviation from normality. They have also found that DSE volatility has changed over time, and is serially correlated implying stock market inefficiency. Gunasekarage and Power (2001) have provided convincing evidence that investors in DSE can earn excess returns by employing technical trading rules. This study has also revealed that the fixed length moving average rule generates excess return of 9.81 percent in Bangladesh.

There is no doubt that a vibrant capital market supports economy but two major catastrophes in the capital market of Bangladesh within a decade and a half do not indicate the existence of a vibrant market; rather these irrational fluctuations prove that the capital market is highly risky and unstable. Moreover, the Finance Minister of the country AMA Muhith termed the stock market as 'naughty' and said 'the economy would not suffer if he does not worry about the market<sup>'2</sup>.

In the above context, the outcome of the research could be noteworthy. A successful innovation of relationship between the macroeconomic indices and the stock market will assist the entire interested group to decide efficiently the operational, management and sustainable growth issues. Investors can ensure maximum return from their investment in the stock market by taking information from this research. Regulator and policy makers may find the outcomes of the research helpful in formulating different policies and taking decisions for ensuring and creating smooth trading and investment atmosphere, controlling market strategies and assessing the degree to which the stock market may need to be reformed.

To sum up, it can be concluded that apart from contributing to the existing literatures on relationship between stock market index and macroeconomic indices, this research extends

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<sup>2</sup> The Financial Express, 13 June 2012.

the existing relevant studies on Bangladesh in several ways. Firstly, most recent data has been used, which is necessary given that the Bangladesh stock market is still undergoing through technical changes, which is likely to increase the efficiency, thus increasing its response to macroeconomic factors.

Secondly, multiple econometric models have been used to cross validate the results. More specifically, in addition to Johansen and Juselius cointegration test, the Autoregressive Distributed Lag (ARDL) cointegration approach has been applied in this study. Thirdly, the study has examined whether the stock market can be used as a leading indicator of future macroeconomic condition or vice versa.

Fourthly, contrary to other studies (Ali, 2011; Quadir, 2012; Khan and Yousuf, 2013), this study has examined the relationships of macroeconomic variables with stock market during bubble, meltdown and recover periods, because the investors have the tendency to react differently to the same type of news during different periods. This study has also aimed to identify the factors responsible for creating the bubble and bubble crash of 1996. Fifthly, since the stock market volatility provides some important implications for policy makers, economic forecasters and investors, this study has examined the relationship between stock market volatility and macroeconomic volatility in Bangladesh.

Finally, the study has also investigated the relationship between the stock market and the real economy of Bangladesh to examine whether any significant link exists between the these two. The study has also attempted to examine this relationship during different conditions of the stock market. In addition, the study has been extended further to examine whether the reform measures and the technical changes implemented for the development of the stock market have increased its efficiency.

# **Chapter 3**

# **Theoretical Framework**

# **3.1 Introduction**

According to the modern financial theory, the value of a financial asset is equal to the sum of its discounted expected cash flows. So, the determinants of stock prices are the expected cash flows from the stock and the required rate of return commensurate with the cash flows' riskiness. For an individual stock, these two aforesaid variables can be affected by influences that are not pervasive or systematic to economy. But returns on market are mainly influenced by systematic risk because idiosyncratic risk on individual stocks is cancelled out through the process of diversification. Furthermore, macroeconomic variables are the indicators or main signposts signaling the trends in economy (Siamwalla et al., 1999) and these variables are considered as economic state variables (Chen et al., 1986). Accordingly, the expected changes in macroeconomic variables have impact on the expected cash flows and/or the required rate of return of stocks and thereby can affect the current stock prices.

The financial theories to carry out research works on various aspects and determinants of stock prices, started in the 1950s, were refined during the following decades and resulting in a unified framework of financial theory during the 1980s. The rapid development of these theories, especially the formation of the theories in defining the nature and working of capital markets, has resulted in the establishment of flexible asset pricing models which are widely applied in capital markets in recent time. These financial theories on asset pricing revolve around two fundamental issues, which when taken together suggest the lack of prolonged arbitrage opportunities. These two fundamental issues are: (1) financial markets are informationally efficient; and (2) market participants are rational. That is why, the Efficient Market Hypothesis (EMH) and the Rational Expectation Hypothesis are considered as the cornerstones of modern financial economics, which assert that stock prices should reflect all available information about the fundamental value of the underlying security (Fama, 1970). The EMH, rational expectations hypothesis and asset pricing models are interrelated topics.

Since the objective of this research is to investigate the relationship between the stock market index and the macroeconomic indices, the understanding of the theoretical foundations of different asset pricing models, such as the Capital Assets Pricing Model (CAPM) and Arbitrage Pricing Model (APM), are crucial in analyzing the determinants of stock prices from the perspective of Efficient Market Hypothesis (EMH) and Rational Expectations Hypothesis. Our review of empirical literatures has also revealed that different studies have used different econometric models within the framework of different asset pricing models to investigate the relationship between stock market and macroeconomic indices.

In view of this, the concept of EMH, rational expectations hypothesis and the evolution of different asset pricing models have been discussed in the next four sections of this chapter. In section 3.2, we have introduced the concept of the efficient market hypothesis. Section 3.3 describes the theory of expectations and stock prices. A review of stock valuation and portfolio selection under uncertainty are discussed in section 3.4. In section 3.5, we have portrayed a detailed overview of relevant asset pricing models. More specifically, the capital asset pricing, intertemporal capital asset pricing and arbitrage pricing models have been described. Finally, summary of the chapter is drawn in section 3.6.

# **3.2 Efficient Market Hypothesis**

A market is said to be efficient with respect to an information set if the price fully reflects that information set (Fama, 1970) i.e. if the price would be unaffected by revealing the information set to all market participants (Malkiel, 1992). It is generally believed that security markets are extremely efficient in reflecting information about individual stocks and about the stock market as a whole. The EMH asserts that when information arises that spreads very quickly and is incorporated into the prices of securities without delay.

Thus, the main engine behind price change is the arrival of new information. In an efficient market prices adjust quickly to new information and, on average, without being biased. So, the current prices of securities reflect all available information at any given point in time and there is no reason to believe that prices are too high or too low. Security prices adjust before an investor has time to trade on and profit from a new piece of information. Presently, with the advent of modern telecommunications facilities, enthusiastic business media and a large number of buyers and sellers, securities markets are much more efficient than before.

Moreover, many investment analysts spend a significant amount of effort and time to detect "mispriced" securities and as more and more analysts compete against each other in their effort to take advantage of over- and under-valued securities, the likelihood of being able to find and exploit such mispriced securities becomes smaller and smaller. In equilibrium, only a small number of analysts can be able to profit from the detection of mispriced securities and mostly by chance. Thus, no one can consistently beat the market.

In the short-run, investors may earn unusual returns even if the market is efficient. For example, an investor could buy a stock today, and tomorrow a major discovery could be announced that would cause its stock price to increase significantly. But it does not mean that the market is inefficient; rather it means that the investor is very skillful or, more likely, very lucky. The question is whether the investor and enough other investors can do this a sufficient number of times in the long-run to earn abnormal profits? Even in the long-run, some people may be lucky given the total number of investors. Thus, neither technical analysis, which is the study of past stock prices to predict future prices, nor the fundamental analysis, which is the analysis of financial information such as company earnings, asset values etc., can help investors to select "undervalued" stocks.

Therefore, none of the market analyses would enable an investor to achieve returns greater than those which could be obtained by holding a randomly selected portfolio of individual stocks with comparable risk. However, market efficiency invariably depends on following two factors: (1) how efficiently investors interpret information (before taking investment decision); and (2) how fast the information is reflected on the asset prices. Since the interpretation of information and the speed at which investors react vary across markets and across assets within the same market, meaning that efficiency is a relative term.

Many investment analysts try to identify securities that are undervalued and are expected to increase in value in the future, and particularly those which will increase more than others. They believe that they can select securities that can outperform the market. They use a variety of forecasting and valuation techniques to aid them to make their investment decisions. But the EMH states that none of these techniques are effective (i.e., the advantage gained does not exceed the transaction and research costs incurred).

Possibly, like EMH, no other theory in economics or finance generates more passionate discussion between its challengers and proponents. For example, noted Harvard financial economist Jensen (1978) has written - "there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis", while investment maven Peter Lynch has claimed in an interview with the Fortune Magazine - "Efficient markets? That's a bunch of junk, crazy stuff" (Fortune, April 1995).

In this context, Malkiel (2003) has made the convincing remarks that markets can be efficient even if many market participants are quite irrational, markets can be efficient even if stock prices exhibit greater volatility than can apparently be explained by fundamentals and many economists who believe in efficiency do so because they view markets as amazingly successful devices for reflecting new information rapidly and, for the most part, accurately. Also, he has added that the records of professional fund managers do not suggest that sufficient predictability exists in the stock market or that there are recognizable and exploitable irrationalities sufficient to produce excess returns. Furthermore, Graham (1965) has suggested that while the stock market in the short-run may be a voting mechanism, in the long run it is a weighing mechanism and true value wins out in the end.

#### **3.2.1 Different Forms of Market Efficiency**

Considering the different information sets, Fama (1970) has identified the following classification of market efficiency depending on three relevant information subsets:

- **Weak Form Efficiency:** The weak form of the efficient market hypothesis asserts that all information contained in historical prices is fully reflected in current prices of securities. This indicates that nobody can detect mispriced securities and "beat" the market by analyzing past prices.
- **Semi-strong Form Efficiency:** The semi-strong form of market efficiency hypothesis suggests that the current price fully incorporates all publicly available

information. Public information includes not only past prices, but also data reported in a company's financial statements, announcements of earnings and dividend, announced merger plans, financial situation of company's competitors, expectations regarding macroeconomic factors etc.

**Strong Form Efficiency:** The strong form of market efficiency states that the current price fully incorporates all existing information, both public and private. The main difference between the semi-strong and strong efficiency is that in the latter case nobody should be able to systematically generate profits even if trading on information that is not publicly known at that time.

Later, Fama (1991) has modified these three forms of market efficiency. He has put forward three test procedures to determine different forms of market efficiency. These are:  $(1)$  Return predictability: whether the past information can be used to forecast present stock returns; (2) Events studies: whether asset price responses to new information as hypothesized; and (3) Test for private information: whether asset prices are related to the private information. The idea of EMH is based on the idea of perfect stock market. Therefore, it is necessary to consider it in relation to perfect capital market.

### **3.2.2 Efficient Market vs Perfect Market**

Perfectly competitive markets (or perfect market for short) are termed as efficient market. A perfect market is one in which there is no arbitrage opportunity because assets are priced with total efficiency. Copeland and Weston (1988) has contrasted the efficient capital market with the theoretical perfect market. They have stipulated following conditions for the market to be perfect market:

• **Markets are perfectly competitive:** There are many buyers and sellers, each firm in the market produces and sells a nondifferentiated or homogeneous product, no barriers to entry and exit, producers supply goods and services at minimum average cost, participants in the market are price takers;

- **Markets are frictionless:** There are no transaction costs, no taxes, all assets are perfectly divisible and perfectly marketable, there are no constraining regulations;
- **Markets are informationally efficient:** Information is costless, and all individuals receive it simultaneously; and
- **Investors are utility maximizer:** All individuals are rational expected utility maximizers.

When these conditions are satisfied both product and security markets are productively, operationally and allocatively efficient.

However, according to Grossman and Stiglitz (1980), the stock market is not a perfectly competitive market. There are some sources of imperfection such as perfectly inelastic supply curve, transaction cost, taxes and informational inefficiency. So, a weaker and economically more sensible version of the market efficiency hypothesis says that prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs (Jensen, 1978). In addition to EMH, theory of expectations is another key concept to understand the stock market.

### **3.3 Expectations and Stock Prices**

Participants in stock markets formulate their expectations of future returns and it is generally believed that security prices are determined by expectations, which concern firm and economic variables (Elton et al., 1981). Expectations of the economic events and especially the macroeconomic variables have significant effect on the stock market returns. However, there is no common method of measuring expectations. The asset valuation models, such as CAPM and APT, are formulated in terms of expectations. So, it is necessary to transform parameters from expectations or ex-ante form (as expectations cannot be measured) to a form that uses observed data (Elton and Gruber, 1991). The betas (βs) in the CAPM and APT are the future betas of the security. Similarly, both the returns on the market and the zero-beta portfolio (which is the minimum variance portfolio and uncorrelated with market portfolio) are also expected future returns (Elton and Gruber 1991). All these facts highlight the importance of expectations and their impact on investments.

In this context, expectations have become central and pervasive to economic analysis (Gertchev, 2007; Figlewski and Wachtel, 1981) because of the role they play in current investment decisions. Modeling of expectations has also gained importance over the time, especially in contemporary macroeconomics. But the expectations are unobservable – they exist or are formed in the mind and are abstract. Expectations formation models are arbitrary assumptions and their use is categorized as a 'positivism' approach (Mlambo, 2012). There are various expectations models. Among these, the two most common ones are adaptive expectations and rational expectations, with the latter being the standard in mainstream economics.

### **3.3.1 Adaptive Expectations**

The adaptive expectations hypothesis states that future expectations of an economic event are based on actual outcomes in the past. These expectations are formed based on the past experiences only. This is equivalent to the technical analysis or the weak form of the EMH. It states that the past experiences determine the future events. People change their decisions according to previous information. They make mistakes time to time, but they learn from past mistakes (Copeland and Weston 1988).

According to Evans and Garey (2003), the adaptive expectations hypothesis introduced by Cagan (1956) and Friedman (1957), was a plausible and empirically meaningful approach to modeling expectations of future variables in the world of uncertainty. They have argued that the apparent empirical success of their studies has led to widespread use of the adaptive expectations hypothesis before it has been swept away by the rational expectations revolution, initiated by Muth (1961) and advanced by Sargent and Wallace (1975). Finally, they have concluded that rational expectations hypothesis has shown greater advantage of providing optimal expectation and under the standard of optimality, adaptive expectations hypothesis suffers by comparison and should be rejected.

### **3.3.2 Rational Expectations**

Rational expectations have two basic forms: weak-form rational expectations and strongform rational expectations. Weak-form rational expectations imply that whatever information people have (no restriction placed on information), they make optimal use of the information in forming their expectations. Conversely, strong-form rational expectations suggest the use of all relevant available information (strong restriction placed on information) in forming expectations.

Moreover, if there is a change in the way a variable is determined, people immediately change their expectations regarding future values of that variable even before seeing any actual changes in that variable. Although forecasts are not always accurate, but forecast errors are not predictable in advance and errors average out to zero. The two reasons why expectations can fail to be rational in the strong-form sense are: (1) investors are aware of all available information but fail to use all the information to formulate the expectations; and (2) investors are unaware of some available information which are relevant to formulate the expectations. The best forecast of a future variable can be made if a forecaster uses all available and relevant information, the latest statistical data and the best available economic models.

The theory of rational expectations and EMH imply that expectations in financial markets are made based on optimal forecasts by using all relevant available information (i.e., investors have strong-form rational expectations). Security prices in financial markets are determined at market clearing level, where supply is equal to demand. Security prices reflect true fundamental (intrinsic) value, meaning that there is no price bubble. Believers in EMH and rational expectations insist that the unexpected changes in economic variables can only affect the returns on the stock market.

In an efficient market, market participants are sophisticated, informed and act only on available information. Since everyone has the access to same information, all securities are appropriately priced at any given time. Therefore, both a novice and expert investor, holding a diversified portfolio, obtain comparable returns regardless of their varying levels of expertise. However, one major strike against this is that some investors routinely beat the market, especially Warren Buffett. The implication is either that some people have better information than others or that some people are better at interpreting information than others. This gives rise to the concept of fundamental analysis which assumes that investors can achieve excess returns by purchasing stocks below their intrinsic value.

# **3.4 Fundamental Analysis vs Portfolio Theory**

The stock investment process looks considerably different depending on the investor's belief about market efficiency. Based on the belief in the degree of market efficiency, two major investment theories emerged that still divide the financial community. One is the fundamental analysis based on the idea of non-efficient markets and other hand is the modern portfolio theory (MPT) with a strong faith in market efficiency. These two different approaches to investment (fundamental analysis and MPT) are based on two fundamentally different understanding of the relationship between intrinsic value and price. Price balances supply and demand for stocks on the stock exchange and can be exactly determined. Intrinsic value is more difficult to establish and measure. Value must be determined through a valuation process. This process requires forecasting the future, hence is unavoidably subjective and various approaches are generally used.

In efficient markets, price should be equal to its intrinsic value, but fundamental analysis assumes that value and price can deviate. It is too simplistic to assume that markets are always efficient, and prices adjust to intrinsic value instantly. Lee (2001) has argued that price convergence towards intrinsic value is characterized by a process, which is accomplished through the interplay between noise traders and information arbitrageurs. Prices move from the intrinsic value as investors trade based on imperfect informational signals. Eventually, through trial and error when the information procession is completed, then prices fully reflect the impact of that information. However, by that time, many new informational signals have arrived, starting a new adjustment process. Consequently, the market is in a continuous state of adjusting prices to intrinsic values.

On the other hand, the underlying philosophy of the modern portfolio theory (MPT) is based on the idea of efficient markets hypothesis, which states that a large number of informed participants ultimately drive the stock prices to its intrinsic value and create an efficient market. In such an environment, mispriced stocks would be detected and the under- or overvaluation would disappear immediately, so no profit could be gained from using any fundamental analysis. In other words, the MPT states that all stocks are fairly priced, and nobody can persistently outperform the market. Consequently, followers of MPT try to reduce risk by diversification and costs by minimizing transaction fees and taxes. The optimal investment strategy is the creation of an efficient portfolio based on covariances of all the stocks in the global marketplace. The natural extensions of the portfolio theory are the equilibrium asset pricing models

# **3.5 Assets Pricing Models**

Valuation is the process of determining the intrinsic value of common stocks. A fundamental principle of finance holds that the economic value of a security is properly measured by the sum of its future cash flows, where the cash flows are adjusted considering the riskiness associated with expected cash flows and the time value of money. A popular model used to value common stock is the dividend discount model (DDM). The DDM argues that competition among rational investors, who want to diversify to optimize the statistical properties of their portfolios, lead to an equilibrium in which prices equal the discounted value of the rationally expected cash flows. So, the price, P of a stock having expected dividend stream E(c) and discount rate k can be express by:

$$
P = \frac{E(c)}{k}
$$

Taking natural logarithm of both sides, we get:

$$
\ln P = \ln E(c) - \ln k \tag{3.1}
$$

Differentiating Equation (3.1), we get:

$$
\frac{dP}{P} = \frac{dE(c)}{E(c)} - \frac{dk}{k}
$$

On the other hand, the total return (TR) from a stock can be given by:

$$
TR = Yield + Price Change
$$

$$
\therefore TR = \frac{c}{P} + \frac{dP}{P}
$$
From equation  $(3.2)$  and  $(3.3)$  we get:

$$
TR = \frac{c}{P} + \frac{dE(c)}{E(c)} - \frac{dk}{k}
$$

So, theoretically, the factors that change the stock returns are unexpected changes in cash flows, *dE(c)* and/or discount factors, *dk*.

The unsystematic and systematic risk are the factors that create unexpected changes in cash flows and/or discount rate. However, the unsystematic risk*,* which is generated by microeconomic factors and is specific to an individual stock or an industry, can be eliminated through the process of diversification. But the systematic risk*,* which is mainly created by macroeconomic factors, cannot be eliminated by diversification. Hence risk and return on a diversified portfolio depend on the pervasive or systematic risk factors which is generated by economic factors and this is the area of concentration of this research.

Portfolio theory integrates the efficient market hypothesis and rational expectations hypothesis. The natural extensions of the portfolio theory are the equilibrium asset pricing models, such as CAPM and APM, which integrate macroeconomic risk factors into the stock valuation process. Portfolio theory is a description of how the rational investors should build efficient portfolios and the asset pricing models indicate how equities should be priced in the efficient capital market.

### **3.5.1 Capital Asset Pricing Model**

The basis of the Capital Asset Pricing Model (CAPM) is the portfolio theory with a riskless asset and unlimited short sales. CAPM does not consider the decision of a single investor, but aggregates them to determine a market equilibrium. In portfolio theory, the price of an asset is exogenously given and could not be influenced by any investor. Given this price, an investor forms his beliefs on the probability distribution. The beliefs can vary across investors. However, in CAPM, the asset prices (or equivalently expected asset returns) are no longer exogenously given, but are determined by the equilibrium state of the market.

The CAPM is also known as the single factor (or single index) asset pricing model, which integrates only one macroeconomic variable, the return on market, to the return on individual stock through the value of the beta  $(\beta)$ . Portfolio theory requires too many calculations to estimate the benefits of diversification. Diversification minimizes the unsystematic risk; however, it cannot minimize the systematic risk generated by macroeconomic variables. The CAPM is an attempt to minimize systematic risk by using asset allocation.

The benefit of asset allocation can be explained by the Markowitz efficient frontier, depicted in Figure 3.1. From the graph, it can be noticed that if an investor has invested solely in investment A, then his risk and return are determined at point A. While that are determined at point B, if he has invested solely in investment B. Now, if that investor invests 50% in investment A and 50% in investment B, then intuitively it seems that his risk and return would be somewhere around point C. But the modern portfolio theory states otherwise. In fact, if an individual decides to invest in both A and B, then his risk and return are determined at somewhere on the blue line (i.e., on the Markowitz efficient frontier). Note that investing heavily in A and a smaller amount in B (riskier than A) leads to a risk and return at point E. It is clear from the graph that at point E, we have a substantially higher return than A with only a small amount of added risk. As more of the risky asset is selected the rate of increasing risk diminishes with respect to rate of increasing return. The convexity of the efficient frontier is also known as the 'free lunch' of investing. Using asset allocation, one can potentially increase return without proportionate increase in risk. However, the benefit from asset allocation is dependent on

the number of assets in the portfolio, the risk and return of each asset in the portfolio and the correlation between the assets.



Figure 3.1 Benefit of Asset Allocation

Following Markowitz efficient frontier, Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), and further contributed to by Lintner (1965a; 1965b) and Mossin (1966). The CAPM has the following form:

$$
R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}
$$

where,

 $R_{it}$  is the actual return on stock *i* in time *t*;

*Rmt* is the actual return on a market index in time *t*;

 $R_f$  is the risk-free rate of return in time *t*;

*εit* is a random error;

*α<sup>i</sup>* is the measure of abnormal risk adjusted performance of the stock in time *t;*

 $\beta$ <sup>*i*</sup> is the slopes from regression of  $R$ <sup>*i*</sup> and  $R$ <sup>*m*</sup>.

The key feature of this model is that only the systematic risk is "rewarded" and nonsystematic risk is not. The CAPM's prediction of not rewarding the nonsystematic risk is the same as saying alpha is not statistically different from zero. The predominant view behind this is that markets are highly efficient, so it is quite unlikely for any individual to earn alpha consistently over time. Randomness or luck is the common explanation assigned to any organization or individual who demonstrate consistent ability to earn alpha over time. Thus, the CAPM can be stated formally in expected form as:

$$
E[R_{it}] = R_{ft} + \beta_i (E[R_{mt}] - R_{ft})
$$
\n
$$
3.6
$$

where E[**·**] implies an expected value.

From the advent of the CAPM in 1964 to the mid-1970s, there was relatively little controversy regarding the CAPM. However, Basu (1977) has showed that after controlling for systematic risk, low P/E stocks outperforms high P/E stocks. This finding run contrary to the predictions of the CAPM. It then seems possible that alpha can be earned consistently via skill, and not luck. Similarly, Banz (1981) and Reinganum (1981), working independently at the University of Chicago, have discovered that small capitalization stocks have outperformed large capitalization stocks after controlling for their exposure to market risk factors. These results are also anomalies - at least from the viewpoint of the CAPM.

Similarly, investigating portfolio returns in the Australian stock market, Kassimatis (2008) has used four factors to examine the significance of the size, book-to-market and momentum risk factors in explaining portfolio returns, and has compared these to the CAPM. The study has used the data between July 1992 to June 2005 and has constructed different portfolios to analyze the year to year returns. The results have shown that the additional factors have significant explanatory power rather than just market factor. Accordingly, the author has argued that the CAPM does not perform adequately in explaining realized returns. These results have justified the usage of alternative multifactor asset pricing models such as the Intertemporal Capital Asset Pricing Model (ICAPM) and the Arbitrage Pricing Model (APM).

### **3.5.2 Intertemporal Capital Asset Pricing Model**

Intertemporal Capital Asset Pricing Model (ICAPM), developed by Merton (1973), is an extension of the CAPM. The ICAPM has a different assumption about investors' objectives. In the CAPM, investors care only about the wealth their portfolio produces at the end of the current period. On the other hand, ICAPM is a consumption-based asset pricing model, and it goes a step further than CAPM in considering how investors participate in the market. Most investors do not participate in the financial market for one year, but instead for multiple years. Over longer time periods, investors consider how their wealth in the future may vary with future variables, including their income, the prices of consumption goods and the nature of portfolio opportunities in future.

Therefore, Merton's (1973) ICAPM shows that investors act to maximize expected utility of lifetime consumption and can trade continuously in time. The assumption of continual trading in assets over time is not assumed in the traditional models. The author has shown that, unlike the one-period model, current demands are affected by the possibility of uncertain changes in future investment opportunities. Fama (1996) has mentioned that Merton has got the exact result without assuming the portfolio is perfectly diversified.

Like CAPM investors, ICAPM investors dislike wealth uncertainty; but ICAPM investors are also concerned with more specific aspects of hedging their future consumptioninvestment opportunities, such as the relative prices of consumption goods and the riskreturn tradeoffs that they face in capital markets. Although ICAPM investors demand high expected return and low risk like the CAPM investors, but they also care about the movement of the returns of the portfolio with other dynamic variables. Therefore, the optimal portfolio will be a factor in many variables and have largest range of possible expected returns.

The ICAPM risk return relation is a natural generalization of the CAPM. It adds risk premiums for factors that must indicate special states of the world where portfolio returns might be very poor, and investors concerned about their payoffs. Hence investors are willing to sacrifice some of the expected return if an asset does well during "hard times". The factors often include macroeconomic variables that may tell us something more about states of the world which influence utility. For instance, consumption is related to interest rates, GDP growth, inflation and other macroeconomic variables. These macroeconomic variables can therefore measure the state of the economy. So, the ICAPM has the following form:

$$
R_{it} - R_{ft} = \alpha_i + \beta_i \left( R_{mt} - R_{ft} \right) + \sum_{s=1}^n \beta_{is} \left( R_{st} - R_{ft} \right) + \varepsilon_{it}
$$
\n
$$
\qquad \qquad 3.7
$$

where.

 $R_{it}$  is the actual return on stock *i* in time *t*;

*Rmt* is the actual return on a market index in time *t*;

 $R_f$  is the risk-free rate of return in time *t*;

*Rst* is the actual return for macroeconomic risk factors at time *t;*

*εit* is a random error;

 $a_i$  is the actual return on stock *i* in time *t* when the market return is zero;

 $\beta_i$  and  $\beta_i$  are the slopes from multiple regression of  $R_i$  and  $R_m$ , and  $R_i$  *and*  $R_s$  respectively.

Fama (1998) has presented a study which has aimed to determine the number of priced state variables in the ICAPM. He has tried to answer the questions that go to the heart of the economics of the ICAPM. Specifically, given ICAPM asset pricing and given that there is a total of S state variables potentially of hedging concern to investors, we need to know the following: (1) how can we determine which of these state variables are, in fact, of hedging concern, and (2) in what sense do these state variables produce special risk premiums in expected returns.

Fama (1998) has added that it is possible to find the set of priced variables when the state variables are identified (named). When the number of state variables is known, but their names are not, confident conclusion about risk premiums are probably impossible. Moreover, the existing literature has failed to identify the specific state variables that produce risk in the context of ICAPM. So, there is no practical solution to manage the systematic risk and to identify significant economic state variables in the context of ICAPM. This has given rise to the usage of alternative multifactor assets pricing models such as the Arbitrage Pricing Model (APM).

### **3.5.3 Arbitrage Pricing Model**

The arbitrage pricing theory (APT) is a multifactor mathematical model used to describe the relation between the risk and expected return of securities in financial markets. It computes the expected return on a security based on the security's sensitivity to movements in multiple risk factors. Furthermore, consistent with the portfolio theory and diversification, modern financial theory has focused on systematic factors as the likely sources of risk. So, the Arbitrage Pricing Model (APM) is designed to capture the sensitivity of the asset's returns to changes in certain macroeconomic variables, which are the economic state variables and are the sources of systematic risk. However, how many factors influence return on a stock and also how sensitive the stock is to a particular factor are virtually impossible to detect. But getting "close enough" is often good enough; in fact, studies use four to five factors to explain a security's return.

The arbitrage pricing theory is based on three assumptions. Firstly, that a factor model can be used to describe the relation between the risk and return of a security. Secondly, idiosyncratic risk can be diversified away. Thirdly, efficient financial markets do not allow for persisting arbitrage opportunities. Based on these assumptions, Ross (1976) has developed the Arbitrage Pricing Theory (APT) and Roll and Ross (1995) have provided a more intuitive explanation of the APT and have discussed its merits for portfolio management. The APT is an alternative approach to the CAPM which has become the major analytic tool for explaining the phenomena observed in capital markets. The APT model has the following form:

$$
R_i = E[R_i] + \beta_{i1}F_1 + \beta_{i2}F_2 + \dots + \beta_{in}F_n + \varepsilon_i
$$

where,

 $R_i$  is the actual (realized) return on security *i*;

 $E(R_i)$  is the expected return on security *i*;

 $\beta_{ij}$  is the sensitivity of actual return on *i*th asset to the *j*th risk factor (*F<sub>i</sub>*);

and  $\varepsilon_i$  is the random error term.

So, the return on any security or portfolio is dependent on expected return on security plus a series of macroeconomic factors. It is important to note that the expected value of factor, F, is zero. Therefore, these factors in Equation (3.8) are measuring the deviation of each factor from its expected value.

The model begins with the assumption that actual return on any security is equal to its expected return plus a series of impacts on expected return (i.e. the impacts of different macroeconomic variables on return). It breaks up the single factor CAPM into several components. The CAPM predicts that security returns are linearly related to a single common factor, the return on market portfolio. On the other hand, the APT is based on a similar intuition but is much more general. The CAPM is viewed as a special case of the APT when the market return is the single relevant factor. There are many multifactor assets pricing models developed in the literature. But all the multifactor asset pricing models developed in the literature can be treated as special theoretical cases of the APT (Sinclair, 1984).

The APT predicts a relationship between the returns of a portfolio or a single asset through a linear combination of variables. The APT approach moves away from the risk versus return logic of the CAPM, and exploits the notion of "pricing by arbitrage" to its fullest possible extent. Ross (1976) has noted that arbitrage theoretic reasoning is not unique to this theory only, but is, in fact, the underlying logic and methodology of virtually all of finance theory.

However, the APT does not provide a guideline as to how many pricing factors should be chosen and, more importantly, what those factors are. In application, researchers have relied either on a statistical method, such as factor analysis, or on fundamental variables (Merville et al., 2001). Thus, there are two different versions of APT: (1) the factor loading model and (2) the macro variable model. These two empirical models are used to implement and test the APT. The factor loading model uses artificial variables while macro variable model uses macroeconomic variables based on the economic transmission mechanism (Groenewold and Fraser, 1997).

Groenewold and Fraser (1997) have compared the factor loading model and the macro variable model of the APT and the CAPM. Both versions of the APT have found to clearly outperform the CAPM, but neither version of the APT is clearly superior to the other in terms of both within and out-of-sample explanatory power. However, Chen (1983) has argued that the APT is more in the spirit of macro variable approach, although he has not named the macroeconomic variables affecting stock return.

Similarly, Chen et al. (1997) have examined returns of real estate investment trusts based on the factor loading model as well as the macro variable model. This study has compared the ability of these two models to explain real estate returns. The results have shown that while the two models perform equally well during the period 1974-1979, the macro variable model outperforms the factor loading model over the periods 1980-1985 and 1986-1991.

Roll and Ross (1980) have tested the APT using the factor analysis technique with artificial variables. It has become a classic article on testing the APT. They have found that there are at least three and probably four significant factors. However, they have failed to determine which factors are significantly priced. Shanken (1985) has responded to Roll and Ross's work and has added that there are two problems with the decomposition of the variance-covariance matrix of returns. Firstly, the number of factors needed to complete the model is indeterminate and secondly, the factors themselves may not be unique. He has concluded that the identification of priced factors is difficult. He has suggested that the solution provided through factor analysis is not unique.

The arguments of Shanken (1985) concerning the number of factors are echoed in the study of Dhrymes et al. (1984). They have criticized the factor analytic technique of Roll and Ross (1980) and have argued that in the factor analytic technique, as the number of stocks increases then the number of artificial factors increases. Similarly, Beenstock and Chan (1986), using the factor analytic technique in UK stock market, have found results like Dhrymes et al. (1984). They have found 20 risk factors in UK stock market and also the number of factors is proportionate to the sample size. According to Merville et al. (2001) construction of a statistical method (like factor analysis) explains most of the crosssectional variations of equity returns. However, it adds little understanding as to why equity returns differ. Economic factors, on the other hand, are important in sorting out the determinants of equity returns.

According to Chen et al. (1986) economic state variables have systematic effects on stock returns. They have added that from the perspective of the efficient market hypothesis and rational expectations, asset prices should depend on their exposures to the state variables that describe the economy. For this reason, following the pioneering work of Chen et al. (1986), there are several works in the literature (Beenstock and Chan, 1988; Groenewold and Fraser, 1997; Shanken and Weinstein, 2006; Tursoy et al., 2008) on relationship between stock market return and macroeconomic forces.

Alongside, Azeez & Yonezawa (2006) have mentioned that the primary advantages of using macroeconomic factors are: (1) the macroeconomic factors in principle can provide economic interpretations, while with a factor analysis approach it is unknown why these factors are being priced; and (2) rather than only explaining the asset-prices, observed macroeconomic variables also provide additional information related to the link between asset-price behavior and macroeconomic events.

In this backdrop, the framework of the macro variable model of the APT has been used in this research to examine the relationship between stock market index and macroeconomic variables in Bangladesh. For this purpose, advanced econometric models have been chosen. Moreover, multiple econometric models have been applied to check the robustness of the results.

# **3.6 Conclusion**

Assets pricing procedure starts with the valuation of a single stock mostly based on predictions of the future cash flows or the profitability of the firm along with the riskiness associated with these future cash flows. Portfolio theory refers to the return from a group of stocks which states that the unsystematic risk is generated by microeconomic factors and is specific to an individual firm or industry. This risk can be eliminated through the process of diversification. But the systematic risk is mainly created by macroeconomic factors and cannot be eliminated through diversification, therefore, is rewarded in the stock market. So, the equilibrium asset pricing models, such as CAPM and APM, refer to the valuation of stocks based on the macroeconomic variables.

Efficient market hypothesis and rational expectation hypothesis suggest that people use all the available information and use the best valuation model. There are many studies trying to identify the number of significant variables in the context of different multifactor valuation models. However, the most widely used model is the macro variable version of APT. Because it has several advantages and the most important one is that the selected variables are economically interpretable factors. Empirical studies have also shown that the macro variable version of APT outperforms the factor loading version of the APT as well as the CAPM.

In this context, the most sophisticated econometric models and methodologies within the framework of macro variable version of Arbitrage Pricing Model have been applied to investigate the relationship between stock market index and macroeconomic indices in Bangladesh. Moreover, multiple econometric models have been used to examine the robustness of the findings.

# **Chapter 4**

# **Long-term Equilibrium and Causal Relationships**

# **4.1 Introduction**

Institutional investors like insurance companies or pension funds have long-term investment horizons of several years or even decades. Thus, a large part of their asset allocation is based on strategic consideration and portfolio optimization. These investors are more interested in long-term expected returns, rather than short-term fluctuations based on business cycles or investors'sentiment. In view of this, a study of long-term equilibrium relationship is of immense importance to address the question as to how a shift in some macroeconomic variables may change long-term stock market returns for the investors. Although there exists a significant long-run equilibrium relationship, there may be disequilibrium in the short-run. This short-run disequilibrium may be adjusted through an error correction mechanism to bring about a stable long-run equilibrium relationship. Hence the study of error correction process is also crucial.

Furthermore, the causal relation between stock market and macroeconomic variables are important to decide on the efficiency of a stock market. Because the direction of causal relationship determines the market efficiency. If changes in the economic variables neither influence nor are influenced by stock price fluctuations, then the two series are independent of one another and the market is informationally efficient. Also, the unidirectional causality running from lagged values of stock prices to economic activities does not violate informational efficiency, rather this suggests that stock prices lead the economic activities and that the stock market makes rational forecasts of the economy.

In contrast, if lagged changes in some economic variables cause variations in stock prices, this implies a unidirectional causality running from economic variables to stock market. This behavior indicates that the market is inefficient as the past economic information is yet to be reflected into the stock prices. Similarly, a market is termed as inefficient if there exists a bi-directional causality between the stock market and economic variables, meaning that the lagged changes in some economic variables cause variations in stock prices and past fluctuations in stock prices cause variations in the economic variables.

Moreover, diagnostic tests of the residuals of the error correction model need to be conducted to examine the viability of the model. Although it is not the primary goal of the investigations, these diagnostic tests are crucial to check the viability and significance of the results. For a good model, the residuals of the regression equation should be homoscedastic, not be serially correlated and should be normally distributed. In addition, different stability tests are also important to investigate the stability of the parameters over the period.

The aforesaid issues are reported in five sections of this chapter. In section 4.2, we have discussed the motivation of selecting macroeconomic variables for our empirical analysis based on our review of theoretical and empirical literatures, own intuition and background knowledge. The methodologies to be used in the analyses have been discussed in section 4.3. More specifically, the econometric models for testing long- and short-run relationships along with the error correction mechanism have been discussed. Also, the procedure for causality test has been described in this section. In section 4.4, the results of the empirical investigations have been reported and explained in light with other relevant studies. Moreover, the findings of the viability tests to check the significance of the results have been portrayed. The results of the stability tests to examine the stability of the parameters have been reported in this section. Finally, in section 4.5, the findings are summarized in the conclusion.

# **4.2 Selection of Research Variables**

The macroeconomic variables, which might have impact on future dividends and/or the discount rate from the perspective of Bangladesh economy, have been selected for the study. Chen et al. (1986) have suggested that the selection of variables requires judgment. Therefore, during the selection of variables, we have considered the existing theory and the empirical evidences. The description of the research variables along with the justification for selection and its hypothesized relationships with the stock market are discussed in the following section.

### **4.2.1 Description of Research Variables**

Based on the previous works of the earlier scholars; such as Maysami et al. (2004), Mukherjee and Naka (1995) and Khan and Yousuf (2013), this study has examined the relationship between the stock market index and the selected macroeconomic variables. From a macroeconomic context, stock holders have an interest to know and understand the relationship between stock market and Gross Domestic Product (GDP), the impact of inflation as well as the implications of money supply, exchange rate and interest rate on equity returns. In addition to these factors, gold is considered as an alternative to stock investment in many countries and as such gold price has effect on stock market (Mukhuti, and Amalendu, 2013). Thus, all these macroeconomic factors have been considered in this research. The research variables are described below in more details.

**Stock Market Index:** A stock market index is a collection of the major firm's stock (Strong, 2005). Rafique et al. (2013) have claimed that stock market performance is measured through movement in its index. The fluctuation in the index is affected by macroeconomic, social, political, international as well as firm specific factors. Market index helps the interested investors to understand the movement of the stock market. In this study, we have used month end DSE General Index to represent the stock market of Bangladesh. The month end index data of 25 years have been collected, then these data have been adjusted considering base value of 100 at the beginning of our sample period i.e. end of January 1991.

**Industrial Production Index (IPI):** For our empirical analysis, monthly data of industrial production index of medium to large scale manufacturing industries with base year 1988- 1989 has been considered as a proxy of GDP, because data on the former variable is available on monthly basis but the latter is not. Moreover, the productive capacity of an economy indeed depends directly on the accumulation of real assets, which in turn contributes to the production capacity of firms. Thus, economies of scale may generate higher profitability due to increased turnover. Tainer (1993) is of the view that the industrial production index is procyclical and can be used as a proxy for the level of real economic activity. Many studies (for example Adrangi et al., 1999; Ibrahim and Aziz, 2003) have represented GDP by industrial production index.

Many authors (Fama, 1981; Chen et al., 1986) have found that aggregate output, such as GDP or industrial production, can partly explain fluctuations in aggregate corporate cash flows of firms and thus stock market returns. Like these studies, the studies of Chan et al. (1985), Mukherjee and Naka (1995), Adrangi et al. (1999) and Humpe and Macmillan (2007) have documented a positive relationship between the industrial production index and the stock market index. Considering the findings of these studies, we have hypothesized a positive relationship between stock market and industrial production index. **Interest Rate:** Interest rate directly changes discount rate in the valuation model of stock and thus influences stock prices. Theoretically, interest rate has a negative relationship with stock prices. When rates on deposits in the bank increase, people redirect their money from capital market to banks and this leads to a decrease in the demand of shares. The opposite is true if deposit rates decrease. When rates on deposits increase, lending rates also increase. This creates a negative impact on investment and hence stock prices and vice versa. The studies of Chan et al. (1985) and Chen et al. (1986) have documented negative relationship between interest rate and stock returns.

In this study, the weighted average deposit rate, offered by commercial banks on three to six months fixed or term deposits, has been considered as interest rate (like the study of Uddin and Alam, 2007). Consistent with the financial theory and findings of the literatures, a negative relationship between interest rate and stock market is hypothesized.

**Inflation:** Generally, inflation is measured in terms of Consumer Price Index (CPI), which tracks the price of a basket of core goods and services over time. Earliest inferences on positive relation between inflation and stock returns are based on hypothesis presented by Irving Fisher (1930). Conversely, Fama (1981) has proposed the proxy hypothesis, which illustrates a negative relationship between inflation and stock prices.

Talla (2013) has argued that inflation can affect stock market either positively or negatively. He has added that when demand exceeds supply, firms tend to increase their products prices, this increase in price leads to higher earnings of the firms. So, this channel creates a positive impact on stock returns. On the other hand, increase in inflation results in increase in discount rate used to determine the value of stock. So, this channel creates a negative impact on stock market return. Thus, the overall relation between the inflation and stock market depends on which factor outweighs the other. Many studies (Fama and Schwert, 1977; Chen et al., 1986; Nelson 1976; Jaffe and Mandelker, 1976) have pointed to a negative relation between inflation and stock prices. However, Maysami et al. (2004) have documented a positive relationship between inflation and Singapore stock market.

This study has hypothesized a negative relationship between stock market and inflation with the justification that an increase in inflation is likely to lead economic tightening policies, which in turn increase the nominal risk-free rate and raise the discount rate in the valuation model. Also, we have considered the argument of DeFina (1991) that nominal contracts disallow the immediate adjustment of the firm's revenues with costs and hence reduce the profit.

**Exchange Rate:** Gunasekarage et al. (2004), and Adam and Tweneboah (2008) have used national currency per United States Dollar (USD) as a proxy for exchange rate. Joseph (2002) has mentioned that changes in exchange rate affect the competitiveness of firms through their impact on input and output prices. When the exchange rate appreciates, the exporters lose their competitiveness in international market and the sales and profits of the exporters shrink, thus the stock prices decline. Conversely, importers gain their competitiveness as domestic currency appreciation results in decrease in the prices of foreign raw materials, leading to increase in the firm's profits, which in turn increase the stock prices. So, the impact of exchange rate on the economy depends on the level of international trade and the trade balance to a large extent. Therefore, the impact is determined by the relative dominance of import and export sectors of the economy.

In line with this, Ibrahim and Aziz (2003) have explained the negative relation between exchange rate and Malaysian stock returns stating that the currency depreciation encourages exports; conversely, it increases costs of production through increasing domestic prices of imported capital and intermediate goods, but the latter effect of currency depreciation on real output seems to be more dominant.

Khan and Yousuf (2013) have hypothesized a positive relationship between exchange rate and stock market stating that increase in exchange rate (Taka depreciation against US dollar) should increase foreign investment in Bangladesh stock market, which in turn increases demand of stocks and, therefore, increases the stock prices. But they have found opposite relationship between exchange rate and stock market. They have argued that depreciation of currency has not increased the foreign investment, conversely, it has increased the imported materials cost and leading to a negative relationship. On the other hand, Buyuksalvarci (2010) has found positive relation between stock returns and exchange rate and has explained this by stating that a depreciation of the Turkish currency in terms of US dollar has attracted more foreign investment in stock market, which has increased the demand of stock and has increased the stock prices.

In this study, exchange rate is measured in terms of Bangladeshi taka (BDT) per US dollar and we have hypothesized a positive relation between exchange rate and stock market index with an anticipation that depreciation of BDT against US dollar has attracted more foreign investment in the stock market and has increased the stock prices.

**Money Supply:** There are several standard measures of the money supply, but Bangladesh Bank includes only M1 and M2. According to Bangladesh Bank, M1 is the sum of currency outside the banks, deposits of financial institutions with Bangladesh Bank (except Deposit Money Banks (DBMs)), demand deposits with DMBs (excluding inter-bank deposits and government deposits), whereas M2 is the sum of M1 and time deposits with DMBs (excluding inter-bank deposits and government deposits). Hamburger and Kochin (1972), Kraft and Kraft (1977) and Sirucek (2011) have used M2 as a proxy of money supply and stated that there is a strong relation between money supply (M2) and stock prices.

Mukherjee and Naka (1995) have argued that theoretically, the relation between these two variables can be positive or negative. The expansionary effect of money supply on real economic activity may create a positive relation. However, if the increase in money supply creates inflation and contributes to inflationary uncertainty, then it may exert a negative influence on the stock prices. Friedman and Schwartz (1963) have explained the relationship between money supply and stock return by simply hypothesizing that an increase in M2 indicates excess liquidity available for buying securities, resulting in higher security prices. However, Ibrahim and Aziz (2003) have explained their finding of negative long-run association between stock prices and M2 mentioning that the continued increase in money supply may exert a negative effect on the stock prices due to increasing inflationary pressures and subsequent policy orientation to contain the pressure.

Considering the expansionary effect of money supply on real economic activity, we have hypothesized a positive relationship between the money supply (M2) and stock market.

**Gold Price:** Gold is a precious and highly liquid instrument that possesses the attributes of both commodity and currency. It has been used throughout the history as money as well as a most popular metal for investment purposes. Due to its currency characteristic, it is said that, it performs as medium of wealth, means of exchange and a unit of value (Tully and Lucey, 2007). Furthermore, gold is also used for industrial purposes, reserve asset, and jewelry. Sumner et al. (2010) have attempted to find the interdependence among gold, stocks and bonds by examining whether gold returns and its volatility can be used to predict the US stock and bond price movement or vice versa. By analyzing volatility spillover, the researchers have concluded that there is no significant relationship between gold and stock returns volatility.

On the other hand, gold price generally remains constant or increases overtime, thus it can be used as an ideal hedge against inflation. People invest in gold because despite high inflation, gold value does not depreciate. Gold price moves up on inflationary expectations, but stocks go down for the same reason. Considering these, we have hypothesized a negative relationship between gold price and stock market.

Month end data of the seven research variables are collected for the period from January 1991 to December 2015. Then, except interest rate, data of the other variables are normalized to a starting value of 100 at January 1991. The interest rates are expressed in terms of one plus the interest rates in percentage. Later, all these variables are expressed in natural logarithmic forms. Table 4.1 shows the selected macroeconomic indices along with their symbols in natural logarithmic format. Also, the hypothesized relationships between the macroeconomic variables and the natural logarithmic of DSE General Index, expressed as LDSEGEN, are shown in the Table 4.1.

Variable	<b>Symbol in Logarithmic Term</b>	<b>Hypothesized Relation</b>
Industrial Production Index	LIPI.	Positive
<b>Interest Rate</b>	<b>LINT</b>	Negative
Consumer Price Index	LCPI	Negative
<b>Exchange Rate</b>	<b>LEXR</b>	Positive
Money Supply	LM2	Positive
Gold Price	<b>LGDPRICE</b>	Negative

**Table 4.1. Selected Macroeconomic Indices and the Hypothesized Relations with Stock Market Index**

### **4.2.2 Sample Period**

Until the mid-1980s, the banking sector in Bangladesh was characterized by a financially repressed regime. The sector witnessed low interest rate, distortion in resource allocation, low rate of savings leading to financial distress. Banks were being used to service the needs of the public sector and a few business houses (Hassan, 1994). The internal control system of commercial banks was weak, the published accounts never reflected the actual financial health, the quality of the assets of the banks was never evaluated on strict accounting principles, profitability and liquidity aspects of portfolio management were unfamiliar concepts among management personnel, and the elements of capital adequacy for banking operations were never given due importance (Raquib, 1999). The cumulative effect of mismanagement in the banking system led to a huge accumulation on non-performing loans for the financial sector, which had risen to more that 40 percent of the total advances of the banking sector at one point (Financial Sector Reform Project, 1996). During that period, the only stock exchange of the country, the Dhaka Stock Exchange, was almost inoperative with only a few enlisted companies.

To counter these problems, the first round of financial sector reform was initiated in 1982 with the denationalization of some commercial banks, followed by the establishment of the National Commission on Money, Banking and Credit in 1984. However, unsuccessful results of the first round of reforms led to second round of reforms in the early 1990s. The second round of reforms led to the adoption of wide-ranging banking reform measures under the World Bank's Financial Sector Reform Project (FSRP). The focus of the reform, among others, was on gradual deregulations of the interest rate structure, providing market-oriented incentives for priority sector lending, and improvement in the debt recovery environment. Moreover, licenses were given for many private commercial banks. Bangladesh Bank started open market operation actively and introduced its own securities, such as 90-day bill in 1990. Later, 30-day Bangladesh Bank Bill was also introduced in 1995 along with 90-day, 180-day and one-year maturity Treasury Bills with active participation of commercial banks. In place of arbitrarily fixed interest rate, Bangladesh Bank introduced a flexible market oriented interest rate from January 1990. The official and secondary market exchange rates were unified at the end of 1991.

The Securities and Exchange Commission (SEC) was established on 8 June 1993, through the enactment of the Securities and Exchange Commission Act, 1993, as a capital market regulator with a mandate to ensure proper issuance of securities, protection of the interest of investors in securities, development and regulation of the capital and securities markets in Bangladesh. On August 10, 1998 DSE introduced screen-based state-of-art automated online real-time trading through Local Area Network (LAN) and Wide Area Network (WAN). The latest up-gradation was web based trading software - MSA Plus, which was introduced on June 10, 2012. Now, investors can submit buy/sale orders on Dhaka stock exchange from anywhere of the world through Internet. Several reforms have been adopted to promote growth of capital market during this time.

Moreover, after nine years of military regime, Bangladesh started its fresh attempt towards a western liberal type of democracy in 1991. Considering the aforesaid factors, we have chosen January 1991 as the starting point of our research period. Furthermore, to include the most recent data, we have collected data up to December 2015.

#### **4.2.3 Source of Data**

The data of the DSE General Index has been collected from the Dhaka Stock Exchange Library. The data of selected six macroeconomic variables are obtained from Monthly Statistical Bulletin published by Bangladesh Bureau of Statistics, Economic Trends published by Statistical Department of Bangladesh Bank and various editions of Economic Survey of Bangladesh. Monthly data over 25 years (from January 1991 to December 2015) have been collected. We have collected monthly data for longer period to capture longterm movements and to avoid the effects of settlement and clearing delays which are known to significantly affect returns over shorter sampling intervals (Faff et al., 2005; Liow et al., 2006).

# **4.3 Methodology**

This section has outlined the empirical method used in this chapter. Nelson and Plosser (1982) have argued that most macroeconomic series have unit root indicating that the series are nonstationary, and this is an important issue for the analysis of macroeconomic variables. Yule (1926) has suggested that regression based on trending time series data can be spurious. This problem of spurious regression has further pursued by Granger and Newbold (1974) and they have developed the concept of cointegration.

The recent developments on cointegration have changed the way time series analysis is conducted (Maddala and Kim, 1999). In this context, cointegration approach has been applied in this chapter to examine the relationship between stock market index and the macroeconomic indices of Bangladesh. However, for cointegration test, it is required to know the order of integration of each variable and unit root tests are used for this purpose. Therefore, the cointegration test starts with unit roots test. At the same time, the trend specification of the variable is also important for cointegration test.

In this context, this section has described the concept of stationary vs nonstationary variables, trend vs differenced stationarity and spurious regression. Later, the most popular unit root tests have been discussed. Finally, the econometric tools to be used in this chapter have been outlined. More specifically, Johansen and Juselius cointegration test, error correction model, Granger causality test and Autoregressive Distributed Lags (ARDL) approach have been explained in detail.

#### **4.3.1 Stationary vs Nonstationary Stochastic Processes**

A time series is said to be stationary if its mean and variance are constant over time, i.e. time invariant along with its covariance. Such a time series tend to return to its mean and fluctuate around this mean and has constant amplitude. So, a stationary process does not drift too far away from its mean value. By contrast, a nonstationary time series has a timevarying mean or a time-varying variance or both. Nonstationary processes are example of Random Walk Model (RWM) with or without a drift and sometimes the processes have deterministic trends.

The autoregressive process is used in modeling empirical time series data, especially in economics. The autoregressive model treats a stochastic variable as depending on its own previous values and on a current independently and identically distributed (*iid*) stochastic term. A stochastic variable can be expressed as a *AR(1)* model, which is a random walk model without drift, as below:

$$
Y_t = Y_{t-1} + \varepsilon_t \qquad \text{where } \varepsilon_t \sim \text{iid}(0, \sigma^2) \tag{4.1}
$$

If  $t = 1$  then Equation (4.1) becomes:

$$
Y_1 = Y_0 + \varepsilon_1
$$
  
If t = 2 then:

 $Y_2 = Y_1 + \varepsilon_1$ 

Putting the value of  $Y_1$  from Equation (4.2), we get:

 $Y_2 = Y_0 + \varepsilon_1 + \varepsilon_2$ 

Similarly, *Y<sup>t</sup>* can be written as:

$$
Y_t = Y_0 + \varepsilon_1 + \varepsilon_2 + \varepsilon_3 \dots + \varepsilon_t
$$
  
\n
$$
\therefore Y_t = Y_0 + \sum_{i=0}^{t-1} \varepsilon_{t-i}
$$
 4.3

Now, the mean of  $Y_t$  is  $E(Y_t) = Y_0$ , since errors have zero expectation. Again  $Y_0$  is a constant, so it contributes nothing to the variance of  $Y_t$ , however, errors have variance  $\sigma^2$ and are uncorrelated with each other, so the variance of  $Y_t$  will be:

$$
Var(Y_t) = 0 + Var \sum_{i=0}^{t-1} \varepsilon_{t-i} = \sigma^2 \sum_{i=0}^{t-1} 1 = \sigma^2 \times t = t\sigma^2
$$
 4.4

The third condition of a series to be stationary is that the covariance must be time invariant. So, for  $t = t + h$  (where  $h > 1$ ), we can get from Equation (4.3):

$$
Y_{t+h} = Y_t + \sum_{i=0}^{h-1} \varepsilon_{t+h-i}
$$

So, the covariance between  $Y_t$  and  $Y_{t+h}$  can be give as:

$$
Cov(Y_t, Y_{t+h}) = Cov\left(Y_t, Y_t + \sum_{i=0}^{h-1} \varepsilon_{t+h-i}\right)
$$

But the covariance between  $Y_t$  and  $\mathcal{E}_{t+h-i}$  is zero, as the error terms are independent. So, the covariance can be written as:

$$
Cov(Y_t, Y_{t+h}) = Cov(Y_t, Y_t) = Var(Y_t) = t\sigma^2
$$
 (from Equation (4.4))

Hence, RWM without a drift is a nonstationary process, because although the mean is constant over time, but the variance and covariance are time invariant. In this model, shocks persist as the current value is equal to the initial value plus a series of random shocks.

Now, consider a random walk with a drift  $\alpha$  as follows:

$$
Y_t = \alpha + Y_{t-1} + \varepsilon_t \quad \text{where } \varepsilon_t \sim \text{iid}(0, \sigma^2) \tag{4.5}
$$

So, 
$$
Y_1 = \alpha + Y_0 + \varepsilon_1
$$
 4.6

Similarly,  $Y_2 = \alpha + Y_1 + \varepsilon_2$ 

Putting the value of  $Y_1$  from Equation (4.6), we get:

$$
or, Y_2 = \alpha + (\alpha + Y_0 + \varepsilon_1) + \varepsilon_2
$$

$$
\therefore Y_2 = 2\alpha + Y_0 + \varepsilon_1 + \varepsilon_2
$$

Similarly,  $Y_t = \alpha t + Y_0 + \sum \varepsilon_{t-i}$  $t-1$  $i=0$ 

Now,  $E(Y_t) = \alpha t + Y_0$  since errors have zero expectation. Also, variance of  $Y_t$  is:

$$
Var(Y_t) = 0 + \sigma^2 \sum_{i=0}^{t-1} 1 = t\sigma^2
$$

and the  $Cov(Y_t, Y_{t+h}) = t\sigma^2$ 

Hence, RWM with a drift is also a nonstationary process, because mean, variance and covariance of the variable increase over time.

Now, let us consider an *AR(1)* process as follows:

$$
Y_t = \rho Y_{t-1} + \varepsilon_t \qquad \text{where } \varepsilon_t \sim \text{iid}(0, \sigma^2) \text{ and } -1 \le \rho \le +1 \tag{4.7}
$$

If  $\rho = 1$  the model becomes a random walk model without drift. So,  $\rho = 1$  is a case of nonstationary time series. For  $\rho \neq 1$ , Equation (4.7) can be expressed as:

$$
Y_t = \rho(\rho Y_{t-2} + \varepsilon_{t-1}) + \varepsilon_t
$$
 [From Equation (4.7), we get  $Y_{t-1} = \rho Y_{t-2} + \varepsilon_{t-1}$ ]

$$
\therefore Y_t = \rho^2 Y_{t-2} + \rho \varepsilon_{t-1} + \varepsilon_t
$$

Then  $Y_t = \rho^2(\rho Y_{t-3} + \varepsilon_{t-2}) + \rho \varepsilon_{t-1} + \varepsilon_t$ 

$$
\therefore Y_t = \rho^3 Y_{t-3} + \rho^2 \varepsilon_{t-2} + \rho \varepsilon_{t-1} + \varepsilon_t
$$

Similarly,  $Y_t = \rho^t Y_0 + \rho^{t-1} \varepsilon_1 + \cdots + \rho \varepsilon_{t-1} + \varepsilon_t$ 

$$
\therefore Y_t = \rho^t Y_0 + \sum_{i=0}^{t-1} \rho^i \varepsilon_{t-i}
$$

Now,  $E(Y_t) = \rho^t E(Y_0)$ , since the errors have zero expectation. So, an *AR(1)* process will have constant mean, if  $E(Y_0) = 0$ . And the variance of  $Y_t$  of  $AR(1)$  process is:

$$
Var(Y_t) = Var(\rho Y_{t-1} + \varepsilon_t)
$$
  
\n∴ Var(Y<sub>t</sub>) = Var(\rho Y<sub>t-1</sub>) + Var(\varepsilon<sub>t</sub>)  
\n∴ Var(Y<sub>t</sub>) = \rho<sup>2</sup>Var(Y<sub>t-1</sub>) + Var(\varepsilon<sub>t</sub>)  
\nIf we apply the condition that  $Var(Y_t) = Var(Y_{t-1})$ , then:  
\n∴ Var(Y<sub>t</sub>) = \rho<sup>2</sup>Var(Y<sub>t</sub>) + \sigma<sup>2</sup>  
\n∴ Var(Y<sub>t</sub>) - \rho<sup>2</sup>Var(Y<sub>t</sub>) = \sigma<sup>2</sup>  
\n∴ Var(Y<sub>t</sub>) = \frac{\sigma<sup>2</sup>}{1-\rho<sup>2</sup>}} 4.8

Now, if  $|\rho| > 1$ ; *Var*(*Y<sub>t</sub>*) becomes negative, but variance cannot be negative.

Now, if  $\rho = 1$ ; *Var*( $Y_t$ ) becomes infinity, but the condition of a series to be stationary is that it must have a finite variance. So, the condition for the process to be stationary is  $|\rho|$  < 1.

# Now, Equation (4.7) can be written as:

$$
Y_{t+2} = \rho Y_{t+1} + \varepsilon_{t+2}
$$
  
\n
$$
\therefore Y_{t+2} = \rho(\rho Y_t + \varepsilon_{t+1}) + \varepsilon_{t+2}
$$
  
\n
$$
\therefore Y_{t+2} = \rho^2 Y_t + \rho \varepsilon_{t+1} + \varepsilon_{t+2}
$$
  
\n
$$
\therefore Y_{t+2} = \rho^2 Y_t + \sum_{i=0}^1 \varepsilon_{t+2-i}
$$

So,  $Y_{t+h}$  can be written as:

$$
Y_{t+h} = \rho^h Y_t + \sum_{i=0}^{h-1} \varepsilon_{t+h-i}
$$

So, the covariance between  $Y_t$  and  $Y_{t+h}$  can be give as:

$$
Cov(Y_t, Y_{t+h}) = Cov\left(Y_t, \rho^h Y_t + \sum_{i=0}^{h-1} \varepsilon_{t+h-i}\right)
$$

But the covariance between  $Y_t$  and  $\varepsilon_{t+h-i}$  is zero, as the error terms are independent. So, the covariance can be written as:

$$
Cov(Y_t, Y_{t+h}) = Cov(Y_t, \rho^h Y_t)
$$
  
\n
$$
\therefore Cov(Y_t, Y_{t+h}) = \rho^h Cov(Y_t, Y_t)
$$
  
\n
$$
\therefore Cov(Y_t, Y_{t+h}) = \rho^h Var(Y_t)
$$
  
\n
$$
\therefore Cov(Y_t, Y_{t+h}) = \rho^h \frac{\sigma^2}{1 - \rho^2}
$$
 (Putting the value from Equation (4.8))

Now, if  $|\rho| > 1$ ;  $Cov(Y_t, Y_{t+h})$  becomes negative, but variance cannot be negative. Now, if  $\rho = 1$ ;  $Cov(Y_t, Y_{t+h})$  becomes infinity, but the condition of a series to be stationary is that it must have a finite variance.

So, the condition for the process to be stationary is  $|\rho|$  < 1.

Now the conditions for an *AR(1)* process to be stationary are:

- i. The initial value  $Y_t$  must equal to zero i.e.  $Y_0 = 0$ .
- ii.  $\rho$  must be less than 1.

Now, let us check the conditions under which *AR(1)* process to be weakly dependence. The correlation between  $Y_t$  and  $Y_{t+h}$  can be given as:

$$
Corr(Y_t, Y_{t+h}) = \frac{Cov(Y_t, Y_{t+h})}{\sqrt{Var(Y_t)}\sqrt{VarY_{t+h}}}
$$
\n
$$
\tag{4.10}
$$

From Equation (4.9) and (4.10), we get:

$$
\therefore Corr(Y_t, Y_{t+h}) = \frac{\rho^h Var(Y_t)}{Var(Y_t)}
$$

$$
\therefore \text{Corr}(Y_t, Y_{t+h}) = \rho^h
$$

when h  $\rightarrow \infty$  then *Corr*(*Y*<sub>*t*</sub>,*Y*<sub>*t+h*</sub>)  $\rightarrow$  0 if  $|\rho|$  < 1, but when  $|\rho|$  > 1 then the series becomes explosive.

So, again an *AR(1)* process to be stationary the condition is  $|\rho| < 1$ .

#### **4.3.2 Trend Stationary and Differenced Stationary Processes**

If the trend in a time series is a function of time, such as  $t$  and  $t^2$ , we call it a deterministic trend (predictable). If it is not predictable, then the trend is a stochastic trend. Let us consider the following *AR(1)* model:

$$
Y_t = \alpha + \beta_1 t + \beta_2 Y_{t-1} + \varepsilon_t \quad \text{where } \varepsilon_t \sim \text{iid}(0, \sigma^2) \tag{4.11}
$$

Reparametrizing Equation (4.11) the following models can be found:

**Pure Random Walk:** Equation (4.11) is a pure random walk, if  $\alpha = 0$ ,  $\beta_1 = 0$ , and  $\beta_2 = 1$ , then the model is:

$$
Y_t = Y_{t-1} + \varepsilon_t \qquad \qquad \text{where } \varepsilon_t \sim \text{iid}(0, \sigma^2) \qquad \qquad 4.12
$$

As describe earlier, this is a nonstationary time series. If we take the 1<sup>st</sup> difference of the series (i.e.  $\Delta Y_t = Y_t - Y_{t-1}$ ), we get  $\Delta Y_t = \varepsilon_t$ . Note that the mean of differenced series is  $E(\Delta Y_t) = E(\varepsilon_t) = 0$ , and  $Var(\Delta Y_t) = Var(\varepsilon_t) = \sigma^2$ . As both the mean and variance of the series are time invariant, hence a random walk without a drift is differenced stationary (DS) process.

The pure random walk has a stochastic trend and may be a good starting point for describing the way many financial market prices and returns seem to behave. However, realization of random walk is not usually being characterized by the tendency to grow over time, which is seen in many macroeconomic time series. That is, the stochastic trend in the random walk is not sufficient to explain the kind of trend behavior we observe in the typical macroeconomic time series.

**Random Walk with Drift:** The model will become a random walk with drift when  $\alpha \neq 0$ ,  $\beta_1 = 0$ , and  $\beta_2 = 1$ . Then, the model is:

$$
Y_t = \alpha + Y_{t-1} + \varepsilon_t \qquad \text{where } \varepsilon_t \sim \text{iid}(0, \sigma^2) \tag{4.13}
$$

This series is also nonstationary. If we take first difference, then  $\Delta Y_t = \alpha + \varepsilon_t$ . This differenced time series has mean  $E(\Delta Y_t) = E(\alpha + \varepsilon_t) = \alpha$  (constant) and the variance is *Var*( $\Delta Y_t$ ) = *Var*( $\alpha + \varepsilon_t$ ) =  $\sigma^2$ , as the errors are serially uncorrelated. So, both the mean and variance of differenced series are time invariant. Hence a random walk with a drift is also differenced-stationary (DS). Also, *Y<sup>t</sup>* is trending upward or downward depending on the sign of the drift  $(\alpha)$ , so, this is called a stochastic trend.

The random walk with drift has a stochastic trend, which includes a trend component that can account for a time series tendency to increase on average over time. Like the pure random walk, it is characterized by a long-run forecast error variance that is increasing without bound as the forecast horizon gets sufficiently long. However, the random walk with drift is still not quite enough, because it assumes that the error terms in the first difference of *Y<sup>t</sup>* are serially uncorrelated.

**Deterministic Trend:** In case of deterministic trend  $\alpha \neq 0$ ,  $\beta_1 \neq 0$ , and  $\beta_2 = 0$  then

$$
Y_t = \alpha + \beta_1 t + \varepsilon_t \qquad \text{where } \varepsilon_t \sim \text{iid}(0, \sigma^2) \qquad (4.14)
$$

Note that the mean of the series is  $E(Y_t) = E(\alpha + \beta_1 t + \varepsilon_t) = \alpha + \beta_1 t$ , which is time varying, but its variance is  $Var(Y_t) = Var(\alpha + \beta_1 t + \varepsilon_t) = \sigma^2$  which is time invariant. Still, due to the time variant mean, the series with a deterministic trend is nonstationary.

We can estimate  $\alpha$  and  $\beta$ <sup>*I*</sup> by regressing the series on *t*. Once we know these values, we can estimate the mean value and forecast it perfectly. Hence, we can subtract the mean from the series and create detrended series, which is  $Y_t = Y_t - E(Y_t) = \varepsilon_t$ . Now the mean of the detrended series is  $E(Y_t) = E(\varepsilon_t) = 0$ , and its variance is  $Var(Y_t) = Var(\alpha + \beta_1 t + \varepsilon_t) = \sigma^2$ . So, both the mean and the variance of the series are time invariant and hence the detrended series is stationary. So, if the deterministic series is detrended, it becomes stationary.

**Random walk with drift and deterministic trend:** We can get a random walk with drift and deterministic trend by putting  $\alpha \neq 0$ ,  $\beta_1 \neq 0$ , and  $\beta_2 = 1$ 

 $Y_t = \alpha + \beta_1 t + Y_{t-1} + \varepsilon_t$  where  $\varepsilon_t \sim \text{iid}(0, \sigma^2)$ ) 4.15

Now, the first difference series is  $\Delta Y_t = \alpha + \beta_I t + \varepsilon_t$  is still time varying and hence the mean of the differenced series is nonstationary. Detrending is still necessary on the differenced series to make it stationary.

### **4.3.3 The Phenomenon of Spurious Regression**

Suppose, we have two random walk series:  $Y_t = Y_{t-1} + \varepsilon_t$  and  $X_t = X_{t-1} + \mu_t$ , where error terms are white noise. If we use these series in a regression, for instance,  $Y_t = \alpha + X_t + v_t$ , where  $v_t$  is white noise error, then we can obtain a spurious regression, meaning that we may get a highly significant slope coefficient but a relatively small  $R^2$  value. On the other hand, in the case of trending variables, we may get a high value for the  $R^2$  as well as highly significant slope coefficient. Based on this result, we may be tempted to conclude that the variable *X* has a significant impact on *Y*, whereas a priori there should be none. In fact, this regression is meaningless.

Also, it must be noted that the differenced series, *∆Y<sup>t</sup>* and *∆X<sup>t</sup>* are stationary and seems can be used in a regression. The differenced series are  $\Delta Y_t = \varepsilon_t$  and  $\Delta X_t = \mu_t$  and regressing one on the other should generate a  $\mathbb{R}^2$  which is practically close to zero (as a random shock regressed over another should show no correlation). This is yet another way to verify that the original series are random walks. Although quite dramatic, but the study of Box and Newbold (1971) has indicated just how easily one can be led to produce a spurious model if sufficient care is not taken over an appropriate formulation for the autocorrelation structure of the errors from the regression equation. So, this is a strong reminder that one should be cautious in running regression with such nonstationary series.

### **4.3.4 Unit Root Tests**

As mentioned earlier, Ordinary Least Squares (OLS) estimates for nonstationary series results in a spurious regression. Therefore, cointegration analysis is used to investigate the long-run relationship among the nonstationary variables. Despite the versatility of cointegration techniques, first we have used Johansen and Juselius cointegration test. Furthermore, to examine the robustness of the findings, we have also used the ARDL Bounds testing procedure proposed by Pesaran et al. (2001) to test for the existence of a linear long-run relationship between stock market and macroeconomic variables.

However, the precondition of Johansen and Juselius cointegration test is that the series must be integrated in the same order. On the other hand, ARDL approach crashes if any of the time series is integrated of order 2, *I(2)*. So, for both the approaches, it is important to know the order of integration of the series under consideration. Unit root tests are used for this purpose. There are various unit root tests. Given the relatively low power of unit root tests, we have used multiple tests including the well-known Augmented Dickey Fuller (ADF) and non-parametric Phillips-Perron (PP) tests along with Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to investigate the order of integration of each series. To understand the evolution of ADF test the following sub-section starts with Dickey-Fuller test, then the ADF and PP tests and finally the KPSS test have been discussed.

#### **4.3.4.1 Dickey-Fuller Unit Root Tests**

Let us consider an *AR(1)* process:

$$
Y_t = \rho Y_{t-1} + \varepsilon_t \qquad \text{where } \varepsilon_t \sim \text{iid } (0, \sigma^2) \tag{4.16}
$$

If  $\rho = 1$ , meaning that the series has a unit root (or the series is nonstationary) and the null hypothesis cannot be rejected. Conversely, the alternative hypothesis is  $\rho < 1$  (as we have already ruled out  $\rho > 1$ ), meaning that the null hypothesis can be rejected, and the conclusion is that there is no unit root and the series is stationary. So, the null and alternative hypotheses are as follows:

 $H_0: \rho = 1$  Unit root [Variable is nonstationary]  $H_A: \rho < 1$  No unit root [Variable is stationary]

The asymptotic distribution of the *t*-statistic under  $\rho = I$  is not standard *t*-distribution, thus using the conventional critical values can lead to considerable over rejection of the null hypothesis of a unit root (Maddala and Kim, 1999). In this context, Fuller (1976) provided the critical values of these statistics to deal with the non-standard distribution issue.

If  $H_0$  is rejected, then any of the following three scenarios can exist:

i) *Y<sup>t</sup>* is stationary with zero mean:

$$
Y_t = \rho Y_{t-1} + \varepsilon_t
$$

ii)  $Y_t$  is stationary with a non-zero mean, say  $\mu$ , in:

$$
Y_t - \mu = \rho (Y_{t-1} - \mu) + \varepsilon_t
$$
  
or 
$$
Y_t = \rho Y_{t-1} + \mu (1 - \rho) + \varepsilon_t
$$

$$
\therefore Y_t = \alpha + \rho Y_{t-1} + \varepsilon_t
$$

where  $\alpha = \mu(1 - \rho)$ 

iii)  $Y_t$  is stationary around a deterministic trend in:

$$
Y_t - a - bt = \rho(Y_{t-1} - a - b(t-1)) + \varepsilon_t
$$
  
or  $Y_t = \rho Y_{t-1} - \rho a - \rho b(t-1) + \varepsilon_t + a + bt$   
or  $Y_t = \rho Y_{t-1} + \{a(1-\rho) + \rho b\} + bt(1-\rho) + \varepsilon_t$   
 $\therefore Y_t = \alpha + \beta t + \rho Y_{t-1} + \varepsilon_t$  where  $\alpha = a(1-\rho) + b\rho$  and  $\beta = b(1-\rho)$ 

In principle, we can run the regression to see whether  $\rho = I$  to check for a nonstationary process. However, regressing the series on its lagged value severely bias the *t-*statistics for the  $\rho$  coefficient in presence of a unit root. Therefore, the Equation (4.16) is manipulated and has been expressed it somewhat differently by subtracting the lagged value from both sides in the following form:

$$
Y_t - Y_{t-1} = (\rho - 1)Y_{t-1} + \varepsilon_t
$$
  
\n
$$
\therefore \Delta Y_t = \gamma Y_{t-1} + \varepsilon_t \qquad \text{where } \gamma = (\rho - 1)
$$

So, the null hypothesis H<sub>0</sub>:  $\rho = I$  is now equivalent to the null hypothesis H<sub>0</sub>:  $\gamma = 0$  (i.e. there is a unit root, and the series is nonstationary) and the alternate hypothesis,  $H_A$ :  $\rho$  < 1 is equivalent to H<sub>A</sub>:  $\gamma < 0$  (i.e. there is no unit root and the series is stationary). If H<sub>0</sub> is rejected, then any of the following three scenarios can exist:

The Equation (4.17) does not include trend and drift as:

$$
\therefore \Delta Y_t = \gamma Y_{t-1} + \varepsilon_t
$$

The Equation (4.17) can include a drift as follows:

$$
\Delta Y_t = \alpha + \gamma Y_{t-1} + \varepsilon_t \tag{4.18}
$$

The Equation (4.17) can also include a drift and a trend variable:

$$
\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \varepsilon_t \tag{4.19}
$$

So, the Dickey-Fuller test is performed for each of the three above models.

The Dickey-Fuller testing procedures assume that the error term  $\varepsilon_t$  follows a white noise process and  $Y_0 = 0$ . These are stringent assumptions for the real world. When the errors are correlated, there is a need to either change the estimation method (adopt another regression model) or modify the statistics to obtain consistent estimators and statistics. Dickey and Fuller (1979) have used the first approach of changing the estimating regressions using the parametric approach, known as Augmented Dickey Fuller test. On the other hand, Phillips and Perron (1988) have followed the second approach of modifying the statistics using a nonparametric approach.

## **4.3.4.2 Augmented Dickey-Fuller Unit Root Tests**

In Augmented Dickey-Fuller (ADF) test the null hypothesis is tested by estimating an autoregression of *∆Y<sup>t</sup>* on its own lags and *∆Yt-1* using Ordinary Least Squares (OLS). The null hypothesis i.e. the presence of unit root is tested following the same DF distribution. Like DF test ADF test has following three main versions:

1. Test for a unit root without drift and deterministic trend

$$
\Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varphi_t
$$

2. Test for a unit root with drift

$$
\Delta Y_t = a_0 + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varphi_t
$$

3. Test for a unit root with drift and deterministic time trend

$$
\Delta Y_t = a_0 + a_1 t + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varphi_t
$$

where  $\varphi_t$  is a white noise,  $a_0$  is the drift term (constant), *t* is the linear trend term and  $a_1$ *γ*, and  $\delta$ *i* are coefficients. This model 3 is a least restrictive model, because it allows a constant and a deterministic trend. Here, *p* is the lagged values of *∆Yt,* to control for the higher-order correlations, assuming the series follows an *AR(p)* process.

The hypotheses for ADF test are as follows:

*H*<sup>0</sup>*:*  $\gamma = 0$  the series has a unit root ("differenced stationary")

*H<sub>A</sub>*:  $\gamma$  < 0 the series has no unit root (meaning that the series is either stationary, or trend stationary).

The null hypothesis is that a series does contain a unit root (nonstationary process) against the alternative of stationary. To test for the presence of a unit root, we need to calculate
the *t*-statistic  $\tau = \frac{\gamma}{\gamma}$  $\frac{V}{se(y)}$  and then compare it to the corresponding critical value given by Dickey and Fuller at different significant level. If the null hypothesis is rejected, it is concluded that a series  $Y_t$ , which includes drift and trend, drift, or none does not contain a unit root.

To perform Augmented Dickey-Fuller (ADF) test; firstly, we need to specify whether to include a constant and a linear trend, a constant, or none in the test regression. Maddala and Kim (1999) have argued that it is hard to believe the *AR(1)* model without deterministic trend can describe well most of the macroeconomic variables. This suggests that it may be appropriate to incorporate the linear trend term in the model. When we include the linear trend term into the model, we can classify the time series into two important classes, which imply the different methods of eliminating the trend. These classes are trend stationary process (TSP) and difference-stationary process (DSP).

Besides the importance of the presence of the deterministic trend in macroeconomic series, the specification of the trend plays an essential role in the unit root testing procedure and it is closely related to the power and size of the unit root tests. Campbell and Perron (1991) have argued that the proper handling of the deterministic trends is a vital prerequisite for dealing with unit roots. Perron (1988) has proposed a sequential testing strategy and has argued that a proper testing strategy should start from the most general trend specification and test down to more restricted specifications.

On the other hand, inclusion of irrelevant regressors in the regression can reduce the power of the test to reject the null hypothesis of a unit root**.** To overcome this problem, the form of test regression should be chosen based on the graphical inspection of a series (Verbeek, 2004). If the plot of the data does not start from the origin, then the estimation equation should include a constant. If the plot of the data indicates apparent upward or downward trend, then the trend term should be contained in the regression.

Furthermore, it is also very important to select the appropriate number of lagged difference term *p.* Too few lags may lead to the over rejecting the null hypothesis when it is true, while too many lags may reduce the power of the test to reject the null. One suggested solution is to determine the optimal lag length using different information criterion - such as LR (Log-Likelihood Ratio Criterion), AIC (Akaike Information Criterion), SIC (Schwarz Information Criterion). FPE (Final Prediction Error), HQ (Hannan-Quinn Information Criterion). All the models are considered as equally good. In this chapter, the lag length which is supported by the maximum number of above information criteria is selected.

The main criticism of the Augmented Dickey-Fuller (ADF) test is that the power of the test is very low when the process is nearly nonstationary which means the process is stationary but with a root close to the nonstationary boundary (Brooks 2002).

# **4.3.4.3 Phillips and Perron Unit Root Tests**

Phillips and Perron (1988) have developed a more comprehensive theory of unit root tests. Phillips and Perron (PP) tests are similar to ADF tests, but they incorporate an automatic correction to the DF procedure to allow for autocorrelated residuals. The PP tests use the standard DF test with modified *t -* ratio of the *γ* coefficient, so that serial correlation does not affect the asymptotic distribution of the test statistic. The hypotheses for PP test are:

*H*<sub>0</sub>*:*  $\gamma = 0$  the series has a unit root ("difference stationary")

*H<sub>A</sub>*:  $\gamma$  < 0 the series has no unit root (meaning that the series is either stationary, or trend stationary).

The PP tests usually give the almost same conclusions as the ADF tests, and the calculation of the test statistics is complex. Like ADF test, the main criticism of PP tests is that the power of the test is low if the process is stationary but with a root close to the nonstationary boundary. For example, the tests are poor at deciding if  $\gamma = 1$  or  $\gamma = 0.95$ , especially with small sample sizes (Brooks 2002).

# **4.3.4.4 Kwiatkowski, Phillips, Schmidt, and Shin Unit Root Tests**

To circumvent the limitations of ADF and PP tests, Kwiatkowski, Phillips, Schmidt, and Shin (1992) proposed an alternative test where the variable is assumed to be stationary under the null. The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test is a Lagrange Multiplier (LM) test and the test statistic can be computed by firstly regressing the dependent variable  $Y_t$  on a constant and a time trend, and then on a constant only. Later, OLS residuals,  $\varepsilon_t$  are saved and compute the partial sums  $S_t = \sum_{s=1}^t \varepsilon_s$  for all *t*. Further the test statistic is given by (Verbeek 2004):

$$
KPSS LM = \sum_{t=1}^{T} \frac{S_t^2}{\hat{\sigma}_{\varepsilon}^2}
$$

where  $\hat{\sigma}_{\varepsilon}^2$  is the variance of the estimated error from the regression of the equations with drift  $(Y_t = \alpha + \varepsilon_t)$  or drift and trend  $(Y_t = \alpha + \beta t + \varepsilon_t)$ . The null and alternative hypotheses of KPSS test are as follows:

*H0*: the series is trend-stationary

*HA*: the series has unit root.

In this chapter, the different versions of unit root tests are set up following the Pantula (1991) principle. As per the principle, the unit root tests are started on level data with the model containing both trend and intercept (constant), because this model is the least restrictive. If the null hypothesis is rejected due to a significant test statistic, there is no need to continue testing and the alternate hypothesis is accepted. If the null cannot be rejected, then the test is carried on level data with an intercept. If the null hypothesis is rejected due to a significant test statistic, then there is no need to continue testing and the alternate hypothesis is accepted. If the null is not rejected it is possible to continue with the model having no trend and constant. But this is seldom a good strategy if the variable is obviously nonstationary, so this most restrictive model has not been checked.

#### **4.3.5 Concept of Cointegration Approach**

The concept of cointegration was first introduced by Granger in 1981. However, Granger (1981) has only outlined the characteristics of integrated series without proposing any procedure for testing cointegration. Later, Engle and Granger (1987) have suggested a procedure for testing the hypotheses of cointegration. They have proposed a simple twostep procedure for testing cointegration using the Ordinary Least Squares (OLS) method. In the first step, a regression is estimated for two variables (at level) and residuals are extracted from the regression analysis. In the second step, the extracted residuals are tested for a unit root. If the residuals are found stationary at level, meaning that the residuals are integrated of order zero, *I(0),* the null hypothesis of no cointegration between the two series is rejected.

However, Engle and Granger's two step procedure has been criticized for several reasons. Firstly, several academics have noted that as it involves a two-step process, any error introduced in the estimation of the error terms in the first step may enter the subsequent error correction model (Brooks, 2008). Secondly, changing the variables from the righthand side to the left-hand side of the regression equation might give different results. For example, in investigating the relationship between income and expenditure, if income is placed on the left-hand side as the dependent variable and expenditure on the right-hand side, then it is possible to conclude that income and expenditure are cointegrated, but the reverse is not necessarily true.

These problems with the Engle and Granger two-step procedure were overcome by Johansen (1988) and Johansen and Juselius (1990). They estimated the cointegrating vector using the maximum likelihood estimation technique. They provided a method of estimating a multivariate vector error correction method (VECM) based on a vector autoregressive VAR(*k*) model with Gaussian errors and its implications on equilibrium. This process has the advantage of capturing both long- and short-term dynamic relationships of a system. Johansen and Juselius (1990) approach has been used to examine whether any long-run relationships exists between the variables.

# **4.3.6 Johansen and Juselius Cointegration Approach**

Johansen and Juselius (1990) test is an extension of the single equation error correction model to a multivariate one. VAR(*k*) model of a (*n x 1*) vector,  $Y_t(y_{1t}, y_{2t}, y_{3t} \cdots y_{nt})$ at level can be given as:

$$
Y_t = D_t + A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \dots + A_k Y_{t-k} + \varepsilon_t
$$
\n
$$
\qquad \qquad 4.20
$$

where  $D_t$  contains the deterministic terms (constant, trend, seasonal dummies etc.),  $A_i$  is a  $(n \times n)$  coefficient matrix,  $t = 1, 2, 3, \dots, T$  and  $\varepsilon_t$  is a  $(n \times 1)$  vector of white noise error terms.

Now,  $Y_t$  is cointegrated if there exist some linear combinations of the variables in  $Y_t$  that are stationary at level i.e.  $I(0)$ . However, if  $Y_t$  is nonstationary at level i.e. the variables are integrated of order 1, *I(1*) and are possibly cointegrated, then the VAR representation is not the most suitable representation for analysis, because the cointegrating relationships are not explicitly apparent. The cointegrating relationships become apparent if the VAR at

level is transformed into the Vector Error Correction Model (VECM). So, reparametrizing the Equation (4.20), that is subtracting  $Y_{t-1}$  from both sides, leads to:

$$
Y_{t} - Y_{t-1} = D_{t} + A_{1}Y_{t-1} + A_{2}Y_{t-2} + A_{3}Y_{t-3} + \cdots + A_{k}Y_{t-k} + \varepsilon_{t} - Y_{t-1}
$$
  
\n
$$
\therefore \Delta Y_{t} = D_{t} - Y_{t-1} + A_{1}Y_{t-1} + A_{2}Y_{t-2} + A_{3}Y_{t-3} + \cdots + A_{k}Y_{t-k} + \varepsilon_{t}
$$
  
\n
$$
\therefore \Delta Y_{t} = D_{t} + (-I + A_{1})Y_{t-1} + A_{2}Y_{t-2} + A_{3}Y_{t-3} + \cdots + A_{k}Y_{t-k} + \varepsilon_{t}
$$
  
\n
$$
\therefore \Delta Y_{t} = D_{t} + (-I + A_{1})Y_{t-1} - (-I + A_{1})Y_{t-2} + (-I + A_{1})Y_{t-2} + A_{2}Y_{t-2} + A_{3}Y_{t-3} + \cdots + A_{k}Y_{t-k} + \varepsilon_{t}
$$
  
\n
$$
\therefore \Delta Y_{t} = D_{t} + (-I + A_{1})(Y_{t-1} - Y_{t-2}) + (-I + A_{1})Y_{t-2} + A_{2}Y_{t-2} + A_{3}Y_{t-3} + \cdots + A_{k}Y_{t-k} + \varepsilon_{t}
$$
  
\n
$$
\therefore \Delta Y_{t} = D_{t} + (-I + A_{1})\Delta Y_{t-1} + (-I + A_{1} + A_{2})Y_{t-2} + A_{3}Y_{t-3} + \cdots + A_{k}Y_{t-k} + \varepsilon_{t}
$$
  
\n
$$
\therefore \Delta Y_{t} = D_{t} + (-I + A_{1})\Delta Y_{t-1} + (-I + A_{1} + A_{2})Y_{t-2} - (-I + A_{1} + A_{2})Y_{t-3}
$$
  
\n
$$
+ (-I + A_{1} + A_{2})Y_{t-3} + A_{3}Y_{t-3} + \cdots + A_{k}Y_{t-k} + \varepsilon_{t}
$$
  
\n
$$
\therefore \Delta Y_{t} = D_{t} + (-I + A_{1})\Delta Y_{t-1} + (-I + A_{1} + A_{2})(Y_{t-2} - Y_{t-3}) +
$$

In this way if we proceed up to  $k \log n$ , the equation can be written as:

$$
\Delta Y_t = D_t + (-I + A_1)\Delta Y_{t-1} + (-I + A_1 + A_2)\Delta Y_{t-2} + (-I + A_1 + A_2 + A_3)\Delta Y_{t-3} + \cdots
$$
  
+ 
$$
(-I + A_1 + A_2 + \cdots + A_{k-1})\Delta Y_{t-k+1} + (-I + A_1 + A_2 + \cdots + A_k)Y_{t-k} + \varepsilon_t
$$
  

$$
\therefore \Delta Y_t = D_t + \Pi Y_{t-k} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \cdots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t
$$
 4.21

where,  $\Pi$  and  $\Gamma$  are  $(n \times n)$  coefficient matrices representing the long-term and short-term dynamics respectively, which are defined as:

$$
\Pi = -I + \sum_{i=1}^k A_i
$$

And

$$
\Gamma_i = -I + \sum_{i=1}^{k-1} A_i
$$

The number of cointegrating vectors is identical to the number of stationary relationships in the  $\Pi$  matrix. If there is no cointegration, all rows in  $\Pi$  must be filled with zeros. On the other hand, if they are cointegrated, all the rows of  $\Pi$  must be cointegrated but not necessarily distinct. This is because the number of distinct cointegrating vectors depends on the row rank of *Π* (Harris, 1995). So, the rank of *Π* matrix, denotes by *r*, determines the number independent rows in  $\Pi$ , and therefore also the number of cointegrating vectors. Since *Π* has rank *r* it can be written as the product of:

$$
\Pi = \alpha \times \beta'
$$

$$
(n \times r) \quad (n \times r) \quad (r \times n)
$$

where  $\alpha$  and  $\beta$  are  $(n \times r)$  matrices with rank  $(\alpha) = \text{rank } (\beta) = r$ . The rows of  $\beta'$ , called the cointegrating matrix, form a basis for the *r* cointegrating vectors and the elements of *α***,**  called feedback or adjustment matrix**,** distribute the impact of the cointegrating vectors to the evolution of  $\Delta Y_t$ . Then the VECM model (4.21) becomes:

$$
\Delta Y_t = D_t + \alpha \beta' Y_{t-k} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \dots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t \quad 4.22
$$

where  $\beta'Y_{t-k} \sim I(0)$  since  $\beta'$  is a matrix of cointegration vectors. The vector series  $\beta'Y_t$  is referred to as the cointegrating series, and  $\alpha$  denotes the impact of the cointegration series on  $\Delta Y_t$ .

It is important to recognize that the  $\Pi = \alpha \beta'$  is not unique since for any  $(r \times r)$  nonsingular matrix  $H$ , then we can write:

$$
A \beta' = \alpha H H^{-1} \beta' = (\alpha H) (\beta' H^{-1'}) = \alpha^* \beta^{*'}
$$

Hence, the factorization  $\Pi = \alpha \beta'$  only identifies the space spanned by the cointegrating relations. To obtain unique values of  $\alpha$  and  $\beta'$  requires further restrictions on the model.

To explore this let us consider the bivariate VAR(*1*) model for  $Y_t = (y_{1t}, y_{2t})'$ 

$$
Y_t = \Pi_1 Y_{t-1} + \varepsilon_t \tag{4.23}
$$

The VECM is:

$$
\Delta Y_t = \Pi Y_{t-1} + \varepsilon_t \text{ ; where } \Pi = \Pi_1 - I_2
$$

$$
\therefore \Delta Y_t = \alpha \beta' Y_{t-1} + \varepsilon_t \tag{4.24}
$$

Assuming  $Y_t$  is cointegrated and there exists a ( $2 \times I$ ) vector  $\beta = (\beta_1, \beta_2)'$  such that:

$$
\beta'Y_t = \beta_1 y_{1t} + \beta_2 y_{2t}
$$
 is  $I(0)$ 

Using the normalization  $\beta_1 = 1$  and  $\beta_2 = -\beta$  the cointegrating relation becomes:

$$
\beta'Y_t = y_{1t} - \beta y_{2t}
$$

This normalization suggests the stochastic long-run equilibrium relation:

$$
y_{1t} = \beta y_{2t} + \mu_t
$$

where  $\mu_t$  is  $I(0)$  and represents the stochastic deviations from the long-run equilibrium, then the equation can be written as:

$$
y_{1t} = \beta y_{2t}
$$

Since  $Y_t$  is cointegrated with one cointegrating vector, so rank  $(II) = 1$  and can be written as:

$$
\mathbf{\Pi} = \alpha \boldsymbol{\beta}' = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} (1 \quad -\beta) = \begin{pmatrix} \alpha_1 & -\alpha_1 \beta \\ \alpha_2 & -\alpha_2 \beta \end{pmatrix}
$$
 4.25

Now putting the value of *Π* from Equation (4.25) to Equation (4.24) we get

$$
\Delta Y_t = \begin{pmatrix} \alpha_1 & -\alpha_1 \beta \\ \alpha_2 & -\alpha_2 \beta \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}
$$
  

$$
\therefore \begin{pmatrix} \Delta y_{1t} \\ \Delta y_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_1 y_{1t-1} - \alpha_1 \beta y_{2t-1} \\ \alpha_2 y_{1t-1} - \alpha_2 \beta y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}
$$
 4.26

The VECM equation from Equation 4.26, can be given as follows:

$$
\Delta y_{1t} = \alpha_1 y_{1t-1} - \alpha_1 \beta y_{2t-1} + \varepsilon_{1t} = \alpha_1 (y_{1t-1} + \beta y_{2t-1}) + \varepsilon_{1t}
$$
  

$$
\Delta y_{2t} = \alpha_2 y_{1t-1} - \alpha_2 \beta y_{2t-1} + \varepsilon_{2t} = \alpha_2 (y_{1t-1} + \beta y_{2t-1}) + \varepsilon_{2t}
$$

The first equation relates the change in  $y_{1t}$  to the lagged disequilibrium error  $\beta' Y_t$  and the second equation relates the change in  $y_{2t}$  to the lagged disequilibrium error as well. We can see that the reactions of  $y_1$  and  $y_2$  to the disequilibrium errors are captured by the

adjustment coefficients  $\alpha_1$  and  $\alpha_2$ . The stability conditions for the bivariate VECM are related to the stability conditions for the disequilibrium error  $\beta' Y_t$ . By multiplying Equation (4.24) by  $\beta'$ , we get:

$$
\beta' \Delta Y_t = \beta' \alpha \beta' Y_{t-1} + \beta' \varepsilon_t
$$
  
\n
$$
\therefore \beta' (Y_t - Y_{t-1}) = \beta' \alpha \beta' Y_{t-1} + \beta' \varepsilon_t
$$
  
\n
$$
\therefore \beta' Y_t - \beta' Y_{t-1} = \beta' \alpha \beta' Y_{t-1} + \beta' \varepsilon_t
$$
  
\n
$$
\therefore \beta' Y_t = \beta' \alpha \beta' Y_{t-1} + \beta' Y_{t-1} + \beta' \varepsilon_t
$$
  
\n
$$
\therefore \beta' Y_t = (I + \alpha \beta') \beta' Y_{t-1} + \beta' \varepsilon_t
$$
 4.27

Equation (4.27) can be written as:

$$
y_t = \varphi y_{t-1} + v_t
$$
  
where  $y_t = \beta' Y_t$ ,  $\varphi = (I + \alpha \beta') = I + (\alpha_1 - \beta \alpha_2)$  and  $v_t = \beta' \varepsilon_t = \varepsilon_{1t} - \beta \varepsilon_{2t}$ .

The *AR(1)* model for  $y_t$  is stable as long as  $|\varphi| = |1 + (\alpha_1 - \beta \alpha_2)| < 1$ . For example, suppose  $\beta = 1$ . Then the stability condition is:

$$
|1 + (\alpha_1 - \alpha_2)| < 1
$$
  
\n
$$
\therefore \{1 + (\alpha_1 - \alpha_2)\}^2 < 1
$$
  
\n
$$
\therefore 1 + 2(\alpha_1 - \alpha_2) + (\alpha_1 - \alpha_2)^2 < 1
$$
  
\n
$$
\therefore (\alpha_1 - \alpha_2)(\alpha_1 - \alpha_2 + 2) < 0
$$
 4.28

So, the conditions to be satisfied for the Equation (4.28) will be:

$$
(\alpha_1 - \alpha_2) < 0
$$
 and  $(\alpha_1 - \alpha_2 + 2) > 0$  i.e.  $\alpha_1 < \alpha_2$  and  $(\alpha_1 - \alpha_2) > -2$ 

If 
$$
\alpha_2 = 0
$$
 then  $\alpha_1 < 0$  and  $\alpha_1 > -2$  i.e.  $-2 < \alpha_1 < 0$  is the condition for stability.

Also, considering *AR(1)* model in the long-run error correction term the VECM equation can be written as:

$$
\Delta Y_t = D_t + \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \dots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t \tag{4.29}
$$

# **4.3.6.1 Steps in Johansen and Juselius Cointegration Approach**

The Johansen and Juselius (1990) Cointegration Approach (JJA) has the following steps: **Step1: Testing for Stationarity of the Variables and its Order of Integration:** The first step in cointegration analysis is to check for the stationarity of the variables and determine the order of integration. For Johansen and Juselius (1990) Cointegration Approach (JJA), all variables must be integrated in the same order. The order of integration of a series refers to the number of times the series must be differenced to make it stationary. A series is integrated in order of *d*, *I(d)*, if it needs to be differenced *d* times to make it stationary. If a series becomes stationary after differencing once, then it is integrated of order 1, *I(1)*.

**Step 2: Optimum Lag Length Selection Process:** It is necessary to determine the dynamic specification of *VAR(k)* model before the cointegration test is carried out. Hence, the selection of appropriate lag length *k* using proper information criteria is required. The determination of the appropriate lag length *k* starts by estimating a VAR model including all the variables in level (non-differenced data). The most common information criterions used for optimum lag selection are LR (Log-Likelihood Ratio Criterion), AIC (Akaike Information Criterion), SIC (Schwarz Information Criterion). FPE (Final Prediction Error), HQ (Hannan-Quinn Information Criterion). All the models are considered as equally good. In this study, we have estimated the VAR model with variables at level, then the stability of the model is also checked. Finally, the lag length is selected based on the lag length supported by the maximum number of above criterions.

**Step 3: Specification of Deterministic Terms:** Our research variables may have non-zero means and deterministic trends or the stochastic trends. Similarly, the cointegrating equations may have intercepts and deterministic trends. The asymptotic distribution of the Likelihood Ratio (LR) test statistic for cointegration does not have the usual  $\chi^2$  distribution and depends on the assumptions made with respect to deterministic trends. Maddala and Kim (1999) have argued that it is hard to believe that the pure *AR(1)* model without the deterministic trend describes well most of the macroeconomic variables. They have added further that almost all variables usually show some tendency to increase over time, this suggests that it may be appropriate to incorporate the linear trend term into the model.

However, based on the linear trend term into the model, we can classify the time series into two important classes which imply the methods of eliminating the trend. These classes are trend-stationary process (TSP) and differenced-stationary process (DSP). Following Johansen (1995), the deterministic terms are restricted to the form:

$$
D_t = d_0 + d_1 t
$$

If the deterministic terms are unrestricted then the time series in  $Y_t$  may exhibit quadratic trends and there may be a linear trend term in the cointegrating relationships. Restricted versions of the trend parameters  $d_0$  and  $d_1$  limit the trending nature of the series in  $Y_t$ . The trend behavior of  $Y_t$  can be classified into five cases:

**Case I:**  $D_t = 0$ . In this case, there is no intercept and no deterministic trend. The restricted VECM Equation (4.29) becomes:

$$
\Delta Y_t = \alpha \beta' Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \dots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t
$$

Here, all the variables in  $Y_t$  are  $I(1)$  without drift and the cointegrating relations  $\beta'Y_t$  have mean zero. However, this is quite unlikely to occur in practice, especially, as the intercept is generally needed to account for adjustment in the unit of measurements of the variables.

**Case II:**  $d_0 = \alpha \rho_0$  and  $d_1 = 0$ . This is a case of restricted intercept and no deterministic trend. The restricted VECM of Equation (4.29) can be written as:

$$
\Delta Y_t = \alpha \rho_0 + \alpha \beta' Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \dots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t
$$
  
 
$$
\therefore \Delta Y_t = \alpha (\rho_0 + \beta' Y_{t-1}) + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \dots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t
$$

All the series in  $Y_t$  are  $I(I)$  without drift and the cointegrating series  $\beta'Y_t$  have non-zero mean  $\rho_0$ . In this case, the intercept is restricted to the long-run model (in the cointegrating series). There are no linear trends in the data, and is appropriate for non-trending *I(1)* data like interest rates and exchange rates.

**Case III:**  $d_1 = 0$  and  $d_0$  is unrestricted. This is a case of unrestricted intercept and no deterministic trend. The restricted VECM of Equation (4.29) is:

 $\Delta Y_t = d_0 + \alpha \beta' Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \cdots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t$ 

The series in  $Y_t$  are  $I(1)$  with drift vector  $d\theta$  and the cointegrating series  $\beta'Y_t$  may have a non-zero mean. In this model, there are no linear trends in the level data, but allows both short-term and long-run specifications to drift around an intercept. However, the intercept in the cointegrating series is assumed to cancel out by the intercept in the VAR, leaving just one intercept in the short-run model. This is appropriate for trending  $I(1)$  data like asset prices, macroeconomic aggregates (real GDP, consumption, employment etc.).

**Case IV:**  $D_t = d_0 + \alpha \rho_1 t$ . This is a case of unrestricted intercepts and restricted deterministic trend. The restricted VECM is:

 $\Delta Y_t = d_0 + \alpha (\rho_1 t + \beta' Y_{t-1}) + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \cdots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t$ The series in  $Y_t$  are  $I(I)$  with drift vector  $d_\theta$  and the cointegrating series  $\beta'Y_t$  have a linear trend term  $\rho_1 t$ . In this model, a trend is included in the cointegrating series as a trend stationary variable to take care of exogenous growth (i.e. technical progress). The model also allows for intercept. The restricted trend case IV is also appropriate for trending *I(1)* as in Case III. However, there is a deterministic trend in the cointegrating series in Case IV as opposed to the stationary series in case III.

**Case V:**  $D_t = d_0 + d_1t$ . This is a case of unrestricted constant and trend. The unrestricted VECM is:

$$
\therefore \Delta Y_t = d_0 + d_1 t + \alpha \beta' Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_3 \Delta Y_{t-3} + \dots + \Gamma_{t-k+1} \Delta Y_{t-k+1} + \varepsilon_t
$$

The series in  $Y_t$  are  $I(I)$  with a linear trend (quadratic trend in levels) and the cointegrating series  $\beta'Y_t$  have a linear trend. This model is appropriate for  $I(1)$  data with a quadratic trend. An example might be nominal price data during times of extreme inflation.

The inclusion of appropriate deterministic components in the cointegration test is often difficult to determine. We have used log-likelihood ratio test to examine the presence of deterministic trend in the series. The main purpose of the test is not to identify the most appropriate model of the deterministic components, but to eliminate the most unlikely models of the deterministic components from consideration. The log-likelihood ratio test is carried out using ADF unit root tests with joint hypothesis of a unit root and no deterministic trend. The most unrestricted ADF unit root test model can be given by:

$$
\Delta Y_t = a_0 + \gamma Y_{t-1} + a_1(trend) + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varepsilon_t
$$

where  $Y_t$  is an individual time series under consideration, the trend in the above equation is a linear deterministic time trend, and  $\varepsilon_t$  is a serially uncorrelated error terms with zero mean and constant variance. So, the null and alternative hypotheses for log-likelihood ratio test are follows:

*H<sub>0</sub>*:  $\gamma = a_1 = 0$  The series has unit root and no deterministic trend  $H_A$ :  $\gamma = 0$ , given  $a_1 > 0$  The series has unit root and deterministic trend.

Let the likelihood function is denoted as  $L(\theta)$ . If  $\theta_0$  be the value of the parameter, within the limit of the null hypothesis, which maximizes the likelihood function and  $\theta_I$  be the value of the parameter which maximizes the likelihood function out of possible value from the alternative hypothesis. Then the test statistic is defined as:

$$
\tau=2Ln[L(\theta_1)-L(\theta_0)]
$$

$$
\therefore \tau = 2[Ln(L(\theta_1) - Ln(L(\theta_0))]
$$

This distribution follows Chi-square distribution and the critical value for one degree of freedom (as there is one restriction) is 3.841 at 5% significance level.

Then, after excluding the most unlikely models, we have applied the Pantula principle, following Johansen (1992), to identify the most appropriate one from the remaining models. The process of Pantula principle is to move from the most restrictive model to the least restrictive model and then to compare the trace and the maximal eigenvalue test statistics to their critical values at each stage. The test is completed when the null hypothesis is not rejected at the first time.

**Step 4: Determining the Number of Cointegrating Vector:** Johansen and Juselius (1990) have developed two likelihood ratio (LR) test statistics; the trace and maximum eigenvalues test, for determining the number of cointegrating relationships. Since the rank of the long-run impact matrix *Π* gives the number of cointegrating relationships in *Yt*, the likelihood statistics of Johansen and Juselius test determine the rank of *Π*. The rank of *Π* is equal to the number of non-zero eigenvalues of  $\Pi$ . The trace statistics are given by:

$$
\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)
$$

where  $\hat{\lambda}_i$  denotes the estimated values of the characteristic roots obtained from the estimated  $\Pi$ , and  $T$  is the number of observations. Johansen proposes a sequential testing procedure that consistently determines the number of cointegrating vectors. First the test is conducted for H<sub>0</sub>:  $r = 0$  against H<sub>A</sub>:  $r > 0$ . If this null is not rejected, then it is concluded that there are no cointegrating vectors among the n variables in  $Y_t$ . If H<sub>0</sub>:  $r = 0$ is rejected, then it is concluded that there is at least one cointegrating vector and proceed to test H<sub>0</sub>:  $r = 1$  against H<sub>A</sub>:  $r > 1$ . If this null is not rejected, then it is concluded that there is only one cointegrating vector. If the null is rejected, then it is concluded that there is at least two cointegrating vectors. The sequential procedure is continued until the null is not rejected. Johansen's second LR statistic i.e. maximum eigenvalue statistic is given by:

$$
\lambda_{max}(r, r+1) = -T\ln(1 - \hat{\lambda}_{r+1})
$$

The computed likelihood values and eigenvalues are compared to the critical values to determine the exact number of cointegrating equations. The critical values depend upon which deterministic terms are included, and whether they are restricted or unrestricted. After the cointegration relation has been established, the resulted long-run cointegration equation(s) is (are) viewed and analyzed based on the objective of the study.

The Johansen and Juselius (1990) approach of testing cointegrating rank is very sensitive to the lag length and the deterministic trend terms included in the VAR system. Therefore, it is important to determine the appropriate lag length and deterministic terms to be used in the cointegration test in order to prevent errors in hypothesis testing (Enders, 2004).

**Step 5: Vector Error Correction Model (VECM):** After establishing the number of cointegrating vectors, the next step is to estimate the Error Correct Model (VECM). The VECM representation is essentially a VAR presented in Equation (4.29) with the shortterm parameters *Γ* and the additional long-run term *ΠYt-1*. This restriction on the differenced VAR ties the individual series of the vector  $Y_t$  together and ensures that the system returns to its long-run equilibrium (Banerjee et al., 1993).

As stated earlier, the matrix  $\boldsymbol{\Pi}$  and its rank  $r = \text{rank}(\boldsymbol{\Pi})$  are of crucial importance for the cointegration relationship of the system. If *Π* has rank of zero, then the term drops out. In this case, Equation (4.29) reduces to a stable VAR in differences with no cointegration relationship (Enders, 2004). If  $\Pi$  has full rank, then this scenario is called trivial cointegration as cointegration is formally present, but the individual series do not share a common stochastic trend. If *Π* is rank deficient, it can be written as  $\Pi = \alpha \beta'$  where  $\beta'$ , called the cointegrating matrix, form a basis for the *r* cointegrating vectors and the elements of *α,* called the loading feedback or adjustment matrix, can be interpreted as the speed of adjustment to errors in the long-run relationship.

If the system is out of equilibrium, that is if  $\beta'Y_t \neq 0$ , the loading matrix controls the change in  $\Delta Y_t$  in the next period to drive the time series back to the relationship given by the cointegrating matrix. Bigger values in *α* correspond to faster adjustment to the long-run equilibrium. The matrices  $\alpha$  and  $\beta'$  are not unique and can be decomposed arbitrarily. A feasible way is therefore to normalize the first component of the cointegration vector to one (Luetkepohl, 2005).

The parameter sequence, *Γ* measures short-term reactions of a series to changes in its own past values, as well as those in other variables in the system just like in the standard noncointegrated VAR. As the differences are stationary, the effect of these short-term fluctuations eventually dies out and does not have an influence on the long-run relationship.

The Maximum Likelihood method developed by Johansen (1988) is a full information approach that estimates the VECM in a single step. This procedure has the advantage that it does not carry over estimation errors of the first step into a second one, as like Engle and Granger (1987) two-stage method, and therefore yields more efficient estimators (Maysami and Koh, 2000).

# **4.3.7 Granger Causality Test**

It is essential to consider the causal relationships among the variables under consideration using the causality test. Causality examines the ability of one variable to predict the others. It is a statistical measure that provides the extent to which lagged values of a set of variables are important in predicting another set of variables, when lagged values of the latter set are also included in the model. The causality test utilizes the concept of Vector Autoregression (VAR) model, which allows for the test of the direction of causality. There are various causality tests that can detect the cause and effect relationships among the variables. However, the most popular causality tests are Granger (1969) causality test, Sims (1972) causality test and Geweke et al. (1983) causality test. Among these, we have used Granger causality test to examine the causal relationships.

A simple definition of Granger causality, in case of two time-series variables, *X* and *Y* is: "*X* is said to Granger-cause *Y* if *Y* can be better predicted using the histories of both *X* and *Y* than it can be by using the history of *Y* alone". We can test for Granger causality by estimating the following VAR model:

$$
Y_t = a_0 + a_1 Y_{t-1} + \dots + a_k Y_{t-k} + b_1 X_{t-1} + \dots + b_k X_{t-k} + \mu_t
$$
 (4.30)

$$
\mathbf{X}_t = \mathbf{c}_0 + \mathbf{c}_1 \mathbf{X}_{t-1} + \dots + \mathbf{c}_k \mathbf{X}_{t-p} + \mathbf{d}_1 \mathbf{Y}_{t-1} + \dots + \mathbf{d}_k \mathbf{Y}_{t-p} + \mathbf{v}_t
$$
\n
$$
\tag{4.31}
$$

where it is assumed that the disturbances,  $\mu_t$  and  $v_t$ , are white noise terms and are uncorrelated. Then, testing of null hypothesis,  $H_0$ *:*  $b_1 = b_2 =$  .......  $= b_k = 0$ , against the alternative hypothesis, *HA: 'H<sup>0</sup>* is not true*'*, is a test that determines whether *X* Grangercause Y or not. Similarly, testing  $H_0$ :  $d_1 = d_2 =$  - ----- =  $d_p = 0$ , against  $H_A$ : ' $H_0$  is not true', is a test that determines whether *Y* Granger-cause *X* or not. In each case, a rejection of the null hypothesis implies that there is a causal relationship.

If the time series are stationary, then a VAR model at level is constructed. If the variables are differenced stationary, or integrated of order one, *I(1)*, the VAR is specified in first differences. If the series are cointegrated then vector error correction (VECM) models are used. Sims et al. (1990) have showed that if the variables are cointegrated and integrated of order 1, Wald tests of Granger non-causality at level VAR could be used based on the error correction model.

Toda and Phillips (1993) has further improved this and point out that the Wald tests are valid asymptotically if there is sufficient cointegration among the variables. Granger representation theorem suggests that if the variables are cointegrated then there must be a causal relationship among them running at least in one direction, therefore VECM Granger-causality test for zero restrictions on the coefficients can be employed.

Therefore, it is important to understand from the beginning the actual meaning of the VECM Granger-causality. The test does not say that changes in one variable cause changes in another. What Granger-causality test gives is the correlation between the current value of one variable and past values of the other variable. That is, if we say that  $X_t$  Grangercause  $Y_t$ , we mean that past value(s) of  $X_{it}$  (where  $i = 1, 2, 3, ..., n$ ) are correlated with the current value of Y<sub>t</sub>. Granger-causality between two variables can go in one direction, both ways, or there is no Granger-causality at all (Brooks, 2008).

# **4.3.8 Autoregressive Distributed Lag Cointegration Approach**

Pesaran et al. (2001) have developed a new approach to cointegration testing which is applicable irrespective of whether the regressors are *I(0), I(1)* or mutually cointegrated. This technique hasseveral advantages. Firstly, the test is based on a single ARDL equation, rather than on a VAR as in Johansen, thus reducing the number of parameters to be estimated. Secondly, unlike the Johansen approach the restrictions on the number of lags can be applied to each variable separately. Thirdly, a dynamic error correction model (ECM) can be derived from ARDL through a simple linear transformation (Banerjee et al., 1993). The ECM integrates the short-run dynamics with the long-run equilibrium, without losing long-run information. Finally, the ARDL approach provides robust results for a smaller sample size of cointegration analysis.

The ARDL model considers a one-period lagged error correction term, which does not have restricted error corrections. Hence, the ARDL approach involves estimating the following Unrestricted Error Correction Model (UECM):

$$
\Delta Y_t = a_{0Y} + \sum_{i=1}^k b_{iY} \Delta Y_{t-i} + \sum_{i=1}^k c_{iY} \Delta X_{t-i} + \theta_{1Y} Y_{t-1} + \theta_{2Y} X_{t-i} + \varepsilon_{1t}
$$
\n
$$
\tag{4.32}
$$

$$
\Delta X_t = a_{0X} + \sum_{i=1}^k b_{ix} \Delta X_{t-i} + \sum_{i=1}^k c_{ix} \Delta Y_{t-i} + \omega_{1X} X_{t-1} + \omega_{2X} Y_{t-i} + \varepsilon_{2t}
$$

where  $\Delta$  is the differenced operator, *k* represents the lag structure,  $Y_t$  and  $X_t$  are the underlying variables, and  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$  are serially independent random errors with mean zero and finite covariance matrix. In Equation (4.32), where  $\Delta Y_t$  is the dependent variable, the null and the alternative hypotheses are:

 $H_0: \theta_{1Y} = \theta_{2Y} = 0$  [there exists no long-run equilibrium relationship]

$$
H_0: \theta_{1Y} \neq 0, \ \theta_{2Y} \neq 0
$$
 [there exists long-run equilibrium relationship]

Similarly, for Equation (4.33), where  $\Delta X_t$  is the dependent variable, the null and alternate hypotheses are:

 $H_0: \omega_{1X} = \omega_{2X} = 0$  [there exists no long-run equilibrium relationship]  $H_0: \omega_{1X} \neq 0$ ,  $\omega_{2X} \neq 0$  [there exists long-run equilibrium relationship]

These hypotheses are tested using the *F*-test and *t*-test. Nevertheless, these tests have nonstandard distributions that depend on the sample size, the inclusion of intercept and trend variable in the equation, and the number of regressors.

In this study, we have used *F-*test. Pesaran et al. (2001) have discussed five cases with different restrictions on the trends and intercepts. The estimated ARDL test statistics are compared to two asymptotic critical values reported in Pesaran et al. (2001) rather than the conventional critical values. If the test statistic is above an upper critical value, the null hypothesis of no long-run relationship can be rejected regardless of the orders of integration of the underlying variables. The opposite is the case if the test statistic falls below a lower critical value. If the sample test statistic falls between these two bounds, the result is inconclusive.

Once cointegration is confirmed, the long-run relationship between stock market and macroeconomic variables using the selected ARDL models are estimated. The last step of ARDL is to estimate the associated ARDL error correction models. Finally, to ascertain the goodness of fit of the ARDL model, the diagnostic tests of the residual and the stability tests of the parameters are conducted. The structural stability test is conducted by employing the Cumulative Sum (CUSUM) and Cumulative Sum Squares (CUSUMSQ) tests of recursive residuals.

# **4.4 Findings of the Study**

In this section, we have reported our empirical findings based on the econometric methods outlined in the previous sections. Firstly, we have summarized the descriptive statistics and cross correlations of the research variables, then the results of different unit root tests are portrayed. Secondly, we have reported the results of cointegration test and interpreted the results of the long-term relationship. Thirdly, the findings of Vector Error Correction Model (VECM) have been presented. Fourthly, we have discussed the results of residual diagnostic tests. Fifthly, the results of Granger Causality test have been portrayed. Sixthly, the results of ARDL test to reexamine cointegration among the variables along with the viability and the stability test of this model have been reported. Finally, summary of the chapter has been drawn.

#### **4.4.1 Descriptive Statistics of the Research Variables**

In this research, we have considered monthly closing DSE General Index to represent the stock market and six macroeconomic variables have been selected which are industrial production index as a proxy of GDP, deposit interest rates to represent the interest rates, consumer price index to represent the inflation, exchange rates, money supply and gold price. The descriptive statistics of the research variables are reported in Panel A and Panel B of Table 4.2 for data at level and at first differences respectively.

The number of observations, the mean, the median, the maximum and the minimum values, the standard deviation are reported. In addition, the skewness, the kurtosis statistics are calculated to examine the symmetry of the distributions of the variables. Table 4.2 also portrays the results of the Jarque-Bera statistics and the associated *p*-values to indicate whether the distributions of the research variables are normal or not.

This study has considered monthly data of 25 years period. The period of the study is quite a long-time span (from January 1991 to December 2015), hence the results are not being specific to any particular time span when unusual stock market as well as economic conditions have prevailed. Several points have emerged from the analysis of the descriptive statistics of the first differenced data, which represent the growth of the research variables.

	<b>LDSEGEN</b>	<b>LIPI</b>	<b>LINT</b>	<b>LCPI</b>	<b>LEXR</b>	LM2	<b>LGDPRICE</b>
<b>Panel A. Data at Level</b>							
Observations	300	300	300	300	300	300	300
Mean	6.070862	5.492377	0.078983	5.222687	5.063380	6.307898	5.353208
Median	5.907646	5.401932	0.076868	5.121192	5.087665	6.216839	4.964467
Maximum	7.803729	6.622444	0.115469	6.046662	5.465296	8.212045	7.004141
Minimum	4.443474	4.409763	0.049647	4.605170	4.605170	4.605170	4.502510
Std. Dev.	0.889767	0.543795	0.016673	0.427009	0.257826	1.069237	0.860716
<b>Skewness</b>	0.095763	0.204078	0.534194	0.375855	$-0.238259$	0.191749	0.652920
Kurtosis	1.924437	2.010907	2.617901	1.908987	1.638059	1.796569	1.798436
Jarque-Bera	14.91896	14.31120	16.09315	21.94220	26.02439	19.94147	39.36220
Probability	0.000576	0.000780	0.000320	0.000017	0.000002	0.000047	0.000000
<b>Panel B. Data at First Difference</b>							
<b>Observations</b>	299	299	299	299	299	299	299
Mean	0.008816	0.006747	$-0.000148$	0.004821	0.002632	0.012063	0.006672
Median	0.004307	0.010174	0.000000	0.003749	0.000000	0.010461	0.000000
Maximum	0.569159	0.244355	0.035289	0.041139	0.062903	0.062209	0.325422
Minimum	$-0.363551$	$-0.221820$	$-0.020508$	$-0.032365$	$-0.035045$	$-0.02523$	$-0.251314$
Std. Dev.	0.090990	0.070792	0.003148	0.009440	0.009479	0.015189	0.045503
<b>Skewness</b>	0.726895	$-0.190557$	3.974944	0.022413	2.483159	0.537413	1.230682
Kurtosis	10.40957	3.164842	61.40010	4.513199	17.43277	3.704922	17.57458
Jarque-Bera	710.3143	2.148069	43277.41	28.55178	2902.408	20.58322	2721.857
Probability	0.000000	0.341627	0.000000	0.000001	0.000000	0.000034	0.000000

**Table 4.2 Descriptive Statistics of the Research Variables**

Notes: LDSEGEN is Log of DSE General Index, LIPI is Log of Industrial Production Index, LINT is Log of Interest Rate, LCPI is Log of Consumer Price Index, LEXR is Log of Exchange Rate, LM2 is Log of Money Supply, and LGDPRICE is Log of Gold Price.

Firstly, the statistics of first differenced data have indicated that the stock market has provided about 0.88% mean monthly return over the period. On the other hand, during the period the mean monthly growth of industrial production, interest rate, inflation, exchange rate, money supply, and gold price are approximately 0.67%, -0.015%, 0.48%, 0.26%, 1.2% and 0.67% respectively. These results reveal that out of the seven research variables, except interest rate, other six have positive mean monthly growth in the total sample period, while interest rate has negative mean monthly growth. These results have revealed that during the total sample period except interest rate other six variables have increased, while interest rate has decreased.

Secondly, the standard deviations of the variables reveal that during the study period monthly stock market return has the highest volatility (9.1%), whereas monthly growth of interest rate has the lowest volatility (0.315%). The highest volatility of the stock market return may be due to the catastrophes of 1996 and 2010.

Thirdly, monthly growth of industrial production is negatively skewed, which indicates the presence of some extreme negative values in the distribution. Conversely, the distributions of stock market return and the growth of remaining five macroeconomic variables are positively skewed suggesting some extreme positive values. The kurtosis value of industrial production is 3.164842, which is close to three, and the Jarque-Bera statistic of this variable shows very high *p*-value (30.21%), meaning that the distribution of growth of industrial production is normal. However, kurtosis and Jarque-Bera statistics of other six variables indicate that these distributions are not normal.

The correlations among the variables at level are reported in Table 4.3, which show that except interest rate, DSE General Index has high positive correlations with other macro variables, while DSE General index has negative correlation with interest rate. Also, except interest rate other macroeconomic variables are strongly positively correlated with each other, whereas interest rate is weakly correlated with other macroeconomic variables.





Notes: LDSEGEN is Log of DSE General Index, LIPI is Log of Industrial Production Index, LINT is Log of Interest Rate, LCPI is Log of Consumer Price Index, LEXR is Log of Exchange Rate, LM2 is Log of Money Supply, and LGDPRICE is Log of Gold Price.

# **4.4.2 Unit Root Tests Results**

The first step of Johansen cointegration test is to check the variables for the stationarity and determine the order of integration. The graphs of the variables at level and at first differences (Figure 4.1 to Figure 4.7) show that all the series seem to be nonstationary at level, while stationary at first difference. Also, the correlograms<sup>3</sup> of the variables show high autocorrelations up to 24 lags at level indicating series are nonstationary, while that for first difference data are decreasing for most of the variables with increasing lag indicating that those series are approaching towards stationarity.



Figure 4.1. Graphs of Log DSE General Index at Level and 1st Difference

Figure 4.2. Graphs of Log Industrial Production Index at Level and 1st Difference



<sup>3</sup> See Appendix A

 $\ddot{\phantom{a}}$ 



Figure 4.3. Graphs of Log Interest Rate at Level and 1st Difference





Figure 4.5. Graphs of Log Exchange Rate at Level and 1st Difference







In addition to the visual inspection of graphs and correlogram of the variables, ADF and KPSS unit root tests are carried out as per the procedure described in the methodology section to examine the stationarity and to determine the order of integration of the variables. If these two tests provide diverse results for any variable, then the PP unit root tests have been used for the final decision.

Before the unit root tests are applied, the stability of the VAR at level and at  $1<sup>st</sup>$  difference for each variable are examined. Then the optimal lag lengths of each variable with exogenous variables trend and constant, and with constant only are determined. The

summary of the results<sup>4</sup> are shown in Table 4.4, which shows that VAR is not stable with intercept only for LCPI, LM2 and LGDPRICE at level. So, unit root tests for those variables at level with intercept only are not carried out.

	Data at Level		Data at 1 <sup>st</sup> Difference		
<b>Variables</b>	<b>Trend and</b> <b>Intercept</b>	<b>Intercept</b>	<b>Trend and</b> <b>Intercept</b>	Intercept	
<b>LDSEGEN</b>					
LIPI					
<b>LINT</b>					
<b>LCPI</b>		VAR is Unstable	12		
<b>LEXR</b>					
LM2		VAR is Unstable	ר ו		
<b>LGDPRICE</b>		VAR is Unstable			

**Table 4.4 Optimal Lag Lengths of the Research Variables** 

Notes: LDSEGEN is Log of DSE General Index, LIPI is Log of Industrial Production Index, LINT is Log of Interest Rate, LCPI is Log of Consumer Price Index, LEXR is Log of Exchange Rate, LM2 is Log of Money Supply, and LGDPRICE is Log of Gold Price.

Table 4.5 shows the summary of ADF and KPSS unit root tests results<sup>5</sup>. Both ADF and KPSS tests reveal that all the series have unit root at level. So, we have concluded that the series are nonstationary at level. However, ADF test results show that except LM2 other series are stationary at first difference and LM2 is stationary at second difference. On the other hand, KPSS test results show that LCPI is stationary with trend and intercept but has unit roots with intercept at first difference, while LGDPRICE has unit root with trend and intercept but stationary with intercept at first difference. Nevertheless, both ADF and KPSS tests confirm that LCPI has significant trend and LGDPRICE has insignificant trend at first difference. So, we have accepted the KPSS test results with trend and intercept for LCPI and with intercept only for LDGPRICE and have concluded that both the series are stationary at first difference i.e. the series are *I(1).* Now, both ADF and KPSS unit root tests confirm that except LM2 all variables are *I(1).* On the other hand, ADF test results

 $\overline{a}$ 

<sup>4</sup> See Appendix B

<sup>5</sup> See Appendix C

indicate LM2 is *I(2)*, while KPSS test results show that the variable is *I(1).*So, the diverse results are related to money supply (LM2) only.

<b>Panel A: Data at Level</b>						
		<b>ADF Unit Roots Test</b>	<b>KPSS Unit Roots Test</b>			
<b>Variables</b>	<b>Trend and</b> <b>Intercept</b>	Intercept	<b>Trend and</b> <b>Intercept</b>	Intercept		
<b>LDSEGEN</b>	$-2.263817$	$-1.262698$	0.716817*			
<b>LIPI</b>	$-2.488473$	0.044380	$0.704326*$			
<b>LINT</b>	$-2.483544$	$-2.827551$	$0.412625*$			
<b>LCPI</b>	$-1.427023$	VAR is Unstable	$0.644902*$			
<b>LEXR</b>	$-1.133125$	$-1.520495$	1.967746*			
LM2	$-2.095373$	VAR is Unstable	$0.533282*$			
<b>LGDPRICE</b>	$-1.794687$	<b>VAR</b> is Unstable	1.104973*			
<b>Panel B: Data at First Difference</b>						
<b>LDSEGEN</b>	$-10.92199*$		0.065762	0.068174		
<b>LIPI</b>	$-10.73396*$		0.023075	0.069558		
<b>LINT</b>	$-7.228364*$		0.106635	0.173518		
<b>LCPI</b>	$-3.659916*$		0.065971	$0.781329*$		
<b>LEXR</b>	$-16.24530*$		0.079713	0.266188		
LM2	$-2.557102$	$-2.409351$	0.109546	0.109546		
<b>LGDPRICE</b>	$-7.275343*$		$0.209403*$	0.410658		
	<b>Panel C: Data at Second Difference</b>					
LM2	$-9.670536*$					

**Table 4.5 Results of Unit Root Tests**

Notes: Critical values at 5% level for ADF test with trend and intercept is -3.424977and with intercept is -2.871029 and that for KPSS test at 5% level with trend and intercept is 0.146and with intercept is 0.463. \* denotes that coefficient is significant at 5% level.

To resolve this, Phillips-Perron (PP) unit root tests have been applied on LM2. PP unit root test results (see Appendix C 3) indicate that LM2 has unit root at level (nonstationary) and stationary at first difference (Table 4.6), meaning that the series is *I(1).*

# **Table 4.6 Results of Phillips-Perron Unit Root Tests for Money Supply**



Notes: Critical values at 5% level for PP test with trend and intercept is -3.424977and with intercept is -2.871029. \* denotes that coefficient is significant at 5% level.

So, finally, we conclude that all the research variables have unit root at level and stationary

at first difference, meaning that series are integrated of order 1, *I(1).* Since the results of

the unit root tests reveal that all the variables are  $I(1)$ . Johansen and Juselius (1990) Cointegration Approach has been applied to examine the long- and shot-run relationships.

## **4.4.3 Johansen and Juselius Cointegration Test Results**

Apart from the unit root tests, the second pre-test for Johansen and Juselius (1990) Cointegration Approach (JJA) is to identify the most appropriate trend specification. The log-likelihood ratio test is used with the joint hypothesis of a unit root and deterministic linear trend for this purpose. In Table 4.7, we have reported the log-likelihood values of ADF unit root tests with a deterministic linear trend and with no deterministic trend (intercept only) in column 1 and column 2 respectively. Column 3 shows the log-likelihood ratio test statistics. This distribution follows Chi-square distribution and the critical value for one degree of freedom (as there is one restriction) is 3.841 at 5% significance level.

Variables	Log-likelihood with joint hypothesis of a unit root	<b>Test</b> <b>Statistics</b>	
	with a deterministic trend with no deterministic trend		
LDSEGEN (lag)	296.4765 (2)	294.6698 (2)	3.6134
$LIPI$ (lag)	413.6999 (6)	410.4800(6)	6.4398*
$LINT$ (lag)	1280.5650 (6)	1280.0490(6)	1 0320
$LCPI$ (lag)	971.2126 (10)	968.7989 (10)	4.8274*
$LEXR$ (lag)	967.5796 (1)	967.1976(1)	0.7640
$LM2$ (lag)	972.6062 (13)	970.1265 (13)	4.9594*
$LGDPRICE$ (lag)	501.3234 (5)	499.2002 (5)	4.2464*

**Table 4.7 Results of Log-Likelihood Ratio Test for Trend Specification**

Notes: This distribution follows Chi-square distribution and the critical value for one degree of freedom is 3.841 at 5% significance level.

The results show that the null hypothesis is rejected at 5% significance level for four variables (LIPI, LCPI, LM2 and LGDPRICE) at level. These results are also validated from our findings of ADF unit root tests (see Appendix C), where we have found that LIPI, LCP, LM2 and LGDPRICE have unit root with significant trend at level. Therefore, the cases 1, 2 and 3 of the cointegration models are highly unlikely, hence either model 4 or model 5 to be selected.

Now, the Pantula selection procedure has been applied to select the appropriate model for the cointegration test. For the purpose, the automatic lag length selection criteria are applied to select the preferred lag length. The lag order selection is based on different Information criteria. The result<sup>6</sup> shows that out of five selection criteria three have supported a lag length of 13, thus we have chosen 13 lags for the Johnsen and Juselius cointegration test.

The Trace and Max-Eigen statistics of the Johansen and Juselius cointegration test, for the two relevant models with lag length 13, have been reported in Table 4.8. R stands for the number of cointegrating vectors and the critical values for 5% significance level are in the parenthesis. Based on the Pantula selection procedure, the results of Table 4.8 indicate that Model 4 should be chosen because for this model the null hypothesis is rejected for the first time.

R		<b>Trace Statistics</b>	<b>Max-Eigenvalue Statistics</b>		
	Model 4	Model 5	Model 4	Model 5	
	193.8972*	188.3363*	54.19770*	53.97990*	
	(150.5585)	(139.2753)	(50.59985)	(49.58633)	
	139.6995*	134.3564*	38.39335	38.22570	
	(117.7082)	(107.3466)	(44.49720)	(43.41977)	
$\mathcal{D}_{\mathcal{L}}$	$101.3062*$	96.13066*	34.91457	34.39270	
	(88.80380)	(79.34145)	(38.33101)	(37.16359)	
3	66.39163*	61.73797*	24.02712	23.02712	
	(63.87610)	(55.24578)	(32.11832)	(30.81507)	
$\overline{4}$	42.36451	38.71084*	18.38763	16.71088	
	(42.91525)	(35.01090)	(25.82321)	(24.25202)	
5	23.97688	21.99997*	16.35119	16.29900	
	(25.87211)	(18.39771)	(19.38704)	(17.14769)	
	7.625683	5.700968*	7.625683	5.700968*	
6	(12.51798)	(3.841466)	(12.51798)	(3.841466)	

**Table 4.8 Model Selection for Johansen and Juselius Cointegration Test**

The above-mentioned test results have indicated that the model 4 is the most appropriate model for the cointegration test. So, we have applied lag 13 and model 4 in Johansen and

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<sup>6</sup> See Appendix D

Juselius Cointegration Approach. The summary of the Johansen and Juselius test result<sup>7</sup> is reported in Table 4.9. The test results show that the trace test rejects the null hypothesis of  $R \le 3$  in favor of R = 4, and the Max-Eigenvalue test rejects the null of R  $\le 0$  in favor of  $R = 1$  at 5% significance level.

Hypothesized Number of CE(s)	(Trace)	<b>Unrestricted Cointegration Rank Test</b>		<b>Unrestricted Cointegration Rank Test</b> (Maximum Eigenvalue)		
	Trace <b>Statistic</b>	Critical Value at 5% Significance	Probability	Max-Eigen <b>Statistics</b>	Critical Value at 5% Significance	Probability
None	193.8972*	150.5585	0.0000	54.19770*	50.59985	0.0203
At most 1	139.6995*	117.7082	0.0010	38.39335	44.49720	0.1981
At most 2	101.3062*	88.80380	0.0047	34.91457	38.33101	0.1173
At most 3	66.39163*	63.87610	0.0303	24.02712	32.11832	0.3468
At most 4	42.36451	42.91525	0.0567	18.38763	25.82321	0.3482
At most 5	23.97688	25.87211	0.0845	16.35119	19.38704	0.1308
At most 6	7.625683	12.5198	0.2838	7.625683	12.51798	0.2838

**Table 4.9 Results of Johansen and Juselius Cointegration Test**

Notes: Trace test indicates 4 cointegrating equations and Max-eigenvalue test indicates 1 cointegrating equation at 5% level.

Gregory (1994) has shown through Monte Carlo simulation that although both tests exhibit size distortion but the maximum eigenvalue performs better, because it uses only one eigenvalue, whereas the trace test uses all the eigenvalues. Patterson (2000) has also mentioned that the maximum eigenvalue performs better. Considering these, we have accepted the test result of maximum eigenvalue and have concluded that there is one cointegration vector.

The long-run equation (Table 4.10), normalized on stock prices, shows that except interest rate (LINT), other variables contributing to the long-term relationship at 5% significance level based on *t*-statistics. The long-run equation also shows that the industrial production (LIPI), interest rate (LINT) and gold price (LGDPRICE) have positive coefficients

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<sup>7</sup>See Appendix E

indicating a positive relation, whereas the consumer price index (LCPI), exchange rate (LEXR) and money supply (LM2) indicate negative relationship with stock prices. Also, the trend is significant at the 5% level, meaning that the trend has rightly included.

<b>LDSEGEN</b>	<b>LIPI</b>	<b>LINT</b>	<b>LCPI</b>	<b>LEXR</b>	LM2	<b>LGDPRICE</b>	@Trend (91M02)
	$-4.0425*$	$-5.9958$	$5.2392*$	$6.9933*$	$5.3292*$	$-1.7386*$	$-0.0797*$
		$(1.33278)$ $(3.99603)$ $(1.54830)$		$(0.90389)$ $(1.66524)$		(0.32970)	(0.01499)
		$[-3.0332]$   $[-1.5004]$	[3.3838]	[7.7369]	[3.2003]	$[-5.273]$	$[-5.319]$
						$\mathbf{M}$ ,	

**Table 4.10 Long-run Coefficients Normalized on Stock Market index**

Notes: (value) gives standard error and [value] is relevant t-value. Asterisk denotes coefficient significance at 5% level.

To check the robustness of the results, we have also reexamined whether macroeconomic variables are significant components in the cointegrating equation using likelihood ratio test. The test is done by putting restrictions sequentially on each of the independent cointegrating coefficients. The null hypothesis of the test is that the coefficient is equal to zero. The *p*-value of the  $\chi^2$  distribution determines whether the null is rejected or not. The summary of the rest results (see Appendix E 2) is reported in Table 4.11. The results show that except interest rate, other macroeconomic variables have entered significantly in the cointegrating equation. So, both the *t-*statistics and the likelihood ratio test have provided the same results indicating the robustness of the results.

**Table 4.11 Significance of Long-run Cointegrating Coefficients with LR Test**

<b>Restriction on</b>	$\gamma^2$ Statistics	<i>p</i> -value
LIPI	4.110282*	0.042623
<b>LINT</b>	1.291469	0.255777
LCPI	6.333333*	0.011849
<b>LEXR</b>	14.22177*	0.000162
LM2	4.918124*	0.026576
<b>LGDPRICE</b>	11.17695*	0.000828

Notes: Asterisk denotes the coefficient is significance at 5% level.

The cointegration equation shows that the relation between the DSE General Index and the industrial production index is positive and significant. This is what we have hypothesized. There are many evidences that stock prices are significantly positively related to the level of economic activity proxies by the industrial production index. Our finding is same as the findings of Mukherjee and Naka (1995) for Japan, Adrangi et al. (1999) for both South Korea and Mexico, and Humpe and Macmillan (2007) for both US and Japan. Fama (1981) has explained that the stock market makes rational forecasts of the real sector. Chen et al. (1986) have argued that the positive relation reflects the value of insuring against real systematic production risk. Besides, Maysami and Koh (2000) have pointed that the changes in productive activity, through their impact on expected dividends, should influence stock market returns.

Our finding shows that the DSE General Index is positively related to interest rate, which is contrary to our hypothesis. Although the relationship is not statistically significant. Theoretically, high interest rates on deposit lead investors to invest less in risky stocks and, consequently, lower stock prices are expected. But our converse result is not uncommon in the literature. Many Studies (Mukherjee and Naka, 1995; Maysami and Koh, 2000; Bulmash and Trivoli, 1991) have found a positive relationship between the short-term interest rates and stock market prices, and a negative relationship between long-term interest rates and stock prices.

In this study, the weighted average interest rate offered by commercial banks on three to six months fixed or term deposits has been used to represent the interest rate. So, this is a representation of short-term interest rate. The relationship between interest rate and stock prices in this study is, therefore, consistent with the results of the short-term interest rates. One possible explanation of this positive relation is that if the short-term interest rate is increased now, it means that it will fall in the near future. So, when investors find that the short-term interest rates have increased, they buy more stocks now with an expectation that falling interest rate in future would increase the stock prices. It is worth mentioning that our finding on relationship between interest rate and stock market index is similar to the finding of Khan and Yousuf (2013) on Bangladesh. They have used data from January 1992 to June 2011 and have found a positive relationship at 10% significance level (weakly significant) between stock market and short-term deposit interest rate.

The long-run cointegrating equation indicates that the relationship between inflation and stock prices is negative and significant. Earliest inference on positive relation between inflation and stock market is based on hypothesis presented by Irving Fisher (1930). On the other hand, Fama (1981) has proposed the proxy hypothesis which has illustrated that the negative relationship between inflation and stock prices are induced by the positive correlation between stock returns and real activity and the negative correlation between inflation and real activity.

Our result is in line with proxy hypothesis. Our finding of negative relationship between inflation and stock prices is consistent with the findings of Chan et al. (1985), Chen et al. (1986), Mukherjee and Naka (1995), and Mohammad et al. (2009). The study of Khan and Yousuf (2013) has also found negative relationship between stock market and consumer price index in their study on Bangladesh.

The results have indicated that exchange rate and the stock market index are significantly negatively related, which is contrary to our hypothesized relationship. Theoretically, it is expected that increasing exchange rate (depreciation of BDT against the U.S. Dollar) should attract foreign investment in the DSE stocks, hence there should be increase in stock prices. However, Ibrahim and Aziz (2003) have found a negative association between stock returns and the exchange rate for Malaysia. They have argued that currency depreciation encourages exports; conversely, it increases costs of production through increasing domestic prices of imported raw materials and capital goods. They have pointed that Malaysian economy is highly dependent on international trade, so the negative channel is prominent in Malaysia and showing this negative relationship.

Perhaps, this has happened in Bangladesh; depreciation of Bangladeshi currency (BDT) has resulted in increased imported raw materials cost leading to higher cost of production. Consequently, this has exerted a negative impact on expected cash flows from the stocks, hence lowers stock prices. This result is also similar to the finding of Khan and Yousuf (2013) on Bangladesh.

The relationship between money supply and stock price is negative and significant at 5% level. This is contrary to our hypothesized relationship. However, this finding is consistent with the findings of Ibrahim and Aziz (2003), Humpe and Macmillan (2007), Mohammad et al. (2009), and Singh et al. (2011). They have explained this negative relationship arguing that the expansionary effect of money supply on real economic activities may have created a positive relation between the stock market and money supply (Mukherjee and Naka, 1995); however, if the increase in money supply creates inflation as well as contributes to inflationary uncertainty, this may exert a negative influence on the stock prices. We think that our finding indicates the dominance of the negative channel.

But our finding on relationship between money supply and stock prices is opposite to the finding of Khan and Yousuf (2013) on Bangladesh. The probable reason for this may be Khan and Yousuf (2013) have considered data from January 1992 to June 2011, but we have considered data from January 1991 to December 2015 and during these two periods the trend of these two variables (DSE general index and money supply) are different. It is evident from Figure 4.8 that both DSE general index and money supply have increasing trend from January 1992 to June 2011; except during the falling market of 1996 which is from November 1996 to December 1999. Conversely, from July 2011 to December 2015 the money supply has sharp increasing trend but the DSE general index has decreasing trend, because of the catastrophe of 2010 (see figure 4.9). This prolonged opposite trend may have caused the negative relationship between money supply and stock market index in this study.



This study has found positive relationship between gold price and stock price at 5% significance level. This is contrary to our hypothesized relationship. Generally, gold is considered as an alternative to stock market investment, so should have a negative relationship. However, Mamipour and Jezeie (2015) have found a long-run direct relation between the stock price and the gold price in Iran. They have argued that this unexpected result may be due to the fact that the gold price in Iran is generally affected by world gold prices. Also, Ahmed and Imam (2007) have examined the impact of gold price on the stock market return along with other macroeconomic variables of Bangladesh by employing Johansen cointegration analysis and Vector Error Correction (VEC) model. Their findings have indicated a significant positive long-run relationship between gold price and stock market. One possible explanation of positive relationship between stock market and gold
price is that gold price in Bangladesh mostly depends on international gold price. Furthermore, during our study period, the gold price has gone up due to the international factors, which is stated in an article of the Global Times<sup>8</sup> - "the price of gold in the country has gone up along with that in the international market<sup>9</sup>". At the same time, during this period stock market has also gone up (see figure 4.10) showing a positive relationship.





#### **4.4.3.1 Results of Vector Error Correction Model**

The Vector Error Correction Model (VECM) provides valuable information about the short-run relationship between variables, while a negative and significant error correction term signifies the speed of adjustment to the long-run equilibrium. The principle behind this model is that there often exists a long-run equilibrium relationship among variables, but in the short-run there may be disequilibrium.

The cointegration results have indicated that the variables tend to move together in the long-run. To further investigate the relationship, the VECM along with Ordinary Least Squares has been used. The summary of the results (see Appendix E 3) is reported in Table

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<sup>8</sup> The Daily Chinese Newspaper http://www.globaltimes.cn/

<sup>9</sup> http://www.globaltimes.cn/content/753288.shtml

4.12. The Error Correction Term (ECT) is negative and significant at 5% level indicating that there exists a long-run equilibrium relationship between the stock market and the macroeconomic variables and the speed of convergence to equilibrium is about 15.30 percent. It confirms the long-run equilibrium relationship. The ECT value indicates that equilibrium agents remove a sizeable percentage of disequilibrium per month.

The  $\mathbb{R}^2$  value indicates that about 30 percent of the stock market return can be explained by the growth of selected macroeconomic variables along with the trend. The remaining 70 percent is explained by other factors, which have not been considered in this study. The Durbin Watson Statistic indicates the presence of non-autocorrelated residuals. We have also examined the short-run relationships between the stock market return and selected macroeconomic variables.

<b>VECM</b> Equation	$D(DSEGEN) = C1*(LDSEGEN(-1) - 4.0425*LIPI(-1) - 5.9958*LINT(-1) +$ $5.2392*LCPI(-1) + 6.9933*LEXR(-1) + 5.3292*LM2(-1) - 1.7386*LGDPRICE(-1)$ $-0.0797*$ @Trend (91M01) $-58.4802$ )								
<b>Variables</b>	<b>Coefficient</b>	<b>t</b> Statistics	<b>Probability</b>						
$\text{ECT (C1)}$	$-0.153014$	$-3.618433$	0.0004						
R-Squared	0.299886								
F-statistic	0.898582								
Probability (F Stat)	0.715895								
Durbin-Watson stat	2.017233								

**Table 4.12 Summary of Vector Error Correction Model Results** 

We have used the Wald Statistics to examine the significance of the short-run relationships running from different lag values of the growth of independent variables (macroeconomic variables) to dependent variable (stock market returns). The test statistics follow  $\chi^2$ distribution, so we have used Chi-square critical values. The summary of the short-run relationships (see Appendix E 3.2) is shown in Table 4.13. The results indicate that none of the macroeconomic variables up to 13 lags can jointly explain the stock market return at 5 percent significance level (as *p-*values are more than 0.05). So, we have concluded that there is no short-run relationship running from lag values of growth of macroeconomic variables to the stock market return.

Independent <b>Variables</b>	<b>Null Hypothesis</b>	$\chi^2$ Statistics	p-value
<b>DLIPI</b>	$C(15) = C(16) = C(17) = C(18) = C(19) = C(20) = C(21)$ $= C(22) = C(23) = C(24) = C(25) = C(26) = C(27) = 0$	9.396882	0.7424
<b>DLINT</b>	$C(28) = C(29) = C(30) = C(31) = C(32) = C(33) = C(34)$ $= C(35) = C(36) = C(37) = C(38) = C(39) = C(40) = 0$	4.423925	0.9858
<b>DLCPI</b>	$C(41) = C(42) = C(43) = C(44) = C(45) = C(46) = C(47)$ $= C(48) = C(49) = C(50) = C(51) = C(52) = C(53) = 0$	17.87379	0.1624
<b>DLEXR</b>	$C(54) = C(55) = C(56) = C(57) = C(58) = C(59) = C(60)$ $= C(61) = C(62) = C(63) = C(64) = C(65) = C(66) = 0$	8.884263	0.7816
DLM <sub>2</sub>	$C(67) = C(68) = C(69) = C(70) = C(71) = C(72) = C(73)$ $= C(74) = C(75) = C(76) = C(77) = C(78) = C(79) = 0$	13.83173	0.3858
<b>DLGDPRICE</b>	$C(80) = C(81) = C(82) = C(83) = C(84) = C(85) = C(86)$ $= C(87) = C(88) = C(89) = C(90) = C(91) = C(92) = 0$	6.631300	0.9201

**Table 4.13 Significance of Short-run Coefficients**

#### **4.4.3.2 Viability and Stability Check of the Model**

For a good regression model, the residuals of the VECM should be homoscedastic, not serially correlated and normally distributed. So, the tests of residuals for normality, autocorrelation, and heteroscedasticity are carried out to examine the viability of the model and the significance of the results. Firstly, we have plotted the residuals (see figure 4.11) to have a visual check of the homoscedasticity of the residuals. The graph indicates that the residuals seem to be homoscedastic.



The correlogram of the residuals<sup>10</sup> is also estimated up to 36 lags. The Ljung-Box  $Q$ statistics are used to investigate the presence of autocorrelations. The high *p-*values for different lags indicate that residuals are not serially correlated. Therefore, we conclude that residuals are independent. To check the robustness of the findings, we have applied diagnostic tests of the residuals, such as Breusch-Godfrey Serial Correlation LM test, Breusch-Pagan-Godfrey test and Jarque-Bera statistic to further examine the serial correlation, homoscedasticity and normality of the residuals respectively.

The results of these diagnostic tests (see Appendix F) show that the residuals are not serially correlated and have no heteroskedasticity. But the Jarque-Bera statistic and its associated *p*-value indicate that the residuals are not normally distributed, which is a weakness of the model. However, it has been suggested by scholars that non-normality in the residual may not be a serious problem as the estimators are still consistent (Adeniji, 2015). Further, we have checked the stationarity of the residuals using ADF, PP and KPSS unit root tests. The summary of the test results is presented in Table 4.14. All the unit root tests have supported that the residuals are stationary at level indicating that the model is a good fit model. Therefore, we can conclude that the results are significant.





Notes: Critical values at 5% level for ADF and PP test with trend and intercept is -3.424977and with intercept is -2.871029, that for KPSS test with trend and intercept is 0.146and with intercept is 0.463. \* denotes that coefficient is significance at 5% level.

Finally, we have applied Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests developed by Brown et al. (1975) to check the stability of the parameters of the equation. The results of both CUSUM and CUSUMSQ tests (Figure 4.12

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<sup>&</sup>lt;sup>10</sup>See Appendix F

and 4.13) have indicated that the slope parameters (coefficients) and conditional variances of the parameters depicted by residuals are stable.



## **4.4.4 Granger Causality Results**

As the variables are cointegrated, the Vector Error Correction (VEC) Granger-Causality test to be applied to examine whether the stock market return Granger-cause the growth of macroeconomic variables or vice versa. Since monthly data have been used in this research and one year is long enough for an efficient market to incorporate the effect of the news related to any change in a variable to other variables, we have used 12 lags in this test. Table 4.14 shows the summary of the results<sup>11</sup> of Granger causality test. The results reveal that stock market return can Granger-cause growth of two macroeconomic variables only, industrial production index and exchange rate, but opposite is not true. This implies that the performance of stock market is a good indicator to explain the future growth of both industrial production index and exchange rate. This result is consistent with the theory that stock market is used as a leading indicator of these two macroeconomic variables. But out of six macroeconomic variables, stock market return can Granger-cause only two macroeconomic variables. Therefore, we can conclude that stock market in Bangladesh is not a leading indicator for most of the macroeconomic factors.

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<sup>&</sup>lt;sup>11</sup> See Appendix G



#### **Table 4.15 Results of Granger Causality Test**

Notes: \* denotes that coefficient is significant at 5% level.

#### **4.4.5 Autoregressive Distributed Lags Test Results**

We have used the ARDL Bounds testing procedure to check the robustness of the results of Johansen cointegration test. The results of Johansen Cointegration Approach have indicated that interest rate is insignificant in the long-run equation, so we have excluded interest rate from the ARDL test. Furthermore, we have found from section 4.4.2 and 4.4.3 that all the variables are *I(1)* and some of the variables have trend component respectively. So, we have applied the ARDL model with restricted trend.

First, we have estimated the lag specification of the dependent and the independent variables using AIC and SIC values. We have started with 12 lags for both dependent and independent variables. Then, we have estimated the AIC and SIC values for different combinations of lag values for dependent and independent variables. We have chosen the optimum lag length based on the lowest values of the AIC and SIC. Table 4.16 shows the AIC and SIC values for different lag specifications of the dependent and independent variables. From the results, we have found that the optimum lags for dependent and independent variables are 12 and 5 respectively.

Lag Length					
<b>Dependent</b> <b>Variable</b>	Independent <b>Variables</b>	<b>AIC Value</b>	<b>SIC Value</b>		
12	12	$-1.730665$	$-0.725895$		
12		$-1.748346$	$-0.807169$		
12		$-1.782735$	$-0.968744$		
12		$-1.811641$	-1.124836		
		$-1.860648$	$-1.301029$		
		$-1.752056$	-0.825934		

**Table 4.16 Lag Length Selection for ARDL Test**

Now, we have applied ARDL test with above lags and restricted trend specification. The summary of the Pesaran Bounds Test with ARDL specification<sup>12</sup> is reported in Table 4.17.

<b>Dependent Variable: D(LDSEEGEN)</b> ARDL Model Specification (12, 5, 5, 5, 5, 5)								
								3.729042 <b>F</b> Statistics
<b>Critical Value Bounds</b>								
Significance	I <sub>0</sub> Bound	$I_1$ Bound						
10%	2.49	3.38						
5%	2.81	3.76						
2.5%	3.11	4.13						
$1\%$	3.50	4.63						
R-squared	0.212278							
Adjusted R-squared	0.073458							
F-statistic	1.529157							
Prob (F-statistic)	0.025220							
Durbin-Watson stat	1.968276							

**Table 4.17 ARDL Specification and Bounds Test Results**

The Bounds test result indicates that there exists a long-run relationship between stock market index and selected macroeconomic indices at 10 percent significance level. We have also examined the long-run relationships (see Appendix H 3) and the summary of the results is reported in Table 4.18. The long-run equation has indicated that except money supply other variables are significant at 5 percent level and trend is also significant. In

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<sup>&</sup>lt;sup>12</sup> See Appendix H

addition, industrial production and gold price have positive relation with stock market index, while inflation, exchange rate and money supply have negative relation with the stock market index. Except the significance of money supply (LM2) our ARDL results are similar to that of Johansen cointegration test.

Independent <b>Variables</b>	<b>Coefficient</b>	<b>Std. Error</b>	<i>t</i> -Statistics	<b>Probability</b>
I IPI	2.805986	1.328399	2.112307	0.0357
I CPI	-5.331708	1.644792	$-3.241570$	0.0014
LEXR.	$-3.817657$	1.419371	$-2.689682$	0.0076
LM2	$-2.314113$	2.009226	$-1.151743$	0.2506
<b>LGDPRICE</b>	1.433363	0.370913	3.864420	0.0001
$@$ TREND	0.043799	0.017795	2.461358	0.0145

**Table 4.18 Long-Run Coefficients of ARDL Test**

Although there exists a long-run equilibrium relationship between the variables, there could be a disequilibrium in the short-run. But the cointegration does not unfold these short-run relationships and the adjustment process to bring about equilibrium in the longrun. To examine the short-term relationships and this adjustment process, ECM has been applied. The size of the error-correction term in ECM indicates the speed of adjustment of the dependent variable to bring about the long-run equilibrium and it is also indicative of the intensity of the arbitrage activities to bring about equilibrium in the long-run.

#### **4.4.5.1 Results of Error Correction Model**

The summary of the results of Error Correction Model (ECM) i.e. the short-run relationships is reported in Table 4.19. The ECM results indicate that the error correction coefficient is -0.1262 (*p*-value 0.0000), which is highly significant and has the correct sign. This implies a moderate speed of adjustment to the equilibrium after a shock. Approximately 12.62% of disequilibria is removed per month. Finally, the *t*-statistics and *p*-value of the coefficients of the  $\Delta$  (i.e. differenced) variables indicate whether the effects of the macroeconomic variables on stock index are significant or not in the short-run.

<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	t-Statistics	<i>p</i> -value
D(LIPI)	$-0.072473$	0.102480	$-0.707194$	0.4801
$D(LIPI(-1))$	$-0.269431$	0.118456	$-2.274533$	0.0238
$D(LIPI(-2))$	$-0.133302$	0.109053	$-1.222362$	0.2228
$D(LIPI(-3))$	$-0.207961$	0.106198	$-1.958240$	0.0513
$D(LIPI(-4))$	$-0.111237$	0.100216	-1.109970	0.2681
D(LCPI)	$-0.697106$	0.652557	$-1.068268$	0.2865
$D(LCPI(-1))$	0.248424	0.659353	0.376769	0.7067
$D(LCPI(-2))$	0.962871	0.660809	1.457110	0.1464
$D(LCPI(-3))$	0.613004	0.659660	0.929272	0.3537
$D(LCPI(-4))$	1.415530	0.653387	2.166449	0.0312
D(LEXR)	0.029960	0.598264	0.050078	0.9601
$D(LEXR(-1))$	0.151044	0.606214	0.249159	0.8034
$D(LEXR(-2))$	0.431284	0.605819	0.711903	0.4772
$D(LEXR(-3))$	0.873915	0.604339	1.446067	0.1494
$D(LEXR(-4))$	$-0.360146$	0.596683	$-0.603580$	0.5467
D(LM2)	0.862471	0.454845	1.896188	0.0591
$D(LM2(-1))$	$-0.252556$	0.479456	$-0.526756$	0.5988
$D(LM2(-2))$	$-0.595640$	0.476573	$-1.249839$	0.2126
$D(LM2(-3))$	0.401219	0.484289	0.828471	0.4082
$D(LM2(-4))$	$-0.339919$	0.447149	$-0.760191$	0.4479
D(LGDPRICE)	0.042509	0.124678	0.340948	0.7334
$D(LGDPRICE(-1))$	$-0.044104$	0.126195	$-0.349489$	0.7270
$D(LGDPRICE(-2))$	$-0.238801$	0.122632	$-1.947300$	0.0526
$D(LGDPRICE(-3))$	$-0.077468$	0.123348	$-0.628043$	0.5306
$D(LGDPRICE(-4))$	$-0.075939$	0.123909	$-0.612860$	0.5405
$\mathcal{C}$	4.818334	0.928736	5.188057	0.0000
D(LIPI)	$-0.072473$	0.102480	$-0.707194$	0.4801
$CointEq(-1)$	$-0.126236$	0.024410	$-5.171574$	0.0000

**Table 4.19 Short-run Coefficients in ARDL Test**

As the independent variables have multiple lags, so we have used the Wald Statistics to examine whether the lagged values of the growth of independent variables can jointly explain the stock market return significantly. The test statistics follow the  $\chi^2$  distribution, so we have used Chi-square critical values. The summary of the Wald Test results (see Appendix H 4) is shown in Table 4.20. The results show that none of the macroeconomic variables with their optimal lag values can jointly explain the shock market return in the short-run at 5% significance level, meaning that there is no short-run relationship between stock market and macroeconomic variables.

Independent <b>Variables</b>	<b>Null Hypothesis</b>	$\chi^2$ Statistics	p-value
LIPI	$C(12) = C(13) = C(14) = C(15) = C(16) = 0$	4.084552	0.5373
$L$ CPI	$C(17) = C(18) = C(19) = C(20) = C(21) = 0$	10.61084	0.0597
<b>LEXR</b>	$C(22) = C(23) = C(24) = C(25) = C(26) = 0$	2.858767	0.7217
LM2	$C(27) = C(28) = C(29) = C(30) = C(31) = 0$	9.679108	0.0849
<b>LGDPRICE</b>	$C(32) = C(33) = C(34) = C(35) = C(36) = 0$	3.341163	0.6475

**Table 4.20 Significance of Short-run Coefficients**

## **4.4.5.2 Viability and Stability Check of the Model**

Like Johansen cointegration test, the tests of residual for normality, autocorrelation, and heteroscedasticity are carried out to examine the significance of the results of the ARDL test. The correlogram of the residuals<sup>13</sup> is estimated up to 36 lags. The Ljung-Box  $Q$ statistics is used to investigate whether there is autocorrelation or not. The high *p-*value indicates that there is no serial correlation. Therefore, we conclude that residuals are independent (stationary).

In addition to the correlogram of the residuals to investigate the robustness of the results related to viability of the model, we have used Breusch-Godfrey Serial Correlation LM test, Breusch-Pagan-Godfrey test and Jarque-Bera statistic to examine the serial correlation, homoscedasticity and normality of the residuals respectively. The results (see Appendix I) indicate that the residuals are not serially correlated and homoskedastic, but the distribution of the residuals is not normal. However, practically it is hard to find a model with completely white noise residuals. So, the non-normal distribution of the residuals does not significantly distort the viability of the model as the residuals are

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<sup>&</sup>lt;sup>13</sup>See Appendix I

stationery, homoskedastic and not autocorrelated. Furthermore, we have applied CUSUM and CUSUMSQ tests to check the stability of the regression parameters, developed by Brown, Durbin and Evans (1975). The results of CUSUM and CUSUMSQ tests (Figure 4.14 and 4.15) have indicated that the slope parameter (coefficients) are stable, however, there is an instability in conditional variance depicted by residuals.



## **4.5 Conclusion**

In this chapter, the long- and short-term relationship between Dhaka Stock Exchange General Index (DSEGEN) and macroeconomic indices of Bangladesh has been investigated using Johansen and Juselius methodology of multivariate cointegration analysis and Vector Error Correction Model. Moreover, the ARDL cointegration test has been applied to check the robustness of the results of the Johansen and Juselius cointegration approach. The macroeconomic indices selected for this study are industrial production index, interest rate, consumer price index, exchange rate, money supply and gold price.

The Johansen and Juselius cointegration approach have revealed that there exists a longrun equilibrium relationship between the stock market index and the macroeconomic variables. The results have also indicated that except interest rate other macroeconomic variables have entered the long-run cointegrating equation significantly at 5% significance level. Although for some macroeconomic variables, the direction of long-run relationships between the stock market index and the macroeconomic variables are found opposite to the hypothesized relationships.

The industrial production index is positively related with the stock market, which is as expected. But the interest rate is positively related with the stock market index, which is unexpected as higher interest rates, theoretically, shift investors away from stock market. But this relationship is statistically insignificant in explaining the stock market. However, this positive relation is not uncommon in the literature. The exchange rate is negatively related with the stock market index, meaning that the depreciation of Bangladeshi currency might have increased the cost of imported raw materials and capital goods for the firms resulting lower stock prices. The consumer price index is found negatively related with stock market, which is consistent with the proxy hypothesis. The money supply is found negatively related with the stock prices, which has indicated that the increase in money supply has created inflation as well as inflationary uncertainty, which in turn has exerted a negative influence on the stock prices. The positive long-run relation between the stock market index and the gold price reveals that gold has not been considered as an alternative investment in Bangladesh and gold price in Bangladesh mostly depends on international gold price.

The VECM results have shown that none of the macroeconomic variables up to 13 lags can jointly explain the stock market return, meaning that there is a disequilibrium in the short-run between the stock market return and growth of macroeconomic variables. The significant error correction term has revealed that about 15.30 percent of the disequilibrium in the short-run is adjusted per month to bring about equilibrium in the long-run.

The results of Granger Causality have indicated that the stock market return has Grangercaused growth of two macroeconomic variables, industrial production and exchange rate, but the opposite is not true, meaning that there exist unidirectional casual relationships running from stock market return to the growth of these two macroeconomic variables. On the other hand, there is no causal relationship between stock market return and growth of other macroeconomic variables. The unidirectional causal relationships running from stock market return to the growth of only two macroeconomic variables imply that the stock market is not a leading indicator for most of the macroeconomic variables.

Residual diagnostic tests of the Johansen and Juselius model have showed that the model is a good fit model, hence the findings are reliable. The plots of CUSUM and CUSUMSQ are drawn to check the stability of the parameters of the cointegration equation. Both the CUSUM and CUSUMSQ plots are within the critical bounds indicating that the coefficients are structurally stable throughout the total sample period.

In addition, the ARDL cointegration test has been applied to examine the robustness of the findings of the Johannsen and Juselius cointegration approach. Since interest rate is found insignificant in the Johansen and Juselius long-run cointegration equation, it has been excluded in the ARDL cointegration test. The results of ARDL approach have also indicated that there exists a significant long-run equilibrium relationship between the stock market index and the macroeconomic variables. Although in the ARDL test money supply is found insignificant in the long-run equation, this variable has entered in the long-run equation significantly in Johansen test.

The error correction models of the two cointegration approaches have confirmed that the lagged values of the growth of macroeconomic variables are not significant in explaining the stock market return in the short-run. Furthermore, the error correction term is found negative and statistically significant in both tests. The coefficient of the error correction term in ARDL model suggests that adjustment process is moderate and about 12.62 percent of the disequilibrium in market index is corrected per month to bring about long-run equilibrium, which is 15.30 percent in Johansen test with an additional regressor, interest rate. So, the findings of ARDL model have confirmed the robustness of the results of the Johansen test. However, both the tests have indicated that only a small percentage of the stock market return can be explained by the selected macroeconomic variables indicating that there are other factors to be considered to increase the explanatory power of the independent variables to explain the stock market return of Bangladesh.

Residual diagnostic tests of the ARDL model have showed that the model is a good fit model and the findings are reliable. The plot of CUSUM is within the critical bounds of 5 percent indicating that the parameters are stable. However, the plot of CUSUMSQ indicates that there is an instability in conditional variance depict by residuals. This finding has indicated a structure instability in conditional variance around the catastrophe of 1996, which is not found in Johansen and Juselius approach.

However, Caporale and Pittis (2004) have mentioned that CUSUM and CUSUMSQ tests perform better in the context of a dynamic model of the ARDL type, which is not affected by serial correlation or nonpredetermined regressors even if over-specified. In this context, we have accepted the result of ARDL approach in relation to the structural instability in the conditional variance around 1996 and further investigations related to this issue have been carried out in the following chapters.

# **Chapter 5**

## **Relationships During Bubble, Meltdown and Recovery Periods**

## **5.1 Introduction**

A bubble is a well-known empirical phenomenon in stock markets, but there is no consensus about the mechanisms behind it. Besides, a bubble is followed by a crash. As the impact of a large stock market crash is considerable on households, banks and finally on overall economy, bubbles and crashes are of profound importance to risk management in investment. Bangladesh stock market has experienced two major bubbles within a decade and a half, one in 1996 and other in 2010. However, our investigations in chapter 4 have revealed that only the catastrophe of 1996 has created a structural instability in the stock market. This has motivated us to examine the relationships between the stock market and the macroeconomic variables around the catastrophe of 1996 - that is during the bubble and meltdown period of 1996. These investigations have helped us describing the relationships during the crisis times. In addition, this study has also aimed to identify the factors responsible for creating the bubble and bubble crash of 1996.

On the other hand, after the catastrophe of 1996, the Capital Market Development Program (CMDP) was undertaken through a strong partnership between the government of Bangladesh and the Asian Development Bank, which became effective on 27 January 1998. The CMDP aimed to broaden market capacity and develop a fair, transparent, and efficient domestic capital market to attract larger amounts of investment capital to augment the capital resources provided through the banking system. The key agenda of the CMDP in achieving this objective was to restore investor confidence, which was significantly damaged when the Bangladesh stock market crashed in 1996 because of excessive speculations, allegedly aggravated by widespread irregular activities. Also, to fulfill the dream of transforming DSE into modern world class exchange, the stock market started its journey of automation on 10 August 1998 and yet is striving for continuous upgradation of its trading platform. As a result, the market capitalization of Dhaka Stock Exchange (DSE) to GDP has increased from 0.94% in June 1991 to about 30.95% in June 2009 (Wahab and Faruq, 2012).

In this backdrop, the scope of this study has been extended further to cover a period in between the two catastrophes of Dhaka Stock Exchange. This period has been named as the recovery period as the aforesaid reform measures for the development of the stock market as well as the automation initiatives to build up a state-of-the-art market surveillance system to increase the transparency of market transactions are supposed to enhance the investors' confidence and improve the efficiency of the stock market. In this context, it is expected that during the recovery period the stock market prices should more precisely reflect the risk generated by the underlying macroeconomic indices.

The relationships between the stock market index and the macroeconomic indices in the bubble, meltdown and recovery periods have been assessed separately to compare the influences of the priced factors across different conditions of the stock market. The remaining discussions of the chapter are presented in six sections. In section 5.2, we have outlined the empirical methods to be used in the analysis. The descriptive statistics of the research variables have been portrayed in section 5.3. In section 5.4, we have summarized the results of different unit root tests to determine the stationarity and order of integration of the variables. In section 5.5, we have reported the results of cointegration tests along with the interpretation of the long-term relationships. Also, the results of Error Correction Model (ECM), the short-term relationships, the viability check of the models along with the stability tests of the parameters for different periods have been described in this section. Finally, conclusions are drawn in section 5.6.

## **5.2 Empirical Methods**

The empirical investigations of this chapter have been made based on the econometric models outlined in the previous chapter. More specifically, the econometric models for unit root tests to check the order of integration of the variables, the Johansen and Juselius, and ARDL cointegration approaches to examine the long- and short-run relationships and the error correction model to investigate the short-run dynamics and significance of error correction term, which have been described in chapter 4, are used in this chapter.

To examine the relationships between the stock market index and the macroeconomic indices in different periods, we have precisely pointed out the periods of bubble starting and crashing of 1996 as well as the recovery period. From the aforesaid information and the visual inspection of the stock index graph (see Figure 5.1), we have considered the data from March 1992 to November 1996 as bubble period, from November 1996 to December 1999 as meltdown period and from January 2000 to December 2009 as recovery period.





The Augmented Dickey-Fuller (ADF) and the Phillips and Perron (PP) unit root tests have been applied to check the stationarity and order of integration of the variables, as per the methodologies described in chapter 4. Whenever, these two tests have given diverse results for a variable, then we have used Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root test for conclusion. Later, based on the order of integrations of the variables, cointegration test has been selected for the investigations. If all variables are integrated of order 1, *I(1),* both the Johansen and ARDL approaches have been applied. But if there is a mix of *I(1)* and *I(0),* only ARDL approach has been used. However, If a variable is integrated of order 2, *I(2)*, then that variable has been excluded from the cointegration analysis, as the ARDL test crashes in presence of *I(2)* variable*.*

## **5.3 Descriptive Statistics of the Variables**

Table 5.1 has provided the descriptive statistics of the research variables for the bubble, meltdown and recovery periods. The statistics of Panel A are for the data at level, and that of Panel B are for data at first differences. As the variables are converted into natural logarithm, so the first difference of a variable represents the growth of that variable. Several points can be noted from the descriptive statistics of Panel B.

Firstly, the stock market has provided approximately 4.5% mean monthly return in the bubble period, and during that period the mean monthly growth of industrial production, interest rate, consumer price index, exchange rate, money supply and gold price are approximately 0.50%, -0.10%, 0.30%, 0.20%, 1.0% and 0.10% respectively. The results reveal that except interest rate other six variables have positive mean monthly growth, meaning that during the period these variables have increased, however, interest rate has decreased during the period. Notably, the mean monthly return from the stock market is very high compared to the other variables.

#### **Table 5.1 Descriptive Statistics of the Research Variables in Different Periods**



Notes: LDSEGEN is Log of DSE General Index, LIPI is Log of Industrial Production Index (IPI), LINT is Log of Interest Rate, LCPI is Log of Consumer Price Index (CPI), LEXR is Log of Exchange Rate (BDT per USD), LM2 is Log of Broad Money Supply (M2) and LGDPRICE is Log of Gold Price.

Secondly, during the meltdown period the stock market has provided very high negative mean return (monthly -4.8%), whereas during that period mean monthly growth of industrial production, interest rate, consumer price index, exchange rate, money supply and gold price are approximately 0.91%, 0.04%, 0.60%, 0.50%, 1.1% and -0.10% respectively. The results indicate that except gold price, other macroeconomic variables have positive mean monthly growth and these monthly growth rates are higher compared to that of the bubble period. Gold price has decreased during the period.

Thirdly, during the recovery period, the mean monthly return from stock market is 1.6% and except interest rate other macroeconomic variables show positive mean monthly growth rate. During this period mean monthly growth of industrial production, interest rate, consumer price index, exchange rate, money supply and gold price are approximately 0.50%, 0.0%, 0.50%, 0.30%, 1.30% and 1.30% respectively.

Fourthly, the standard deviations of monthly stock market return for the both bubble and meltdown periods are 11.8% and 11.1% respectively, indicating that the stock market has showed very high volatility during these periods. During the recovery period, the standard deviation of stock market return is 6.6%. On the other hand, the standard deviations of the selected macroeconomic variables are almost steady across the three periods.

Finally, for the level data, the Jarque-Bera statistics and the associated *p*-values have confirmed that except interest rate, the distributions of other six research variables are normal during the bubble period. During meltdown period, except DSE general index, the distributions of the six macroeconomic variables are normal. On the other hand, in the recovery period, only the distribution of interest rate is normal. For the first differences, which indicate the growth of the variables, three macroeconomic factors - namely industrial production, consumer price index and money supply, are normally distributed in the bubble period. In meltdown period stock market return and the growth of both industrial production and money supply are normally distributed. On the other hand, in the recovery period, only the growth of industrial production is normally distributed.

Panel A: Bubble Period (March 1992 to November 1996)									
	<b>LDSEGEN</b>	<b>LIPI</b>	<b>LINT</b>	<b>LCPI</b>	<b>LEXR</b>	LM <sub>2</sub>	<b>LGDPRICE</b>		
<b>LDSEGEN</b>	$\mathbf{1}$								
<b>LIPI</b>	0.792408	$\mathbf{1}$							
<b>LINT</b>	$-0.679890$	$-0.769154$	$\mathbf{1}$						
<b>LCPI</b>	0.847163	0.789564	$-0.549380$	$\mathbf{1}$					
<b>LEXR</b>	0.906854	0.730759	$-0.531510$	0.835114	$\mathbf{1}$				
LM <sub>2</sub>	0.918397	0.918270	$-0.750782$	0.916811	0.882823	$\mathbf{1}$			
<b>LGDPRICE</b>	0.829522	0.832504	$-0.715493$	0.834571	0.805667	0.901250	$\mathbf{1}$		
				<b>Panel B: Meltdown Period (November 1996 to December 1999)</b>					
<b>LDSEGEN</b>	$\mathbf{1}$								
<b>LIPI</b>	$-0.490437$	$\mathbf{1}$							
<b>LINT</b>	$-0.824683$	0.321995	$\mathbf{1}$						
<b>LCPI</b>	$-0.871275$	0.536405	0.827569	$\mathbf{1}$					
<b>LEXR</b>	$-0.895355$	0.536072	0.814644	0.983922	$\mathbf{1}$				
LM2	$-0.822522$	0.577986	0.735452	0.964552	0.969537	$\mathbf{1}$			
<b>LGDPRICE</b>	0.650660	$-0.353859$	$-0.777308$	$-0.855747$	$-0.808034$	$-0.794401$	$\mathbf{1}$		
				Panel C: Recovery Period (January 2000 to December 2009)					
<b>LDSEGEN</b>	1.0000								
<b>LIPI</b>	0.9171	1.0000							
<b>LINT</b>	$-0.3240$	$-0.3561$	1.0000						
<b>LCPI</b>	0.9551	0.9633	$-0.2930$	1.0000					
<b>LEXR</b>	0.8713	0.9334	$-0.4795$	0.9196	1.0000				
LM2	0.9417	0.9704	$-0.3535$	0.9917	0.9453	1.0000			
<b>LGDPRICE</b>	0.9265	0.9540	$-0.2777$	0.9836	0.9057	0.9802	1.0000		

**Table 5.2. Cross Correlations of the Research Variables at Level in Different Periods** 

Notes: LDSEGEN is Log of DSE General Index, LIPI is Log of Industrial Production Index (IPI), LINT is Log of Interest Rate, LCPI is Log of Consumer Price Index, LEXR is Log of Exchange Rate, LM2 is Log of Money Supply (M2), and LGDPRICE is Log of Gold Price.

Table 5.2 provides the correlation coefficients amongst the research variables at level in different periods. The correlation figures of bubble period (Panel A) show that except interest rate, DSE General Index has very high positive correlations with other macroeconomic variables. Interest rate has high negative correlation with DSE index. On the other hand, except interest rate other macroeconomic variables are strongly positively correlated with each other, interest rate is negatively correlated with other macro variables.

The correlations in the meltdown period (Panel B) indicate that except gold price other macro variables are negatively correlated with stock index. Gold price is positively correlated with stock index. Also, gold price is negatively correlated with other macroeconomic variables, while the remaining macro variables are positively correlated with each other.

Cross correlations for the recovery period (Panel C) show that except interest rate other macroeconomic variables are positively correlated with the stock market index and interest rate is negatively correlated with the stock market index. Except interest rate other macroeconomic variables are positively correlated with each other. However, interest rate is negatively correlated with other macro variables.

## **5.4 Unit Root Tests Results**

Unit root tests are applied as per the procedure described in chapter 4. Before applying unit root tests, the stability of the VAR of each variable under two conditions - with exogenous variables trend and intercept, and with intercept are checked. If VAR is found stable with any exogenous variable, then the optimal lag length of the variable for that condition is determined using lag selection criterion. The summary of the optimal lag lengths<sup>14</sup> is reported in Table 5.3. These lag lengths are used in unit root tests for different periods. The summary of the ADF and PP unit root tests<sup>15</sup> for are reported in Table 5.4.

 14 See Appendix J

 $15$  See Appendix K

		<b>Bubble Period</b>			<b>Meltdown Period</b>					<b>Recovery Period</b>			
		Level		1 <sup>st</sup> Difference		Level		1 <sup>st</sup> Difference		Level	1 <sup>st</sup> Difference		
Variables	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept	
<b>LDSEGEN</b>	$\overline{4}$	VAR is unstable	$\mathbf{0}$	$\overline{2}$	$\overline{2}$	3	$\overline{2}$	$\overline{2}$	10	VAR is unstable	9	9	
<b>LIPI</b>	$\mathbf{1}$	5	4	$\overline{4}$	$\overline{c}$	$\mathbf{1}$	3	3	12	12	11	11	
<b>LINT</b>	1	1	$\mathbf{0}$	1	$\overline{2}$	$\overline{2}$	$\mathbf{1}$	$\mathbf{1}$	9	9	8	8	
<b>LCPI</b>	4	$\mathbf{1}$	$\mathbf{0}$	$\mathbf{0}$	$\overline{2}$	$\mathbf{1}$	$\mathbf{0}$	$\mathbf{0}$	10	VAR is unstable	13	13	
<b>LEXR</b>	$\mathbf{1}$	VAR is unstable	$\mathbf{0}$	$\Omega$	$\mathbf{1}$	3	$\mathbf{2}$	$\overline{2}$	10	10	9	9	
LM2	3	3	8	8	$\mathbf{1}$	VAR is unstable	3	3	13	VAR is unstable	12	12	
<b>LGDPRICE</b>	1	3	$\overline{2}$	$\mathbf{2}$	1	$\mathbf{1}$	$\theta$	$\mathbf{0}$	5	VAR is unstable	6	6	

**Table 5.3 Optimal Lag Lengths of the Research Variables in Different Periods**

**Bubble Period:** ADF test indicates that LDSEGEN, LINT, LCPI, LEXR and LGDPRICE are integrated of order one, *I(1)*, while LIPI is stationary at level, *I(0)* and LM2 is integrated of order two, *I(2).* On the other hand, PP test shows that LDSEGEN, LCPI, LEXR, LM2 and LGDPRICE are integrated of order 1, *I(1)*, while LIPI is stationary at level, *I(0)* and LINT is nonstationary with trend and constant but stationary with constant at level. In addition, PP test shows that LINT series has significant trend, so we accept the result with trend and conclude that LINT is *I(1).* Therefore, only for LM2 the results of two tests are different. Thus, the KPSS test is applied to check the order of integration of LM2. The KPSS test results (see Appendix K 1.3) indicate that LM2 is *I(1)*. So, we can conclude that the research variables are either *I(1)* or *I(0)*.

**Meltdown Period:** ADF and PP tests show that LDSEGEN and LIPI are stationary at level, *I(0)*, while LINT, LCPI, LEXR, LM2 and LGDPRICE are integrated of order 1, *I(1).* So, the research variables in the meltdown period are either *I(0)* or *I(1).*

		<b>Bubble Period</b>					<b>Meltdown Period</b>		<b>Recovery period</b>			
	<b>ADF Test</b>		PP Test		<b>ADF Test</b>		PP Test		<b>ADF Test</b>		PP Test	
Variables	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept	and Intercept Trend	Intercept
					<b>Panel A: Data at Level</b>							
<b>LDSEGEN</b>	$-2.053$	VAR is unstable	$-1.298$	VAR is unstable	$-2.093$	$-3.386*$	$-2.647$	$-5.271*$	$-2.444$	VAR is unstable	$-2.248$	VAR is unstable
<b>LIPI</b>	$-4.264*$		$-4.495*$		$-3.760*$		$-3.594*$		$-1.594$	0.736	$-6.954*$	
<b>LINT</b>	$-0.241$	$-2.772$	$-0.194$	$-3.014*$	$-0.107$	$-2.772$	$-0.998$	$-1.764$	$-1.610$	$-1.591$	$-1.080$	$-1.433$
<b>LCPI</b>	$-3.361$	$-0.930$	$-2.696$	$-0.917$	$-2.857$	$-0.464$	$-2.457$	$-0.419$	$-2.935$	VAR is unstable	$-2.875$	VAR is unstable
<b>LEXR</b>	$-1.057$	VAR is unstable	$-1.108$	VAR is unstable	$-3.021$	0.036	$-3.355$	0.059	$-1.664$	$-1.587$	$-1499$	$-1.766$
LM2	$-1.643$	$-0.778$	$-3.000$	$-0.850$	$-1.865$	VAR is unstable	$-2.877$	VAR is unstable	$-0.727$	VAR is unstable	$-2.458$	VAR is unstable
<b>LGDPRICE</b>	$-2.830$	$-0.913$	$-3.058$	$-1.064$	$-1.272$	$-1.262$	$-1.410$	$-1.342$	$-2.783$	VAR is unstable	$-3.063$	VAR is unstable
					<b>Panel B: Data at 1st Difference</b>							
<b>LDSEGEN</b>	$-6.626*$		$-6.626*$						$-3.053$	$-2.986*$	$-10.13*$	
<b>LIPI</b>									$-7.480*$		$-9.514*$	
<b>LINT</b>	$-7.238*$				$-5.019*$		$-8.331*$		$-2.376$	$-2.493$	$-6.848*$	
<b>LCPI</b>	$7.061*$		$-7.061*$		$-5.391*$		$-5.391*$		$-2.730$	$-1.517$	$-6.224*$	
<b>LEXR</b>	$-7.589*$		$-7.589*$		$-4.160*$		$-7.472*$		$-2.744$	$-2.471$	$-11.36*$	
LM <sub>2</sub>	$-2.191$	$-2.141$	$-12.03*$		$-4.782*$		$-9.564*$		$-2.251$	$-1.851$	$-21.35*$	
<b>LGDPRICE</b>	$-5.080*$		$-8.680*$		$-6.178*$		$-6.178*$		$-4.703$		$-13.18*$	
					<b>Panel C: Data at 2<sup>nd</sup> Difference</b>							
LM2	$-3.954*$								$-12.04*$			
<b>LINT</b>									$-7.000*$			
<b>LCPI</b>									$-8.971*$			
<b>LEXR</b>									$-6.787*$			

**Table 5.4 Results of Unit Root Tests in Different Periods**

Notes: Critical values at 5% level for ADF test with trend and intercept is -3.424977and with intercept is -2.871029. Critical values at 5% level for KPSS with trend and intercept is 0.146and with intercept is 0.463. \* denotes that coefficient is significant at 5%.

**Recovery Period:** ADF test indicates that LINT, LCPI, LEXR and LM2 are *I(2)*, while LGDPRICE, LIPI, and LGDPRICE are *I(1)*. Conversely, PP test reveals that LIPI is *I(0)*  and other six variables are *I(1)*. So, we have checked whether LINT, LCPI, LEXR and LM2 are  $I(1)$  or  $I(2)$  using KPSS test. The results of the KPSS test (see Appendix K 3.3) indicate that these four series are *I(1).* So, we can conclude that the series are either *I(0)* or *I(1)*.

## **5.5 Cointegration Analysis for Different Periods**

Like unit root test, the test for trend specification of each variable is another pre-test for cointegration analysis. To identify the most appropriate trend specification, log-likelihood ratio test for the joint hypothesis of a unit root and deterministic linear trend is used. The summary of the results of log-likelihood test is reported in Table 5.5.

	<b>Bubble Period</b>			<b>Meltdown Period</b>			<b>Recovery Period</b>			
		Log-likelihood with joint hypothesis of a unit root and		Log-likelihood with joint hypothesis of a unit root and			Log-likelihood with joint hypothesis of a unit root and			
Variable	deterministic linear trend with a	deterministic trend with no linear	Statistics Test	deterministic trend with linear	deterministic linear trend with no	Statistics Test	deterministic linear trend ದ with	deterministic trend with no linear	Statistics Test	
<b>LDSEGEN</b>	43.740	42.634	2.212	38.850	38.430	0.840	173.745	170.153	7.184*	
<b>LIPI</b>	81.346	74.234	14.224*	50.435	46.584	$7.702*$	212.278	210.694	3.168	
<b>LINT</b>	275.703	273.366	$4.674*$	174.294	174.140	0.308	591.291	591.149	0.284	
<b>LCPI</b>	171.564	168.697	5.734*	131.651	127.561	8.180*	439.505	431.737	15.536*	
<b>LEXR</b>	234.429	233.256	2.346	133.640	129.040	$9.200*$	389.000	388.069	1.862	
LM2	155.094	153.747	2.694	106.058	104.002	$4.112*$	413.069	412.707	0.724	
<b>LGDPRICE</b>	161.281	157.909	$6.744*$	94.579	94.265	0.628	182.423	177.915	$9.016*$	

**Table 5.5 Results of LR Test for Trend Specification in Different Periods**

Notes: This distribution follows Chi-square distribution and the critical value for one degree of freedom is 3.841 at 5% significance level.

The test follows Chi-squared distribution and the critical value for one degree of freedom (as there is one restriction) is 3.841 at 5% level of significance. The results show that for some of the variables in different periods the null hypothesis of "no deterministic trend"

are rejected at 5% significance level, indicating that those variables have deterministic trend.

#### **5.5.1 Cointegration Results for the Bubble Period**

The results of the unit root tests indicate that in the bubble period the variables are either *I(0)* or *I(1)*. So, the ARDL model is applied to examine the long- and short-run cointegration relationships between the stock market index and macroeconomic indices. For this, we need to select the optimal lag lengths for both the dependent variable (LDSEGEN) and the regressors (LIPI, LINT, LCPI, LEXR, LM2 and LGDPRICE). From Table 5.3, we have found that at level the dependent variable LDSEGEN has 4 lags, and among the regressors, LINT has the highest 5 lags. So, we have set maximum lags for the dependent variable and the regressors at 4 and 5 respectively and then the automatic lag selection option is applied to allow the software to select the optimal lag length for each variable within the set limits.

Later, we need to select the trend specification for the model. Table 5.5 shows that during the bubble period LIPI, LINT, LCPI and LGDPRICE have significant trend. So, in ARDL test we have included trend in the cointegration equation. The results of ARDL specification along with the Pesaran Bounds  $Test<sup>16</sup>$  are summarized in Table 5.6. The Bounds test results indicate that null hypothesis of "no long-run relationship exists" is rejected and the alternative hypothesis "there exists long-run relationship" is accepted at 5% significance level, meaning that there exists a long-run relationship between stock market index (dependent variable) and six macroeconomic indices (independent variables) in the bubble period.

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<sup>&</sup>lt;sup>16</sup> See Appendix L

The Bounds test results have showed that  $R^2$  is 0.5268, which indicates that about 52.68 percent of the variations in stock prices can be explained by the changes in macroeconomic indices along with the trend. The remaining 47.33 percent is explained by other factors, which have not been considered in this research. The F value is significant at 5% level, meaning that the regression coefficients are significant. The Durbin Watson statistic confirms the presence of non-autocorrelated residuals.

**Table 5.6 ARDL Specification and Bounds Test Results for the Bubble Period**

<b>Dependent Variable: D(LDSEEGEN)</b>							
ARDL Model Specification (1, 4, 0, 2, 5, 0, 0)							
<b>F</b> Statistics	3.963162						
<b>Critical Value Bounds</b>							
Significance	$I_0$ Bound	$I_1$ Bound					
10%	2.49	3.38					
5%	2.81	3.76					
2.5%	3.11	4.13					
$1\%$	3.5	4.63					
R-squared	0.526781						
Adjusted R-squared	0.283777						
F-statistic	2.370647						
Prob (F-statistic)	0.013704						
Durbin-Watson stat	2.131741						

As there exists a cointegration relationship between the stock market and the macroeconomic variables, so we have examined the cointegrating form and long-run relationship (see Appendix L 1.3). The summary of the results is shown in Table 5.7. The results show that LIPI, LCPI, LEXR and LM2 are positively related with stock market index and LINT and LGDPRICE are negatively related with the stock market index. However, only LEXR is significant at 5% significance level and LIPI and LGDPRICE are significant at 10% significant level. Alongside, the pairwise graphs of each variable with the stock market index are shown in Figure 5.2 to Figure 5.7 show that there is a long-run co-movement of each macroeconomic variable with the stock market index.





Cointeq = LDSEGEN - (4.7009\*LIPI - 9.0076\*LINT + 4.4548\*LCPI + 69.5462 \*LEXR + 2.2446\*LM2 - 7.4229\*LGDPRICE - 0.1122\*@TREND)



Notes:  $*$  and  $**$  denote the significance of the coefficient at 5% and 10% level respectively.









Figure 5.4 Graphs of Market Index and Consumer Price Index for Bubble Period

During the bubble period, the long-run equation shows that the exchange rate is significantly positively related with the stock market index at 5 percent significance level. Also, the coefficient of exchange rate is significantly large compared to the coefficients of other macroeconomic variables indicating the dominance of exchange rate on stock prices. Moreover, the positive relation between stock market index and exchange rate specifies that the depreciation of Bangladeshi currency (BDT) with respect the US dollar may have attracted more foreign investment in the stock market, which has created higher demand for stock and thus the stock prices have increased.

Further investigations have revealed that during the bubble period, Bangladeshi currency (BDT) has depreciated by 8.93 percent and foreign investment in Bangladesh stock market has increased significantly (see Table 5.8). Also, the interest rate has decreased during the period, which has created a positive impact on stock prices. So, we can conclude that the exchange rate has played a key role in the bubble creation and the falling interest rate has further intensified it. This is an important finding of this research.

<b>Period</b>	<b>Purchase of Shares</b> in Million BDT	<b>Sale of Shares</b> in Million BDT	<b>Net Investment</b> in Million BDT
April $92 -$ June $92$	50.80		50.80
July $92 -$ June $93$	387.50	81.20	306.30
July $93 -$ June $94$	3101.80	965.10	2136.70
July $94 -$ June $95$	2982.70	133.42	2849.28
July $95 -$ June $96$	716.80	1877.10	$-1160.30$

**Table 5.8 Foreign Investment in Bangladesh Stock Market (July 92 – June 96)**

Source: Bangladesh Securities and Exchange Commission (BSEC) Annual Report 2005 - 2006

The existence of the cointegration relationship indicates that there exists a long-run equilibrium relationship between the stock market index and the macroeconomic indices. However, there could be a short-run disequilibrium which may be adjusted by the error correction mechanism to bring the system back to the long-run equilibrium, but the cointegration does not unfold this short-run adjustment process. To understand the shortrun relationships, we need to examine the error-correction process of the model. In the error correction model, the size of the coefficient of the error-correction term indicates the speed of adjustment of the disequilibrium in the dependent variable due to a shock to bring about long-run equilibrium. It is also indicative of the intensity of the arbitrage activities to bring the system back to equilibrium in the long-run.

#### **5.5.1.1 Results of Error Correction Model**

The short-run relationships between the macroeconomic variables and the stock market index are presented in Table 5.9. The error correction term (ECT) is -0.2606 and the corresponding *p*-value is 0.0 (see Table 5.7), which indicate that ECT is highly significant and has the correct sign. This ECT confirms a moderate speed of adjustment to equilibrium after a shock and indicates that approximately 26.06 percent of the disequilibria from the long-run equilibrium path is corrected per month. Finally, the *t*-statistics and the corresponding *p*-value of the coefficients of the 1<sup>st</sup> differences of the independent variables indicate whether these variables can significantly explain the stock market return in the short-run.

<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<i>t</i> -Statistics	<i>p</i> -value
D(LIPI)	0.288372	0.313918	0.918620	0.3642
$D(LIPI(-1))$	$-0.908279$	0.461527	$-1.967987$	0.0566
$D(LIPI(-2))$	$-0.403653$	0.398482	$-1.012978$	0.3176
$D(LIPI(-3))$	$-0.764019$	0.323497	$-2.361751$	0.0236
D(LCPI)	2.300926	1.460061	1.575911	0.1236
$D(LCPI(-1))$	-1.758072	1.506494	$-1.166996$	0.2507
D(LEXR)	4.947807	4.593005	1.077248	0.2883
$D(LEXR(-1))$	$-8.278757$	4.763788	-1.737852	0.0906
$D(LEXR(-2))$	-12.34567	4.258267	$-2.899224$	0.0063
$D(LEXR(-3))$	$-5.640530$	3.873974	$-1.456006$	0.1538
$D(LEXR(-4))$	-13.41595	3.771929	-3.556789	0.0010
$\mathsf{C}$	$-81.00451$	24.39265	$-3.320858$	0.0020
@TREND	$-0.018506$	0.017228	$-1.074205$	0.2897

**Table 5.9 Estimated Short-run Coefficients Using ARDL Approach in Bubble Period**

Notes: \* denote that coefficient is significant at 5%.

From Table 5.9, we have found that among the independent variables industrial production has 4 lags, interest rate has zero lag, inflation has 2 lags, exchange rate has 5 lags, and both money supply and gold price have zero lag. If an independent variable has zero lag, it indicates that the variable does not have relation with the dependent variable in the shortrun. When a variable has one lag, then the significance of the variable in explaining the stock market return in short-run is determined by *t-*statistic and corresponding *p-*value. Whereas, if a variable has multiple lags, we have used the Wald Statistics to examine whether the coefficients of the lagged terms of that variable can jointly explain the stock market return.

The test statistics follow  $\chi^2$  distribution, so we have used Chi-squared critical value. Table 5.9 shows that LIPI, LCPI and LEXR have multiple lags, so the Wald Test has been used to check the significance of the variables in explaining stock market return. The summary of the Wald Test results (see Appendix L 1.4) is shown in Table 5.10. The results show that only exchange rate can explain the stock market return in the short-run. So, the results indicate that only exchange rate has both significant long- and shot-run relationships with stock market return.

Independent <b>Variables</b>	<b>Null Hypothesis</b>	$\gamma^2$ Statistics	p-value
LIPI	$C(1) = C(2) = C(3) = C(4) = 0$	6.872732	0.1428
$\overline{L}$ $\overline{C}$ $\overline{P}$ $\overline{L}$	$C(5) = C(6) = 0$	2.883884	0.0895
LEXR.	$C(7) = C(8) = C(9) = C(10) = C(11) = 0$	18.02663	0.0029

**Table 5.10 Significance of Short-run Coefficients in Bubble Period**

## **5.5.1.2 Viability and Stability Check of the Model**

To check the viability of the model, we have used Breusch-Godfrey Serial Correlation LM test, Breusch-Pagan-Godfrey test and Jarque-Bera statistic to examine the serial correlation, homoscedasticity and normality of the residuals respectively. The results<sup>17</sup> indicate that the residuals are not serially correlated and homoscedastic, but the distribution of the residuals is not normal. However, practically it is hard to find a model with completely white noise residuals. The non-normal distribution of the residuals does not significantly distort the viability of the model as the residuals are homoscedastic and not autocorrelated. So, the model is a good fit model and results are significant.

We have also applied Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) test to check the stability of the parameters. The results of CUSUM and CUSUMSQ tests (Figure 5.8 and 5.9) indicate that the coefficients are almost stable over the period except there is a slight instability in conditional variance of the residuals at the 3<sup>rd</sup> quarter of 1996.

 $\ddot{\phantom{a}}$ 

<sup>&</sup>lt;sup>17</sup> See Appendix M



#### **5.5.2 Cointegration Results for the Meltdown Period**

In section 5.4, we have already found that the research variables during the meltdown period are either *I(0)* or *I(1)*. So, the ARDL model is applied to examine the long- and short-run cointegration relationships between the stock market index and macroeconomic indices. First, we have selected the lag length for both the dependent variable (stock market index, LDSEGEN) and the regressors (macroeconomic indices: LIPI, LINT, LCPI, LEXR, LM2 and LGDPRICE). From Table 5.3, we have found that in the meltdown period the dependent variable LDSEGEN has maximum 3 lags, and among the regressors LEXR has the highest 3 lags at level. So, we have set maximum lags for the dependent variable and the regressors at 3. Then the automatic lag selection is applied to allow the software to select the optimal lags for each variable within the set limits.

Table 5.5 also shows that in the meltdown period, LIPI, LCPI, LEXR and LM2 have significant deterministic trend. So, in the ARDL test, we have included trend in the cointegration equation. The results of ARDL specification along with the Pesaran Bounds Test (see Appendix L 2.2) are summarized in Table 5.11. The Bounds test results indicate that null hypothesis of "no long-run relationship exists" cannot be rejected, meaning that there exists no long-run relationship between the stock market index and the six macroeconomic indices in the meltdown period.

<b>Dependent Variable: DLDSEEGEN</b>				
ARDL Model Specification $(2, 0, 0, 0, 0, 0, 0)$				
<b>F</b> Statistics	1.867293			
<b>Critical Value Bounds</b>				
Significance	$I_0$ Bound	$I_1$ Bound		
10%	2.49	3.38		
5%	2.81	3.76		
2.5%	3.11	4.13		
1%	3.5	4.63		
R-squared	0.361423			
Adjusted R-squared	0.156166			
F-statistic	1.760830			
Prob (F-statistic)	0.121482			
Durbin-Watson stat	2.355889			

**Table 5.11 ARDL Specification and Bounds Test Results for the Meltdown Period**

The  $\mathbb{R}^2$  value indicates that about 36.14 percent of the variations in stock prices can be explained by the variations of the macroeconomic variables (LIPI, LINT, LCPI, LEXR, LM2 and LGDPRICE) along with trend. The remaining 63.86 percent is explained by other factors, which have not been considered. The *F-*statistic is insignificant at 5% level, meaning that the regression coefficients are not significant. However, the Durbin Watson statistic indicates the presence of non-autocorrelated residuals.

Alongside, the pairwise graphs of macroeconomic variables with the stock market index (Figure 5.10 to Figure 5.15) also indicate that during the meltdown period stock market index and macroeconomic indices are not moving together.





The cointegrating form and long-run coefficients are reported in Table 5.12.





Notes: \* and \*\* denote the significance of the coefficient at 5% and \*\*10% level respectively.

From Table 5.12, it is evident that the coefficients of interest rate and exchange rate are higher compared to the other macroeconomic indices both in short- and long-term equations. Both the variables have negative impacts on stock prices. However, only exchange rate is significant at 5% significance level in the short-run and at 10% significance level in the long-run. During this period the interest rate and exchange rate have increased significantly (see Figure 5.11 and 5.13). We have also checked the foreign investments in Bangladesh stock market from 1996 to 1999 (see Table 5.13), which indicate withdrawals of significant foreign investments in 1995-1996 and 1996-1997.

Thus, the depreciation of domestic currency seems to be unsuccessful in attracting foreign investment, rather a significant foreign investment has been withdrawn in this period. This has contributed a negative impact on stock market. Conversely, depreciation of Bangladeshi currency has increased the cost of raw-materials and capital goods for firms, which has also created a negative impact on stock prices. So, the withdrawal of foreign investment and the increase in production cost have played a key role in the stock market fall from 1996 to 1999. At the same time, increase in interest rate has also worsen the situation a bit more.

<b>Period</b>	<b>Purchase of Shares</b> in Million BDT	<b>Sale of Shares</b> in Million BDT	Net Investment in Million BDT
July $95 -$ June $96$	716.8	1877.1	$-1,160.30$
July $96 -$ June $97$	518.00	6,186.80	$-5,668.80$
July $97 -$ June $98$	316.00	517.50	$-201.50$
July $99 -$ June $99$	$-45.60$	410.70	$-315.10$

**Table 5.13 Foreign Investment in Bangladesh Stock Market (July 95 – June 99)**

Source: Bangladesh Securities and Exchange Commission (BSEC) Annual Report 2005 - 2006

#### **5.5.2.1 Viability and Stability Check of the Model**

For a good fit model, the residual should be homoscedastic, not serially correlated and normally distributed. So, we have used Breusch-Godfrey Serial Correlation LM test,
Breusch-Pagan-Godfrey test and Jarque-Bera statistic to check the serial correlation, homoscedasticity and normality of the residuals respectively. The results (see Appendix M 2) indicate that the residuals are not serially correlated and homoscedastic, but the distribution of the residuals is not normal. However, practically it is hard to find a model with completely white noise residuals. So, the non-normal distribution of the residuals does not significantly distort the viability of the model as the residuals are homoscedastic and not autocorrelated.

Furthermore, we have applied Cumulative Sum (CUSUM) test to check coefficient stability and Cumulative Sum of Squares (CUSUMSQ) test to check variance stability developed by Brown, Durbin and Evans (1975). This is a recursive testing procedure that is meant to study the stability of regression relationships over time. The results of both CUSUM and CUSUMSQ tests (Figure 5.16 and 5.17) indicate that the slope parameter (coefficients) and the conditional variance are unstable. So, we conclude that during the post-bubble period the parameters are unstable.



### **5.5.3 Cointegration Results for the Recovery Period**

The results of the unit root tests for the recovery period (see Section 5.4) reveal that the research variables are either *I(0)* or *I(1)*. So, the ARDL model is applied to examine the long- and short-run relationships between the stock market index and selected macroeconomic indices. From Table 5.3, we have also found that at level the dependent variable LDSEGEN has 10 lags, and among the regressors LM2 has the highest 13 lags at level. However, EVIEWS software allows maximum 12 lags for the regressors. So, we have set maximum lags for the dependent variable at 10 and for the regressors at 12. Then, automatic lag selection is applied to allow the software to select the optimal lag for each variable within the set limits.

Later, we have selected the trend specification for the model. Table 5.5 shows that in the recovery period LDSEGEN, LCPI and LGDPRICE have significant trend. So, in ARDL test we have included trend in the cointegration equation. The results of ARDL specification along with the Pesaran Bounds Test (see Appendix L 3) are summarized in Table 5.14. The Bounds test results indicate that null hypothesis of "no long-run relationship exists" is rejected and the alternative hypothesis is accepted at 5% significance level, meaning that there exists a long-run relationship between stock market index (dependent variable) and six macroeconomic indices (independent variables).

<b>Dependent Variable: D(LDSEEGEN)</b>					
ARDL Model Specification (7, 1, 0, 3, 6, 10, 0)					
<b>F</b> Statistics	4.879556				
<b>Critical Value Bounds</b>					
Significance	$I_0$ Bound	$I_1$ Bound			
10%	2.49	3.38			
5%	2.81	3.76			
2.5%	3.11	4.13			
1%	3.5	4.63			
R-squared	0.557041				
Adjusted R-squared	0.379858				
F-statistic	3.143866				
Prob (F-statistic)	0.000011				
Durbin-Watson stat	1.985193				

**Table 5.14 ARDL Specification and Bounds Test Results for the Recovery period**

The  $\mathbb{R}^2$  value indicates that about 55.70 percent of the variations in stock prices can be explained by the changes in macroeconomic indices along with the trend and about 44.30 percent is explained by other factors, which have not been considered in this research. The *F-*statistic is significant at 5% level indicating that the coefficients of the regression are significant. The Durbin Watson statistic indicates that the residuals are not serially correlated. We have also examined the cointegrating form and long-run relationship (see Appendix L 3.3) and the summary of the result is shown in Table 5.15.

<b>Independent</b> <b>Variables</b>	<b>Coefficient</b>	<b>Std. Error</b>	t-Statistics	<b>Probability</b>
		<b>Cointegrating Form</b>		
$D(LDSEGEN(-1))$	$-0.0131$	0.0859	$-0.1529$	0.8788
$D(LDSEGEN(-2))$	$-0.1577$	0.0835	$-1.8886$	0.0624
$D(LDSEGEN(-3))$	0.0989	0.0848	1.1672	0.2464
$D(LDSEGEN(-4))$	0.0877	0.0814	1.0773	0.2844
$D(LDSEGEN(-5))$	0.2076	0.0831	2.4990	0.0144
$D(LDSEGEN(-6))$	0.3710	0.0886	4.1869	0.0001
D(LIPI)	-0.0228	0.0896	$-0.2546$	0.7996
D(LINT)	$-5.9377$	2.7771	$-2.1381$	0.0354
D(LCPI)	0.3820	0.7245	0.5273	0.5993
$D(LCPI(-1))$	$-1.8334$	0.7799	$-2.3510$	0.0210
$D(LCPI(-2))$	$-1.8553$	0.7742	$-2.3964$	0.0187
D(LEXR)	0.0895	0.4613	0.1941	0.8466
$D(LEXR(-1))$	$-0.5424$	0.4562	$-1.1891$	0.2377
$D(LEXR(-2))$	$-0.8031$	0.4402	$-1.8242$	0.0716
$D(LEXR(-3))$	$-0.1354$	0.4720	$-0.2869$	0.7749
$D(LEXR(-4))$	$-0.8801$	0.4555	$-1.9322$	0.0567
$D(LEXR(-5))$	0.8681	0.4705	1.8449	0.0685
D(LM2)	2.2774	0.4716	4.8287	0.0000
$D(LM2(-1))$	$-2.5512$	0.5606	$-4.5507$	0.0000
$D(LM2(-2))$	$-1.7982$	0.5332	$-3.3726$	0.0011
$D(LM2(-3))$	$-1.7865$	0.5216	-3.4253	0.0009
$D(LM2(-4))$	$-2.8047$	0.5178	$-5.4165$	0.0000
$D(LM2(-5))$	$-1.7726$	0.5484	$-3.2324$	0.0017
$D(LM2(-6))$	$-3.3342$	0.5583	$-5.9723$	0.0000
$D(LM2(-7))$	$-1.5397$	0.5620	$-2.7395$	0.0075
$D(LM2(-8))$	$-1.7688$	0.5357	$-3.3016$	0.0014
$D(LM2(-9))$	$-0.9276$	0.5186	$-1.7886$	0.0772
D(LGDPRICE)	$-0.2183$	0.0856	$-2.5496$	0.0126
$\mathcal{C}$	$-14.2468$	2.0389	$-6.9876$	0.0000

**Table 5.15 Cointegrating Form and Long-Run Coefficients for the Recovery Period**

Independent <b>Variables</b>	<b>Coefficient</b>	<b>Std. Error</b>	<i>t</i> -Statistics	<b>Probability</b>
$CointEq(-1)$	$-0.1943$	0.0278	$-6.9946$	0.0000
	Cointeq = LDSEGEN - $(0.7988*LIPI - 31.4197*LINT + 8.5894*LCPI - 1.2037$			
	*LEXR + 11.1053*LM2 - 1.0625*LGDPRICE - 0.1591*@TREND)			
		<b>Long-run Coefficients</b>		
<b>LIPI</b>	0.7988	0.7704	1.0368	0.3028
<b>LINT</b>	$-31.4197*$	13.1868	$-2.3827$	0.0194
LCPI <sup>1</sup>	8.5894*	1.9635	4.3746	0.0000
<b>LEXR</b>	$-1.2037$	1.1497	$-1.0470$	0.2981
LM2	$11.1053*$	5.4306	2.0449	0.0440
<b>LGDPRICE</b>	$-1.0625*$	0.3630	$-2.9268$	0.0044
@TREND	$-0.1591*$	0.0737	$-2.1583$	0.0337

**Table 5.15 Cointegrating Form and Long-Run Coefficients for the Recovery Period (cont'd)**

Notes: \* and \*\* denote the significance of the coefficient 5% and 10% level respectively.

From Table 5.15, we have found that in the long-run LINT, LEXR and LGDPRICE are negatively related with stock market index and LIPI, LCPI and LM2 are positively related with the stock market index. However, LINT, LCPI, LM2 and LGDPRICE are statistically significant at 5% significance level. The long-run coefficients of LINT, LCPI and LM2 are higher compared to other macroeconomic variables indicating their dominance on stock market index. The pairwise graphs of each macroeconomic variable with the stock market index (Figure 5.18 to Figure 5.22) indicate the existence of long-run relationship between macroeconomic variables and stock market index.





We have examined the error-correction process of the model to examine the existence of short-run relationships as well as the error-correction mechanism.

## **5.5.3.1 Results of Error Correction Model**

The short-run relationships between the macroeconomic variables and the stock market index are presented in Table 5.16. The results of Error Correction Model (see Appendix L 3.4) show that the error correction coefficient is -0.1943 (*p*-value 0.0000), which indicates that the error-correction term (ECT) is highly significant and approximately 19.43 percent of disequilibria from the long-run equilibrium is adjusted per month. Finally, the *t*-statistics and the corresponding  $p$ -values of the coefficients of the  $1<sup>st</sup>$  differences of the independent variables indicate whether the growth of the variables can significantly explain the stock market return in the short-run.

<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	t-Statistics	$p$ -value
$D(LDSEGEN(-1))$	$-0.0045$	0.1015	$-0.0444$	0.9647
$D(LDSEGEN(-2))$	$-0.1546$	0.0988	$-1.5655$	0.1212
$D(LDSEGEN(-3))$	0.0943	0.0998	0.9448	0.3474
$D(LDSEGEN(-4))$	0.0758	0.0948	0.7996	0.4262
$D(LDSEGEN(-5))$	0.1580	0.0924	1.7103	0.0909
$D(LDSEGEN(-6))$	0.3077	0.0997	3.0864	0.0027
D(LIPI)	0.0028	0.1251	0.0221	0.9824
D(LCPI)	0.1925	0.8249	0.2333	0.8161
$D(LCPI(-1))$	$-1.2932$	0.8337	$-1.5513$	0.1246
$D(LCPI(-2))$	$-1.6517$	0.8690	$-1.9007$	0.0607
D(LEXR)	$-0.0973$	0.5394	$-0.1803$	0.8574
$D(LEXR(-1))$	$-0.4582$	0.5329	$-0.8599$	0.3923
$D(LEXR(-2))$	$-0.7168$	0.5127	$-1.3979$	0.1658
$D(LEXR(-3))$	$-0.6500$	0.5184	$-1.2538$	0.2134
$D(LEXR(-4))$	$-0.7229$	0.5096	$-1.4184$	0.1597
$D(LEXR(-5))$	0.7280	0.5172	1.4076	0.1629
D(LM2)	1.9831	0.5447	3.6408	0.0005
$D(LM2(-1))$	$-2.8830$	0.8969	$-3.2142$	0.0018
$D(LM2(-2))$	$-1.9531$	0.8004	$-2.4403$	0.0168
$D(LM2(-3))$	$-1.7701$	0.7927	$-2.2329$	0.0282
$D(LM2(-4))$	$-2.8941$	0.8505	$-3.4026$	0.0010
$D(LM2(-5))$	$-1.8878$	0.8215	$-2.2980$	0.0240
$D(LM2(-6))$	$-3.2281$	0.7405	$-4.3594$	0.0000
$D(LM2(-7))$	$-1.5306$	0.7350	$-2.0825$	0.0403
$D(LM2(-8))$	$-2.0200$	0.6866	$-2.9419$	0.0042
$D(LM2(-9))$	$-1.2408$	0.6026	$-2.0592$	0.0425
С	$-13.3009$	3.9010	$-3.4096$	0.0010
@TREND	$-0.0322$	0.0112	$-2.8723$	0.0051

**Table 5.16 Short-run Coefficients using ARDL Approach for the Recovery Period**

Notes: \* denote that coefficient is significant at 5%.

From Table 5.16, we have found that among the independent variables industrial production has 1 lag, interest rate has zero lag, inflation has 3 lags, exchange rate has 6 lags, money supply has 10 lags and gold price has zero lag. If an independent variable has zero lag, it indicates that the variable does not have short-run relationship with the dependent variable. When a variable has one lag, then the significance of the variable in explaining the stock market return in short-run is determined by *t-*statistic and corresponding *p-*value. However, when a variable has multiple lags, then the Wald Test is applied to examine whether the coefficients of lagged terms of that variable can jointly explain the stock market return. Table 5.16 shows that LIPI, LCPI and LEXR have multiple lags, so the Wald Test has been applied to check the significance of those variables in explaining stock market return. The summary of the Wald Test (see Appendix L 3.4) is shown in Table 5.17. The results show that only money supply can significantly explain the shock market return in the short-run. So, except money supply other macroeconomic variables show disequilibrium in the short-run.

Independent <b>Variables</b>	<b>Null Hypothesis</b>	$\gamma^2$ Statistics	p-value
I LCPI	$C(8) = C(9) = C(10) = 0$	7.556038	0.0561
<b>LEXR</b>	$C(15) = C(12) = C(12) = C(13) = C(14) = C(15) = C(16) = 0$	8.563479	0.1997
LM2	$C(17) = C(18) = C(19) = C(20) = C(21) = C(22) = C(23) =$ $C(24) = C(25) = C(26) = 0$	43.04306	0.0000

**Table 5.17 Significance of Short-run Coefficients in the Recovery Period**

# **5.5.3.2 Viability and Stability Check of the Model**

The tests of residuals for normality, autocorrelation, and heteroscedasticity are important to check the viability of the model and the significance of the results. So, we have applied Breusch-Godfrey Serial Correlation LM test, Breusch-Pagan-Godfrey test and Jarque-Bera statistic (see Appendix M 3) to check the residuals for serial correlation, homotheticity and normality respectively. The results indicate that the residuals are normally distributed, not serially correlated and homoscedastic. So, the model is a good fit model as the residuals have satisfied all the conditions.

Moreover, we have applied Cumulative Sum (CUSUM) test to check coefficient stability and Cumulative Sum of Squares (CUSUMSQ) test to check variance stability. The results of both tests (Figure 5.23 and 5.24) indicate that the coefficients are stable.



# **5.6 Conclusion**

In this chapter, we have investigated the long- and short-term relationships between the stock market and the macroeconomic indices in different periods, viz.; bubble, meltdown and recovery periods. Considering the stock market situations as well as the timing of the reform measures initiated for the development of Dhaka Stock Exchange (DSE), we have represented March 1992 to November 1996 as the bubble period, November 1996 to December 1999 as the meltdown period and January 2000 to December 2009 as the recovery period. The relationships in these periods are separately assessed to compare the influences of the priced factors in different conditions of the stock market.

We have found a long-run relationship between the stock market and the macroeconomic indices at 5 percent significance level in the bubble period and about 52.68 percent of the of the stock market return can be explained by the growth of the macroeconomic indices in this period. The results have shown that industrial production index, consumer price index, exchange rate and money supply are positively related with the stock market index. On the other hand, interest rate and gold price are negatively related with the stock market index. However, only exchange rate is found significant at 5 percent level and industrial production and gold price are significant at 10 percent level. The results of Error Correction Model (ECM) have shown that approximately 26.06 percent of the disequilibria is adjusted per month to bring about equilibrium in the long-run. The results of CUSUM and CUSUMSQ tests indicate that the slope parameter (coefficients) are almost stable over the entire period, only there is a negligible instability in conditional variance depicted by residuals at the 3rd quarter of 1996.

Additionally, during the bubble period, the long-run equation shows that the coefficient of exchange rate is very large compared to the coefficients of other independent variables, which indicates the dominance of exchange rate on stock prices. Further investigations have revealed that both exchange rate and foreign investments in Bangladesh stock market have increased significantly during this period. These results indicate that the depreciation of domestic currency has attracted significant foreign investment in the stock market, which has increased the demand of stocks and has increased the prices. So, the exchange rate has played a key role in bubble creation. Moreover, from the starting of 1992 to the end 1995, there has been a continuous fall in the interest rate, which has created a positive impact on equity prices. Therefore, we can conclude that exchange rate and interest rate are at least partly responsible for the bubble creation in the stock market in 1996.

The investigations of the meltdown period have revealed that there exists no long-run relationship between the stock market index and the macroeconomic indices. The results have also shown that about 36.14 percent of the stock market return can be explained by the variations of the macroeconomic indices. The remaining 63.86 percent is explained by other factors, which have not been considered in this research. Although the diagnostic tests of the residuals have revealed that the model is a good fit model, both the CUSUM and CUSUMSQ tests indicate that the coefficients and the conditional variance of the parameters are unstable in the period.

The long-run equation of the meltdown period has shown that the coefficients of interest rate and exchange rate are larger compared to other macroeconomic indices, also the signs of these two coefficients have indicated that both the variables have negative impact on stock prices. Furthermore, during the period interest rate and exchange have increased significantly. But depreciation of the domestic currency has not been successful in attracting foreign investment, rather a significant foreign investment has been withdrawn in this period implying a negative impact on stock market. Moreover, depreciation of domestic currency has increased the cost of raw-materials and capital goods for the firms, contributing a negative impact on equity prices. Increase in interest rate also has created a negative impact on stock market. Therefore, we can conclude that exchange rate and interest rate are at least partially responsible for the bubble crash of 1996.

In the recovery period, the test results have indicated that there exists a long-run relationship between the stock market index and the selected macroeconomic indices. Also, about 55.70 percent of the stock market return can be explained by the changes in macroeconomic indices. The results of error correction model have shown that approximately 19.43 percent of disequilibria is adjusted per month to bring about long-run equilibrium. The viability tests of the model have indicated that the model is a good fit model, thus the results are significant. The results of both CUSUM and CUSUMSQ tests have indicated that the coefficients are stable.

During this period, we have found that industrial production index, inflation and money supply are positively related with stock market index. On the other hand, interest rate, exchange rate and gold price are negatively related with the stock market index. However, impact of interest rate, inflation, and money supply are found statistically significant. Moreover, interest rate, money supply and inflation have larger impact on stock prices compared to other macroeconomic factors. At the same, changes in the money supply is also found significantly related to the stock market return in the short-run.

The findings on relationships between stock market index and macroeconomic indices reveal that the relationships are different in different periods. Furthermore, the sign as well as the magnitude of the impact of a macroeconomic variable on stock market index vary across periods. In addition, the explanatory power of the macroeconomic variables to explain the stock market return also vary across different market conditions indicating that sometimes the stock prices are partially driven by fad and fashions, which may be unrelated to the economic conditions.

The cross-sectional analyses of the relationships between the stock market index and the macroeconomic variables in Bangladesh across different periods have revealed that the relationship is more consistent with the financial theories in the recovery period and least consistent with the financial theories in the meltdown period. During the bubble period, there exists a long-run relationship and a significant percentage of the market return can be explained by the macroeconomic variables. Alongside, the important outcome of the study is that exchange rate and interest rate are found at least partially responsible for the bubble creation as well for bubble crash of 1996.

# **Chapter 6**

# **Relationship between Stock Market and Macroeconomic Volatilities**

# **6.1 Introduction**

Traditional research in financial economics has concentrated on relationship between stock market and macroeconomic variables. However, considering the number of crashes in stock markets and the size of their impact on households, banks and finally on overall economy have increased the interest of practitioners, regulators and researchers towards the relationship between stock market and macroeconomic volatilities. Theoretically, stock prices are the discounted present value of expected future cash flows. Besides, future macroeconomic condition obviously has impact on the future cash flows of a firm. Hence the volatility of stock market return changes when there is uncertainty about the future health of the economy (Chowdhury et al., 2006). In other words, stock markets may be volatile simply because economic activities fluctuate (Zukarnain and Sofian, 2012).

The dividend discount model (DDM), capital asset pricing model (CAPM) and arbitrage pricing theory (APT) provide important theoretical frameworks which show the conduits through which macroeconomic variables are factored into stock prices. These models predict that any shock to macroeconomic variables is a major source of systematic risk and there is no way that even a well-diversified portfolio like market portfolio constructed from stock market index can shift it to anywhere else, hence it is obvious that shock to macroeconomy must influence the stock market return (Chowdhury et al., 2006).

Since macroeconomic variables have been considered as the powerful tool to forecast the volatility of stock market return all over the globe, knowledge on the nexus between stock market volatility and macroeconomic volatility is crucial to the investors as well as to the policy makers. Additionally, the risk return behavior analysis of stock market is more important in developing countries, like Bangladesh, because these markets are very volatile. The higher volatility of these stock markets compels the investors to demand higher risk premium, which creates higher cost of capital and slows down the economic development (Mala and Reddy, 2007).

Alongside, Bangladesh stock market has experienced two major irrational fluctuations within a decade and a half, one in 1996 and other in 2010. Siddikee and Begum (2016) have mentioned that the stock market volatility in Bangladesh is mostly influenced by trade syndication or the decisions of other regulatory bodies like Bangladesh Bank. In this backdrop, it is very important to study the relationship between stock market volatility and macroeconomic volatility in Bangladesh to examine whether the expected changes in the macroeconomic volatility over time, measured by the conditional variances, can be used to explain the time-varying conditional volatility of the stock market return or some other factors are creating the market volatility.

There are five sections in this chapter. In section 6.2, we have described the methodologies to be used in the analysis. The findings of the empirical investigations have been portrayed in section 6.3. Also, we have outlined the diagnostic and stability tests of the residuals of the model to check the significance of the results. Finally, in section 6.4, we have summarized the findings in the conclusion.

# **6.2 Methodology**

To forecast the stock market return and its relation to the growth of macroeconomic factors need modern econometric techniques and models. This issue has been addressed by the recent advancement in the econometric literatures with the introduction of Autoregressive Conditional Heteroskedasticity (ARCH) family models which are capable of forecasting volatility of stock market returns. The ARCH family models can be used for various statistical problems with time series data and these models are particularly valuable for financial time series where returns are unpredictable and have a substantial number of extreme values and both the extremes and calm periods are clustered in time.

The ARCH model defines the current conditional variance as a function of the past squared error terms (Engle, 1982), which is consistent with volatility clustering. Later, Bollerslev (1986) has generalized the ARCH (GARCH) model in such a way that the current conditional variance is a function of the past conditional variances and the preceding squared error terms. The GARCH(1,1) specification is the workhorse of financial applications and it is remarkable that this single model can be used to explain the volatility dynamics of almost every financial return series (Engle, 2004).

However, the GARCH model has some weaknesses, the main one of which is that it does not capture asymmetry, which normally characterizes stock markets (Chinzara, 2010). With this implication, there are modifications to the GARCH model. The exponential GARCH (EGARCH) proposed by Nelson (1991) is the first asymmetric GARCH model and followed by the threshold GARCH (TARCH) model proposed by Zakoian (1994). It is also known as the GJR (Glosten, Jagannathan, and Runkle) model, which has been proposed by Glosten et al. (1993).

In this section, the evolution of different GARCH models has been discussed. We have also defined the research variables which have been used for the investigations. The econometric models for the estimation of conditional variances of the research variables and to examine the relationship between the conditional variances of stock market return and that of macroeconomic variables have been detailed in this section.

#### **6.2.1 Sample Data**

Monthly data of DSE General Index, industrial production index, interest rate, inflation, exchange rate, money supply and gold price for the period from January 1991 to December 2015 have been considered in this study. The data of the DSE General Index has been collected from the Dhaka Stock Exchange Library. The data of six macroeconomic variables are obtained from Monthly Statistical Bulletin of Bangladesh Bureau of Statistics, Economic Trends published by Statistical Department of Bangladesh Bank and various editions of Economic Survey of Bangladesh. We have collected monthly data for longer period to capture long-term movements and to avoid the effects of settlement and clearing delays which are known to significantly affect returns over shorter sampling intervals (Faff el al., 2005; Liow et al., 2006).

Then, data on stock market index are converted into continuously compounded returns by subtracting the logarithm of the previous month's index from the logarithm of the current month's index. Consistent with the relevant literature (Beltratti and Morana, 2006; Diebold and Yilmaz, 2007), the same logarithmic transformation is applied to the selected macroeconomic variables to capture the growth of the macroeconomic variables. In the empirical analysis, these transformed data have been used. The conditional volatility of stock market return and that of the growth of the macroeconomic variables are estimated using GARCH family models. Later, these conditional variances are used to fit in the cointegration approach to examine the long- and short-run relationships between the stock market and macroeconomic volatilities. The descriptions of our research variables are given in Table 6.1.

Symbol	Variable	Measurement
<b>DLDSEGEN</b>	<b>Monthly Stock Market</b> Returns	First difference of natural logarithm of normalized month end Dhaka Stock Exchange General Index (DSEGEN).
<b>DLIPI</b>	Monthly Growth of <b>Industrial Production Index</b>	First difference of natural logarithm of normalized monthly industrial production index of medium to large scale manufacturing industries.
<b>DLINT</b>	Monthly Growth of Interest Rate	First difference of natural logarithm of 1 plus month end deposit interest rate in percent.
<b>DLCPI</b>	Monthly Growth of <b>Consumer Price Index</b>	First difference of natural logarithm of normalized month end consumer price index.
<b>DLEXR</b>	Monthly Growth of <b>Exchange Rate</b>	First difference of natural logarithm of normalized month end price of US dollar in Bangladeshi taka (BDT).
DLM <sub>2</sub>	Monthly Growth of Money Supply	First difference of natural logarithm of normalized month end broad money supply (M2).
<b>DLGDPRICE</b>	Monthly Growth of Gold Price	First difference of natural logarithm of normalized month end gold price in Bangladesh.
<b>Conditional Variance Data</b>		
<b>VDLDSEGEN</b>	Variance of Stock Market Return	Conditional Variance of Monthly Stock Market Return.
<b>VDLIPI</b>	Variance of growth of <b>Industrial Production Index</b>	Conditional Variance of Growth of Industrial Production Index.
<b>VDLINT</b>	Variance of growth of <b>Interest Rate</b>	Conditional Variance of Growth of Interest Rate.
<b>VDLCPI</b>	Variance of growth of <b>Consumer Price Index</b>	Conditional Variance of Growth of Consumer Price Index.
<b>VDLEXR</b>	Variance of growth of <b>Exchange Rate</b>	Conditional Variance of Growth of Exchange Rate.
DLM <sub>2</sub>	Variance of growth of Money Supply	Conditional Variance of Growth of Money Supply.
<b>VDLGDPRICE</b>	Variance of growth of Gold Price	Conditional Variance of Growth of Gold Price.

**Table 6.1. Definition of Research Variables**

## **6.2.2 Pre-tests of Variables for Econometric Models**

Advancements in econometrics have exposed that most of the economic and financial time series are nonstationary and to scrutinize such series with ordinary least squares (OLS) leads to incorrect conclusion. So, it is important to check for stationarity of variables before moving further towards model estimation. There are many tests to check the stationarity of the variables, but we have used Augmented Dickey-Fuller Test (ADF) and Philips and Perron (PP) Test for this purpose. The methodologies of these tests have been described in section 4.3. In addition to the stationarity of the variables, presence of autocorrelation and heteroscedasticity in the residuals of the ordinary least squares estimation are also required pre-conditions for GARCH model. For this purpose, the Breusch-Godfrey Serial Correlation LM test and Autoregressive Conditional Heteroscedasticity (ARCH) test have been used to examine the presence of autocorrelation and heteroskedasticity respectively in the residuals of the ordinary least squares estimation.

#### **6.2.3 Autoregressive Conditional Heteroskedasticity (ARCH) Model**

Engle (1982) has recommended the Autoregressive Conditional Heteroskedasticity (ARCH) Model as a choice to handle the typical time series. The model allows the conditional variance to vary with time and implies that variance at present time relies on the preceding squared error terms. The basic  $ARCH(q)$  model has two equations, the mean equation and the conditional variance equation. Both equations must be estimated simultaneously as the variance is a function of the mean. The presence of ARCH means the normal distribution is not always the best approximation to be used. The mean and variance equations of an ARCH(*q*) process can be given as follows:

Mean equation: 
$$
Y_t = \pi_0 + \sum_{i=1}^q \pi_i Y_{t-i} + \varepsilon_t
$$
 where  $\varepsilon_t \sim \text{iid}(0, \sigma_t^2)$  6.1

Variance equation: 
$$
\sigma_t^2 = \gamma_0 + \sum_{j=1}^q \gamma_j \varepsilon_{t-j}^2
$$
 6.2

where,  $Y_{t-i}$  is a set of regressors, and  $\pi_i$  and  $\gamma_i$  are coefficients and  $\varepsilon_t$  is independently distributed residual terms. One shortcoming of the ARCH model is that it resembles extra moving average pattern than autoregression.

### **6.2.4 Generalized ARCH (GARCH) Model**

A useful generalization of ARCH model is GARCH model introduced by Bollerslev (1986). The GARCH model has been considered as the most commonly employed class of time series model in the recent finance literature for studying volatility. The appeal of this model is its ability to capture both volatility clustering and unconditional return distribution with heavy tails. GARCH model considers conditional variance to depend on both autoregressive (AR) and moving average (MA) terms. In general, the GARCH(*p,q*) in the simplest form can be written as:

Mean equation: 
$$
Y_t = \lambda_0 + \sum_{i=1}^k \lambda_i Y_{t-i} + \varepsilon_t ;
$$
  $\varepsilon_t \sim N(0, \sigma_t^2)$  6.3

Variance equation: 
$$
\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2
$$
 6.4

Equation (6.3), the conditional mean equation, is an autoregressive process of order *k*, AR(*k*). Parameter  $\lambda_0$  is the constant, *k* is the lag length,  $\varepsilon_t$  is the heteroskedastic error terms with its conditional variance given in Equation (6.4). In the conditional variance equation *q* is the number of ARCH terms, and *p* is the number of GARCH terms.

### **6.2.5 Exponential GARCH (EGARCH) Model**

Nelson (1991) has developed non-linear GARCH model, which is known as Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model. The mean equation of EGARCH model is same as the mean equation of GARCH model. However, the variance equation of EGARCH model is expressed in logarithmic term. This model is superior to GARCH model because it ignores the non-negativity constraint and it doesn't impose any constraint on the parameters. The variance equation of EGARCH model can be written as:

Variance equation: 
$$
ln \sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{i=1}^q \gamma_j \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^p \beta_j ln \sigma_{t-j}^2
$$
 6.5

In the variance equation  $\alpha$ ,  $\gamma$  and  $\beta$  are the parameters. On the left side of equation natural logarithm of series is taken to compose exponential leverage effect. The model is symmetric, if  $\gamma_1 = \gamma_2 = \cdots = \gamma_q = 0$ , meaning that there is no leverage effect. However,  $\gamma$ <sup>*j*</sup>  $\leq$  *0* indicates more impact of negative news on next period's volatility than positive news, which indicates leverage effect, while  $\gamma$ <sup>*j*</sup>  $> 0$  represents the other way around.

### **6.2.6 Threshold GARCH (TGARCH) Model**

The threshold GARCH (TGARCH) model proposed by Zakoian (1994), which is also similar to GJR GARCH model studied by Glosten et al. (1993), is simply a re-specification of the GARCH (1,1) model with an additional term in the conditional variance equation to account for asymmetry. The mean equation of TGARCH model is same as  $GARCH(1,1)$ model. However, the variance equation can be written as follows:

$$
\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma D_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2
$$

where  $D_{t-1}$  is the indicator function having the following values:

$$
D_{t-1} = \begin{cases} 1, & \varepsilon_{t-1} < 0 \\ 0, & \varepsilon_{t-1} \ge 0 \end{cases}
$$

The *γ* is known as the asymmetry or leverage parameter. For good news ( $\varepsilon_{t-1} > 0$ ) and for bad news ( $\varepsilon_{t-1}$  < 0). So, the good or bad news have differential effect on conditional variance. While good news has an impact of  $\alpha_1$ , bad news has an impact of  $\alpha_1 + \gamma$ . Thus, if  $\gamma$  is significant and positive, then negative shocks have a larger effect on  $\sigma_t^2$  than the positive shocks, while the other way around if  $\gamma$  is significant and negative.

The first step of modeling volatility is to estimate the mean and variance equations simultaneously using the best fitted GARCH model. The selection of model is an important issue in the estimation process. In this study, we have used the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) as a goodness-of-fit tests to rank the different GARCH models as discussed earlier to choose the best fitted GARCH model for our purpose.

#### **6.2.7 Measuring the Volatility**

The second objective of this chapter is to investigate whether the changes in Bangladesh stock market volatility over time, as measured by the conditional variance of stock market return, can be explained by the time-varying conditional volatility of the growth of macroeconomic variables or the vice versa. For this purpose, the conditional variances of the research variables are estimated using best fitted GARCH model.

Several literatures (Akgiray, 1989; Baillie and DeGennaro, 1990; Bera and Higgins, 1993; Floros, 2008) have showed that a simple GARCH model is parsimonious and generally gives significant results. Therefore, the best fitted GARCH model has been used with or without autoregressive term of order 1 to estimate the conditional variances of the research variables based on the presence of significant asymmetric term and information criterion.

#### **6.2.8 Estimation of Cointegration Relationship**

We have also examined the cointegration relationship between conditional volatility of the stock market return and the conditional volatilities of the selected macroeconomic variables using cointegration test. If the conditional volatilities of all the research variables are  $I(1)$ , the Johansen and Juselius cointegration test has been applied. In addition, to check the robustness of the results, the Autoregressive Distributed Lags cointegration (ARDL) cointegration approach has been used. If there is a combination of  $I(1)$  and  $I(0)$ , only ARDL approach has been applied. The empirical methods for these cointegration tests have been described in chapter 4.

# **6.3 Findings of the Study**

In this section, empirical findings based on the econometric methods outlined in the earlier section have been reported. Firstly, we have reported the results of GARCH model, where the mean and the variance equations are estimated simultaneously. Then, we have selected the best model to estimate the conditional variance of each research variable. Finally, we have used the cointegration approach to examine the long- and short-term relationships between the stock market volatility and the volatilities of the macroeconomic variables.

#### **6.3.1 Results of Volatility Modeling with GARCH Model**

The first step of volatility modeling is to estimate the mean and variance equations simultaneously with stock market return as dependent variable and growth of the selected macroeconomic variables as independent variables. The 1<sup>st</sup> difference of each variable represents the growth of that variable. We have already found that the first differences of the research variables are stationary (see section 4.4.2), which is the first pre-condition for the volatility estimation.

The second pre-test of the estimation is to examine the residuals of the ordinary least squares (OLS) estimation for the presence of serial correlation and heteroskedasticity, because the GARCH model can only be applied if the residuals of the Ordinary Least Squares (OLS) show serial correlation and heteroskedasticity. To check the serial correlation and heteroscedasticity of the residuals, we have fitted the research variables into Ordinary Least Squares (OLS) with the stock market return as dependent variable and the growth of six macroeconomic variables as independent variables. Then the residuals are tested for autocorrelation and heteroskedasticity using Breusch-Godfrey Serial Correlation LM Test and Autoregressive Conditional Heteroscedasticity (ARCH) Test respectively. The results of these tests<sup>18</sup> show that the null hypotheses that the residuals are "not serially correlated" and have "no heteroskedasticity" are rejected at 5 percent

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<sup>&</sup>lt;sup>18</sup> See Appendix N

significance level, indicating that the residuals are serially correlated and heteroskedastic. The plot of residuals(see Figure 6.1) also confirms the volatility clustering of the residuals, meaning that the variance appears to be high during certain periods and low in other periods. These results have revealed that the nonlinear GARCH model to be applied for estimation of the mean and variance equations.





Now, we need to select the best fitted GARCH model for volatility modeling. For this purpose, we have used the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Loglikelihood test. Table 6.2 shows these values for different GARCH models, which have been considered for the estimation. As per the selection procedure, the best fitted model has been chosen based on the lowest values of AIC and SIC, and the highest Loglikelihood statistic. The values of Table 6.2 have indicated that EGARCH $(1,1,1)$  is the best model for our purpose. So, we have used EGARCH $(1,1,1)$ model to estimate the mean and variance equations.

**Model AIC Value SIC Value Loglikelihood Value** GARCH(1,1) -2.195368 -2.071607 338.2075 **EGARCH(1,1,1) -2.258027 -2.121891 348.5751**  $TGARCH(1,1,1)$  -2.194906 -2.058770 339.1385

**Table 6.2 Test Statistics for Selection of Best Fitted GARCH Model** 

Table 6.3 shows the summary of the results of EGARCH model<sup>19</sup>, the mean and variance equations are estimated with the stock market return as dependent variable and growth of the macroeconomic variables as independent variables.

<b>Mean Equation</b>				
<b>Variables</b>	<b>Coefficient</b>	<b>Std. Error</b>	z-Statistic	<b>Probability</b>
<b>DLIPI</b>	$-0.0369$	0.0603	$-0.6128$	0.5400
<b>DLINT</b>	$-0.2606$	1.1484	$-0.2269$	0.8205
<b>DLCPI</b>	1.1277	0.3442	3.2758	0.0011
<b>DLEXR</b>	$-0.7049$	0.3249	$-2.1696$	0.0300
DLM <sub>2</sub>	1.4038	0.2299	6.1049	0.0000
<b>DLGDPRICE</b>	0.1014	0.0596	1.7021	0.0887
Constant	$-0.0077$	0.0043	$-1.7931$	0.0730
		<b>Variance Equation</b>		
$\omega$ (Constant)	1.82E-05	0.0137	0.0013	0.9989
$\alpha$ (ARCH effect)	$-0.0665$	0.0131	$-5.0913$	0.0000
$\gamma$ (asymmetry effect)	0.1513	0.0171	8.8658	0.0000
$\beta$ (GARCH effect)	0.9889	0.0000	26729.38	0.0000
$\alpha + \beta$	0.9224			
<b>Diagnostic Test</b>				
Heteroskedasticity Test: ARCH LM Test				
<b>F</b> Statistics	0.202596 Probability of F Statistics			0.6530
Prob. Chi-squared				0.6751

**Table 6.3 Results of EGARCH(1,1,1) Model**

Several points can be noted from the results of  $EGARCH(1,1,1)$  model of Table 6.3. Firstly, the mean equation shows that the coefficients of growth of consumer price index (DLCPI) and money supply (DLM2) are positively related with the stock market return at 1 percent level of significance, while growth of exchange rate (DLEXR) is negatively related to the stock market return at 5 percent significance level. On the other hand, growth of gold price (DLGDPRICE) is positively related with the stock market return at 10 percent significance level. Whereas the coefficients of growth of industrial production (DLIPI) and interest rate (DLINT) are statistically insignificant in explaining the stock market

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<sup>19</sup> See Appendix O

return. So, the results have confirmed that most of the selected macroeconomic variables can significantly explain the stock market return.

Secondly, the conditional variance equation reveals the following facts:

- The ARCH term  $(\alpha)$ , and the GARCH term  $(\beta)$  are significant at 1 percent level, meaning that the conditional variance of the stock market return depends on both autoregressive (AR) and moving average (MA) terms;
- The estimated  $\beta$  is considerably higher than the  $\alpha$ , which reveals that the stock market volatility is more sensitive to its lagged values than to new surprises;
- The sum of  $\alpha$  and  $\beta$  is 0.9253 which indicates that a shock persists over many future periods;
- The coefficient  $\gamma \neq 0$  and is significant at 1 percent level, this result indicates the presence of asymmetric effect of good and bad news on the stock market volatility;
- The coefficient  $\gamma$  is positive, which discloses that the positive shock, created by good news, implies a higher next period conditional variance in the stock market return compared to the negative shock of same magnitude created by the bad news.

Finally, the ARCH-LM test results show that the null hypothesis of "no ARCH effect" can't be rejected at 5 percent significance percent level indicating that the mean and variance equations are well specified.

# **6.3.2 Estimation of Conditional Variances of Research Variables**

To estimate the conditional variance of each research variable, two sets of univariate models are considered. In the first set, we have applied three univariate GARCH models namely  $GARCH(1,1)$ ,  $EGARCH(1,1,1)$  and  $TGARCH(1,1,1)$ , with constant only in the mean equation. In the second set, the mean equation includes a constant and a autoregressive term of order 1, *AR(1)*, of the same variable. The summary of the results for the model selection<sup>20</sup> is shown in Table 6.4. The best model for estimation of the conditional volatility of growth of each research variable is chosen based on the Akaike Information Criterion (AIC) and the following conditions:

- If asymmetry coefficient (*γ*) is found significant for a variable, then the  $GARCH(1,1)$  model is not considered for that variable because  $GARCH(1,1)$  does not capture the asymmetry in the variable;
- If for any model  $(a + \beta) > 1$  for a research variable, then the series becomes explosive. As an explosive series cannot be considered in the estimation process, so the model for that variable is excluded from the choice;
- The presence of heteroskedasticity in the residuals means the model is not well specified. So, if the residuals for any model shows heteroskedasticity, then that model is excluded from the choice. ARCH Lagrange Multiplier Test is used to examine the presence of heteroskedasticity in the residuals.

Based on the above-mentioned conditions and the lowest AIC value, model to estimate conditional variance of each variable has been selected. Based on the results, the models chosen (see Table 6.4) for different variables are as follows - TGARCH(1,1,1) model for the stock market return;  $AR(1)-GARCH(1,1)$  for the growth of both production index and inflation rate;  $AR(1)-TGARCH(1,1,1)$  for changes in both interest rate and money supply;  $AR(1)-EGARCH(1,1,1)$  for growth of exchange rate; EGARCH(1,1,1) for growth of gold price. Then, EVIEWS software is used to estimate these conditional variances of the growth of different research variables.

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<sup>20</sup> See Appendix P



## **Table 6.4 Model Selection for Estimation of Conditional Variances of Growth of Research Variables**

Notes: \* and \*\* denote the significance of the coefficients at 1% and 5% level respectively.

#### **6.3.3 Descriptive Statistics of the Conditional Variances**

The descriptive statistics of the conditional variances of the monthly stock market return and the monthly growth of the macroeconomic variables are presented in Table 6.5.

<b>Description</b>	<b>VDLDSEGEN</b>	<b>VDLIPI</b>	<b>VDLINT</b>	<b>VDLCPI</b>	<b>VDLEXR</b>	VDLM2	<b>VDLGDPRICE</b>
<b>Observations</b>	298	298	298	298	298	298	298
Mean	0.008187	0.004863	1.17E-05	8.29E-05	0.000101	0.000181	0.001966
Median	0.005327	0.00486	5.50E-06	7.05E-05	7.11E-05	0.0002	0.001812
Maximum	0.126459	0.005727	0.0003	0.000182	0.000844	0.000349	0.010769
Minimum	0.003123	0.004701	$1.11E-06$	2.58E-05	6.88E-07	7.15E-05	0.000226
Std. Dev.	0.010412	8.50E-05	2.79E-05	4.00E-05	0.000113	$6.96E-0.5$	0.000889
<b>Skewness</b>	6.682812	6.189831	7.14885	0.627003	3.198088	$-0.19478$	5.051623
<b>Kurtosis</b>	63.90082	55.40078	61.80473	2.22551	17.99147	2.019498	42.66837
Jarque-Bera	48270.41	35997.13	45475.06	26.97	3298.55	13.82	20806.05
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000

**Table 6.5 Descriptive Statistics of Conditional Variances**

Statistics of Table 6.5 reveal that the conditional variance of stock market return has the highest mean value (0.81%), this may be due to the catastrophes in the stock market during the study period. On the other hand, except money supply, the conditional variances of the growth of the other research variables exhibit positive skewness indicating extreme positive values, while opposite is true for money supply. Also, the Kurtosis values indicate that the distributions of all the conditional variances of the growth of research variables are not normal. Moreover, the Jarque-Bera statistics of the conditional variances confirm that the null hypothesis of "distribution is normal" are rejected at 1% significance level for all research variables, meaning that the distributions of the conditional variances of the growth of research variables are not normal.

### **6.3.4 Unit Root Test Results**

ADF and PP unit root tests are used as per the procedure described in section 4.3 to check the stationarity of the conditional variances. For this purpose, the lag length of each variable to be used in unit root tests are determined using automatic lag selection criterion of VAR model. The summary of the results of optimal lag length selection<sup>21</sup> and unit root tests<sup>22</sup> are depicted in Table 6.6 and Table 6.7 respectively.

		Data at Level	Data at 1 <sup>st</sup> Difference	
<b>Variables</b>	<b>Trend and</b> Intercept	<b>Intercept</b>	<b>Trend and</b> Intercept	Intercept
<b>VDLDSEGEN</b>				
<b>VDLIPI</b>				
<b>VDLINT</b>				
<b>VDLCPI</b>				
<b>VDLEXR</b>				
VDLM2				
<b>VDLGDPRICE</b>				

**Table 6.6 Optimal Lag Lengths of Conditional Variances**





Notes: Critical values at 5% level for ADF and PP tests with trend and intercept is -3.424977and with intercept is -2.871029. \* denotes that significance of coefficient at 5%.

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 $21$  See Appendix Q

 $22$  See Appendix R

The results of ADF and PP tests reveal that conditional variances of both inflation (VDLCPI) and money supply (VDLM2) are *(1)*, while other conditional variances are *I(0)*.

### **6.3.5 Cointegration Test Results**

The results of the unit root tests indicate that the conditional variances of the research variables are either *I(0)* or *I(1)*. So, the ARDL cointegration approach has been applied to examine the long- and short-run relationships between the conditional variance of the stock market return and the conditional variances of the growth of macroeconomic indices. From Table 6.6, we have found that the dependent variable, conditional variance of the stock market return, has 1 lag, while among the regressors conditional variance of the growth of money supply has the highest 7 lags. So, in the ARDL approach, we have set maximum 1 lag for dependent variable and 7 lags for regressors and then we have allowed the EVIEWS software to choose the optimal lag length for each variable within the set limits.

Later, the log-likelihood ratio test for the joint hypothesis of unit root and deterministic linear trend is used to identify the trend specification of the variables. This distribution follows Chi-squared distribution and the critical value for one degree of freedom (as there is one restriction) is 3.841 at 5% significance level. The results of the log-likelihood ratio test are reported in Table 6.8, which show that none of the variables has trend. So, in ARDL test we include constant in the cointegration equation.

The results of ARDL specification along with the Pesaran Bounds  $Test^{23}$  are summarized in Table 6.9. The bounds test results indicate that the null hypothesis of "no long-run relationships exist" is rejected and the alternative hypothesis "there exists long-run relationship" is accepted at 1 percent significance level, meaning that there exists a long-

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<sup>23</sup> See Appendix S

run relationship between the conditional volatility of stock market return (dependent variable) and conditional volatilities of growth of six macroeconomic variables (independent variables).

Variables	Log-likelihood with joint hypothesis of a unit root	<b>Test Statistics</b>		
	with a deterministic trend with no deterministic trend			
LDSEGEN (lag)	1044.162(1)	1043.568(1)	1 188	
$LIPI$ (lag)	2748.232 (1)	2748.141(1)	0.182	
$LINT$ (lag)	2800.137 (6)	2799.56 (6)	1 154	
$LCPI$ (lag)	3057.174(1)	3056.523(1)	1.302	
$LEXR$ (lag)	2380.233 (3)	2379.811 (3)	0.844	
$LM2$ (lag)	3089.008 (7)	3087.156 (7)	3.704	
$LGDPRICE$ (lag)	1660.912(4)	1660.26(4)	1 304	

**Table 6.8 Log-likelihood Ratio Test Results for Trend Specification**

Notes: This distribution follows Chi-squared distribution and the critical value for one degree of freedom is 3.841 at 5% significance level.

<b>Dependent Variable: D(LDSEEGEN)</b>					
ARDL Model Specification (1, 0, 0, 0, 0, 0,0)					
<b>F</b> Statistics	7.224021				
	<b>Critical Value Bounds</b>				
Significance	$I_0$ Bound	$I_1$ Bound			
10%	2.12	3.23			
5%	2.45	3.61			
2.5%	2.75	3.99			
$1\%$	3.15	4.43			
R-squared	0.148919				
Adjusted R-squared	0.128305				
F-statistic	7.224021				
Prob (F-statistic)	0.000000				
Durbin-Watson stat	2.023549				

**Table 6.9 Results of ARDL Specification and Bounds Test**

The  $\mathbb{R}^2$  value indicates that only 14.89 percent of the conditional variance of the stock market return can be explained by the conditional variances of the growth of selected macroeconomic indices. The remaining 85.11 percent can be explained by the factors which have not been considered in the research. The F value is significant at 1% level, meaning that the regression coefficients are significant. The Durbin Watson statistic indicates that the residuals are uncorrelated. However, the results have indicated that a very small percentage of conditional variance of the stock market return can be explained by the macroeconomic conditional variances.

As there exists cointegration relationship, so we have examined the cointegrating form and long-run relationship (see Appendix S 3) and summary of the results is presented in Table 6.10. The results show that the conditional variances of growth of industrial production, consumer price index and exchange rate are positively related with conditional volatility of the stock market return and the conditional variances of interest rate, money supply and gold price are negatively related with the conditional volatility of stock market return. However, none of the coefficients of the independent variables is statistically significant, meaning that none of the macroeconomic volatilities can significantly explain the conditional volatility of the stock market return in the long-run.

<b>Independent</b> <b>Variables</b>	<b>Coefficient</b>	<b>Std. Error</b>	<i>t</i> -Statistics	<b>Probability</b>
		<b>Cointegrating Form</b>		
D(VDLIPI)	16.1356	14.1312	1.1418	0.2545
D(VDLINT)	$-2.4846$	24.0569	$-0.1033$	0.9178
D(VDLCPI)	$-15.0721$	54.0001	$-0.2791$	0.7804
D(VDLEXR)	$-0.5323$	5.3113	$-0.1002$	0.9202
D(VDLM2)	$-21.8343$	52.8713	$-0.4130$	0.6799
D(VDLGDPRICE)	0.0930	0.3072	0.3029	0.7622
C	$-0.0033$	0.0006	$-5.1986$	0.0000
$CointEq(-1)$	$-0.2911$	0.0409	$-7.1139$	0.0000
		Cointeq = VDLDSEGEN - $(3.2256*VDLIPI - 27.2636*VDLINT + 55.4220$		
*VDLCPI + 4.8936*VDLEXR - 4.0855*VDLM2 - 0.0856*VDLGDPRICE - 0.0114)				
		<b>Long Run Coefficients</b>		
<b>LIPI</b>	3.225608	18.540106	0.173980	0.8620
<b>LINT</b>	$-27.263562$	55.472937	$-0.491475$	0.6235
<b>LCPI</b>	55.421955	43.320414	1.279350	0.2018
<b>LEXR</b>	4.893638	14.317226	0.341801	0.7327
LM2	$-4.085459$	27.190930	$-0.150251$	0.8807
<b>LGDPRICE</b>	$-0.085621$	1.666623	$-0.051374$	0.9591

**Table 6.10 Cointegrating Form and Long-run Coefficients**

Similarly, the short-run relationships show that all the independent variables have zero lag, meaning that there exist no short-run relationships between the variance of stock market return and the variances of growth of macroeconomic variables. So, there is a short-run disequilibrium between stock market volatility and macroeconomic volatility. However, the results of Error Correction Model (ECM) show that the error correction coefficient is -0.2911 (*p*-value 0.0000), which specifies that the error-correction term (ECT) is highly significant. Moreover, the ECT has the correct sign which implies a moderate speed of adjustment to equilibrium after a shock. The ECT indicates that approximately 29.11 percent of the short-run disequilibria is adjusted per month to bring about long-run equilibrium.

#### **6.3.6 Viability and Stability Check of the Model**

Finally, we have checked the viability as well as the stability of the model. A model is viable if the residuals are homoscedastic, not serially correlated and normally distributed. So, the tests of residual for normality, autocorrelation, and heteroscedasticity are carried out to examine the significance of the results. The correlogram of the residuals (see Appendix R 4.1) is estimated up to 36 lags. The Ljung-Box Q statistics is used to investigate whether the residuals are serially correlated. The high *p-*value indicates that the residuals are not serially correlated. Therefore, we conclude that residuals are independent (stationary).

Furthermore, we have used Breusch-Godfrey Serial Correlation LM test, Breusch-Pagan-Godfrey test and Jarque-Bera statistic to examine residuals for the serial correlation, homoscedasticity and normality respectively to check the robustness of the results. The results of these tests (see Appendix S 4) have indicated that the residuals are not serially correlated, however, the residuals show heteroskedasticity and the distribution of the residuals is not normal. So, the results have indicated that the model is not a good fit model. So, the results of the cointegration test and the error correction model are not reliable.

In addition, we have applied Cumulative Sum (CUSUM) test to check the stability of the coefficients and Cumulative Sum Squares (CUSUMSQ) test to check the stability of the variances of the coefficients. The plot of CUSUM control chart (see Figure 5.1) has indicated that the slope parameters (coefficients) are unstable around 1996. Also, the CUSUMSQ chart (see Figure 5.2) shows that the variances of the residuals are unstable for most of the period. So, the results indicate that the coefficients are not stable over most of the period, meaning that the relationship is not stable over the period.



The above results have indicated that the cointegration model for total sample period (from January 1991 to December 2015) is not a good fit model and the coefficients are not stable over the period. In addition, long- and short-run coefficients of the macroeconomic volatilities are not found statistically significant to explain stock market volatility. So, the findings of the model are not reliable and significant. One of the reasons of this instability may be due to the catastrophes of 1996 and 2010. However, findings indicate that the catastrophe of 1996 is more prominent than that of 2010.

For the total sample period, we have found volatility clustering of the residuals and higher volatilities are seen around 1996 and 2010. These results have motivated us to apply the volatility estimation model over the period between the catastrophes of 1996 and 2010, which is named as the recovery period in this study.

#### **6.3.7 Volatility Modeling for the Recovery Period**

In chapter 5, we have considered the period from January 2000 to December 2009 as recovery period because between the catastrophes of 1996 and 2010, this period is considered as the most stable period of our stock market. Moreover, numerous reform measures have been implemented during this period to achieve a sustainable development of the stock market and also the automation and upgradation of the trading platform have been implemented since August 1998 to build up a state-of-the-art market surveillance system to increase the transparency of the transactions as well as to strengthen the surveillance system. These steps are expected to enhance the investors' confidence and to improve the efficiency of the stock market.

To modeling volatility of the recovery period, the first pre-test of the estimation process is to check the stationarity of the variables. The first difference of the research variables in the recovery period are stationary (see section 5.4). Furthermore, the second pre-test for volatility modeling is to check the residuals for autocorrelation and heteroscedasticity. For the purpose, the research variables are fitted the into Ordinary Least Squares (OLS) with the stock market return as dependent variable and the growth of macroeconomic variables as independent variables. Then the residuals of the OLS are checked for autocorrelation and heteroskedasticity using Breusch-Godfrey Serial Correlation LM and Autoregressive Conditional Heteroscedasticity (ARCH) Tests respectively. The results of Breusch-Godfrey Serial Correlation LM and Autoregressive Conditional Heteroscedasticity (ARCH) tests (see Appendix T) show that the residuals are not serially correlated and not heteroskedastic respectively at 5 percent significance level.

So, the results reveal that the GARCH model cannot be applied for estimation for this period, because the GARCH model can only be applied when the residuals are serially correlated and heteroskedastic. The plot of residuals (see figure 6.4) also depicts that there is no volatility clustering during the period.

Figure 6.4 Residuals of Ordinary Least Squares Estimation for the Recover Period



Moreover, the OLS results shows that among the independent variables only the growth of money supply is statistically significant (see Appendix T) and has the highest sensitivity among the determinants suggesting that in the recovery period the of growth of money supply has the highest impact on the stock market return. This result is consistent with the result of cointegration test of chapter 5, where we have found that the only the growth of money supply is significant in explaining the stock market return in the recovery period.

# **6.4 Conclusion**

The residuals of Ordinary Least Squares (OLS) estimation of research variables for the total sample period (from January 1991 to December 2015) with stock market return as dependent variable and the growth of macroeconomic variables as independent variables have showed serial correlation and heteroskedasticity, which has warranted the use of GARCH family models to estimate the relationship. Among the different GARCH models the EGARCH(1,1,1) model has been found as the best suited model for the estimation.

The mean equation of the EGARCH model has shown that both the growth of inflation and money supply are significantly positively related with the stock market return, while growth of exchange rate is significantly negative relatively with the stock market return. On the other hand, the growth of other macroeconomic variables - namely industrial production index, interest rate and gold price, are not significantly related with the stock market return at 5 percent significance level. These results indicate the importance of inflation, exchange rate and money supply for Bangladesh stock market.

The variance equation has shown the presence of asymmetric effect of good and bad news on the stock market conditional volatility, with good news imply a higher next period conditional variance compared to the bad news of the same magnitude. This result has indicated that the conditional volatility of stock market return in Bangladesh does not have any leverage effect. Also, highly significant ARCH and GARCH coefficients have indicated that the new surprise as well as the lagged values of volatilities of stock market return have significant impact on current stock market volatility. Nevertheless, the estimated GARCH coefficient is higher compared to the estimated ARCH coefficient indicating that the stock market volatility is more sensitive to its past volatilities than to new surprises. Furthermore, the summation of GARCH and ARCH coefficients is very high indicating that a shock persists over many future periods.

Although the residuals of Ordinary Least Squares (OLS) estimation for the total sample period (from January 1991 to December 2015) have shown serial correlation and heteroskedasticity, but the residuals of OLS estimation for the recovery period (from January 2000 to December 2009) are not serially correlated and homoscedastic. Moreover, the volatility clustering is observed in the total sample period, while this is not found in the recovery period. The non-linearity and volatility clustering in the stock market return
might have been observed in the total sample period due to the catastrophes of 1996 and 2010.

On the other hand, the results of cointegration have shown that there exists a long-run cointegrating relationship between the stock market conditional volatility and the conditional volatilities of the growth of macroeconomic variables. But none of the coefficients in the long-run equation is found statistically significant at 5 percent level. The Bounds test results have revealed that only 14.89 percent of the conditional variance of the stock market return can be explained by the selected macroeconomic variables' volatilities, meaning that remaining 85.11 percent is explained by other factors which have not been considered in this research. This result indicates that only a small percentage of stock market volatility can be explained by the selected macroeconomic variables' volatilities. So, we can conclude that stock market volatility has been driven by factors, which have not been considered in the research.

The result of Error Correction Model (ECM) has shown that the error correction term (ECT) is highly significant and has the correct sign. The ECT also indicates that approximately 29.11 percent of the short-run disequilibria is adjusted per month to bring about long-run equilibrium. Also, all the independent variables have zero lag indicating that there exist no short-run relationships between stock market volatility and macroeconomic volatility.

The results of the viability check of the model have indicated that although the residuals are not serially correlated, but residuals are heteroskedasticity and the distribution is not normal, suggesting that the ARDL cointegration model used is not a good fit model. In addition, the results of the stability tests of the coefficients have indicated that the coefficients are unstable over most of the period indicating that the relationship between the stock market volatility and the macroeconomic volatilities are unstable during the period.

Therefore, we can conclude that the findings of this chapter have indicated nonlinear relationship between the stock market return and the growth of macroeconomic variables, and the presence of volatility clustering of the residuals over the total sample period. In addition, the stock market volatility cannot be reliably explained by the macroeconomic variables' volatilities. The stock market volatility has been found very unstable over the period. On the other hand, in the recovery period, no nonlinearity has been observed, which indicates that the catastrophes of 1996 and 2010 has created this nonlinearity and volatility clustering in the stock market.

# **Chapter 7**

# **Relationship between Stock Market and Real Economy**

## **7.1 Introduction**

In the last three empirical investigation chapters, the relationships between stock market index and macroeconomic indices of Bangladesh have been investigated from different perspectives. However, out of the six macroeconomic variables selected for the study, five have been chosen from financial sector and one from real sector of economy. Stock market is also a financial sector macroeconomic variable. Therefore, it may give the impression that the research has examined relationship between one financial sector variable, the stock market index, and the macroeconomic factors which are mostly chosen from the financial sector, leaving a gap on relationship between the stock market and the real sector macroeconomic variable to understand the impact of stock market on real economy.

There is a widespread agreement that a viable stock market provides diversified channels for limited resources from surplus units to deficit units, hence it is supposed to play a significant role in economy in the sense that it mobilizes domestic resources and channels them to productive investments. This implies that an economy with well-functioning stock markets will experience a higher growth rate of productivity. For this reason, a stock market is seen as a general measure of the state of the real economy of a country where it operates. Harvey (1989) has mentioned that stock market contains valuable information about real economic activities.

Kar and Mandal (2011) have argued that stock prices can have a direct impact on economic output through the financial accelerator and wealth effect channels. The financial accelerator channel focuses on the impact that stock prices have on firms' balance sheets (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). As the ability of firms to borrow depends substantially on the collateral they can pledge, hence higher credit can be raised if stock price increases. This additional fund can be used for investment purposes, which in turn triggers an expansion in real economic activities. Alongside, the wealth effect channel suggests that with the rise in stock prices investors become wealthier and their propensity to consume more results in expansion of economy. Thus, a positive relationship exists between efficient stock markets and economic growth both in the short- and longrun primarily through the effect of stock markets on investment (Masoud, 2013).

Conversely, opponents to this view argue that stock markets are just a side show of total financing activities of a country, since firms raise relatively little cash from public markets. Therefore, stock markets play a minor role in channeling savings to investments, and stock prices passively reflect real economic conditions without affecting them. Many studies have supported this view. For example, Binswanger (2001) has argued that the relation has broken down. In a similar vein, Stock and Watson (2001) have showed that certain asset prices predict output growth in some countries in some periods.

Despite all these controversies, economic theory suggests that there should be a strong link between economic activities and security prices (Duca, 2007). Many empirical studies have confirmed the link between stock prices and real sector variables (Fama, 1981; Schwert, 1990). However, the empirical evidence, particularly in the South Asian region, regarding the direction of causality between stock prices and the real sector variables is not conclusive. Krchniva (2013) has argued that the relationship between the stock market and the real economy depends on the size and maturity of the economy and its stock market.

In this connection, it is worth mentioning that Bangladesh stock market and its economy have been passing through numerous liberalization and deregulation processes since 1991. The measures taken for economic liberalization, privatization, relaxation of foreign exchange controls, and the opening of the stock markets to international investors are supposed to have great impacts on the economy and the stock market. As a result, the indicators like stock market capitalization, trading volume and the market index have shown phenomenal growth during this period. The market capitalization of Dhaka Stock Exchange (DSE) to GDP has increased from 0.94% in June 1991 to about 30.95% in June 2009 (Wahab and Faruq, 2012). Also, the size of the economy has increased significantly. In this context, it would be very interesting to investigate the relationship of the stock market with the dynamics of real economic activities of Bangladesh.

Moreover, Bangladesh stock market has experienced two major bubbles within a decade and a half, one in 1996 and other in 2010. However, our investigations have revealed that only the catastrophe of 1996 has created a structural instability in the stock market. This has motivated us to examine the relationships between the stock market and the real economy around the catastrophe of 1996, that is during the bubble and meltdown periods of 1996. In fact, these investigations have been conducted to describe the relationships during the crisis times of the stock market.

On the other hand, following the crash of 1996, several capital market development programs have been implemented through a strong partnership between the government of Bangladesh and the Asian Development Bank to broaden the market capacity and develop a fair, transparent, and efficient domestic capital market. The main objective of these programs has been set forth to restore investors' confidence, which has significantly damaged after the market crash of 1996, because of excessive speculations, allegedly aggravated by widespread irregular activities. In addition, the stock market has been striving for continuous upgradation of its trading platform since August 1998 to fulfill the dream of transforming Dhaka Stock Exchange (DSE) into modern world class exchange. In these perspectives, this study has also examined whether these initiatives have increased the response of stock market to real economy of Bangladesh.

This chapter is organized into six sections. In section 7.2, we have discussed the methodology to be used in the analyses. In section 7.3, the results of the investigations for different periods have been reported. To examine the significance of the results, the diagnostic tests of the residuals have been conducted. Furthermore, the stability tests have been applied to investigate the stability of the regression parameters. Finally, in section 7.4, the findings of the investigations are summarized in the conclusion.

# **7.2 Empirical Method**

In this research, the industrial production index is the only macroeconomic variable chosen from the real sector. Furthermore, the industrial production index has been used as a proxy of GDP, because data on the former is available on monthly basis but the latter is not. Moreover, the productive capacity of an economy indeed depends directly on the accumulation of real assets, which in turn contributes to the production capacity of firms. Thus, economies of scale may generate higher profitability due to increased turnover. Tainer (1993) has argued that the industrial production index is procyclical and can be used as a proxy of the level of economic activities.

In this context, the industrial production index has been used to represent the real economy of Bangladesh. On the other hand, the Dhaka Stock Exchange General Index has been used to represent the stock market. The month end data of 25 years of the aforesaid variables have been collected, then these data are adjusted considering a base value 100 at the beginning of our sample period i.e. the end of January 1991.

The empirical investigations of this chapter have been carried out using the econometric models outlined in chapter 4. More specifically, the econometric models for unit root tests to check the presence of unit root and the order of integration of the research variables, the Johansen and Juselius cointegration test and the ARDL cointegration approach to examine the long-run relationships along with the error correction model to investigate the shortrun dynamics and significance of error correction mechanism have been used in the analyses.

The empirical investigations have been carried out to examine the relationships between stock market and real economy of Bangladesh in different periods. Firstly, the relationships have been examined on total sample period. Later, the relationships have been examined around the catastrophe of 1996, that is during the bubble and meltdown periods of 1996. Finally, the study has been extended further to cover the period between the two catastrophes of Dhaka Stock Exchange to examine whether the reform measures for the development of the stock market as well as the automation initiatives to build up a state-of-the-art market surveillance system to increase the transparency of market transactions have enhanced the investors' confidence and improved the efficiency of the stock market.

# **7.3 Findings of the Study**

The results of empirical investigations on relationships between stock market and real economy of Bangladesh in different periods are reported in this section. Firstly, we have summarized the results of unit root tests and the trend specification of the research variables. Secondly, results of the cointegration test have been reported. Thirdly, the findings of Error Correction Model (ECM) have been presented. Fourthly, we have checked the viability of the model using residuals diagnostic tests. Additionally, the stability of the parameters of the equations have been examined. Finally, the results of Granger Causality test have been portrayed.

## **7.3.1 Unit Root Tests Results**

In section 4.4.2, we have found that DSE General Index and Industrial Production Index for the period from January 1991 to December 2015 are integrated of order 1, *I(1)*. Also, in section 5.4, we have found that DSE General Index and Industrial Production Index are *I(1)* and *I(0)* respectively in the bubble period, both the variables are *I(0)* in the meltdown period. In the recovery period, ADF test indicates that both the variables are *I(1)*. On the other hand, PP test indicates DSE General Index is *I(1)*, but Industrial Production Index is *I(0)*. As PP test is robust to general forms of heteroskedasticity in the error terms, we have accepted the PP test result and concluded that DSE General Index and Industrial Production Index are *I(1)* and *I(0)* respectively.

## **7.3.2 Trend Specification of the Variables**

After the unit root tests, the second pre-test for cointegration analysis is to identify the most appropriate trend specification. From section 4.4.3, we have found that industrial production index for the period from January 1991 to December 2015 at level has significant trend. Also, from section 5.5, we have found that industrial production index has significant trend in both the bubble and meltdown periods and DSE general index has significant trend in the recovery period. Based on the results of unit root tests and the trend specification, we have applied cointegration tests as per the procedure described in chapter 4 and the results are reported in the following sub-sections.

## **7.3.3 Relationships in the Total Sample Period**

As DSE General Index and Industrial Production Index for the period from January 1991 to December 2015 are integrated of order 1, *I(1)*, so both the cointegration tests has been applied to examine the long- and short-run relationships between the stock market and the real economy. Furthermore, it is found that industrial production index has significant trend in this period, so the restricted trend has been included in the cointegration tests.

### **7.3.3.1 Johansen and Juselius Cointegration Results**

The optimal lag length for the Johansen and Juselius cointegration model is determined using the automatic lag length selection criteria. The result<sup>24</sup> shows that out of five selection criteria three have supported 14 lags, hence lag length 14 has been used in the cointegration analysis. The results of the cointegration test<sup>25</sup> (see Table 7.1) show that the variables are not cointegrated, meaning that there exists no cointegration relationship between the stock market and the real economy.

Hypothesized Number of CE(s)	<b>Unrestricted Cointegration Rank Test</b> (Trace)			<b>Unrestricted Cointegration Rank Test</b> (Maximum Eigenvalue)		
	Trace <b>Statistic</b>	Critical Value at 5% Significance	Probability	Max-Eigen <b>Statistics</b>	Critical Value at 5% Significance	Probability
None	13.13324	25.87211	0.7278	10.51561	19.38704	0.5639
At most 1	2.617633	12.51798	0.9185	2.617633	12.51798	0.9185

**Table 7.1 Results of Johansen and Juselius Cointegration Test on Total Sample Period**

As the variables are not cointegrated, so the Vector Autoregression (VAR) Model has been applied instead of Vector Error Correction Model (VECM) to examine the short-run relationships between the stock market and the real economy. The VAR has been applied on 1<sup>st</sup> differences of the variables, which represent the growth of the variables.

 $\overline{a}$ 

<sup>&</sup>lt;sup>24</sup> See Appendix U

 $25$  See Appendix V

To apply the VAR model, we need to choose the optimal lag length. Again, the lag length selection criteria have been used to estimate the optimal lag length to be used in the VAR model. The result shows (see Appendix V 2.1) that the preferred lag length is 13. Thus, lag length 13 has been used in the VAR estimation. The summary of the results (see Appendix V 2.2) is portrayed in Table 7.2. The results show that lagged values of growth of industrial production do not jointly explain the stock market return at 5% significance level, while the lagged values of stock market return can jointly explain the growth of industrial production at 5% significance level. Thus, the VAR result is consistent with the financial theory that the stock market is a leading indicator of industrial production, meaning that the stock market is a leading indicator of the real economy.

**Table 7.2 Significance of the Independent Variable in VAR Model on Total Sample Period**

Independent <b>Variables</b>	<b>Null Hypothesis</b>	$\chi^2$ Statistics	<i>p</i> -value
<b>DLIPI</b>	$C(14) = C(15) = C(16) = C(17) = C(18) = C(19) = C(20)$ $= C(21) = C(22) = C(23) = C(24) = C(25) = C(26) = 0$	6.821183	0.9111
<b>DLDSEGEN</b>	$C(28) = C(29) = C(30) = C(31) = C(32) = C(33) = C(34)$ $= C(35) = C(36) = C(37) = C(38) = C(39) = C(40) = 0$	36.78324*	0.0004

Notes: \* denotes the significance of the coefficient at 5% level.

## **7.3.3.2 Granger Causality Test Results**

The Granger Causality test is carried out for 12 lags, considering that the market is efficient and one year is quite long time to propagate the impact of one variable to the other. The results of the Granger causality (see Appendix V 2.3) have been portrayed in Table 7.3, the results indicate that there is a unidirectional causality running from stock market return to growth of industrial production index. This result is consistent with the results of Granger causality test of chapter 4 (see section 4.4.4), where VECM Granger Causality Test has been applied with stock market return as dependent variable and all the macroeconomic variables as independent variables and the results have indicated a unidirectional causality running from the stock market return to growth of industrial

production index. Thus, we can conclude that the stock market is a leading indicator of economic growth represented by the industrial production.

**Table 7.3 Results of Granger Causality Test on Total Sample Period**

Null Hypothesis	$\gamma^2$ Statistics	<b>Probability</b>
D(LIPI) does not Granger Cause D(LDSEGEN)	0.97146	0.4765
D(LDSEGEN) Does not Granger Cause D(LIPI)	2.09862*	0.0174

Notes: \* denotes that coefficient is significant at 5% level.

#### **7.3.3.3 ARDL Cointegration Test Results**

We have used the ARDL Bounds testing procedure to check the robustness of the results of Johansen and Juselius cointegration test. For ARDL model, we need to select the optimal lag lengths for both the dependent variable, DSE General Index (LDSEGEN), and the regressor, Industrial Production Index (LIPI). From Table 4.4, we have found that at level the dependent variable (i.e., LDSEGEN) has 2 lags and regressor (i.e., LIPI) has 6 lags. So, we have used these two lag values in the ARDL test.

It is mentioned earlier that industrial production index has significant trend. So, in the ARDL test, we have included trend in the cointegration equation. The results of ARDL specification and the Pesaran Bounds Test are summarized in Table 7.4. The Bounds test result indicates that null hypothesis of "no long-run relationship exists" cannot be rejected at 5% significance level, meaning that there is no cointegration relationship between stock market index (dependent variable) and industrial production index (independent variables) in the total sample period.

Besides, the Bounds test results also have showed that  $R^2$  is 0.0543, which indicates that about 5.43 percent of the variation in stock market return can be explained by the changes of industrial production index. The F value is significant at 10% level, meaning that the regression coefficients are weakly significant. The Durbin Watson statistic confirms the presence of non-autocorrelated residuals. The results of error correction model (see Appendix V 3.4) indicate that the lagged values of industrial production index cannot jointly explain the stock market return. These results are similar to that of Johansen and Juselius cointegration test and the VAR model, which confirm the robustness of the results.

<b>Dependent Variable: D(LDSEEGEN)</b>				
<b>ARDL Model Specification (2,6)</b>				
<b>F</b> Statistics	1.992034			
<b>Critical Value Bounds</b>				
Significance	$I_0$ Bound	$I_1$ Bound		
10%	2.49	3.38		
5%	2.81	3.76		
2.5%	3.11	4.13		
1%	3.50	4.63		
R-squared	0.054349			
Adjusted R-squared	0.020934			
F-statistic	1.626468			
Prob (F-statistic)	0.098602			
Durbin-Watson stat	2.024204			

**Table 7.4 ARDL Specification and Bounds Test Results on Total Sample Period**

The viability tests (see Appendix V 3.4) of the model show that the residuals are not serially correlated. However, the residuals are heteroskedastic, and the distribution of the residuals are not normal. These results reveal that the model is not a good fit model. Moreover, the CUSUM and CUSUMSQ plots of the residuals (Figure 7.1 and Figure 7.2) indicate that the regression parameters are not stable.



### **7.3.4 Relationships in the Bubble Period**

As the DSE General Index and Industrial Production Index are *I(1)* and *I(0)* respectively and industrial production index has significant trend in the bubble period, so we have applied the ARDL approach with restricted trend to examine the cointegration relationship between the stock market and industrial production index.

## **7.3.4.1 ARDL Cointegration Test Results**

From Table 5.3, we have found that at level the dependent variable (i.e., LDSEGEN) has 4 lags and regressor (i.e., LIPI) has 1 lag. So, we have used these two lag values in ARDL test. The results of ARDL specification and the Pesaran Bounds Test (see Appendix W 1.1 and W 1.2) are summarized in Table 7.5. The results indicate that null hypothesis of "no long-run relationship exists" cannot be rejected at 5% significance level, meaning that there is no cointegration relationship between stock market index and industrial production index in the bubble period.

<b>Dependent Variable: D(LDSEEGEN)</b>					
<b>ARDL Model Specification (4,1)</b>					
<b>F</b> Statistics	2.269957				
<b>Critical Value Bounds</b>					
Significance	$I_0$ Bound	$I_1$ Bound			
10%	4.05	4.49			
5%	4.68	5.15			
2.5%	5.30	5.83			
$1\%$	6.10	6.73			
R-squared	0.201779				
Adjusted R-squared	0.087747				
F-statistic	1.769501				
Prob (F-statistic)	0.114957				
Durbin-Watson stat	1.990436				

**Table 7.5 ARDL Specification and Bounds Test Results on Bubble Period**

The Bounds test have also indicated that about 20.18 percent of the stock market return can be explained by the changes of industrial production index. The F value is not significant, meaning that the regression coefficients are not significant. The Durbin Watson statistic confirms the presence of non-autocorrelated residuals. The results of error correction model (see Appendix W 1.3) indicate that industrial production index has 1 lag and the *t*-statistic along with associated *p*-value show that industrial production index cannot explain the stock market return in the short-run.

The viability tests of the model (see Appendix W 1.4) show that the residuals are not serially correlated. However, the residuals are heteroskedastic, and the distribution of the residuals is not normal. These results indicate that though the residuals are not serially correlated, other two conditions are not fulfilled, hence the model is not a good fit model. Moreover, the CUSUM and CUSUMSQ plots of the residuals (Figure 7.3 and Figure 7.4) indicate that the regression parameters are not stable over the period.



#### **7.3.4.2 Granger Causality Test Results**

The Granger Causality test is carried out for 12 lags, considering that the market is efficient and one year is quite long to propagate the impact of one variable to the other. The results of the granger causality (see Appendix W 1.5) are shown in Table 7.6, which indicate that there is no causal relation between stock market return and growth of industrial production index.



#### **Table 7.6 Results of Granger Causality Test on Bubble Period**

Notes: \* denotes that coefficient is significant at 10% level.

### **7.3.5 Relationships in the Meltdown Period**

In the meltdown period, both DSE General Index and Industrial Production Index are *I(0)*, and industrial production index has significant trend, so we have applied the ARDL approach with restricted trend to examine the cointegration relationship between the stock market and industrial production index.

## **7.3.5.1 ARDL Cointegration Test Results**

From Table 5.3, we have found that at level both the dependent variable (i.e., LDSEGEN) and the regressor (i.e., LIPI) have 2 lags in the meltdown period. So, we have used these lag values in ARDL test. The results of ARDL and Bounds tests (see Appendix W 2.1 and W 2.2) are summarized in Table 7.7, which indicate that the null hypothesis of "no longrun relationship exists" cannot be rejected at 5% significance level, meaning that there is no cointegration relationship between stock market index and industrial production index.

<b>Dependent Variable: D(LDSEEGEN)</b> <b>ARDL Model Specification (2,2)</b>				
				<b>F</b> Statistics
<b>Critical Value Bounds</b>				
Significance	$I_0$ Bound	$I_1$ Bound		
10%	4.05	4.49		
5%	4.68	5.15		
2.5%	5.3	5.83		
$1\%$	6.1	6.73		
R-squared	0.351140			
Adjusted R-squared	0.225554			
F-statistic	2.796016			
Prob (F-statistic)	0.027220			
Durbin-Watson stat	2.464886			

**Table 7.7 ARDL Specification and Bounds Test Results on Meltdown Period**

The Bounds test results also have indicated that  $\mathbb{R}^2$  is 0.3511, meaning that about 35.11 percent of the stock market return can be explained by the growth of industrial production index. The F value is significant at 5% level, meaning that the regression coefficients are significant. However, the Durbin Watson statistic indicates the presence of autocorrelated residuals. The results of error correction model (see Appendix W 2.4) indicate that industrial production index cannot jointly explain the stock market return.

The viability tests of the model (see Appendix W 2.5) show that the residuals are serially correlated, and the distribution of the residuals is not normal. However, the residuals do not show heteroskedasticity. These results indicate that the model is not a good fit model. Moreover, the CUSUM and CUSUMSQ plots of the residuals (Figure 7.5 and Figure 7.6) indicate that the regression parameters are not stable over the period.



### **7.3.5.2 Granger Causality Test Results**

The Granger Causality test is carried out for 12 lags, considering that the market is efficient and one year is quite long to propagate the impact of one variable to the other. The results of the granger causality (see Appendix W 2.6) are reported in Table 7.8, the results indicate that there is a unidirectional causal relation between stock market return and growth of industrial production index running from DSE general index to industrial production index at 10% significance level.



#### **Table 7.8 Results of Granger Causality Test on Meltdown Period**

Notes: \* denotes that coefficient is significant at 10% level.

#### **7.3.6 Relationships in the Recovery Period**

In the recovery period, DSE General Index and Industrial Production Index are *I(1)* and *I(0)* respectively and DSE General Index has significant trend, so we have applied the ARDL approach with restricted trend to examine the cointegration relationship between the stock market and industrial production index.

#### **7.3.6.1 ARDL Cointegration Test Results**

For ARDL model, we need to choose the optimal lag lengths for both the dependent and independent variables. From Table 5.3, we have found that the dependent variable (i.e., LDSEGEN) and the independent variable (i.e., LIPI) at level have 10 and 12 lags respectively. So, we have used these lag values in ARDL test. The results of ARDL specification and the Pesaran Bounds Test (see Appendix W 3.1 and W 3.2) are summarized in Table 7.7. The Bounds test result indicates that null hypothesis cannot be rejected at 5% significance level, meaning that there is no cointegration relationship between stock market index and industrial production index in recovery period.

The Bounds test results also have indicated that about 37.41 percent of the variation in stock market return can be explained by the changes of industrial production index. The F statistic is significant at 5% level, meaning that the regression coefficients are significant. Also, the Durbin Watson statistic indicates the presence of non-autocorrelated residuals. The results of error correction model (see Appendix W 3.4) indicate that industrial production index cannot jointly explain the stock market return.

<b>Dependent Variable: D(LDSEEGEN)</b> <b>ARDL Model Specification (10,12)</b>				
<b>Critical Value Bounds</b>				
Significance	I <sub>0</sub> Bound	$I_1$ Bound		
10%	4.05	4.49		
5%	4.68	5.15		
2.5%	5.30	5.83		
$1\%$	6.10	6.73		
R-squared	0.374052			
Adjusted R-squared	0.215918			
F-statistic	2.365410			
Prob (F-statistic)	0.001710			
Durbin-Watson stat	2.019811			

**Table 7.9 ARDL Specification and Bounds Test Results on Recovery Period**

The viability tests of the model (see Appendix W 3.5) show that the residuals are not serially correlated, do not show heteroskedasticity, and the distribution of the residuals is normal. These results indicate that the model is a good fit model. Moreover, the CUSUM and CUSUMSQ plots of the residuals (Figure 7.7 and Figure 7.8) indicate that the regression parameters are stable over the period. The viability and stability test have confirmed that the results of the model are stable and significant.



### **7.3.6.2 Granger Causality Test Results**

The Granger Causality test is carried out for 12 lags, considering that the market is efficient and one year is quite long time to propagate the impact of one variable to the other. The results of the granger causality (see Appendix W 3.6) are shown in Table 7.8, the results indicate that there is a unidirectional causal relation between stock market return and growth of industrial production index with direction of causality running from growth of industrial production index to DSE general index at 10% significance level, hence indicating the inefficiency of the stock market during the recovery period.

**Table 7.10 Results of Granger Causality Test on Recovery Period**

Null Hypothesis	$\gamma^2$ Statistics	<b>Probability</b>
D(LIPI) does not Granger Cause D(LDSEGEN)	$1.66724*$	0.0865
D(LDSEGEN) Does not Granger Cause D(LIPI)	0.66191	0.7834

Notes: \* denotes that coefficient is significant at 10% level.

# **7.4 Conclusion**

In this research, industrial production index has been considered as a proxy of GDP, hence it is used to represent the real sector of economy to examine the relationship between stock market and real economy of Bangladesh. Firstly, the empirical investigations have been conducted on total sample period i.e. on 25 years data. Later, the relationships have been examined around the catastrophe of 1996, that is during the bubble and meltdown periods of 1996, to assess the relationships during the crisis times. Moreover, following the crash of 1996, several capital market development programs as well as automation and upgradation of the trading platform are being implemented to broaden market capacity and to develop a fair, transparent, and efficient domestic capital market. In this context, the study has been extended further to cover the period from January 2000 to December 2009 to examine whether these initiatives have enhanced the investors' confidence and improved the efficiency of the stock market.

The findings of the Johansen and Juselius cointegration test on total sample period have showed that there exists no cointegration relationship between the stock market and industrial production index. The ARDL cointegration approach has also provided the same results indicating the robustness of the results. As the variables are not cointegrated, the Vector Autoregression (VAR) Model has been applied to examine the short-run relationships among the variables.

The results of VAR model have showed that lagged values of growth of industrial production do not significantly explain the stock market return, while the lagged values of stock market return can significantly explain the growth of industrial production. This result is consistent with the financial theory that the stock market is a leading indicator of industrial production. The result of Granger Causality has also provided the same results.

Alongside, the results of ARDL model have indicated that only 5.43 percent of the variation in stock market return can be explained by the growth of industrial production index. The results of the viability check of the model have indicated that the model is not a good fit model. In addition, the CUSUM and CUSUMSQ tests have showed that the regression parameters are not stable, and an instability is observed around the catastrophe of 1996. So, we can conclude that due to the structural instability in the stock market in 1996, our findings are not stable and significant for the total sample period.

The results of ARDL have indicated that no cointegration relationships exist between stock market index and industrial production in the bubble, meltdown and recovery periods. The Bounds test results have revealed that about 21.18, 35.11 and 37.41 percent of the variations in stock market return can be explained by the growth of industrial production index in the bubble, meltdown and recovery periods respectively. The results of error correction model have confirmed that in these three periods there exist no short-run relationships between industrial production index and the stock market return.

The results of the Granger Causality Tests have indicated four types of causal relationships in four periods. These are: (1) a unidirectional causal relation running from DSE general index to industrial production index at 5% significance level in the total sample period; (2) no causal relation in the bubble period; (3) a unidirectional causal relation running from DSE general index to industrial production index at 10% significance level in the meltdown period; and (4) a unidirectional causal relation running from industrial production index to DSE general index at 10% significance level in the recovery period. The causal relations in the total sample and meltdown period have indicated that the stock market is a leading indicator of the economic growth, but the causal relation in the recovery period has exposed that the stock market is inefficient.

However, the viability tests of the models have indicated that for the total sample, bubble and meltdown periods the models are not good fit models and the CUSUM and CUSUMSQ plots of the residuals have showed that the regression parameters are not stable in these three periods. These results indicate that the findings of these periods are not viable and significant.

On the other hand, the viability tests of the model for the recovery period have specified that the model is a good fit model and the CUSUM and CUSUMSQ plots of the residuals have showed that the regression parameters are stable over the period. Thus, the results of this period are viable and significant. The results of this period clearly indicate that the past (current) information about the economic activities are useful in predicting current (future) stock prices. The finding suggests that despite numerous reforms and automation initiatives the stock market is still not that developed to play its due role in influencing the real sector of economy of Bangladesh.

# **Chapter 8**

# **Findings and Conclusion**

# **8.1 Introduction**

General belief is that stock markets can predict future states of economy. In order to find empirical evidence to the belief, we examined relationships between Dhaka Stock Exchange (DSE), represented by DSE General Index (DSEGEN), and macroeconomic indices representing the economy of Bangladesh. Based on the objectives, this research attempted to find answers to the following specific research questions:

- 1. Does any significant long-run equilibrium relationship exist between Dhaka Stock Exchange General Index (DSEGEN) and six macroeconomic variables namely Industrial Production Index, Interest Rate, Inflation, Exchange Rate, Money Supply and Gold Price?
- 2. Is there any short-term relationship between DSEGEN and the macroeconomic variables?
- 3. Is there any causal relationship between DSEGEN and the macroeconomic variables?
- 4. Are the relationships same between DSEGEN and the macroeconomic variables in different periods, i.e., in bubble, meltdown and recovery periods of the stock market?
- 5. Is there any relationship between DSEGEN volatility and the macroeconomic volatility?
- 6. What is the relationship between DSEGEN and the real economy of Bangladesh?

The rest of the chapter has three main sections. The first is to present a summary of the empirical evidence and findings that we have obtained to answer the research questions. The second is to highlight the contributions of the research and the third is to indicate few potential pathways for further research. The chapter ends with an overall conclusion.

## **8.2 Summary of the Research and Its Findings**

The literature review in chapter 2 has revealed that numerous studies have tried to investigate both theoretically and empirically the relationship between macroeconomic variables and stock market in the last three decades. The summary of the literature review has indicated that different studies have found different relationships; even a single study has found varied relationships for different countries as well as in different periods within the same country. This divergence of the findings creates rooms for further research in this area.

Though most of the studies on developed countries have documented a great deal of evidence that fundamental economic activities are strongly linked to stock market return, it is unclear if such a relationship exists in emerging stock markets of developing countries. Findings of the studies on Bangladesh are widely diverse. Because of absence of strong regulatory system and lack of information transparency, our stock market is not proficient to boost the confidence of the investors (Mondal and Imam, 2011). In addition, our economy may have been influenced to a far greater extent by global economic indicators rather than domestic economic factors, and/or foreign investment in the stock market may have weaken the link between national economic variables and the stock market return (Gunasekarage et al., 2004). Investors have also lack of knowledge (fundamental and technical) about capital market (Mondal and Imam, 2011). In this backdrop, the hypothesis that changes in macroeconomic variables have a pervasive impact on stock market has been subjected to extensive research for Bangladesh.

The literature review has also disclosed an issue whether the relationship is a contemporaneous or lead-lag one and many studies on the relationship between stock market and macroeconomic variables also have examined stock market's predictability (Tangjitprom, 2012b). The findings of the existing literature on this issue are also mixed. In addition, most of the studies on Bangladesh has hitherto concentrated primarily on contemporaneous relationship leaving a research gap in causal relationship.

Risk return behavior analysis of stock market is very important for any developing countries because these markets are very volatile. As most of the investors are riskaverse, so the volatility of stock market compels them to demand higher risk premium which creates higher cost of capital and thus slows down the economic development (Mala and Reddy, 2007). This is an important issue from Bangladesh perspective. However, a very few studies have tried to find the relationship between stock market volatility and macroeconomic volatility in Bangladesh. The findings of the studies are also mixed and not as strong as described in the standard financial theory indicating requirement of further research on this issue.

After identifying the research gap through the literature review, we have studied the issues related to the asset valuation models in chapter 3. These are valuation of shares, portfolio theory, the CAPM, the ICAPM and the APT. These theories have been discussed to determine the way in which macroeconomic variables affect the stock market return. The common asset valuation models, together with the EMH and rational expectations theory, integrate the micro and macro risk factors into the asset prices. However, microeconomic factors are considered as the sources of unsystematic risks which can be minimized through diversification. Conversely, macroeconomic variables are considered as the likely sources of the systematic risks, which cannot be eliminated by the simple approach of diversification.

Thus, equilibrium asset pricing models, such as the CAPM and APT, deal with the valuation of stocks using macroeconomic factors. The basic CAPM relates only one factor, the market factor. Hence it omits the other factors that are important in asset pricing. Conversely, APT allows for a set of factors and is consistent with capital market equilibrium. In APT, the expected return on an asset is a function of multiple factors rather than a single market factor. It suggests that return on a security or a portfolio is dependent on impacts of a series of factors.

The APT has two different versions: the factor loading model and the macro variable model. The factor loading model uses artificial variables, while the macro variable model uses macroeconomic variables based on the economically interpretable effects. However, none of the versions of the APT provide guidelines for identification of the common macroeconomic factors which are the sources of the systematic risk. The outcome of chapter 3 reveals that the macro variable version of the APT is the most widely used valuation method in the literature. As such, the effects of macroeconomic variables on the stock market return in Bangladesh have been investigated using the macro variable version of APT within the framework of semi-strong form of EMH.

Based on this groundwork, chapter 4 of this thesis has focused on the first three research questions. Additionally, we have used multiple econometric models within the framework of multi-factor asset pricing model of APT to check the robustness of the findings. Similarly, Chapter 5, chapter 6 and chapter 7 have dealt with the fourth, fifth, and sixth question respectively.

#### **8.2.1 Long-term Equilibrium and Causal Relationships**

Our findings with Johansen and Juselius cointegration approach revealed that there existed a long-run equilibrium relationship between the stock market index and the selected macroeconomic indices. However, out of the six macroeconomic variables, viz.; industrial production index, interest rate, inflation, exchange rate, money supply and gold price, only interest rate did not enter the long-run equation significantly at 5 percent level. On the other hand, the results of short-term relationships up to 13 months (up to 13 lags) revealed that none of the macroeconomic variables was significant in explaining the stock market return indicating that there existed disequilibrium in the short-run between the stock market return and the growth of macroeconomic variables. Nevertheless, about 15.30 percent of the short-run disequilibrium was adjusted per month to bring about equilibrium in the long-run.

The empirical investigations also revealed that the DSE General Index had unidirectional causal relationships with only two macroeconomic variables, industrial production index and exchange rate, but the opposite was not true. The unidirectional causal relation running from stock market return to the growth of both industrial production index and exchange rate indicated that the performance of stock market was a leading indicator to explain the future changes of only two macroeconomic variables. Therefore, the stock market was not a leading indicator for most of the macroeconomic variables.

To check the robustness of the results, the Autoregressive Distributed Lag (ARDL) cointegration approach was applied. This test also indicated that there existed a long-run relationship between stock market index and macroeconomic indices. The cointegrating equation showed that the industrial production, consumer price index, exchange rate and gold price were significant in determining stock prices in the long-run, while money supply had insignificant long-run effect on stock market index. The investigations on short-run relationships showed that the changes in macroeconomic variables at different lags were not statistically significant in explaining the stock market return indicating that there was no short-run relationship between stock market return and the growth of macroeconomic variables. The error correction model based on ARDL approach suggested that about 12.62 percent of the short-run disequilibrium was corrected per month to bring about equilibrium in the long-run.

The results of both tests confirmed the existence of long-run equilibrium relationship and short-run disequilibrium between the stock market and the selected macroeconomic variables. However, Johansen Juselius approach showed that about 30 percent of the variations in stock prices could be explained by the changes in macroeconomic variables considered, while ARDL approach indicated that about 21 percent of the variations could be explained by the changes in macroeconomic variables. The explanatory power of the macroeconomic variables in ARDL approach might have decreased since interest rate was dropped from the list in ARDL approach as it had been found insignificant in the Johansen cointegration approach. These results revealed that substantial percentage of the stock market return was explained by the factors which had not been considered in this research.

The diagnostic tests of the residuals of ARDL cointegration approach indicated a structural instability around the catastrophe of 1996, meaning that the cointegration coefficients had changed suddenly (instable) around 1996. In contrast, the coefficients were found stable throughout the total sample period with Johansen and Juselius cointegration approach. On the other hand, the study of Caporale and Pittis (2004) suggested that stability tests perform better in the context of a dynamic model of the ARDL type because this is not affected by serial correlation or nonpredetermined regressors even if over-specified. Therefore, the result of ARDL model was accepted and concluded that there was a structural instability around 1996. Conversely, no such instability was seen around the catastrophe of 2010.

This inspired us to examine the relationships between the stock market and the macroeconomic variables around the catastrophe of 1996 - that was during the bubble and meltdown periods of 1996. The study also considered several capital market development programs as well as the automation and upgradation of the trading platform initiated in 1998, following the crash of 1996, to develop a fair, transparent, and efficient domestic capital market. To examine whether these initiatives had enhanced the investors' confidence and improved the efficiency of the stock market the study was extended further to cover the period from January 2000 to December 2009.

#### **8.2.2 Relationships During Bubble, Meltdown and Recovery Periods**

In view of the aforesaid capital market development programs, the automation and upgradation of the trading platform, and the visual inspection of the graph of Dhaka Stock Exchange (DSE) General Index, we demarcated precisely the periods of bubble creation and the bubble crash of 1996 as well as the recovery period to examine the relationships between the stock market index and the macroeconomic indices in these periods. Accordingly, we considered the period from March 1992 to November 1996 as bubble, from November 1996 to December 1999 as meltdown, and from January 2000 to December 2009 as recovery period.

The findings indicated the existence of long-run relationship between the stock market index and the macroeconomic indices and about 52.68 percent of the stock market return was explained by the changes in macroeconomic indices in the bubble period. The results showed that industrial production index, inflation, exchange rate and money supply were positively related, while interest rate and gold price were negatively related with the stock market index. However, only exchange rate was found significant at 5 percent level, and industrial production and gold price were found significant at 10 percent level.

The long-run equation of the bubble period showed that the coefficient of exchange rate had the highest sensitivity among the macroeconomic variables, which had indicated the dominance of exchange rate on stock prices. Further investigations revealed that both the exchange rate and the foreign investment in Bangladesh stock market had increased significantly during this period. Moreover, the interest rate had decreased consistently during this period. These findings revealed that the increase in exchange rate and the subsequent increase in foreign investment had significant contribution in bubble creation and at the same time the falling interest rate had further intensified it.

The analysis of the meltdown period revealed that there existed no long-run relationship between the stock market index and the selected macroeconomic indices. The result also showed that only 36.14 percent of the stock market return was explained by the growth of the macroeconomic indices indicating that the remaining 63.86 percent had explained by some other factors, which were not considered in this research.

The long-run equation of meltdown period, showed that the coefficients of interest rate and exchange rate were larger than the coefficients of other macroeconomic indices and both the variables showed negative impact on stock prices. During the period both the variables had increased significantly and most of the foreign investment, which had been invested during the bubble period, were withdrawn from Bangladesh stock market during this period. These findings indicated that the increased exchange rate had failed to attract foreign investment. Conversely, a significant amount of foreign investment had been withdrawn during this period which had created negative impact on stock market. The increased exchange rate had also increased the cost of production of the firms creating negative impact on equity prices. Thus, the exchange rate has played a key role in market crash and increased interest rate had further worsened the situation.

The results of recovery period indicated that there existed a long-run relationship between stock market index and macroeconomic indices and about 55.70 percent of the stock market return was explained by the growth of macroeconomic indices. Here the long-run equation revealed that the interest rate, exchange rate and gold price were negatively related with stock market index. On the other hand, industrial production index, inflation and money supply were positively related with the stock market index. The size of the long-run coefficients indicated that interest rate had the highest negative impact, followed by money supply and inflation with positive impact on stock market. Nevertheless, the coefficient of gold price showed a very low negative impact on stock market index.

The results of the stability check of the models for different periods revealed that in bubble period conditional variance of the residuals showed slight instability at  $3<sup>rd</sup>$  quarter of 1996 indicating a sudden change in the coefficients at that time. But during meltdown period, the coefficients were unstable for longer period. On the other hand, during the recovery period the coefficients were found stable.

#### **8.2.3 Stock Market Volatility and Macroeconomic Volatility**

The residuals of Ordinary Least Squares (OLS) estimation, with stock market return as dependent variable and the selected macroeconomic variables as independent variables, showed serial correlation and heteroskedasticity. Also, the plot of residuals confirmed the volatility clustering of the residuals, meaning that the variances were high during certain periods and low in other periods. These results indicated that the nonlinear GARCH model should be applied for estimation of the mean and variance equations.

In this context, the mean and variance equations were estimated using best fitted GARCH model. The results showed that the EGARCH model was the best fitted model for the purpose. The results of the EGARCH model exhibited that the growth of inflation and money supply were significantly positively related with the stock market return, while change in exchange rate had significant negative relation with the stock return. Conversely, growth of other selected macroeconomic variables (industrial production index, interest rate and gold price) were not found significantly related to the stock market return. These results signified the importance of inflation, exchange rate and money supply on stock market return in Bangladesh.

On the other hand, the variance equation indicated asymmetric effect of good and bad news on stock market volatility, with a higher impact of good news on stock market volatility compared to bad news of the same magnitude. This result revealed that Bangladesh stock market did not show any leverage effect. The result also indicated that the new surprises as well as the past values of market volatility had significant impact on stock market volatility. However, the stock market volatility was more sensitive to its past values than to new surprises. The results also revealed that a shock persisted for many future periods.

The cointegration test showed that there existed a long-run relationship between the stock market volatility and the macroeconomic volatility. However, none of the coefficients of the macroeconomic volatility in the long-run equation was found statistically significant, meaning that none of the macroeconomic volatility could significantly explain the stock market volatility in the long-run. Also, there existed a short-term disequilibrium between stock market volatility and macroeconomic volatility. The error correction term showed that approximately 29.11 percent of disequilibria were corrected per month to bring about an equilibrium in the long-run.

The Bounds test revealed that only 14.89 percent of the conditional variance of the stock market return was explained by the selected macroeconomic variables' volatilities, meaning that remaining 85.11 percent was explained by other factors which were not considered in this research. This result specified that only a small percentage of stock market volatility could be explained by the macroeconomic volatility.

#### **8.2.4 Relationship between Stock Market and the Economy**

In this analysis, the industrial production index, which was used as a proxy of GDP, represented the real sector of economy of Bangladesh. The findings of the Johansen and Juselius cointegration test over the total sample period showed that there existed no cointegration relationship between the stock market and industrial production index. The ARDL cointegration approach also provided the same result indicating the robustness of the results. As the variables were not cointegrated, hence the Vector Autoregression (VAR) Model was used to examine the short-run relationships among the variables.

The results of VAR model exhibited that lagged values of growth of industrial production did not significantly explain the stock market return, while the lagged values of stock market return could significantly explain the growth of industrial production index. The result of VAR model was consistent with the financial theory that the stock market was a leading indicator of industrial production index. The result of Granger Causality Test also provided the same results.

The results indicated that only 5.43 percent of the stock market return was explained by the growth of industrial production index. The results of the viability check of the model indicated that the model was not a good fit model. In addition, the stability tests exposed that the regression parameters were not stable, and an instability was observed around the catastrophe of 1996. This structural instability as well as the nonviability of the model revealed that the results were not significant.

The structural instability of 1996 motivated us to investigate the relationships in crisis time. Moreover, the relationship was also examined in recovery period. The results indicated that there existed no cointegration relationships between the stock market index and industrial production in the bubble, meltdown and recovery periods. The Bounds test results revealed that about 21.18, 35.11 and 37.41 percent of the variations in stock market return could be explained by the changes in industrial production index in the bubble, meltdown and recovery periods respectively.

Besides, the results of the Granger Causality Test provided three diverse causal relationships between stock market return and growth of industrial production in three different periods. These were: (1) no causal relationship in the bubble period; (2) a unidirectional weakly causal relation running from stock market return to growth of industrial production index in the meltdown period; and (3) a unidirectional weakly causal relationship running from growth of industrial production index to stock market return in the recovery period. The causal relationship in the meltdown period indicated that the stock market was a leading indicator of the economic growth, but the causal relation in the recovery period exposed that the stock market was inefficient, though these two causal relationships were found weakly significant.

Alongside, the viability tests of the models of different periods indicated that for the bubble and meltdown periods the models were not good fit models. In addition, the stability tests also showed that the regression parameters were not stable in these two periods. Conversely, the viability tests of the model for recovery period specified that the model was a good fit model. Also, the stability tests confirmed that the regression parameters were stable. Thus, the results of recovery period were significant. Therefore, the above results indicated that out of the four different periods; the total sample period, bubble, meltdown and recovery periods, the relationship between the stock market and the real sector of economy was found significant only in the recovery period.

# **8.3 Research Contributions**

Most of the studies to examine link between stock market and macroeconomic variables have used a single econometric model for investigations. This study has employed multiple cointegration techniques to check the robustness of the findings. Furthermore, a very few studies have used ARDL approach to examine the relationship between stock market and economic state variables in the emerging economy like Bangladesh. This study has attempted to fill this gap by exploring the relationship between stock market index and macroeconomic variables in Bangladesh applying ARDL approach on monthly time series data.

Another contribution of this research is the study of causal relationships between the

stock market return and the growth of macroeconomic forces to investigate the stock market's predictability. The findings of the existing literature on this implication are mixed. Moreover, most of the studies, if not all, on Bangladesh have concentrated primarily on contemporaneous relationship between stock market return and growth of macroeconomic variables. This study contributes to fill the gap related to the causal relationships between stock market return and growth of macroeconomic variables in Bangladesh.

Another important contribution of this research is that it has focused on the relationships between the stock market and the macroeconomic factors in different conditions of the stock market – such as in bubble, meltdown and recovery periods. None of the studies on Bangladesh has concentrated on this implication leaving a serious gap in the literature. The relationships in different periods have been assessed separately to compare the influences of the priced factors in different periods. The outcome of these analyses is noteworthy as it brings out which macroeconomic factors are at least partially responsible for bubble creation as well as for bubble crash in 1996. The analyses also have uncovered that sometimes our stock market has partially driven by fad and fashions which are not related to the economic conditions.

The risk return behavior analysis of stock market is very important for developing countries, because the stock markets of these countries are very volatile. Specifically, this type of study has become essential for Bangladesh considering two irrational fluctuations of stock prices within one and a half decades and the size of their effects in our socio-economic life. However, the comprehensive review of literatures has indicated that no such study on Bangladesh has been made using non-linear model to estimate the mean and variance equations simultaneously as well as to identify or quantify the asymmetry in the conditional volatility of the stock market return. This study has contributed to fill up this gap. This study has been extended further to estimate the conditional variances of the research variables using the best fitted GARCH model. Later, the cointegration approach has been applied to examine the long- and short-term relationships between the stock market volatility and the macroeconomic volatility.

In addition, empirically the predictive content of stock prices for economic growth is less clear-cut and it depends on size of the economy and the stock market of a country (Krchniva, 2013). Although Bangladesh stock markets have grown significantly during the last decade, still the size is relatively small compared to other Asian Markets. Bangladesh stock market is passing through different reforms to set the foundation for sustainable market development and the automation and continuous upgradation of its trading platform is ongoing to build up a state-of-the-art market surveillance system to increase the transparency of market transactions and contribute significantly to enhance investor confidence. But a very few studies have investigated the relationship between the stock market and real economy of Bangladesh from the perspectives of these reform measures. None of the study has investigated whether these initiatives have improved the efficiency of the stock market. This study has focused on these issues to address the void in the literature on Bangladesh.

Therefore, this research may be considered as an extension to the existing relevant studies on Bangladesh. The outcomes of the study are expected to offer financial regulators and policy makers some insights into the mistakes they have made earlier in terms of formulating economic and financial policies to regulate the stock market. Also, the regulator and policy makers may find the outcomes of the research helpful in formulating different policies for ensuring and creating smooth trading and investment
atmosphere, controlling market strategies and assessing the degree to which the stock market may need to be reformed. Moreover, the results can help investors and portfolio managers in extending their understanding of the risk return relationship as well as pricing of macroeconomic risk.

## **8.4 Recommendation for Further Research**

This research has selected six macroeconomic variables to represent the economy of Bangladesh. However, only these six variables may not completely represent the macroeconomic condition of the country. Other relevant macroeconomic variables such as long-term interest rate, balance of trade, oil price, employment rate and so on might be considered to obtain more precise result. Future research may consider those macroeconomic factors to investigate the relationship between stock market and macroeconomic variables.

Since different segments of the market don't always move in tandem, the response to macroeconomic factors vary across different segments of the market. For example, banking industry stocks are heavily affected by interest rates because their business is selling money. Similarly, some industries are less sensitive to inflation risk, such as food industries, while some industries are highly sensitive to inflation risk, such as home building, hotels and motels and luxury goods. This study has focused on aggregate market-level data, ignoring sector-level data, thus creating potential loss of industry-level information. So, future research may focus on this implication.

Stock market in Bangladesh has experienced two major catastrophes since its inception, one in 1996 and other in 2010. Our investigations have revealed that the catastrophe of 1996 has created a structural instability. Thus, the relationships between the stock market and the macroeconomic variables around the catastrophe of 1996, that is during the bubble and meltdown period of 1996, have been investigated. Also, the macroeconomic factors responsible for bubble creation and bubble burst have been identified. The further study may be carried out to examine the relationships around these two crises to compare the role of different macroeconomic factors around these two catastrophes.

Another important point is that this study is based on actual past data. However, the APT is based on the expected variables. Thus, there could be another research using the expected data estimated from actual past data for estimating the relationship between the stock market and macroeconomic variables in Bangladesh. For this purpose, the current data set could be derived from past data set with appropriate lag lengths. Then, expected variables might be estimated from one-period-ahead forecasts of the current data.

# **8.5 The Overall Conclusion**

In pursuit of the findings of this research, our intention was to draw the attention of investors, policymakers and regulators to what had happened in the stock market of Bangladesh from January 1991 to December 2015. Our analysis on twenty-five years data revealed that there existed a long-run equilibrium relationship, but a short-run disequilibrium between the stock market and the selected macroeconomic variables in Bangladesh. However, a small percentage of the stock market return could be explained by the selected macroeconomic variables, which disclosed the fact that there were other key factors which had significant explanatory power, but were not considered in the research. The empirical investigations also revealed that the stock market return Grangercaused only two macroeconomic variables, industrial production index and exchange rate, but the opposite was not true. No other causal relationship was found between stock market and macroeconomic variables, meaning that the stock market performance was not a leading indicator for most of the macroeconomic variables.

The bubble and bubble crash of 1996 had created structural instability in the stock market, but this instability was more prominent in the meltdown period. The exchange rate and the interest rate were found at least partially responsible for bubble creation as well as for the bubble burst. In addition, the explanatory power of the macroeconomic variables was the highest in the recovery period followed by the bubble period, and in the meltdown period this was the lowest. These results indicated that the stock market returns were sometimes partially driven by fad and fashions which were not related to the economic conditions. Interestingly, we did not find any structural instability around 2010, though a bubble was created at the end of 2010.

The stock market in Bangladesh did not show any leverage effect, meaning that negative news did not have higher impact on stock market volatility compared to good news. For the total sample period, there existed volatility clustering indicating that high volatility was followed by high volatility and low volatility was followed by low volatility. This volatility clustering might have occurred due to the bubble and bubble crash of 1996, which was confirmed from the results of recovery period, where we did not find any evidence of volatility clustering.

Moreover, stability test of the model showed structural instability in the total sample period as well as in the bubble and meltdown periods, which indicated that the volatility of the market was a problem in Bangladesh. This finding is justifiable in the case of emerging market mainly due to the dominance of non-institutional investors and the existence of information asymmetry problem among investors. These factors could contribute to the weak relationship between the stock market volatility and the macroeconomic volatility in Bangladesh.

The relationship between the stock market and the real sector of economy in recovery period was found stable and significant. The results of this period showed that the stock market led economic activity, which suggested that despite numerous reforms and automation initiatives Bangladesh stock market was not developed to that extent to play its due role to influence the real sector of the economy. The results indicated the inefficiency of the stock market in incorporating the information related to the economic growth in the stock prices.

The outcomes of the research are expected to offer regulators and policy makers some insights into the mistakes they have made in the past in formulating policies to regulate the stock market. Besides, they may get valuable information from this research in formulating different policies for ensuring and creating smooth trading and investment atmosphere, controlling market strategies and assessing the degree to which the stock market may need to be reformed. The investors and portfolio managers may also use the outcomes of this research in extending their understanding of the risk return relationship as well as pricing of macroeconomic risk. Moreover, considering the shortcomings of the research, we have also suggested some potential pathways for further research.

To sum up, it can be concluded that among the catastrophes of 1996 and 2010, structural instability is observed around 1996 only. The noteworthy outcome of the research is that it has brought out the macroeconomic factors which are at least partially responsible for the bubble and bubble crash of 1996. The findings have also indicated that our stock market is sometimes partially driven by fad and fashions, which are not related to the economic factors. The market volatility has showed instability throughout the period revealing that the volatility of the market is a problem in Bangladesh. Moreover, despite numerous reforms and automation initiatives the stock market is still not that developed to play its due role in influencing the real sector of economy of Bangladesh. These outcomes are expected to offer regulators and policy makers some insights into the mistakes they have made earlier in terms of formulating policies to regulate the stock market, which may help them to take future course of actions.

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# **Appendix A: Correlogram of Research Variables**

## **A 1 Correlogram of Log DSE General Index (LDSEGEN)** Sample: 1991M01 2015M12

Included observations: 300



## **A 2 Correlogram of 1st Difference of Log DSE General Index (DLDSEGEN)** Sample: 1991M01 2015M12

Included observations: 299



# **A 3 Correlogram of Log Industrial Production Index (LIPI)**

Sample: 1991M01 2015M12 Included observations: 300



## **A 4 Correlogram of 1st Difference of Log Industrial Production Index (DLIPI)** Sample: 1991M01 2015M12

Included observations: 299



### **A 5 Correlogram of Log Interest Rate (LINT)**

Sample: 1991M01 2015M12 Included observations: 300



### **A 6 Correlogram of 1st Difference of Log Interest Rate (DLINT)**



## **A 7 Correlogram of Log Consumer Price Index (LCPI)**

Sample: 1991M01 2015M12 Included observations: 300



### **A 8 Correlogram of 1st Difference of Log CPI (DLCPI)**



## **A 9 Correlogram of Log Exchange Rate (LEXR)**

Sample: 1991M01 2015M12 Included observations: 300



# **A 10 Correlogram of 1st Difference of Log Exchange Rate (DLEXR)**



# **A 11 Correlogram of Log Money Supply (LM2)**

Sample: 1991M01 2015M12 Included observations: 300



## **A 12 Correlogram of 1st Difference of Log Money Supply (DLM2)**



# **A 13 Correlogram of Log Gold Price (LGDPRICE)**

Sample: 1991M01 2015M12 Included observations: 300



#### **A 14 Correlogram of 1st Difference of Log Gold Price (DLGDPRICE)** Sample: 1991M01 2015M12

Included observations: 299



## **APPENDIX B: Stability of VAR and Optimal Lag Length Selection**

**Roots of Characteristic Polynomial** Endogenous variables: **LDSEGEN** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/26/16 Time: 23:45



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables: **LDSEGEN** Exogenous variables: **C @TREND** Sample: 1991M01 2015M12 Included observations: 292





\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial** Endogenous variables: **LDSEGEN** Exogenous variables: **C** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables: **LDSEGEN** Exogenous variables: **C** Sample: 1991M01 2015M12 Included observations: 292

Inverse Roots of AR Characteristic Polynomial



Lag LogL LR FPE AIC SC HQ -372.0815 NA 0.753878 2.555353 2.567945 2.560397 284.3725 1303.915 0.008464 -1.934058 -1.908875 -1.923971 288.0831 7.345111\* 0.008308\* -1.952624\* -1.914849\* -1.937493\*



\* indicates lag order selected by the criterion

**Roots of Characteristic Polynomial** Endogenous variables**: DLDSEGEN** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/26/16 Time: 23:49



No root lies outside the unit circle. VAR satisfies the stability condition.

**VAR Lag Order Selection Criteria**

Endogenous variables: **DLDSEGEN** Exogenous variables: **C @TREND** Date: 12/26/16 Time: 23:49 Sample: 1991M01 2015M12 Included observations: 291

Inverse Roots of AR Characteristic Polynomia





\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial** Endogenous variables: **DLDSEGEN** Exogenous variables: **C** Lag specification: 1 1



No root lies outside the unit circle.

VAR satisfies the stability condition.




#### **VAR Lag Order Selection Criteria**

Endogenous variables: DLDSEGEN Exogenous variables: C Date: 12/26/16 Time: 23:50 Sample: 1991M01 2015M12 Included observations: 291



\* indicates lag order selected by the criterion

## **Roots of Characteristic Polynomial**

Endogenous variables: **LIPI** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/26/16 Time: 23:51



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables**: LIPI** Exogenous variables: **C @TREND** Sample: 1991M01 2015M12 Included observations: 292



\* indicates lag order selected by the criterion

## **Roots of Characteristic Polynomial**



Inverse Roots of AR Characteristic Polynomia



Inverse Roots of AR Characteristic Polynomial



#### **VAR Lag Order Selection Criteria**

Endogenous variables: **LIPI** Exogenous variables: **C** Date: 12/26/16 Time: 23:57 Sample: 1991M01 2015M12 Included observations: 292



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial**

Endogenous variables: **DLIPI** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/26/16 Time: 23:58







No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables: DLIPI Exogenous variables: C @TREND Sample: 1991M01 2015M12 Included observations: 291



\* indicates lag order selected by the criterion

### **Roots of Characteristic Polynomial**

Endogenous variables: **DLIPI** Exogenous variables: **C** Lag specification: 1 1 Date: 12/26/16 Root Modulus -0.164650 0.164650

No root lies outside the unit circle.

### Inverse Roots of AR Characteristic Polynomial



#### **VAR Lag Order Selection Criteria** Endogenous variables: **DLIPI** Exogenous variables: **C** Date: 12/26/16 Time: 23:59 Sample: 1991M01 2015M12

Included observations: 291



\* indicates lag order selected by the criterion

## **Roots of Characteristic Polynomial**

Endogenous variables: **LINT** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/26/16 Time: 23:59



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables: **LINT** Exogenous variables: **C @TREND** Date: 12/27/16 Time: 00:00 Sample: 1991M01 2015M12 Included observations: 292

Inverse Roots of AR Characteristic Polynomial





\* indicates lag order selected by the criterion



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: DLINT Exogenous variables: C @TREND** Lag specification: 1 1 Date: 12/27/16 Time: 00:02



No root lies outside the unit circle. VAR satisfies the stability condition.

Inverse Roots of AR Characteristic Polynomial



## **VAR Lag Order Selection Criteria** Endogenous variables: **DLINT** Exogenous variables: **C @TREND** Date: 12/27/16 Time: 00:02 Sample: 1991M01 2015M12 Included observations: 291



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial**

Endogenous variables: **DLINT** Exogenous variables: **C** Lag specification: 1 1 Date: 12/27/16 Time: 00:02



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables: **DLINT** Exogenous variables: **C** Date: 12/27/16 Time: 00:02 Sample: 1991M01 2015M12 Included observations: 291

Inverse Roots of AR Characteristic Polynomial





\* indicates lag order selected by the criterion



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial**

Endogenous variables: **LCPI** Exogenous variables: **C** Lag specification: 1 1 Date: 12/27/16 Time: 00:04



Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

Inverse Roots of AR Characteristic Polynomial



## **Roots of Characteristic Polynomial** Endogenous variables: **DLCPI** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/27/16 Time: 00:05



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables: **DLCPI** Exogenous variables**: C @TREND** Date: 12/27/16 Time: 00:05 Sample: 1991M01 2015M12 Included observations: 284





\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial**

Endogenous variables: **DLCPI** Exogenous variables: **C** Lag specification: 1 1 Date: 12/27/16 Time: 00:06

Root Modulus 0.239669 0.239669

No root lies outside the unit circle.

VAR satisfies the stability condition.

#### Inverse Roots of AR Characteristic Polynomial



#### **VAR Lag Order Selection Criteria** Endogenous variables**: DLCPI** Exogenous variables: **C** Date: 12/27/16 Time: 00:06 Sample: 1991M01 2015M12 Included observations: 284



\* indicates lag order selected by the criterion



# VAR satisfies the stability condition. **VAR Lag Order Selection Criteria**

Endogenous variables: LEXR Exogenous variables: **C @TREND** Date: 12/27/16 Time: 00:08 Included observations: 292

Inverse Roots of AR Characteristic Polynomial





\* indicates lag order selected by the criterion



Endogenous variables: **DLEXR**

Exogenous variables: **C @TREND** Date: 12/27/16 Time: 00:09 Included observations: 291





Lag LogL LR FPE AIC SC HQ

\* indicates lag order selected by the criterion



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial**

Endogenous variables: **LM2** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/27/16 Time: 00:10



No root lies outside the unit circle. VAR satisfies the stability condition.

Inverse Roots of AR Characteristic Polynomial



## **VAR Lag Order Selection Criteria** Endogenous variables: **LM2** Exogenous variables: **C @TREND** Date: 12/27/16 Time: 00:11 Included observations: 285



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial**

Endogenous variables: **LM2** Exogenous variables: **C** Lag specification: 1 1 Date: 12/27/16 Time: 00:11



Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

## **Roots of Characteristic Polynomial**

Endogenous variables**: DLM2** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/27/16 Time: 00:12 Root Modulus



No root lies outside the unit circle. VAR satisfies the stability condition. Inverse Roots of AR Characteristic Polynomial



Inverse Roots of AR Characteristic Polynomial



## **VAR Lag Order Selection Criteria**

Endogenous variables: **DLM2** Exogenous variables: **C @TREND**

Included observations: 284



\* indicates lag order selected by the criterion

## **Roots of Characteristic Polynomial**

Endogenous variables: **DLM2** Exogenous variables: **C** Lag specification: 1 1



VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria**

Endogenous variables: **DLM2** Exogenous variables: **C**

Included observations: 284







\* indicates lag order selected by the criterion

#### Endogenous variables: **LGDPRICE** Exogenous variables: **C @TREND** Lag specification: 1 1 Date: 12/27/16 Time: 00:13 Root Modulus 0.984872 0.984872 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria** Endogenous variables: **LGDPRICE** Exogenous variables: **C @TREND** Date: 12/27/16 Time: 00:14 Sample: 1991M01 2015M12 Included observations: 292 Lag LogL LR FPE AIC SC HQ 0 -81.61673 NA 0.103813 0.572717 0.597901 0.582805 1 490.4677 1132.414 0.002077 -3.338820 -3.301045\* -3.323689 2 492.6417 4.288265 0.002061 -3.346861 -3.296494 -3.326686 3 493.7281 2.135732 0.002059 -3.347453 -3.284495 -3.322234 4 495.2901 3.059712 0.002052 -3.351302 -3.275752 -3.321040 5 497.9886 5.267576\* 0.002028\* -3.362935\* -3.274794 -3.327629\* 6 498.9231 1.817871 0.002029 -3.362487 -3.261754 -3.322137 7 499.1989 0.534540 0.002039 -3.357526 -3.244202 -3.312133 8 499.7057 0.978941 0.002046 -3.354149 -3.228232 -3.303712 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 Inverse Roots of AR Characteristic Polynomial

\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial** Endogenous variables: **LGDPRICE** Exogenous variables: **C** Lag specification: 1 1 Date: 12/27/16 Time: 00:14 Root Modulus 1.000867 1.000867

Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

Inverse Roots of AR Characteristic Polynomial



# **Roots of Characteristic Polynomial**



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial**

Endogenous variables: DLGDPRICE Exogenous variables: C Lag specification: 1 1 Date: 12/27/16 Time: 00:15



No root lies outside the unit circle. VAR satisfies the stability condition.

Inverse Roots of AR Characteristic Polynomial



## **VAR Lag Order Selection Criteria**

Endogenous variables: DLGDPRICE Exogenous variables: C Date: 12/27/16 Time: 00:15 Sample: 1991M01 2015M12 Included observations: 291



\* indicates lag order selected by the criterion

## **APPENDIX C: Unit Root Tests**

## **C 1 ADF Unit Root Tests**

## **C 1.1 ADF Unit Root Tests on Log DSE General Index**

## **Null Hypothesis: LDSEGEN has a unit root** Exogenous: **Constant, Linear Trend**

Lag Length: 2 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 12/27/16 Time: 21:24 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



#### **Null Hypothesis: LDSEGEN has a unit root**

Exogenous: **Constant**

Lag Length: 2 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 12/27/16 Time: 21:25 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



## **C 1.2 ADF Unit Root Tests on 1st Difference of Log DSE General Index**

**Null Hypothesis: D(LDSEGEN) has a unit root** Exogenous: **Constant, Linear Trend**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN,2) Method: Least Squares Date: 12/27/16 Time: 21:25 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



 $\sim 10^{-1}$ 

## **C 1.3 ADF Unit Root Tests on Log Industrial Production Index**

**Null Hypothesis: LIPI has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 6 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LIPI) Method: Least Squares Date: 12/27/16 Time: 21:26 Sample (adjusted): 1991M08 2015M12 Included observations: 293 after adjustments



## **Null Hypothesis: LIPI has a unit root**

Exogenous**: Constant** Lag Length: 6 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LIPI) Method: Least Squares Sample (adjusted): 1991M08 2015M12 Included observations: 293 after adjustments



## **C 1.4 ADF Unit Roots Tests on 1st Difference of Log Industrial Production Index**

**Null Hypothesis: D(LIPI) has a unit root** Exogenous: **Constant, Linear Trend**

Lag Length: 5 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LIPI,2) Method: Least Squares Sample (adjusted): 1991M08 2015M12 Included observations: 293 after adjustments



## **C 1.5 ADF Unit Root Tests on Log Interest Rate**

**Null Hypothesis: LINT has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 6 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT) Method: Least Squares Sample (adjusted): 1991M08 2015M12 Included observations: 293 after adjustments



#### **Null Hypothesis: LINT has a unit root**

Exogenous: **Constant**

Lag Length: 10 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT) Method: Least Squares Sample (adjusted): 1991M12 2015M12 Included observations: 289 after adjustments





## **C 1.6 ADF Unit Root Tests on 1st Difference of Log Interest Rate**

## **Null Hypothesis: D(LINT) has a unit root** Exogenous: **Constant, Linear Trend**

Lag Length: 5 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Sample (adjusted): 1991M08 2015M12 Included observations: 293 after adjustments



## **C 1.7 ADF Unit Root Tests on Log Consumer Price Index**

**Null Hypothesis: LCPI has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 10 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI) Method: Least Squares Date: 12/27/16 Time: 21:33 Sample (adjusted): 1991M12 2015M12 Included observations: 289 after adjustments



## **C 1.8 ADF Unit Root Tests on 1st Difference of Log Consumer Price Index**

## **Null Hypothesis: D(LCPI) has a unit root**

Exogenous: Constant, Linear Trend Lag Length: 12 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Dependent Variable: D(LCPI,2) Method: Least Squares Date: 12/27/16 Time: 21:33 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments



## **C 1.9 ADF Unit Root Tests on Log Exchange Rate**

#### **Null Hypothesis: LEXR has a unit root**

Exogenous: Constant, Linear Trend Lag Length: 1 (Fixed)





\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 12/27/16 Time: 21:34 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments





## **Null Hypothesis: LEXR has a unit root**

Exogenous: **Constant**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR) Method: Least Squares Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



## **C 1.10 ADF Unit Root Tests on 1st Difference of Log Exchange Rate**

**Null Hypothesis: D(LEXR) has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 0 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 12/27/16 Time: 21:34 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



## **C 1.11 ADF Unit Root Tests on Log Money Supply**

**Null Hypothesis: LM2 has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 13 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 12/27/16 Time: 21:35 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments





## **C 1.12 ADF Unit Root Tests on 1st Difference of Log Money Supply**

**Null Hypothesis: D(LM2) has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 12 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 12/27/16 Time: 21:35 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments



## **Null Hypothesis: D(LM2) has a unit root** Exogenous: **Constant** Lag Length: 12 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 12/28/16 Time: 21:11 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments



## **C 1.13 ADF Unit Root Tests on 2nd Difference of Log Money Supply**

**Null Hypothesis: D(LM2,2) has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 7 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,3) Method: Least Squares Sample (adjusted): 1991M11 2015M12 Included observations: 290 after adjustments



## **C 1.14 ADF Unit Root Tests on Gold Price**

### **Null Hypothesis: LGDPRICE has a unit root** Exogenous: **Constant, Linear Trend** Lag Length: 5 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Sample (adjusted): 1991M07 2015M12 Included observations: 294 after adjustments





## **C 1.15 ADF Unit Root Tests on 1st Difference of Log Gold Price Null Hypothesis: D(LGDPRICE) has a unit root**

Exogenous: **Constant, Linear Trend** Lag Length: 4 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE,2) Method: Least Squares Sample (adjusted): 1991M07 2015M12 Included observations: 294 after adjustments



## **C 2 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Unit Root Tests**

## **C 2.1 KPSS Unit Root Tests on Log DSE General Index**

## **Null Hypothesis: LDSEGEN is stationary**

Exogenous: Constant, Linear Trend

Bandwidth: 2 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: LDSEGEN Method: Least Squares Date: 12/27/16 Time: 21:40 Sample: 1991M01 2015M12 Included observations: 300



#### **C 2.2 KPSS Unit Root Tests on 1 st Difference of Log DSE General Index**

## **Null Hypothesis: D(LDSEGEN) is stationary** Exogenous: **Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel







## **Null Hypothesis: D(LDSEGEN) is stationary**

## Exogenous: **Constant**

Bandwidth: 1 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 12/27/16 Time: 21:41 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



## **C 2.3 KPSS Unit Root Tests on Log Industrial Production Index**

## **Null Hypothesis: LIPI is stationary**

Exogenous: **Constant, Linear Trend**

Bandwidth: 6 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: LIPI Method: Least Squares Date: 12/27/16 Time: 21:41 Sample: 1991M01 2015M12 Included observations: 300



## **C 2.4 KPSS Unit Root Tests on 1st Difference of Log Industrial Production Index**

## **Null Hypothesis: D(LIPI) is stationary**

Exogenous: **Constant, Linear Trend**

Bandwidth: 5 (Used-specified) using Bartlett kernel



Residual variance (no correction)<br>
HAC corrected variance (Bartlett kernel)<br>
0.001177 HAC corrected variance (Bartlett kernel)

## KPSS Test Equation Dependent Variable: D(LIPI) Method: Least Squares Date: 12/27/16 Time: 21:41 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



## **Null Hypothesis: D(LIPI) is stationary**

Exogenous: **Constant**

Bandwidth: 5 (Used-specified) using Bartlett kernel



Method: Least Squares Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



## **C 2.5 KPSS Unit Root Tests on Log of Interest Rate**

## **Null Hypothesis: LINT is stationary**

Exogenous: **Constant, Linear Trend** Bandwidth: 6 (Used-specified) using Bartlett kernel



Method: Least Squares Sample: 1991M01 2015M12 Included observations: 300





## **C 2.6 KPSS Unit Root Tests on 1st Difference of Log of Interest Rate**

## **Null Hypothesis: D(LINT) is stationary**

## Exogenous: **Constant, Linear Trend**

Bandwidth: 5 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 12/27/16 Time: 21:42 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



## **Null Hypothesis: D(LINT) is stationary**

Exogenous: **Constant**

Bandwidth: 5 (Used-specified) using Bartlett kernel





\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: D(LINT) Method: Least Squares Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



## **C 2.7 KPSS Unit Root Tests on Log of Consumer Price Index**

## **Null Hypothesis: LCPI is stationary**

Exogenous: **Constant, Linear Trend**

Bandwidth: 10 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: LCPI Method: Least Squares Sample: 1991M01 2015M12 Included observations: 300



## **C 2.8 KPSS Unit Root Tests on 1st Difference of Log of Consumer Price Index**

# **Null Hypothesis: D(LCPI) is stationary**

Exogenous: **Constant, Linear Trend**

Bandwidth: 12 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LCPI) Method: Least Squares Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



## **Null Hypothesis: D(LCPI) is stationary**

Exogenous: **Constant**

Bandwidth: 12 (Used-specified) using Bartlett kernel




### **C 2.9 KPSS Unit Root Tests on Log of Exchange Rate**

## **Null Hypothesis: LEXR is stationary**

Exogenous**: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel



HAC corrected variance (Bartlett kernel) 0.004492

KPSS Test Equation Dependent Variable: LEXR Method: Least Squares Sample: 1991M01 2015M12 Included observations: 300



#### **C 2.10 KPSS Unit Root Tests on 1st Difference of Log of Exchange Rate**

**Null Hypothesis: D(LEXR) is stationary**

Exogenous: **Constant, Linear Trend**

Bandwidth: 0 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: D(LEXR) Method: Least Squares Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



#### **Null Hypothesis: D(LEXR) is stationary** Exogenous: **Constant**

Bandwidth: 0 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: D(LEXR) Method: Least Squares Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



#### **C 2.11 KPSS Unit Root Tests on Log of Money Supply**

## **Null Hypothesis: LM2 is stationary**

Exogenous: **Constant, Linear Trend**

Bandwidth: 13 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: LM2 Method: Least Squares Sample: 1991M01 2015M12 Included observations: 300



#### **C 2.12 KPSS Unit Root Tests on 1st Difference of Log of Money Supply**

#### **Null Hypothesis: D(LM2) is stationary**

Exogenous: **Constant, Linear Trend**

Bandwidth: 12 (Used-specified) using Bartlett kernel







#### **Null Hypothesis: D(LM2) is stationary**

### Exogenous**: Constant**

Bandwidth: 12 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 12/27/16 Time: 21:46 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



#### **C 2.13 KPSS Unit Root Tests on Log of Gold Price**

Null Hypothesis: LGDPRICE is stationary Exogenous: Constant, Linear Trend Bandwidth: 5 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: LGDPRICE Method: Least Squares Date: 12/27/16 Time: 21:47 Sample: 1991M01 2015M12 Included observations: 300



## **C 2.14 KPSS Unit Root Tests on 1st Difference of Log of Gold Price**

#### **Null Hypothesis: D(LGDPRICE) is stationary** Exogenous: **Constant, Linear Trend**

Bandwidth: 4 (Used-specified) using Bartlett kernel





KPSS Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 12/27/16 Time: 21:47 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



### **Null Hypothesis: D(LGDPRICE) is stationary**

Exogenous: **Constant**

Bandwidth: 4 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments



## **C 3 Phillips-Perron (PP) Unit Root Tests**

#### **C 3.1 PP Unit Root Tests on Log Money Supply**

#### **Null Hypothesis: LM2 has a unit root**

Exogenous: **Constant, Linear Trend**

@TREND("1991M01")

Bandwidth: 46 (Newey-West automatic) using Bartlett kernel



C 0.095463 0.046078 2.071759 0.0392



#### **C 3.2 PP Unit Root Tests on 1 st Difference of Log Money Supply**

# **Null Hypothesis: D(LM2) has a unit root**

Exogenous: **Constant, Linear Trend** Bandwidth: 12 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments





## **Appendix D: Optimal Lag Selection for Johansen Cointegration Test**

No root lies outside the unit circle.

VAR satisfies the stability condition.

VAR Lag Order Selection Criteria Endogenous variables: LDSEGEN LIPI LINT LCPI LEXR LM2 LGDPRICE Exogenous variables: C @TREND Date: 12/30/16 Time: 20:42 Sample: 1991M01 2015M12 Included observations: 285



\* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

## **APPENDIX E: Johansen and Juselius Cointegration Test**

## **E 1 Results of Cointegration Test**

Date: 11/19/16 Time: 23:21 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments Trend assumption: Linear deterministic trend (restricted) Series: LDSEGEN LIPI LINT LCPI LEXR LM2 LGDPRICE Lags interval (in first differences): 1 to 13



Unrestricted Cointegration Rank Test (Trace)

Trace test indicates 4 cointegrating eqn(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values



Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'\*S11\*b=I):



D(LDSEGEN) D(LIPI)	0.020182 $-0.000573$	0.011538 0.002797	$-0.000265$ 0.006518	$-0.010156$ $-0.002611$	$-0.000171$ $-0.000708$		$-0.000727$ $-0.005971$	0.006691 $-0.002819$
D(LINT)	$-0.000240$	$-0.000564$	7.47E-05	$-0.000351$	0.000192		$-1.51E-05$	0.000125
D(LCPI)	3.80E-05	$-0.000320$	$-0.000203$	$-0.001082$	$-0.000789$		0.000488	$-0.000541$
D(LEXR)	0.000181	$-0.000366$	0.002215	0.000200	$-0.000366$		0.000844	9.90E-05
D(LM2)	0.000500	$-0.000510$	4.47E-05	0.000236	$-0.001230$		$-0.000837$	0.000214
D(LGDPRICE)	$-0.010963$	0.006031	0.001066	$-0.001030$	$-0.002693$		0.000700	0.002649
1 Cointegrating Equation(s):		Log likelihood		5805.098				
Normalized cointegrating coefficients (standard error in parentheses)								
<b>LDSEGEN</b>	<b>LIPI</b>	<b>LINT</b>	<b>LCPI</b>	<b>LEXR</b>	LM <sub>2</sub>	<b>LGDPRICE</b>		@TREND(91M02)
1.000000	$-4.042541$	$-5.995813$	5.239176	6.993263	5.329227	$-1.738619$		$-0.079734$
	(1.33278)	(3.99603)	(1.54830)	(0.90389)	(1.66524)	(0.32970)		(0.01499)
Adjustment coefficients (standard error in parentheses)								
D(LDSEGEN)	$-0.153014$							
	(0.04229)							
D(LIPI)	0.004341							
	(0.02092)							
D(LINT)	0.001823							
	(0.00129)							
D(LCPI)	$-0.000288$							
	(0.00350)							
D(LEXR)	$-0.001370$							
	(0.00422)							
D(LM2)	$-0.003792$							
	(0.00356)							
D(LGDPRICE)	0.083118							
	(0.01953)							
2 Cointegrating Equation(s):		Log likelihood		5824.294				

Unrestricted Adjustment Coefficients (alpha):











## **E 2 Significance of Cointegrating Coefficients**

Vector Error Correction Estimates Date: 11/19/16 Time: 23:42 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments Standard errors in ( ) & t-statistics in [ ]

## **Cointegration Restrictions:**

**B(1,2)=0** Convergence achieved after 22 iterations. Not all cointegrating vectors are identified LR test for binding restrictions (rank = 1):<br>Chi-square(1)  $4.110282$ Chi-square(1) 4.110282<br>Probability 0.042623 Probability



## **Cointegration Restrictions:**

**B(1,3)=0**

Convergence achieved after 16 iterations. Not all cointegrating vectors are identified LR test for binding restrictions (rank = 1):<br>Chi-square(1)  $1.291469$  $Chi-square(1)$ Probability 0.255777



#### **Cointegration Restrictions: B(1,4)=0**

Convergence achieved after 33 iterations. Not all cointegrating vectors are identified LR test for binding restrictions (rank  $= 1$ ): Chi-square(1) 6.333333<br>Probability 0.011849 Probability



# **Cointegration Restrictions:**

## **B(1,5)=0**

## **Convergence achieved after 124 iterations.**

Not all cointegrating vectors are identified LR test for binding restrictions (rank = 1): Chi-square(1) 14.22177<br>Probability 0.000162 Probability



## **Cointegration Restrictions:**

#### **B(1,6)=0**

 $\equiv$ 

Convergence achieved after 24 iterations. Not all cointegrating vectors are identified LR test for binding restrictions (rank =  $1$ ): Chi-square(1) 4.918124 Probability 0.026576 Cointegrating Eq: CointEq1



## **Cointegration Restrictions:**

## **B(1,7)=0**

Convergence achieved after 59 iterations. Not all cointegrating vectors are identified LR test for binding restrictions (rank  $= 1$ ): Chi-square(1) 11.17695 Probability 0.000828



**E 3 Vector Error Correction Estimates E 3.1 Long and Short-Term Equation Estimation** Dependent Variable: D(LDSEGEN) Method: Least Squares (Gauss-Newton / Marquardt steps) Date: 11/20/16 Time: 23:48 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments D(LDSEGEN) = C(1)\*( LDSEGEN(-1) - 4.04254061888\*LIPI(-1) - 5.99581318154\*LINT(-1) + 5.23917593595\*LCPI(-1) + 6.99326292363 \*LEXR(-1) + 5.32922712656\*LM2(-1) - 1.73861861672\*LGDPRICE(-1) - 0.0797336257223\*@TREND(91M01) - 58.4801737269 ) + C(2) \*D(LDSEGEN(-1)) + C(3)\*D(LDSEGEN(-2)) + C(4)\*D(LDSEGEN(-3)) + C(5)\*D(LDSEGEN(-4)) + C(6)\*D(LDSEGEN(-5)) + C(7)\*D(LDSEGEN( -6)) + C(8)\*D(LDSEGEN(-7)) + C(9)\*D(LDSEGEN(-8)) + C(10) \*D(LDSEGEN(-9)) + C(11)\*D(LDSEGEN(-10)) + C(12)\*D(LDSEGEN( -11)) + C(13)\*D(LDSEGEN(-12)) + C(14)\*D(LDSEGEN(-13)) + C(15) \*D(LIPI(-1)) + C(16)\*D(LIPI(-2)) + C(17)\*D(LIPI(-3)) + C(18)\*D(LIPI(-4)) + C(19)\*D(LIPI(-5)) + C(20)\*D(LIPI(-6)) + C(21)\*D(LIPI(-7)) + C(22) \*D(LIPI(-8)) + C(23)\*D(LIPI(-9)) + C(24)\*D(LIPI(-10)) + C(25)\*D(LIPI( -11)) + C(26)\*D(LIPI(-12)) + C(27)\*D(LIPI(-13)) + C(28)\*D(LINT(-1)) +  $C(29)^*D(LINT(-2)) + C(30)^*D(LINT(-3)) + C(31)^*D(LINT(-4)) + C(32)$ \*D(LINT(-5)) + C(33)\*D(LINT(-6)) + C(34)\*D(LINT(-7)) + C(35)\*D(LINT(  $-8$ )) + C(36)\*D(LINT(-9)) + C(37)\*D(LINT(-10)) + C(38)\*D(LINT(-11)) +  $C(39)^*D(LINT(-12)) + C(40)^*D(LINT(-13)) + C(41)^*D(LCPI(-1)) + C(42)$ \*D(LCPI(-2)) + C(43)\*D(LCPI(-3)) + C(44)\*D(LCPI(-4)) + C(45)\*D(LCPI(  $(-5)$ ) + C(46)\*D(LCPI(-6)) + C(47)\*D(LCPI(-7)) + C(48)\*D(LCPI(-8)) +  $C(49)^*D(LCPI(-9)) + C(50)^*D(LCPI(-10)) + C(51)^*D(LCPI(-11)) + C(52)$ \*D(LCPI(-12)) + C(53)\*D(LCPI(-13)) + C(54)\*D(LEXR(-1)) + C(55) \*D(LEXR(-2)) + C(56)\*D(LEXR(-3)) + C(57)\*D(LEXR(-4)) + C(58) \*D(LEXR(-5)) + C(59)\*D(LEXR(-6)) + C(60)\*D(LEXR(-7)) + C(61) \*D(LEXR(-8)) + C(62)\*D(LEXR(-9)) + C(63)\*D(LEXR(-10)) + C(64) \*D(LEXR(-11)) + C(65)\*D(LEXR(-12)) + C(66)\*D(LEXR(-13)) + C(67) \*D(LM2(-1)) + C(68)\*D(LM2(-2)) + C(69)\*D(LM2(-3)) + C(70)\*D(LM2(-4)) + C(71)\*D(LM2(-5)) + C(72)\*D(LM2(-6)) + C(73)\*D(LM2(-7)) + C(74) \*D(LM2(-8)) + C(75)\*D(LM2(-9)) + C(76)\*D(LM2(-10)) + C(77)\*D(LM2( -11)) + C(78)\*D(LM2(-12)) + C(79)\*D(LM2(-13)) + C(80)\*D(LGDPRICE( -1)) + C(81)\*D(LGDPRICE(-2)) + C(82)\*D(LGDPRICE(-3)) + C(83) \*D(LGDPRICE(-4)) + C(84)\*D(LGDPRICE(-5)) + C(85)\*D(LGDPRICE(  $-6$ )) + C(86)\*D(LGDPRICE(-7)) + C(87)\*D(LGDPRICE(-8)) + C(88) \*D(LGDPRICE(-9)) + C(89)\*D(LGDPRICE(-10)) + C(90)\*D(LGDPRICE( -11)) + C(91)\*D(LGDPRICE(-12)) + C(92)\*D(LGDPRICE(-13)) + C(93)







#### **E 3.2 Significance of Short-run Coefficients**

**E 3.2.1 Industrial Production Index**

Wald Test: Equation: Untitled



```
Null Hypothesis: C(15)=C(16)=C(17)=C(18)=C(19)=C(20)=
```
**C(21)=C(22)=C(23)=C(24)=C(25)=C(26)=C(27)=0**

**Null Hypothesis Summary:**



Restrictions are linear in coefficients.

#### **E 3.2.2 Interest Rate**

Wald Test:



## Appendix E 333



Restrictions are linear in coefficients.

#### **E 3.2.3 Consumer Price Index**

Wald Test:

Equation: Untitled



**Null Hypothesis: C(41)=C(42)=C(43)=C(44)=C(45)=C(46)= C(47)=C(48)=C(49)=C(50)=C(51)=C(52)=C(53)=0 Null Hypothesis Summary:**



Restrictions are linear in coefficients.

#### **E 3.2.4 Exchange Rate**





**Null Hypothesis: C(54)=C(55)=C(56)=C(57)=C(58)=C(59)= C(60)=C(61)=C(62)=C(63)=C(64)=C(65)=C(66)=0 Null Hypothesis Summary:**



## Appendix E 334



Restrictions are linear in coefficients.

### **E 3.2.5 Money Supply**

Wald Test: Equation: Untitled



#### **Null Hypothesis: C(67)=C(68)=C(69)=C(70)=C(71)=C(72)= C(73)=C(74)=C(75)=C(76)=C(77)=C(78)=C(79)=0 Null Hypothesis Summary:**



Restrictions are linear in coefficients.

### **E 3.2.6 Gold Price**





**Null Hypothesis: C(80)=C(81)=C(82)=C(83)=C(84)=C(85)= C(86)=C(87)=C(88)=C(89)=C(90)=C(91)=C(92)=0 Null Hypothesis Summary:**



# Appendix E 335



Restrictions are linear in coefficients.

## **APPENDIX F: Viability Check of the Model**

## **F 1 Correlogram of the Residuals**

Date: 11/21/16 Time: 00:01 Sample: 1991M01 2015M12 Included observations: 286



## **F 2 Normality Test of the Residuals**



#### F-statistic 0.662436 Prob. F(13,180) 0.7977<br>Obs\*R-squared 13.05825 Prob. Chi-Square(13) 0.4433 Prob. Chi-Square(13) Test Equation: Dependent Variable: RESID Method: Least Squares Date: 11/25/16 Time: 18:35 Sample: 1992M03 2015M12 Included observations: 286<br>Presample missing value la Presample missing value lagged residuals set to zero.  $\blacksquare$ Variable Coefficient Std. Error t-Statistic Prob.  $\overline{a}$ C(1) 0.092883 0.080882 1.148378 0.2523 C(2) 0.177512 0.417690 0.424986 0.6714 C(3) 0.160850 0.371050 0.433500 0.6652



## **F 3 Breusch-Godfrey Serial Correlation LM Test:**



R

F

## **F 4 Heteroscedasticity Test: Breusch-Pagan-Godfrey**



Dependent Variable: RESID^2 Method: Least Squares Date: 11/25/16 Time: 18:38 Sample: 1992M03 2015M12 Included observations: 286





## **APPENDIX G: Granger Causality Test**

#### **VEC Granger Causality/Block Exogeneity Wald Tests**

Sample: 1991M01 2015M12 Included observations: 287

# **Dependent variable: D(LDSEGEN)** Excluded Chi-sq df Prob. D(LIPI) 8.324574 12 0.7593 D(LINT) 4.883428 12 0.9618 D(LCPI) 11.36160 12 0.4982 D(LEXR) 4.698369 12 0.9673 D(LM2) 12.67572 12 0.3930 D(LGDPRICE) 6.075535 12 0.9122 All 48.19141 72 0.9861 **Dependent variable: D(LIPI)** Excluded Chi-sq df Prob. **D(LDSEGEN) 33.57122 12 0.0008** D(LINT) 24.53852 12 0.0172 D(LCPI) 9.594977 12 0.6514 D(LEXR) 19.63923 12 0.0742 D(LM2) 34.56602 12 0.0005 D(LGDPRICE) 19.02375 12 0.0880 All 140.2462 72 0.0000 **Dependent variable: D(LINT)** Excluded Chi-sq df Prob. D(LDSEGEN) 17.24099 12 0.1408 D(LIPI) 10.37142 12 0.5834 D(LCPI) 13.72147 12 0.3188 D(LEXR) 47.56735 12 0.0000 D(LM2) 11.84145 12 0.4585 D(LGDPRICE) 16.41006 12 0.1732 All 131.3906 72 0.0000 **Dependent variable: D(LCPI)** Excluded Chi-sq df Prob. D(LDSEGEN) 12.33650 12 0.4190 D(LIPI) 19.30204 12 0.0815 D(LINT) 7.828167 12 0.7984 D(LEXR) 4.186493 12 0.9798

D(LM2) 12.02703 12 0.4435 D(LGDPRICE) 7.320290 12 0.8357

All 63.27458 72 0.7588



## **Dependent variable: D(LEXR)**

## **Appendix H: ARDL Test**

## **H 1 Dependent Variable: LDSEGEN Method: ARDL**

Sample (adjusted): 1992M01 2015M12 Included observations: 288 after adjustments Dependent lags: 12 (Fixed) Dynamic regressors (5 lags, fixed): LIPI LCPI LEXR LM2 LGDPRICE Fixed regressors: C @TREND



\*Note: p-values and any subsequent tests do not account for model selection

### **H 2 ARDL Bounds Test**

Date: 02/20/17 Time: 10:31 Sample: 1992M01 2015M12 Included observations: 288

## **Null Hypothesis: No long-run relationships exist**



#### Critical Value Bounds



Test Equation:

#### **Dependent Variable: D(LDSEGEN) Method: Least Squares** Date: 02/20/17 Time: 10:31 Sample: 1992M01 2015M12 Included observations: 288





#### **H 3 ARDL Cointegrating And Long Run Form Dependent Variable: LDSEGEN**

**Selected Model: ARDL(12, 5, 5, 5, 5, 5)** Date: 04/14/17 Time: 22:35 Sample: 1991M01 2015M12 Included observations: 288







#### **H 4 VECM Results for Significance Test of the Coefficients**

#### **Estimation Command:**

========================= LS DLDSEGEN D(LDSEGEN(-1)) D(LDSEGEN(-2)) D(LDSEGEN(-3)) D(LDSEGEN(-4)) D(LDSEGEN(-5)) D(LDSEGEN(-6)) D(LDSEGEN(-7)) D(LDSEGEN(-8)) D(LDSEGEN(-9)) D(LDSEGEN(-10)) D(LDSEGEN(- 11)) D(LIPI) D(LIPI(-1)) D(LIPI(-2)) D(LIPI(-3)) D(LIPI(-4)) D(LCPI) D(LCPI(-1)) D(LCPI(-2)) D(LCPI(-3))  $D(\overleftrightarrow{LCPI(-4)})$   $D(\overleftrightarrow{LEXR})$   $D(\overleftrightarrow{LEXR(-1)})$   $D(\overleftrightarrow{LEXR(-3)})$   $D(\overleftrightarrow{LEXR(-4)})$   $D(\overleftrightarrow{LM2})$   $D(\overleftrightarrow{LM2(-1)})$   $D(\overleftrightarrow{LM2(-2)})$ D(LM2(-3)) D(LM2(-4)) D(LGDPRICE) D(LGDPRICE(-1)) D(LGDPRICE(-2)) D(LGDPRICE(-3)) D(LGDPRICE(-4)) C @TREND LIPI(-1) LCPI(-1) LEXR(-1) LM2(-1) LGDPRICE(-1) LDSEGEN(-1)

#### **Estimation Equation:**

========================= DLDSEGEN = C(1)\*D(LDSEGEN(-1)) + C(2)\*D(LDSEGEN(-2)) + C(3)\*D(LDSEGEN(-3)) + C(4)\*D(LDSEGEN(-4)) + C(5)\*D(LDSEGEN(-5)) + C(6)\*D(LDSEGEN(-6)) + C(7)\*D(LDSEGEN(-7)) + C(8)\*D(LDSEGEN(-8)) + C(9)\*D(LDSEGEN(-9)) + C(10)\*D(LDSEGEN(-10)) + C(11)\*D(LDSEGEN(-11)) + C(12)\*D(LIPI) + C(13)\*D(LIPI(-1)) + C(14)\*D(LIPI(-2)) + C(15)\*D(LIPI(-3)) + C(16)\*D(LIPI(-4)) + C(17)\*D(LCPI) + C(18)\*D(LCPI(-1)) + C(19)\*D(LCPI(-2)) + C(20)\*D(LCPI(-3)) + C(21)\*D(LCPI(-4)) + C(22)\*D(LEXR) + C(23)\*D(LEXR(-1)) + C(24)\*D(LEXR(-2)) + C(25)\*D(LEXR(-3)) + C(26)\*D(LEXR(-4)) + C(27)\*D(LM2) + C(28)\*D(LM2(-1)) + C(29)\*D(LM2(-2)) + C(30)\*D(LM2(-3)) + C(31)\*D(LM2(-4)) +  $C(32)^*D(LGDPRICE) + C(33)^*D(LGDPRICE(-1)) + C(34)^*D(LGDPRICE(-2)) + C(35)^*D(LGDPRICE(-3)) +$ C(36)\*D(LGDPRICE(-4)) + C(37) + C(38)\*@TREND + C(39)\*LIPI(-1) + C(40)\*LCPI(-1) + C(41)\*LEXR(-1) +  $C(42)^*LM2(-1) + C(43)^*LGDPRICE(-1) + C(44)^*LDSEGEN(-1)$ 

#### **Substituted Coefficients:**

========================= DLDSEGEN = 0.18590260982\*D(LDSEGEN(-1)) + 0.0728933053537\*D(LDSEGEN(-2)) + 0.123865273807\*D(LDSEGEN(-3)) + 0.106481071258\*D(LDSEGEN(-4)) - 0.0327983107168\*D(LDSEGEN(-5)) - 0.0301766843322\*D(LDSEGEN(-6)) +  $0.106488235831*D(LDSEGEN(-7)) + 0.116733995803*D(LDSEGEN(-8)) +$ 0.0519501279797\*D(LDSEGEN(-9)) + 0.0598372544249\*D(LDSEGEN(-10)) + 0.0648043230683\*D(LDSEGEN(-11)) - 0.0724732184792\*D(LIPI) - 0.269431039656\*D(LIPI(-1)) - 0.133302102048\*D(LIPI(-2)) - 0.207961041338\*D(LIPI(-3)) - 0.111236634768\*D(LIPI(-4)) - 0.697105671694\*D(LCPI) + 0.248423905767\*D(LCPI(-1)) + 0.962871222108\*D(LCPI(-2)) + 0.613003713159\*D(LCPI(-3)) + 1.41552982129\*D(LCPI(-4)) + 0.0299597749816\*D(LEXR) + 0.151043879936\*D(LEXR(-1)) + 0.431284442344\*D(LEXR(-2)) + 0.873914613052\*D(LEXR(-3)) - 0.360146054298\*D(LEXR(-4)) + 0.862470847062\*D(LM2) - 0.252556327558\*D(LM2(-1)) -  $0.595639571038^*D(LM2(-2)) + 0.401219430886^*D(LM2(-3)) - 0.339918759338^*D(LM2(-4)) +$ 0.0425086899614\*D(LGDPRICE) - 0.0441039432065\*D(LGDPRICE(-1)) - 0.238801079244\*D(LGDPRICE(-2)) - 0.0774680318815\*D(LGDPRICE(-3)) - 0.07593911187\*D(LGDPRICE(-4)) + 4.81280489031 + 0.00552899059958\*@TREND + 0.354215506046\*LIPI(-1) - 0.673051717555\*LCPI(-1) - 0.481924494306\*LEXR(-1) - 0.292123624614\*LM2(-1) + 0.180941493131\*LGDPRICE(-1) - 0.126235675352\*LDSEGEN(-1)

#### **Wald Test:** Equation: Untitled



Null Hypothesis: C(12)=C(13)=C(14)=C(15)=C(16)=0 Null Hypothesis Summary:



Restrictions are linear in coefficients.

#### **Wald Test:**



Null Hypothesis: C(17)=C(18)=C(19)=C(20)=C(21)=0 Null Hypothesis Summary:



Restrictions are linear in coefficients.

#### **Wald Test:**





Restrictions are linear in coefficients.

 $C(26)$  -0.360146

#### **Wald Test:** Equation: Untitled



Null Hypothesis: C(27)=C(28)=C(29)=C(30)=C(31)=0 Null Hypothesis Summary:



Restrictions are linear in coefficients.

### **Wald Test:**

Equation: Untitled



Null Hypothesis: C(32)=C(33)=C(34)=C(35)=C(36)=0 Null Hypothesis Summary:



Restrictions are linear in coefficients.

#### **Wald Test:**

Equation: Untitled



Null Hypothesis: C(39)=C(40)=C(41)=C(42)=C(43)=C(44)=0 Null Hypothesis Summary:



Restrictions are linear in coefficients.

## **APPENDIX I: Viability Check of the ARDL Model**

## **I 1 Correlogram of the Residuals**

Date: 04/15/17 Time: 17:38 Sample: 1991M01 2015M12 Included observations: 288 Q-statistic probabilities adjusted for 12 dynamic regressors



\*Probabilities may not be valid for this equation specification.



## **I 2 Normality Test of the Residuals**

## **I 3 Breusch-Godfrey Serial Correlation LM Test:**



Test Equation: Dependent Variable: RESID Method: ARDL Date: 04/15/17 Time: 17:40 Sample: 1992M01 2015M12 Included observations: 288 Presample missing value lagged residuals set to zero.




# **I 4 Heteroscedasticity Test: Breusch-Pagan-Godfrey**



Test Equation: Dependent Variable: RESID^2 Method: Least Squares Date: 04/15/17 Time: 17:40 Sample: 1992M01 2015M12 Included observations: 288

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# **Appendix J: Stability of VAR and Optimal Lags of Variables for Different Periods**

#### **Roots of Characteristic Polynomial Endogenous variables: LDSEGEN Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 00:08 Root Modulus 0.962000 0.962000 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: LDSEGEN Exogenous variables: C @TREND** Date: 04/19/17 Time: 00:10 Sample: 1992M03 1996M11 Included observations: 57 -1.5 -1.0 -0.5  $0.0$ 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 Inverse Roots of AR Characteristic Polynomial

Lag LogL LR FPE AIC SC HQ 3.671099 NA 0.055217 -0.058635 0.013051 -0.030775 42.99385 74.50626 0.014392 -1.403293 -1.295764\* -1.361503 43.74040 1.388316 0.014523 -1.394400 -1.251028 -1.338681 46.03995 4.195679\* 0.013878 -1.439998 -1.260783 -1.370349 47.54994 2.702089 0.013637\* -1.457893\* -1.242835 -1.374314\* 47.56789 0.031484 0.014121 -1.423435 -1.172534 -1.325926

\* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

**J.1 For Bubble Period (March 1992 to November 1996)**

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

**Roots of Characteristic Polynomial Endogenous variables: LDSEGEN Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 00:13



Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.







# **Roots of Characteristic Polynomial Endogenous variables: DLDSEGEN Exogenous variables: C @TREND** Lag specification: 1 1

Date: 04/19/17 Time: 00:15



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLDSEGEN Exogenous variables: C @TREND**

Date: 04/19/17 Time: 00:16 Sample: 1992M03 1996M11 Included observations: 57





\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: DLDSEGEN Exogenous variables: C** Lag specification: 1 1

Date: 04/19/17 Time: 00:16



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLDSEGEN Exogenous variables: C**

Date: 04/19/17 Time: 00:16 Sample: 1992M03 1996M11 Included observations: 57

 $-1.0$ . -0.5 0.0 0.5 1.0 1.5

Inverse Roots of AR Characteristic Polynomial





### **Roots of Characteristic Polynomial Endogenous variables: LIPI Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 00:20



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LIPI Exogenous variables: C @TREND** Date: 04/19/17 Time: 00:20

Sample: 1992M03 1996M11 Included observations: 57





\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: LIPI Exogenous variables: C** Lag specification: 1 1

Date: 04/19/17 Time: 00:20



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: LIPI Exogenous variables: C**

Date: 04/19/17 Time: 00:21 Sample: 1992M03 1996M11 Included observations: 57

Inverse Roots of AR Characteristic Polynomial





# **Roots of Characteristic Polynomial Endogenous variables: DLIPI Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 00:22



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLIPI Exogenous variables: C @TREND**

Date: 04/19/17 Time: 00:22 Sample: 1992M03 1996M11 Included observations: 57





\* indicates lag order selected by the criterion

### **Roots of Characteristic Polynomial Endogenous variables: DLIPI Exogenous variables: C** Lag specification: 1 1

Date: 04/19/17 Time: 00:22



No root lies outside the unit circle. VAR satisfies the stability condition.

### **VAR Lag Order Selection Criteria Endogenous variables: DLIPI Exogenous variables: C** Date: 04/19/17 Time: 00:22

Sample: 1992M03 1996M11 Included observations: 57

Inverse Roots of AR Characteristic Polynomial







#### **Roots of Characteristic Polynomial Endogenous variables: LINT Exogenous variables: C** Lag specification: 1 1<br>Data: 04/10/17 Fina: 00:04  $D_{\text{obs}}$ : 04/10/17



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LINT**

**Exogenous variables: C** Date: 04/19/17 Time: 00:24 Sample: 1992M03 1996M11 Included observations: 57

Inverse Roots of AR Characteristic Polynomial





### **Roots of Characteristic Polynomial Endogenous variables: DLINT Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 00:25



No root lies outside the unit circle. VAR satisfies the stability condition.

### **VAR Lag Order Selection Criteria Endogenous variables: DLINT Exogenous variables: C @TREND** Date: 04/19/17 Time: 00:25

Sample: 1992M03 1996M11 Included observations: 57





 $\overline{\phantom{0}}$ 

\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: DLINT Exogenous variables: C**

Lag specification: 1 1 Date: 04/19/17 Time: 00:26



No root lies outside the unit circle. VAR satisfies the stability condition.

**VAR Lag Order Selection Criteria Endogenous variables: DLINT Exogenous variables: C** Date: 04/19/17 Time: 00:26 Sample: 1992M03 1996M11 Included observations: 57

Inverse Roots of AR Characteristic Polynomial







#### **Roots of Characteristic Polynomial Endogenous variables: LCPI Exogenous variables: C** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LCPI Exogenous variables: C** Date: 04/19/17 Time: 00:28 Sample: 1992M03 1996M11 Included observations: 57

Inverse Roots of AR Characteristic Polynomial







# **Roots of Characteristic Polynomial Endogenous variables: DLCPI Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 00:29 Root Modulus

0.045662 0.045662

No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLCPI Exogenous variables: C** Date: 04/19/17 Time: 00:29 Sample: 1992M03 1996M11 Included observations: 57







# **Roots of Characteristic Polynomial Endogenous variables: LEXR Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 00:31



Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

Inverse Roots of AR Characteristic Polynomial





# **Roots of Characteristic Polynomial Endogenous variables: DLEXR Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 00:33 Root Modulus 0.000202 0.000202

No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLEXR Exogenous variables: C**

Date: 04/19/17 Time: 00:33 Sample: 1992M03 1996M11 Included observations: 57









# **Roots of Characteristic Polynomial Endogenous variables: LM2 Exogenous variables: C**



# **Endogenous variables: LM2 Exogenous variables: C** Date: 04/19/17 Time: 00:36 Sample: 1992M03 1996M11 Included observations: 57







Inverse Roots of AR Characteristic Polynomial

#### **Roots of Characteristic Polynomial Endogenous variables: DLM2 Exogenous variables: C @TREND** Lag specification: 1 1 Root Modulus -0.358079 0.358079 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: DLM2 Exogenous variables: C @TREND** Sample: 1992M03 1996M11 Included observations: 57 Lag LogL LR FPE AIC SC HQ 0 147.1675 NA 0.000359 -5.093595 -5.021909 -5.065735 1 151.0792 7.411684 0.000324 -5.195761 -5.088232 -5.153971 2 153.5486 4.592171 0.000308 -5.247318 -5.103946 -5.191599 3 153.6253 0.140078 0.000318 -5.214924 -5.035709 -5.145275 4 154.8530 2.196889 0.000316 -5.222912 -5.007854 -5.139334 5 160.8723 10.56013 0.000265 -5.399027 -5.148126 -5.301519 6 171.0563 17.50941 0.000192 -5.721275 -5.434531 -5.609836 7 174.5193 5.832457\* 0.000176 -5.807696 -5.485109\* -5.682328 8 176.4725 3.220944 0.000171\* -5.841139\* -5.482709 -5.701841\* 9 176.7138 0.389483 0.000176 -5.814519 -5.420246 -5.661291 -1.5  $-1.0$ -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

\* indicates lag order selected by the criterion

### **Roots of Characteristic Polynomial Endogenous variables: DLM2 Exogenous variables: C** Lag specification: 1 1

Date: 04/19/17 Time: 00:38



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLM2 Exogenous variables: C**

Date: 04/19/17 Time: 00:38 Sample: 1992M03 1996M11 Included observations: 57

Inverse Roots of AR Characteristic Polynomial







#### **Roots of Characteristic Polynomial Endogenous variables: LGDPRICE Exogenous variables: C** Lag specification: 1 1



VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LGDPRICE Exogenous variables: C** Date: 04/19/17 Time: 00:39 Sample: 1992M03 1996M11 Included observations: 57

#### Inverse Roots of AR Characteristic Polynomial





# **Roots of Characteristic Polynomial Endogenous variables: DLGDPRICE Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 00:40



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLGDPRICE Exogenous variables: C @TREND**

Date: 04/19/17 Time: 00:40 Sample: 1992M03 1996M11 Included observations: 57





\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: DLGDPRICE Exogenous variables: C** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLGDPRICE Exogenous variables: C** Date: 04/19/17 Time: 00:41 Sample: 1992M03 1996M11 Included observations: 57

Inverse Roots of AR Characteristic Polynomial





# **J.2 For Meltdown Period (November 1996 to December 1999)**



\* indicates lag order selected by the criterion

### **Roots of Characteristic Polynomial Endogenous variables: LDSEGEN Exogenous variables: C** Lag specification: 1 1



0.889354 0.889354

No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LDSEGEN Exogenous variables: C** Date: 04/19/17 Time: 15:33

Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial





### **Roots of Characteristic Polynomial Endogenous variables: DLDSEGEN Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 15:33



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLDSEGEN Exogenous variables: C @TREND**

Date: 04/19/17 Time: 15:34 Sample: 1996M11 1999M12 Included observations: 38





\* indicates lag order selected by the criterion

### **Roots of Characteristic Polynomial Endogenous variables: DLDSEGEN Exogenous variables: C** Lag specification: 1 1

Date: 04/19/17 Time: 15:35



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLDSEGEN Exogenous variables: C**

Date: 04/19/17 Time: 15:35 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial





# **Roots of Characteristic Polynomial Endogenous variables: LIPI Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 15:36



No root lies outside the unit circle. VAR satisfies the stability condition.

### **VAR Lag Order Selection Criteria Endogenous variables: LIPI Exogenous variables: C @TREND** Sample: 1996M11 1999M12 Included observations: 38





\* indicates lag order selected by the criterion

Roots of Characteristic Polynomial **Endogenous variables: LIPI Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 15:36



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LIPI**

**Exogenous variables: C** Date: 04/19/17 Time: 15:37 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial







### **Roots of Characteristic Polynomial Endogenous variables: DLIPI Exogenous variables: C** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

### **VAR Lag Order Selection Criteria Endogenous variables: DLIPI Exogenous variables: C** Date: 04/19/17 Time: 15:38

Sample: 1996M11 1999M12 Included observations: 38



#### Inverse Roots of AR Characteristic Polynomial

Lag LogL LR FPE AIC SC HQ 41.83337 NA\* 0.006826 -2.149125 -2.106030\* -2.133792\* 41.83579 0.004587 0.007195 -2.096620 -2.010432 -2.065955 43.63453 3.313472 0.006900 -2.138659 -2.009376 -2.092661 45.58921 3.497850 0.006565\* -2.188906\* -2.016528 -2.127575 46.43357 1.466521 0.006624 -2.180714 -1.965242 -2.104051

Inverse Roots of AR Characteristic Polynomial

#### **Endogenous variables: LINT Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 15:39 Root Modulus 0.832444 0.832444 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: LINT Exogenous variables: C @TREND** Date: 04/19/17 Time: 15:39 Sample: 1996M11 1999M12 Included observations: 38 Lag LogL LR FPE AIC SC HQ 0 158.0837 NA 1.58e-05 -8.214930 -8.128742 -8.184265 1 172.9593 27.40253\* 7.63e-06 -8.945228 -8.815945\* -8.899230 2 174.2677 2.341218 7.52e-06\* -8.961456\* -8.789078 -8.900125\* 3 174.2938 0.045388 7.92e-06 -8.910200 -8.694728 -8.833537 4 174.3347 0.068862 8.34e-06 -8.859720 -8.601154 -8.767724 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

5 174.5723 0.387771 8.69e-06 -8.819597 -8.517937 -8.712269

\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: LINT Exogenous variables: C**  $\overline{\phantom{a}}$ nacification: 1 1

**Roots of Characteristic Polynomial**



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LINT Exogenous variables: C** Date: 04/19/17 Time: 15:40 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial







#### **Roots of Characteristic Polynomial Endogenous variables: DLINT Exogenous variables: C** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

### **VAR Lag Order Selection Criteria Endogenous variables: DLINT Exogenous variables: C** Date: 04/19/17 Time: 15:41 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial





#### **Roots of Characteristic Polynomial Endogenous variables: LCPI Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 19:37 Root Modulus 0.755458 0.755458 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: LCPI Exogenous variables: C @TREND** Date: 04/19/17 Time: 19:37 Sample: 1996M11 1999M12 Included observations: 38 -1.5 -1.0  $-0.5$ 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 Inverse Roots of AR Characteristic Polynomial



\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: LCPI**

**Exogenous variables: C** Lag specification: 1 1





No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LCPI Exogenous variables: C** Date: 04/19/17 Time: 19:38 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial





#### **Roots of Characteristic Polynomial Endogenous variables: DLCPI Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 19:38 Root Modulus 0.098247 0.098247 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: DLCPI Exogenous variables: C @TREND** Date: 04/19/17 Time: 19:38 Sample: 1996M11 1999M12 Included observations: 38 Lag LogL LR FPE AIC SC HQ 0 127.2602 NA\* 8.02e-05\* -6.592644\* -6.506455\* -6.561979\* 1 127.4466 0.343331 8.38e-05 -6.549822 -6.420539 -6.503824 2 127.4511 0.007994 8.83e-05 -6.497426 -6.325048 -6.436095 3 127.9866 0.930082 9.06e-05 -6.472978 -6.257506 -6.396315 4 128.3793 0.661335 9.36e-05 -6.441013 -6.182447 -6.349017 5 128.6264 0.403310 9.76e-05 -6.401392 -6.099731 -6.294063 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 Inverse Roots of AR Characteristic Polynomial

\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: DLCPI Exogenous variables: C**

Lag specification: 1 1 Date: 04/19/17 Time: 19:39



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLCPI Exogenous variables: C** Date: 04/19/17 Time: 19:39 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial







#### **Roots of Characteristic Polynomial Endogenous variables: LEXR Exogenous variables: C** Lag specification: 1 1





No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LEXR Exogenous variables: C** Date: 04/19/17 Time: 15:43 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial





#### **Roots of Characteristic Polynomial Endogenous variables: DLEXR Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 15:44 Root Modulus -0.200165 0.200165 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: DLEXR Exogenous variables: C @TREND** Date: 04/19/17 Time: 15:44 Sample: 1996M11 1999M12 Included observations: 38 Lag LogL LR FPE AIC SC HQ 0 128.3510 NA\* 7.58e-05 -6.650052 -6.563864\* -6.619387 1 129.1219 1.420060 7.67e-05 -6.637994 -6.508711 -6.591996 2 131.0574 3.463495 7.31e-05\* -6.687230\* -6.514852 -6.625899\* 3 131.0771 0.034247 7.70e-05 -6.635636 -6.420164 -6.558973 4 131.1544 0.130186 8.09e-05 -6.587073 -6.328506 -6.495077 5 131.1992 0.073159 8.52e-05 -6.536801 -6.235140 -6.429473 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 Inverse Roots of AR Characteristic Polynomial

\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: DLEXR Exogenous variables: C** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLEXR Exogenous variables: C** Date: 04/19/17 Time: 15:44 Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial







# **Roots of Characteristic Polynomial Endogenous variables: LM2 Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 15:45



Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

Inverse Roots of AR Characteristic Polynomial





**Roots of Characteristic Polynomial Endogenous variables: DLM2 Exogenous variables: C** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

### **VAR Lag Order Selection Criteria Endogenous variables: DLM2 Exogenous variables: C** Date: 04/19/17 Time: 15:47

Sample: 1996M11 1999M12 Included observations: 38

Inverse Roots of AR Characteristic Polynomial





# **Roots of Characteristic Polynomial Endogenous variables: LGDPRICE Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 15:48



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LGDPRICE Exogenous variables: C @TREND**

Date: 04/19/17 Time: 15:48 Sample: 1996M11 1999M12 Included observations: 38





\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: LGDPRICE Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 15:48

Root Modulus 0.912045 0.912045

No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LGDPRICE Exogenous variables: C** Date: 04/19/17 Time: 15:48

Sample: 1996M11 1999M12 Included observations: 38







# **Roots of Characteristic Polynomial Endogenous variables: DLGDPRICE Exogenous variables: C @TREND** Lag specification: 1 1 Date: 04/19/17 Time: 15:49



No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLGDPRICE Exogenous variables: C @TREND**

Date: 04/19/17 Time: 15:49 Sample: 1996M11 1999M12 Included observations: 38





\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: DLGDPRICE Exogenous variables: C** Lag specification: 1 1 Date: 04/19/17 Time: 15:49 Root Modulus -0.114506 0.114506 No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLGDPRICE Exogenous variables: C**

Date: 04/19/17 Time: 15:49 Sample: 1996M11 1999M12 Included observations: 38

# Inverse Roots of AR Characteristic Polynomial





# **J.3 For Recovery Period (January 2000 to December 2009)**





\* indicates lag order selected by the criterion

**Roots of Characteristic Polynomial Endogenous variables: LDSEGEN Exogenous variables: C** Lag specification: 1 1 Date: 06/12/17 Time: 15:22

Root Modulus 1.004780 1.004780

Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

Inverse Roots of AR Characteristic Polynomial







0 156.6513 NA 0.004374 -2.594189 -2.570960\* -2.584755\*

12 170.9619 0.645615 0.004284 -2.616031 -2.290824 -2.483963





# **Roots of Characteristic Polynomial Endogenous variables: LIPI Exogenous variables: C @TREND** Lag specification: 1 1

Date: 06/12/17 Time: 15:24

Root Modulus 0.397188 0.397188

No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: LIPI Exogenous variables: C @TREND** Date: 06/12/17 Time: 15:25

Sample: 2000M01 2009M12 Included observations: 120











No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLIPI Exogenous variables: C @TREND** Date: 06/12/17 Time: 15:26 Sample: 2000M01 2009M12 Included observations: 120







# **Roots of Characteristic Polynomial Endogenous variables: DLIPI Exogenous variables: C** Lag specification: 1 1

Date: 06/12/17 Time: 15:26 Root Modulus -0.177227 0.177227

No root lies outside the unit circle. VAR satisfies the stability condition.

# **VAR Lag Order Selection Criteria Endogenous variables: DLIPI Exogenous variables: C**

Date: 06/12/17 Time: 15:27 Sample: 2000M01 2009M12 Included observations: 120

Inverse Roots of AR Characteristic Polynomial







#### **Roots of Characteristic Polynomial Endogenous variables: LINT Exogenous variables: C**

Lag specification: 1 1 Date: 06/12/17 Time: 15:28



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria Endogenous variables: LINT Exogenous variables: C** Date: 06/12/17 Time: 15:28

Sample: 2000M01 2009M12 Included observations: 120

Inverse Roots of AR Characteristic Polynomial






\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: DLINT Exogenous variables: C @TREND** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLINT Exogenous variables: C @TREND** Sample: 2000M01 2009M12

Included observations: 120





\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: DLINT Exogenous variables: C** Lag specification: 1 1 Date: 06/12/17 Time: 15:29 Root Modulus 0.135422 0.135422

No root lies outside the unit circle.

VAR satisfies the stability condition.

Inverse Roots of AR Characteristic Polynomial



#### **VAR Lag Order Selection Criteria Endogenous variables: DLINT Exogenous variables: C** Sample: 2000M01 2009M12 Included observations: 120



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: LCPI Exogenous variables: C @TREND** Lag specification: 1 1

Date: 06/12/17 Time: 15:30



No root lies outside the unit circle. VAR satisfies the stability condition.

### **VAR Lag Order Selection Criteria Endogenous variables: LCPI Exogenous variables: C @TREND** Sample: 2000M01 2009M12

Included observations: 120

Inverse Roots of AR Characteristic Polynomial





\* indicates lag order selected by the criterion



#### **Roots of Characteristic Polynomial Endogenous variables: LCPI Exogenous variables: C** Lag specification: 1 1 Date: 06/12/17 Time: 15:30 Root Modulus 1.008313 1.008313 Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition. **Roots of Characteristic Polynomial Endogenous variables: DLCPI Exogenous variables: C @TREND** Lag specification: 1 1 Root Modulus 0.367982 0.367982 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: DLCPI Exogenous variables: C @TREND** Sample: 2000M01 2009M12 Included observations: 120 Lag LogL LR FPE AIC SC HQ 0 408.5360 NA 6.68e-05 -6.775600 -6.729142 -6.756733 1 417.2051 16.90484 5.88e-05 -6.903419 -6.833732 -6.875119 2 421.9930 9.256498 5.52e-05 -6.966550 -6.873633\* -6.928816 3 421.9968 0.007297 5.61e-05 -6.949947 -6.833801 -6.902779 4 424.0612 3.922433 5.51e-05 -6.967687 -6.828313 -6.911087 5 424.8179 1.425004 5.54e-05 -6.963631 -6.801028 -6.897597 6 426.3915 2.937512 5.49e-05 -6.973192 -6.787360 -6.897725 7 428.5593 4.010394 5.38e-05 -6.992655 -6.783594 -6.907754 8 428.9395 0.696960 5.44e-05 -6.982325 -6.750034 -6.887990 9 434.3193 9.773352 5.05e-05 -7.055322 -6.799802 -6.951554 10 434.8605 0.974162 5.09e-05 -7.047675 -6.768926 -6.934474 11 435.3637 0.897386 5.14e-05 -7.039395 -6.737417 -6.916761 12 444.0300 15.31049\* 4.52e-05 -7.167167 -6.841960 -7.035099\* 13 445.1176 1.903280 4.52e-05\* -7.168627\* -6.820191 -7.027125 14 445.6571 0.935102 4.55e-05 -7.160952 -6.789286 -7.010017  $-1.5$ -1.0 -0.5  $0.0$ 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5  $-1.5 + ...$ -1.0 -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 Inverse Roots of AR Characteristic Polynomial

\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: DLCPI Exogenous variables: C** Lag specification: 1 1 Root Modulus



No root lies outside the unit circle.

VAR satisfies the stability condition.





#### **VAR Lag Order Selection Criteria Endogenous variables: DLCPI Exogenous variables: C** Sample: 2000M01 2009M12 Included observations: 120



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: LEXR Exogenous variables: C @TREND** Lag specification: 1 1

Date: 06/12/17 Time: 15:33 Root Modulus



No root lies outside the unit circle. VAR satisfies the stability condition.

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#### **VAR Lag Order Selection Criteria Endogenous variables: LEXR Exogenous variables: C @TREND** Sample: 2000M01 2009M12 Included observations: 120

Inverse Roots of AR Characteristic Polynomial





\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: LEXR Exogenous variables: C** Lag specification: 1 1 Root Modulus 0.984316 0.984316 No root lies outside the unit circle. VAR satisfies the stability condition. **VAR Lag Order Selection Criteria Endogenous variables: LEXR Exogenous variables: C** Sample: 2000M01 2009M12 Included observations: 120 Lag LogL LR FPE AIC SC HQ 0 104.8549 NA 0.010370 -1.730914 -1.707685 -1.721481 1 376.5257 534.2860 0.000114 -6.242095 -6.195636\* -6.223228\* 2 376.5512 0.049781 0.000116 -6.225853 -6.156166 -6.197553 3 376.7617 0.406869 0.000117 -6.212694 -6.119778 -6.174960 4 377.3594 1.145635 0.000118 -6.205990 -6.089844 -6.158822 5 377.5947 0.447138 0.000120 -6.193245 -6.053871 -6.136645 6 377.8091 0.403721 0.000121 -6.180151 -6.017548 -6.114117 7 380.4940 5.011806 0.000118 -6.208233 -6.022400 -6.132765 8 380.7854 0.539130 0.000119 -6.196423 -5.987361 -6.111522 9 381.0106 0.412802 0.000121 -6.183509 -5.951218 -6.089175 10 387.9607 12.62611\* 0.000109\* -6.282679\* -6.027158 -6.178911 11 388.0693 0.195372 0.000111 -6.267821 -5.989072 -6.154620 12 388.0700 0.001262 0.000113 -6.251166 -5.949188 -6.128531 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 Inverse Roots of AR Characteristic Polynomial

\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: DLEXR Exogenous variables: C @TREND** Lag specification: 1 1

Date: 06/12/17 Time: 15:35



No root lies outside the unit circle. VAR satisfies the stability condition.

## **VAR Lag Order Selection Criteria Endogenous variables: DLEXR Exogenous variables: C @TREND** Sample: 2000M01 2009M12

Included observations: 120

Inverse Roots of AR Characteristic Polynomial







\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: DLEXR Exogenous variables: C**

Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLEXR Exogenous variables: C** Sample: 2000M01 2009M12

Included observations: 120

Inverse Roots of AR Characteristic Polynomial





\* indicates lag order selected by the criterion

# **Roots of Characteristic Polynomial Endogenous variables: LM2 Exogenous variables: C @TREND** Lag specification: 1 1 Date: 06/12/17 Time: 15:37



No root lies outside the unit circle.

VAR satisfies the stability condition.





#### **VAR Lag Order Selection Criteria Endogenous variables: LM2 Exogenous variables: C @TREND** Sample: 2000M01 2009M12 Included observations: 120



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: LM2 Exogenous variables: C** Lag specification: 1 1



Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

#### **Roots of Characteristic Polynomial Endogenous variables: DLM2 Exogenous variables: C @TREND** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLM2 Exogenous variables: C @TREND** Sample: 2000M01 2009M12

Included observations: 120

Inverse Roots of AR Characteristic Polynomial



Inverse Roots of AR Characteristic Polynomial







\* indicates lag order selected by the criterion

## **Roots of Characteristic Polynomial Endogenous variables: DLM2 Exogenous variables: C**

Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLM2 Exogenous variables: C** Sample: 2000M01 2009M12 Included observations: 120







\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: LGDPRICE Exogenous variables: C @TREND** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.





#### **VAR Lag Order Selection Criteria Endogenous variables: LGDPRICE Exogenous variables: C @TREND** Sample: 2000M01 2009M12 Included observations: 120



\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: LGDPRICE Exogenous variables: C** Lag specification: 1 1



Warning: At least one root outside the unit circle. VAR does not satisfy the stability condition.

#### **Roots of Characteristic Polynomial Endogenous variables: DLGDPRICE Exogenous variables: C @TREND** Lag specification: 1 1



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria**

Endogenous variables: DLGDPRICE Exogenous variables: C @TREND Date: 06/12/17 Time: 15:47 Sample: 2000M01 2009M12 Included observations: 120

Inverse Roots of AR Characteristic Polynomial



#### Inverse Roots of AR Characteristic Polynomial







\* indicates lag order selected by the criterion

#### **Roots of Characteristic Polynomial Endogenous variables: DLGDPRICE Exogenous variables: C**

Lag specification: 1 1

Date: 06/12/17 Time: 15:47



No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLGDPRICE Exogenous variables: C** Date: 06/12/17 Time: 15:48

Sample: 2000M01 2009M12 Included observations: 120

Inverse Roots of AR Characteristic Polynomial





\* indicates lag order selected by the criterion

# **Appendix K: Unit Root Tests of the Variables for Different Periods**

# **K 1 For Bubble Period**

**K 1.1 ADF Unit Root Tests Null Hypothesis: LDSEGEN has a unit root Exogenous: Constant, Linear Trend** Lag Length: 4 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 04/20/17 Time: 18:11 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LDSEGEN) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 0 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN,2) Method: Least Squares Date: 04/20/17 Time: 18:16 Sample: 1992M03 1996M11 Included observations: 57



### **Null Hypothesis: LIPI has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LIPI) Method: Least Squares Date: 04/20/17 Time: 18:16 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LINT has a unit root Exogenous: Constant, Linear Trend** Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 04/20/17 Time: 18:17 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LINT has a unit root**

**Exogenous: Constant**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 04/20/17 Time: 18:17 Sample: 1992M03 1996M11 Included observations: 57





#### **Null Hypothesis: D(LINT) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 0 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Date: 04/20/17 Time: 18:18 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LCPI has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 4 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI) Method: Least Squares Date: 04/20/17 Time: 18:18 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: LCPI has a unit root Exogenous: Constant**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI) Method: Least Squares Date: 04/20/17 Time: 18:19 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LCPI) has a unit root Exogenous: Constant, Linear Trend** Lag Length: 0 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI,2) Method: Least Squares Date: 04/20/17 Time: 18:19 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: LEXR has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 04/20/17 Time: 18:20 Sample: 1992M03 1996M11 Included observations: 57





#### **Null Hypothesis: D(LEXR) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 0 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 04/20/17 Time: 18:20 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LM2 has a unit root Exogenous: Constant, Linear Trend** Lag Length: 3 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 04/20/17 Time: 18:21 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: LM2 has a unit root Exogenous: Constant**

Lag Length: 3 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 04/20/17 Time: 18:21 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LM2) has a unit root Exogenous: Constant, Linear Trend** Lag Length: 8 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 04/20/17 Time: 18:22 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LM2) has a unit root Exogenous: Constant**

Lag Length: 8 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 04/20/17 Time: 18:22 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LM2,2) has a unit root**

**Exogenous: Constant, Linear Trend**

Lag Length: 10 (Automatic - based on SIC, maxlag=10)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,3) Method: Least Squares Date: 04/21/17 Time: 17:52 Sample: 1992M03 1996M11 Included observations: 57





#### **Null Hypothesis: LGDPRICE has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 04/20/17 Time: 18:23 Sample: 1992M03 1996M11 Included observations: 57



### **Null Hypothesis: LGDPRICE has a unit root**

**Exogenous: Constant**

Lag Length: 3 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 04/20/17 Time: 18:23 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: D(LGDPRICE) has a unit root**

**Exogenous: Constant, Linear Trend**





\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE,2) Method: Least Squares Date: 04/20/17 Time: 18:23 Sample: 1992M03 1996M11 Included observations: 57



## **K 1.2 PP Unit Root Tests**

#### **Null Hypothesis: LDSEGEN has a unit root**

## **Exogenous: Constant, Linear Trend**

Bandwidth: 4 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 04/24/17 Time: 16:30 Sample: 1992M03 1996M11 Included observations: 57



### **Null Hypothesis: D(LDSEGEN) has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 0 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LDSEGEN,2) Method: Least Squares Date: 04/24/17 Time: 16:31 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LIPI has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LIPI) Method: Least Squares Date: 04/24/17 Time: 16:31 Sample: 1992M03 1996M11 Included observations: 57



# **Null Hypothesis: LINT has a unit root**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 04/24/17 Time: 16:31 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: LINT has a unit root**

**Exogenous: Constant**

Bandwidth: 1 (Used-specified) using Bartlett kernel





Phillips-Perron Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 04/24/17 Time: 16:33 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LCPI has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 4 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LCPI) Method: Least Squares Date: 04/24/17 Time: 16:34 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: LCPI has a unit root Exogenous: Constant**

Bandwidth: 1 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LCPI) Method: Least Squares Date: 04/24/17 Time: 18:17 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LCPI) has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 0 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LCPI,2) Method: Least Squares Date: 04/24/17 Time: 16:35 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LEXR has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 04/24/17 Time: 16:35 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LEXR) has a unit root Exogenous: Constant, Linear Trend** Bandwidth: 0 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 04/24/17 Time: 16:35 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LM2 has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 3 (Used-specified) using Bartlett kernel





Phillips-Perron Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 04/24/17 Time: 16:36 Sample: 1992M03 1996M11 Included observations: 57



# **Null Hypothesis: LM2 has a unit root**

**Exogenous: Constant**

Bandwidth: 3 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 04/24/17 Time: 16:36 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: D(LM2) has a unit root Exogenous: Constant**

Bandwidth: 8 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 04/24/17 Time: 16:36 Sample: 1992M03 1996M11 Included observations: 57



#### **Null Hypothesis: LGDPRICE has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel





Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 04/24/17 Time: 16:36 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: LGDPRICE has a unit root Exogenous: Constant**

Bandwidth: 3 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 04/24/17 Time: 16:37 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: D(LGDPRICE) has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 2 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE,2) Method: Least Squares Date: 04/24/17 Time: 16:37 Sample: 1992M03 1996M11 Included observations: 57



## **K 1.3 KPSS Unit Root Tests**

#### **Null Hypothesis: LM2 is stationary**

## **Exogenous: Constant, Linear Trend**

Bandwidth: 3 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



#### KPSS Test Equation Dependent Variable: LM2 Method: Least Squares Date: 05/09/17 Time: 13:23 Sample: 1992M03 1996M11 Included observations: 57



## **Null Hypothesis: D(LM2) is stationary Exogenous: Constant, Linear Trend**

Bandwidth: 8 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 05/09/17 Time: 13:24 Sample: 1992M03 1996M11 Included observations: 57

HAC corrected variance (Bartlett kernel)



## **Null Hypothesis: D(LM2) is stationary**

**Exogenous: Constant**

Bandwidth: 8 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LM2) Method: Least Squares Sample: 1992M03 1996M11 Included observations: 57



# **K 2 For Meltdown Period**

#### **K 2.1 ADF Unit Root Test**

**Null Hypothesis: LDSEGEN has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 2 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38





#### **Null Hypothesis: LDSEGEN has a unit root Exogenous: Constant**

Lag Length: 3 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



#### **Null Hypothesis: LIPI has a unit root Exogenous: Constant, Linear Trend** Lag Length: 2 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LIPI) Method: Least Squares Date: 12/14/16 Time: 20:40 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LINT has a unit root**

**Exogenous: Constant, Linear Trend**

Lag Length: 2 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 12/14/16 Time: 20:41 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: D(LINT) has a unit root Exogenous: Constant, Linear Trend** Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values. Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Date: 12/14/16 Time: 20:42 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: D(LINT) has a unit root**

**Exogenous: Constant**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Date: 12/14/16 Time: 20:42 Sample: 1996M11 1999M12 Included observations: 38





# **Null Hypothesis: LCPI has a unit root**

**Exogenous: Constant, Linear Trend**

Lag Length: 2 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI) Method: Least Squares Date: 12/14/16 Time: 20:42 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LCPI has a unit root Exogenous: Constant**

Lag Length: 1 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI) Method: Least Squares Date: 12/14/16 Time: 20:42 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: D(LCPI) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 0 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI,2) Method: Least Squares Date: 12/14/16 Time: 20:43 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LEXR has a unit root Exogenous: Constant, Linear Trend** Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 12/14/16 Time: 20:43 Sample: 1996M11 1999M12 Included observations: 38



## **Null Hypothesis: LEXR has a unit root**

**Exogenous: Constant**

Lag Length: 3 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 04/21/17 Time: 21:09 Sample: 1996M11 1999M12 Included observations: 38





# **Null Hypothesis: D(LEXR) has a unit root**

**Exogenous: Constant, Linear Trend** Lag Length: 2 (Fixed)



\*MacKinnon (1996) one-sided p-values. Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 12/14/16 Time: 20:43 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LM2 has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 1 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 12/14/16 Time: 20:44 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: D(LM2) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 3 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 12/14/16 Time: 20:44 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LGDPRICE has a unit root Exogenous: Constant, Linear Trend** Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 12/14/16 Time: 20:45 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LGDPRICE has a unit root**

## **Exogenous: Constant**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 12/14/16 Time: 20:45 Sample: 1996M11 1999M12 Included observations: 38





### **Null Hypothesis: D(LGDPRICE) has a unit root**

**Exogenous: Constant, Linear Trend** Lag Length: 0 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE,2) Method: Least Squares Date: 12/14/16 Time: 20:45 Sample: 1996M11 1999M12 Included observations: 38



## **K 2.2 PP Unit Root Test**

**Null Hypothesis: LDSEGEN has a unit root Exogenous: Constant, Linear Trend** Bandwidth: 2 (Used-specified) using Bartlett kernel





Phillips-Perron Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 05/09/17 Time: 14:44 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LDSEGEN has a unit root**

**Exogenous: Constant**

Bandwidth: 3 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 05/09/17 Time: 14:46 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LIPI has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 2 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LIPI) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



# **Null Hypothesis: LINT has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 2 (Used-specified) using Bartlett kernel







### **Null Hypothesis: LINT has a unit root Exogenous: Constant**

Bandwidth: 2 (Used-specified) using Bartlett kernel





Phillips-Perron Test Equation Dependent Variable: D(LINT) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



#### **Null Hypothesis: D(LINT) has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel





Phillips-Perron Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LCPI has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 2 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LCPI) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



## **Null Hypothesis: LCPI has a unit root Exogenous: Constant**

Bandwidth: 1 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LCPI) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: D(LCPI) has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 0 (Used-specified) using Bartlett kernel





### **Null Hypothesis: LEXR has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LEXR) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LEXR has a unit root Exogenous: Constant**

Bandwidth: 3 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 05/09/17 Time: 14:52 Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: D(LEXR) has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 2 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 05/09/17 Time: 14:52 Sample: 1996M11 1999M12 Included observations: 38



## **Null Hypothesis: LM2 has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel



## **Null Hypothesis: D(LM2) has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 3 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 05/09/17 Time: 14:53 Sample: 1996M11 1999M12 Included observations: 38



# **Null Hypothesis: LGDPRICE has a unit root**

**Exogenous: Constant, Linear Trend** Bandwidth: 1 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



### **Null Hypothesis: LGDPRICE has a unit root Exogenous: Constant**

Bandwidth: 1 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



## **Null Hypothesis: D(LGDPRICE) has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 0 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE,2) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38





# **K 3 For Recovery Period**

### **K 3.1 ADF Unit Root**

### **Null Hypothesis: LDSEGEN has a unit root Exogenous: Constant, Linear Trend** Lag Length: 10 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Included observations: 120



## **Null Hypothesis: D(LDSEGEN) has a unit root**

**Exogenous: Constant, Linear Trend** Lag Length: 9 (Fixed)



\*MacKinnon (1996) one-sided p-values. Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN,2) Method: Least Squares Date: 06/12/17 Time: 15:54 Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: D(LDSEGEN) has a unit root Exogenous: Constant**

Lag Length: 9 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LDSEGEN,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





### **Null Hypothesis: LIPI has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 12 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LIPI) Method: Least Squares Date: 06/12/17 Time: 15:55 Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: LIPI has a unit root Exogenous: Constant**

Lag Length: 12 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LIPI) Method: Least Squares Date: 06/12/17 Time: 15:55 Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(LIPI) has a unit root**

**Exogenous: Constant, Linear Trend**

Lag Length: 11 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LIPI,2) Method: Least Squares Date: 06/12/17 Time: 15:55 Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: LINT has a unit root**

**Exogenous: Constant, Linear Trend**

Lag Length: 9 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 06/12/17 Time: 15:56 Sample: 2000M01 2009M12 Included observations: 120





## **Null Hypothesis: LINT has a unit root**

**Exogenous: Constant**

Lag Length: 9 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT) Method: Least Squares Date: 06/12/17 Time: 15:56 Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: D(LINT) has a unit root Exogenous: Constant, Linear Trend** Lag Length: 8 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: D(LINT) has a unit root Exogenous: Constant**

Lag Length: 8 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





## **Null Hypothesis: D(LINT,2) has a unit root**

**Exogenous: Constant, Linear Trend**

Lag Length: 4 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LINT,3) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: LCPI has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 10 (Fixed)



\*MacKinnon (1996) one-sided p-values. Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(LCPI) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 13 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





#### **Null Hypothesis: D(LCPI) has a unit root**

**Exogenous: Constant**

Lag Length: 13 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: D(LCPI,2) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 11 (Automatic - based on SIC, maxlag=12)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LCPI,3) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: LEXR has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 10 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: LEXR has a unit root Exogenous: Constant**

Lag Length: 10 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





### **Null Hypothesis: D(LEXR) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 9 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 06/12/17 Time: 16:01 Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: D(LEXR) has a unit root Exogenous: Constant** Lag Length: 9 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 06/12/17 Time: 16:01 Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(LEXR,2) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 9 (Fixed)



Augmented Dickey-Fuller Test Equation Dependent Variable: D(LEXR,3) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: LM2 has a unit root Exogenous: Constant, Linear Trend** Lag Length: 13 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





## **Null Hypothesis: D(LM2) has a unit root**

**Exogenous: Constant, Linear Trend**

Lag Length: 12 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: D(LM2) has a unit root Exogenous: Constant** Lag Length: 12 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: D(LM2,2) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 10 (Automatic - based on SIC, maxlag=12)


Augmented Dickey-Fuller Test Equation Dependent Variable: D(LM2,3) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



#### **Null Hypothesis: LGDPRICE has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 5 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





# **Null Hypothesis: D(LGDPRICE) has a unit root**

**Exogenous: Constant, Linear Trend** Lag Length: 6 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(LGDPRICE,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **K 3.2 PP Unit Root Test**

## **Null Hypothesis: LDSEGEN has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 10 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: D(LDSEGEN) has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 9 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LDSEGEN,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: LIPI has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 12 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LIPI) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: LINT has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 9 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LINT) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





## **Null Hypothesis: LINT has a unit root Exogenous: Constant**

Bandwidth: 9 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LINT) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: D(LINT) has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 8 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LINT,2) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



### **Null Hypothesis: LCPI has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 10 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LCPI) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(LCPI) has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 13 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LCPI,2) Method: Least Squares Date: 06/12/17 Time: 16:10 Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: LEXR has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 10 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 06/12/17 Time: 16:10 Sample: 2000M01 2009M12 Included observations: 120





## **Null Hypothesis: LEXR has a unit root Exogenous: Constant**

Bandwidth: 10 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 06/12/17 Time: 16:10 Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: D(LEXR) has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 9 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LEXR,2) Method: Least Squares Date: 06/12/17 Time: 16:10 Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: LM2 has a unit root**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 13 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 06/12/17 Time: 16:11 Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(LM2) has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 12 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LM2,2) Method: Least Squares Date: 06/12/17 Time: 16:11 Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: LGDPRICE has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 5 (Used-specified) using Bartlett kernel



\*MacKinnon (1996) one-sided p-values.



Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE) Method: Least Squares Date: 06/12/17 Time: 16:12 Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: D(LGDPRICE) has a unit root**

**Exogenous: Constant, Linear Trend** Bandwidth: 6 (Used-specified) using Bartlett kernel



Phillips-Perron Test Equation Dependent Variable: D(LGDPRICE,2) Method: Least Squares Date: 06/12/17 Time: 16:12 Sample: 2000M01 2009M12 Included observations: 120



## **K 3.3 KPSS Unit Root Test**

# **Null Hypothesis: INT is stationary**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 9 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: INT Method: Least Squares Date: 06/12/17 Time: 22:03 Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: D(INT) is stationary**

**Exogenous: Constant, Linear Trend**

Bandwidth: 8 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



## KPSS Test Equation Dependent Variable: D(INT) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(INT) is stationary**

## **Exogenous: Constant**

Bandwidth: 8 (Used-specified) using Bartlett kernel



## KPSS Test Equation Dependent Variable: D(INT) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: LCPI is stationary**

## **Exogenous: Constant, Linear Trend**

Bandwidth: 10 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: LCPI Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



#### **Null Hypothesis: D(LCPI) is stationary**

**Exogenous: Constant, Linear Trend**

Bandwidth: 13 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LCPI) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(LCPI) is stationary Exogenous: Constant**

Bandwidth: 13 (Used-specified) using Bartlett kernel



## KPSS Test Equation Dependent Variable: D(LCPI) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: LEXR is stationary**

**Exogenous: Constant, Linear Trend**

Bandwidth: 10 (Used-specified) using Bartlett kernel





# **Null Hypothesis: D(LEXR) is stationary**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 9 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: D(LEXR) Method: Least Squares Date: 06/12/17 Time: 22:06 Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: D(LEXR) is stationary**

**Exogenous: Constant**

Bandwidth: 9 (Used-specified) using Bartlett kernel



## KPSS Test Equation Dependent Variable: D(LEXR) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: LM2 is stationary**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 13 (Used-specified) using Bartlett kernel



KPSS Test Equation Dependent Variable: LM2 Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



# **Null Hypothesis: D(LM2) is stationary**

**Exogenous: Constant, Linear Trend**

Bandwidth: 12 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 06/12/17 Time: 22:07 Sample: 2000M01 2009M12 Included observations: 120



## **Null Hypothesis: D(LM2) is stationary Exogenous: Constant**

Bandwidth: 13 (Used-specified) using Bartlett kernel



\*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)



KPSS Test Equation Dependent Variable: D(LM2) Method: Least Squares Date: 06/12/17 Time: 22:08 Sample: 2000M01 2009M12 Included observations: 120



# **Appendix L: ARDL Tests for Different Periods**

# **L 1 For Bubble Period**

**L 1.1 ARDL Specification Dependent Variable: LDSEGEN Method: ARDL** Date: 04/24/17 Time: 22:36 Sample: 1992M03 1996M11 Included observations: 57 Maximum dependent lags: 4 (Automatic selection) Model selection method: Akaike info criterion (AIC) Dynamic regressors (5 lags, automatic): LIPI LINT LCPI LEXR LM2 **LGDPRICE** Fixed regressors: C @TREND Number of models evalulated: 186624 Selected Model: ARDL(1, 4, 0, 2, 5, 0, 0)



\*Note: p-values and any subsequent tests do not account for model selection.

### **L 1.2 Bound Test ARDL Bounds Test**

Date: 04/24/17 Time: 22:37 Sample: 1992M03 1996M11 Included observations: 57 Null Hypothesis: No long-run relationships exist



Test Equation:

## **Dependent Variable: D(LDSEGEN) Method: Least Squares** Date: 04/24/17 Time: 22:37 Sample: 1992M03 1996M11 Included observations: 57



### **L 1.3 Short- and Long-run Coefficients ARDL Cointegrating And Long Run Form Dependent Variable: LDSEGEN** Selected Model: ARDL(1, 4, 0, 2, 5, 0, 0)

Sample: 1992M03 1996M11 Included observations: 57



Cointeq = LDSEGEN - (4.7009\*LIPI -9.0076\*LINT + 4.4548\*LCPI + 69.5462 \*LEXR + 2.2446\*LM2 -7.4229\*LGDPRICE -0.1122\*@TREND )



## **L 1.4 VECM and Significance Test of the Coefficients**

#### **Estimation Command:**

========================= LS DLDSEGEN DLIPI DLIPI(-1) DLIPI(-2) DLIPI(-3) DLCPI DLCPI(-1) DLEXR DLEXR(-1) DLEXR(-2) DLEXR(-3) DLEXR(-4) C @TREND LIPI(-1) LINT(-1) LCPI(-1) LEXR(-1) LM2(-1) LGDPRICE(-1) LDSEGEN(-1) **Estimation Equation:**

=========================

========================= DLDSEGEN = C(1)\*DLIPI + C(2)\*DLIPI(-1) + C(3)\*DLIPI(-2) + C(4)\*DLIPI(-3) + C(5)\*DLCPI +  $C(6)^*DLCPI(-1) + C(7)^*DLEXR + C(8)^*DLEXR(-1) + C(9)^*DLEXR(-2) + C(10)^*DLEXR(-3) +$ C(11)\*DLEXR(-4) + C(12) + C(13)\*@TREND + C(14)\*LIPI(-1) + C(15)\*LINT(-1) + C(16)\*LCPI(-1) +  $C(17)^*$ LEXR(-1) + C(18)\*LM2(-1) + C(19)\*LGDPRICE(-1) + C(20)\*LDSEGEN(-1) **Substituted Coefficients:**

DLDSEGEN = 0.288371849926\*DLIPI - 0.908278876222\*DLIPI(-1) - 0.403653397024\*DLIPI(-2) - 0.764018909884\*DLIPI(-3) + 2.30092619918\*DLCPI - 1.75807243676\*DLCPI(-1) + 4.94780689569\*DLEXR - 8.27875670273\*DLEXR(-1) - 12.345670906\*DLEXR(-2) - 5.64052962371\*DLEXR(-3) - 13.4159520442\*DLEXR(-4) - 81.0045118756 - 0.0185060214746\*@TREND + 1.28663150214\*LIPI(-1) - 0.97999310276\*LINT(-1) + 1.38685621325\*LCPI(-1) + 16.4879068585\*LEXR(-1) - 0.525485976367\*LM2(-1) - 1.03670370519\*LGDPRICE(-1) - 0.230341072067\*LDSEGEN(-1)

# **Wald Test:**

Equation: Untitled



## Null Hypothesis: C(1)=C(2)=C(3)=C(4)=0 Null Hypothesis Summary:



Restrictions are linear in coefficients.

## **Wald Test:**

Equation: Untitled



### Null Hypothesis: C(5)=C(6) Null Hypothesis Summary:



Restrictions are linear in coefficients.

## **Wald Test:**

Equation: Untitled





Restrictions are linear in coefficients.

## **L 2 For Meltdown Period**

# **L 2.1 ARDL Specification**

**Dependent Variable: LDSEGEN Method: ARDL** Sample: 1996M11 1999M12 Included observations: 38 Maximum dependent lags: 3 (Automatic selection) Model selection method: Akaike info criterion (AIC) Dynamic regressors (3 lags, automatic): LIPI LINT LCPI LEXR LM2 LGDPRICE Fixed regressors: C @TREND Number of models evalulated: 12288 Selected Model: ARDL(2, 0, 0, 0, 0, 0, 0)



\*Note: p-values and any subsequent tests do not account for model selection.

## **L 2.2 Bound Test**

**ARDL Bounds Test** Sample: 1996M11 1999M12 Included observations: 38 Null Hypothesis: No long-run relationships exist



Test Equation:

Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38





## **L 2.3 Short- and Long-run Coefficients**

**ARDL Cointegrating And Long Run Form** Dependent Variable: LDSEGEN Selected Model: ARDL(2, 0, 0, 0, 0, 0, 0) Sample: 1996M11 1999M12 Included observations: 38



Cointeq = LDSEGEN - (0.1825\*LIPI -25.2840\*LINT + 2.7415\*LCPI -15.6002\*LEXR -2.8238\*LM2 -0.4256\*LGDPRICE + 0.0660\*@TREND )



## **L 3 For Recovery Period**

**L 3.1 ARDL Specification**

**Dependent Variable: LDSEGEN**

**Method: ARDL** Sample: 2000M01 2009M12 Included observations: 120 Maximum dependent lags: 10 (Automatic selection) Model selection method: Akaike info criterion (AIC) Dynamic regressors (12 lags, automatic): LIPI LINT LCPI LEXR LM2 LGDPRICE Fixed regressors: C @TREND



Number of models evalulated: 48268090 Selected Model: ARDL(7, 1, 0, 3, 6, 10, 0)

\*Note: p-values and any subsequent tests do not account for model selection



Critical Value Bounds



Test Equation:

Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120



## **L 3.3 Short- and Long-run Coefficients ARDL Cointegrating And Long Run Form Dependent Variable: LDSEGEN**

Selected Model: ARDL(7, 1, 0, 3, 6, 10, 0) Date: 06/12/17 Time: 16:15 Sample: 2000M01 2009M12 Included observations: 120







## **L 3.4 VECM Results for Significance Test of the Coefficients**

#### **Estimation Command:**

========================= LS DLDSEGEN DLDSEGEN(-1) DLDSEGEN(-2) DLDSEGEN(-3) DLDSEGEN(-4) DLDSEGEN(-5) DLDSEGEN(-6) DLIPI DLCPI DLCPI(-1) DLCPI(-2) DLEXR DLEXR(-1) DLEXR(-2) DLEXR(-3) DLEXR(-4) DLEXR(-5) DLM2 DLM2(-1) DLM2(-2) DLM2(-3) DLM2(-4) DLM2(-5) DLM2(-6) DLM2(-7) DLM2(-8) DLM2(-9) C @TREND LIPI(-1) LINT(-1) LCPI(-1) LEXR(-1) LM2(-1) LGDPRICE(-1) LDSEGEN(-1)

#### **Estimation Equation:**

========================= DLDSEGEN = C(1)\*DLDSEGEN(-1) + C(2)\*DLDSEGEN(-2) + C(3)\*DLDSEGEN(-3) + C(4)\*DLDSEGEN(-4) + C(5)\*DLDSEGEN(-5) + C(6)\*DLDSEGEN(-6) + C(7)\*DLIPI + C(8)\*DLCPI + C(9)\*DLCPI(-1) + C(10)\*DLCPI(-2) + C(11)\*DLEXR + C(12)\*DLEXR(-1) + C(13)\*DLEXR(-2) + C(14)\*DLEXR(-3) + C(15)\*DLEXR(-4) + C(16)\*DLEXR(-5) + C(17)\*DLM2 + C(18)\*DLM2(-1) + C(19)\*DLM2(-2) +  $\overline{C(20)}^*$ DLM2(-3) +  $\overline{C(21)}^*$ DLM2(-4) +  $\overline{C(22)}^*$ DLM2(-5) +  $\overline{C(23)}^*$ DLM2(-6) +  $\overline{C(24)}^*$ DLM2(-7) +  $C(25)^*$ DLM2(-8) + C(26)\*DLM2(-9) + C(27) + C(28)\*@TREND + C(29)\*LIPI(-1) + C(30)\*LINT(-1) + C(31)\*LCPI(-1) + C(32)\*LEXR(-1) + C(33)\*LM2(-1) + C(34)\*LGDPRICE(-1) + C(35)\*LDSEGEN(-1)

#### **Substituted Coefficients:**

========================= DLDSEGEN = -0.00450245633882\*DLDSEGEN(-1) - 0.154595957557\*DLDSEGEN(-2) + 0.0942546600057\*DLDSEGEN(-3) + 0.075784367071\*DLDSEGEN(-4) + 0.158024178525\*DLDSEGEN(-5) + 0.307716164144\*DLDSEGEN(-6) + 0.00276991139801\*DLIPI + 0.192476936745\*DLCPI - 1.29324123244\*DLCPI(-1) - 1.65169790128\*DLCPI(-2) - 0.0972520775654\*DLEXR - 0.45822598621\*DLEXR(-1) - 0.716764509838\*DLEXR(-2) - 0.649964064344\*DLEXR(-3) - 0.722895195207\*DLEXR(-4) + 0.728023920266\*DLEXR(-5) + 1.98312513656\*DLM2 -2.88295954138\*DLM2(-1) - 1.95308115168\*DLM2(-2) - 1.77011198142\*DLM2(-3) - 2.89410430761\*DLM2(-4) - 1.88784496947\*DLM2(-5) - 3.22808151864\*DLM2(-6) - 1.53056149652\*DLM2(-7) - 2.01995730342\*DLM2(-8) - 1.24081540016\*DLM2(-9) - 13.3008865961 - 0.0321544914927\*@TREND + 0.171626658246\*LIPI(-1) - 6.31701298302\*LINT(-1) + 1.3664907124\*LCPI(-1) - 0.326184946103\*LEXR(-1) + 2.29141628363\*LM2(-1) - 0.139068878537\*LGDPRICE(-1) - 0.180373271671\*LDSEGEN(-1)

### **Wald Test:**

Equation: Untitled



Null Hypothesis: C(8)=C(9)=C(10)=0 Null Hypothesis Summary:



Restrictions are linear in coefficients.

#### **Wald Test:**

Equation: Untitled



Null Hypothesis: C(11)=C(12)=C(13)=C(14)=C(15)=C(16)=0 Null Hypothesis Summary:

Normalized Restriction $(= 0)$	Value	Std. Err.
C(11)	$-0.097252$	0.539442
C(12)	$-0.458226$	0.532902
C(13)	$-0.716765$	0.512749
C(14)	$-0.649964$	0.518398
C(15)	$-0.722895$	0.509646
C(16)	0.728024	0.517205

Restrictions are linear in coefficients.

## **Wald Test:**

Equation: Untitled



Null Hypothesis: C(17)=C(18)=C(19)=C(20)=C(21)=C(22)=

 $C(23)=C(24)=C(25)=C(26)=0$ 

Null Hypothesis Summary:



Restrictions are linear in coefficients.

# **Appendix M: Residual Diagnostic Tests for Different Periods**

# **M 1 For Bubble Period**



## **M 1.2 Breusch-Godfrey Serial Correlation LM Test**



Test Equation: Dependent Variable: RESID Method: ARDL Sample: 1992M03 1996M11 Included observations: 57 Presample missing value lagged residuals set to zero.







Test Equation: Dependent Variable: RESID^2

Method: Least Squares Sample: 1992M03 1996M11 Included observations: 57



# **M 2 For Meltdown Period**



# **M 2.1 Normality Test of Residuals**





Test Equation: Dependent Variable: RESID Method: ARDL Sample: 1996M11 1999M12 Included observations: 38 Presample missing value lagged residuals set to zero.



## **M 2.3 Heteroskedasticity Test: Breusch-Pagan-Godfrey**



Test Equation: Dependent Variable: RESID^2 Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38





# **M 3 For Recovery Period**

## **M 3.1 Normality Test of Residuals**

Histogram - Normality Test



## **M 3.2 Breusch-Godfrey Serial Correlation LM Test:**



Test Equation: Dependent Variable: RESID Method: ARDL Sample: 2000M01 2008M12 Included observations: 108 Presample missing value lagged residuals set to zero.







# **M 3.3 Heteroskedasticity Test: Breusch-Pagan-Godfrey**



Test Equation: Dependent Variable: RESID^2 Method: Least Squares Sample: 2000M01 2008M12 Included observations: 108




# **Appendix N: Ordinary Least Squares Estimation**

## **N 1 OLS Estimation Dependent Variable: DLDSEGEN Method: Least Squares** Date: 03/05/17 Time: 20:02 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments





## **N 2 Breusch-Godfrey Serial Correlation LM Test:**

## **N 3 Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: RESID^2 Method: Least Squares Date: 03/05/17 Time: 20:03 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



# **Appendix O: Volatility Modeling with EGARCH(1,1,1) Model**

## **Dependent Variable: DLDSEGEN**

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 22:03 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Failure to improve likelihood (non-zero gradients) after 100 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(8) + C(9)^*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(10)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(11)\*LOG(GARCH(-1))



#### **Heteroskedasticity Test: ARCH**



Test Equation:

Dependent Variable: WGT\_RESID^2 Method: Least Squares Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



# **Appendix P: Model Selection for Conditional Variance Estimation**

## **Dependent Variable: DLDSEGEN**

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:13 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 22 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)$ 



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:14 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:14 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 19 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:15 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:15 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 27 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(2) + C(3)^*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(5)\*LOG(GARCH(-1))



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:15 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:16 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 35 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(3) + C(4)^*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(6)\*LOG(GARCH(-1))



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:16 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:16 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 22 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(2) + C(3)\*RESID(-1)^2 + C(4)\*RESID(-1)^2\*(RESID(-1)<0) +  $C(5)$ \*GARCH(-1)



Heteroskedasticity Test: ARCH



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:16 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:17 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 22 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2 * (RESID(-1) < 0) +$  $C(6)$ \*GARCH $(-1)$ 



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:17 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:17 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 23 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)$ 







Test Equation:

Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:18 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:18 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 35 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:18 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:18 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 30 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)$ 

\*RESID(-1)/@SQRT(GARCH(-1)) + C(5)\*LOG(GARCH(-1))



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:18 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:19 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 34 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(6)\*LOG(GARCH(-1))



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:19 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:19 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 25 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(2) + C(3)\*RESID(-1)^2 + C(4)\*RESID(-1)^2\*(RESID(-1)<0) +

C(5)\*GARCH(-1)



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:19 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:19 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 45 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2 * (RESID(-1) < 0) +$ 

C(6)\*GARCH(-1)



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:19 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:20 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 19 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)$ 







Test Equation:

Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:20 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:20 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 22 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:21 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:21 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 42 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)$ 

\*RESID(-1)/@SQRT(GARCH(-1)) + C(5)\*LOG(GARCH(-1))



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:21 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:21 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 49 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(3) + C(4)^*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)$ 

\*RESID(-1)/@SQRT(GARCH(-1)) + C(6)\*LOG(GARCH(-1))



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:21 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:22 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 21 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(2) + C(3)\*RESID(-1)^2 + C(4)\*RESID(-1)^2\*(RESID(-1)<0) +





#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:22 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:22 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 21 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2 * (RESID(-1) < 0) +$ 

C(6)\*GARCH(-1)



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:22 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:23 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 30 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)$ 







Test Equation:

Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:23 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:23 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 30 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:23 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:24 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 63 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(6)\*LOG(GARCH(-1))



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:24 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:24 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 30 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(2) + C(3)\*RESID(-1)^2 + C(4)\*RESID(-1)^2\*(RESID(-1)<0) +  $C(5)$ \*GARCH(-1)



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:24 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:24 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 45 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2 * (RESID(-1) < 0) +$ 

C(6)\*GARCH(-1)



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:25 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:25 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 22 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)$ 



## **Heteroskedasticity Test: ARCH**



Test Equation:

Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:25 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:25 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 22 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:26 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:26 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Failure to improve likelihood (singular hessian) after 64 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(2) + C(3)^*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)$ 

\*RESID(-1)/@SQRT(GARCH(-1)) + C(5)\*LOG(GARCH(-1))



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:48 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:26 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Failure to improve likelihood (non-zero gradients) after 87 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(6)\*LOG(GARCH(-1))

Variable Coefficient Std. Error z-Statistic Prob. C 2.45E-08 0.000263 9.32E-05 0.9999 AR(1) 0.180667 0.033329 5.420722 0.0000 Variance Equation C(3) -0.568453 0.088811 -6.400700 0.0000 C(4) -0.100627 0.017289 -5.820248 0.0000 C(5) 0.454247 0.026648 17.04594 0.0000 C(6) 0.949290 0.010697 88.74597 0.0000 R-squared -0.062564 Mean dependent var 0.002640 Adjusted R-squared -0.066153 S.D. dependent var 0.009494 S.E. of regression 0.009803 Akaike info criterion -6.936002 Sum squared resid  $0.028443$  Schwarz criterion -6.861564<br>
Log likelihood 1039.464 Hannan-Quinn criter. -6.906205 Log likelihood 1039.464 Hannan-Quinn criter. Durbin-Watson stat 2.103607 Inverted AR Roots .18

## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:26 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:27 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Failure to improve likelihood (singular hessian) after 62 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(2) + C(3)\*RESID(-1)^2 + C(4)\*RESID(-1)^2\*(RESID(-1)<0) +  $C(5)$ \*GARCH(-1)



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:27 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:27 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Failure to improve likelihood (non-zero gradients) after 138 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2 * (RESID(-1) < 0) +$  $C(6)$ \*GARCH $(-1)$ 



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:27 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:28 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Failure to improve likelihood (non-zero gradients) after 420 iterations Coefficient covariance computed using outer product of gradients WARNING: Singular covariance - coefficients are not unique Presample variance: backcast (parameter = 0.7)  $GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)$ 



#### **Dependent Variable: DLM2**

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:28 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 25 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:28 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



#### **Dependent Variable: DLM2**

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:29 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 24 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(2) + C(3)^*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(5)\*LOG(GARCH(-1))



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:29 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



#### **Dependent Variable: DLM2**

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:29 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Failure to improve likelihood (singular hessian) after 87 iterations Coefficient covariance computed using outer product of gradients WARNING: Singular covariance - coefficients are not unique Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(6)\*LOG(GARCH(-1))



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:29 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 31 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(2) + C(3)\*RESID(-1)^2 + C(4)\*RESID(-1)^2\*(RESID(-1)<0) +





#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:55 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments


### **Dependent Variable: DLM2**

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:30 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Failure to improve likelihood (non-zero gradients) after 205 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2 * (RESID(-1) < 0) +$ C(6)\*GARCH(-1)



## **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:30 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:30 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 17 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)$ 







Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:30 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:31 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 18 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:58 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:31 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Convergence achieved after 36 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(2) + C(3)^*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(5)\*LOG(GARCH(-1))



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:31 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:31 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Convergence achieved after 32 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)$ \*RESID(-1)/@SQRT(GARCH(-1)) + C(6)\*LOG(GARCH(-1))



### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 22:00 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:32 Sample (adjusted): 1991M02 2015M12 Included observations: 299 after adjustments Failure to improve likelihood (non-zero gradients) after 9 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(2) + C(3)\*RESID(-1)^2 + C(4)\*RESID(-1)^2\*(RESID(-1)<0) +  $C(5)$ \*GARCH $(-1)$ 



#### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:32 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments



Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Date: 06/15/17 Time: 21:32 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Failure to improve likelihood (non-zero gradients) after 39 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7)  $GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2 * (RESID(-1) < 0) +$  $C(6)$ \*GARCH $(-1)$ 



### **Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: WGT\_RESID^2 Method: Least Squares Date: 06/15/17 Time: 21:32 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments





# **Appendix Q: Optimal Lag Selection for Conditional Variances**

\* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLDSEGEN Exogenous variables: C** Date: 05/16/17 Time: 22:41

Sample: 1991M01 2015M12 Included observations: 291



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: D(VDLDSEGEN) Exogenous variables: C @TREND** Sample: 1991M01 2015M12

Included observations: 290





### **VAR Lag Order Selection Criteria Endogenous variables: VDLDSEGEN Exogenous variables: C** Sample: 1991M01 2015M12

Included observations: 291



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLIPI Exogenous variables: C @TREND** Sample: 1991M01 2015M12 Included observations: 290



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLIPI Exogenous variables: C**

Sample: 1991M01 2015M12

Included observations: 290





### **VAR Lag Order Selection Criteria Endogenous variables: D(VDLIPI) Exogenous variables: C @TREND** Sample: 1991M01 2015M12 Included observations: 289



\* indicates lag order selected by the criterion

## **VAR Lag Order Selection Criteria Endogenous variables: D(VDLIPI) Exogenous variables: C**

Sample: 1991M01 2015M12 Included observations: 289



\* indicates lag order selected by the criterion

## **VAR Lag Order Selection Criteria Endogenous variables: VDLINT Exogenous variables: C @TREND**

Sample: 1991M01 2015M12 Included observations: 290





## **VAR Lag Order Selection Criteria Endogenous variables: VDLINT Exogenous variables: C** Sample: 1991M01 2015M12 Included observations: 290



\* indicates lag order selected by the criterion

## **VAR Lag Order Selection Criteria Endogenous variables: D(VDLINT) Exogenous variables: C @TREND** Sample: 1991M01 2015M12

Included observations: 289



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: D(VDLINT) Exogenous variables: C** Sample: 1991M01 2015M12 Included observations: 289



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLCPI Exogenous variables: C @TREND** Date: 05/16/17 Time: 22:57 Sample: 1991M01 2015M12

Included observations: 290



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLCPI Exogenous variables: C** Sample: 1991M01 2015M12 Included observations: 290



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: D(VDLCPI) Exogenous variables: C @TREND** Sample: 1991M01 2015M12 Included observations: 289



\* indicates lag order selected by the criterion

VAR Lag Order Selection Criteria

**Endogenous variables: D(VDLCPI) Exogenous variables: C** Sample: 1991M01 2015M12 Included observations: 289

Lag	LogL	LR	<b>FPE</b>	<b>AIC</b>	SC	HQ
$\Omega$	2984.240	$NA^*$	$6.33e-11*$	$-20.64526*$	$-20.63257*$	$-20.64017*$
	2984.343	0.205829	6.37e-11	$-20.63905$	$-20.61368$	$-20.62889$
2	2985.088	1.473597	6.38e-11	$-20.63728$	$-20.59923$	$-20.62203$
3	2985.188	0.197060	6.42e-11	$-20.63106$	$-20.58031$	$-20.61072$
4	2985.309	0.238013	6.46e-11	$-20.62497$	$-20.56154$	$-20.59956$
5	2986.157	1.660553	6.47e-11	$-20.62392$	$-20.54780$	$-20.59342$
6	2986.181	0.048470	6.51e-11	$-20.61717$	$-20.52837$	$-20.58159$
7	2987.708	2.968241	6.49e-11	$-20.62082$	$-20.51932$	$-20.58015$
8	2988.087	0.734185	6.51e-11	$-20.61652$	$-20.50234$	$-20.57077$

### **VAR Lag Order Selection Criteria Endogenous variables: VDLEXR Exogenous variables: C @TREND** Sample: 1991M01 2015M12

Included observations: 290



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLEXR Exogenous variables: C**

Sample: 1991M01 2015M12 Included observations: 290



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: D(VDLEXR) Exogenous variables: C @TREND** Sample: 1991M01 2015M12 Included observations: 289



\* indicates lag order selected by the criterion

## **VAR Lag Order Selection Criteria Endogenous variables: D(VDLEXR) Exogenous variables: C**

Sample: 1991M01 2015M12 Included observations: 289



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLM2 Exogenous variables: C @TREND** Sample: 1991M01 2015M12 Included observations: 290



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: VDLM2 Exogenous variables: C** Sample: 1991M01 2015M12 Included observations: 290



\* indicates lag order selected by the criterion

### **VAR Lag Order Selection Criteria Endogenous variables: D(VDLM2) Exogenous variables: C @TREND** Date: 05/16/17 Time: 23:20 Sample: 1991M01 2015M12 Included observations: 282



\* indicates lag order selected by the criterion

# **VAR Lag Order Selection Criteria Endogenous variables: D(VDLM2) Exogenous variables: C**

Date: 05/16/17 Time: 23:21 Sample: 1991M01 2015M12 Included observations: 282





### **VAR Lag Order Selection Criteria Endogenous variables: VDLGDPRICE Exogenous variables: C @TREND** Date: 05/16/17 Time: 23:21

Sample: 1991M01 2015M12 Included observations: 291



\* indicates lag order selected by the criterion

# **VAR Lag Order Selection Criteria Endogenous variables: VDLGDPRICE**

**Exogenous variables: C** Date: 05/16/17 Time: 23:22 Sample: 1991M01 2015M12 Included observations: 291



\* indicates lag order selected by the criterion

## **VAR Lag Order Selection Criteria Endogenous variables: D(VDLGDPRICE) Exogenous variables: C @TREND** Date: 05/16/17 Time: 23:22 Sample: 1991M01 2015M12

Included observations: 290



\* indicates lag order selected by the criterion

## **VAR Lag Order Selection Criteria Endogenous variables: D(VDLGDPRICE) Exogenous variables: C** Date: 05/16/17 Time: 23:23 Sample: 1991M01 2015M12 Included observations: 290



\* indicates lag order selected by the criterion

# **Appendix R: Unit Root Tests of Conditional Variances**

# **R 1 ADF Unit Root Test**

# **Null Hypothesis: VDLDSEGEN has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLDSEGEN) Method: Least Squares Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments



#### **Null Hypothesis: VDLIPI has a unit root**

**Exogenous: Constant, Linear Trend** Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLIPI) Method: Least Squares Sample (adjusted): 1991M05 2015M12 Included observations: 296 after adjustments





# **Null Hypothesis: VDLINT has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 6 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLINT) Method: Least Squares Sample (adjusted): 1991M10 2015M12 Included observations: 291 after adjustments



### **Null Hypothesis: VDLCPI has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 1 (Fixed)



\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

### Dependent Variable: D(VDLCPI) Method: Least Squares Sample (adjusted): 1991M05 2015M12 Included observations: 296 after adjustments



# **Null Hypothesis: VDLCPI has a unit root**

**Exogenous: Constant** Lag Length: 1 (Fixed)

![](_page_595_Picture_320.jpeg)

\*MacKinnon (1996) one-sided p-values.

### Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLCPI) Method: Least Squares Sample (adjusted): 1991M05 2015M12 Included observations: 296 after adjustments

![](_page_595_Picture_321.jpeg)

# **Null Hypothesis: D(VDLCPI) has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 0 (Fixed)

![](_page_595_Picture_322.jpeg)

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

### Dependent Variable: D(VDLCPI,2) Method: Least Squares Date: 05/16/17 Time: 23:43 Sample (adjusted): 1991M05 2015M12 Included observations: 296 after adjustments

![](_page_596_Picture_300.jpeg)

## **Null Hypothesis: VDLEXR has a unit root Exogenous: Constant, Linear Trend**

Lag Length: 3 (Fixed)

![](_page_596_Picture_301.jpeg)

\*MacKinnon (1996) one-sided p-values.

### Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLEXR) Method: Least Squares Date: 05/16/17 Time: 23:43 Sample (adjusted): 1991M07 2015M12 Included observations: 294 after adjustments

![](_page_596_Picture_302.jpeg)

#### **Null Hypothesis: VDLM2 has a unit root Exogenous: Constant, Linear Trend** Lag Length: 7 (Fixed)

![](_page_597_Picture_329.jpeg)

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLM2) Method: Least Squares Sample (adjusted): 1991M11 2015M12 Included observations: 290 after adjustments

![](_page_597_Picture_330.jpeg)

#### **Null Hypothesis: VDLM2 has a unit root Exogenous: Constant**

Lag Length: 7 (Fixed)

![](_page_597_Picture_331.jpeg)

\*MacKinnon (1996) one-sided p-values.

### Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLM2) Method: Least Squares Sample (adjusted): 1991M11 2015M12 Included observations: 290 after adjustments

![](_page_597_Picture_332.jpeg)

![](_page_598_Picture_426.jpeg)

#### **Null Hypothesis: D(VDLM2) has a unit root**

**Exogenous: Constant, Linear Trend** Lag Length: 13 (Fixed)

![](_page_598_Picture_427.jpeg)

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLM2,2) Method: Least Squares Sample (adjusted): 1992M06 2015M12 Included observations: 283 after adjustments

![](_page_598_Picture_428.jpeg)

### **Null Hypothesis: VDLGDPRICE has a unit root Exogenous: Constant, Linear Trend** Lag Length: 4 (Fixed)

![](_page_599_Picture_265.jpeg)

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation Dependent Variable: D(VDLGDPRICE) Method: Least Squares Date: 05/16/17 Time: 23:44 Sample (adjusted): 1991M07 2015M12 Included observations: 294 after adjustments

![](_page_599_Picture_266.jpeg)

# **R 2 PP Unit Root Test**

## **Null Hypothesis: VDLDSEGEN has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel

![](_page_599_Picture_267.jpeg)

### Phillips-Perron Test Equation Dependent Variable: D(VDLDSEGEN) Method: Least Squares Date: 05/16/17 Time: 23:45 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments

![](_page_600_Picture_283.jpeg)

# **Null Hypothesis: VDLIPI has a unit root**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel

![](_page_600_Picture_284.jpeg)

Phillips-Perron Test Equation Dependent Variable: D(VDLIPI) Method: Least Squares Date: 05/16/17 Time: 23:45 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments

![](_page_600_Picture_285.jpeg)

# **Null Hypothesis: VDLINT has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 6 (Used-specified) using Bartlett kernel

![](_page_601_Picture_269.jpeg)

Phillips-Perron Test Equation Dependent Variable: D(VDLINT) Method: Least Squares Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments

![](_page_601_Picture_270.jpeg)

## **Null Hypothesis: VDLCPI has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 1 (Used-specified) using Bartlett kernel

![](_page_601_Picture_271.jpeg)

Included observations: 297 after adjustments

![](_page_601_Picture_272.jpeg)

![](_page_602_Picture_263.jpeg)

# **Null Hypothesis: VDLCPI has a unit root**

**Exogenous: Constant**

Bandwidth: 1 (Used-specified) using Bartlett kernel

![](_page_602_Picture_264.jpeg)

HAC corrected variance (Bartlett kernel) 6.57E-11

Phillips-Perron Test Equation Dependent Variable: D(VDLCPI) Method: Least Squares Date: 05/16/17 Time: 23:46 Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments

![](_page_602_Picture_265.jpeg)

Null Hypothesis: D(VDLCPI) has a unit root Exogenous: Constant, Linear Trend

Bandwidth: 0 (Used-specified) using Bartlett kernel

![](_page_602_Picture_266.jpeg)

\*MacKinnon (1996) one-sided p-values.

![](_page_603_Picture_287.jpeg)

Phillips-Perron Test Equation Dependent Variable: D(VDLCPI,2) Method: Least Squares Sample (adjusted): 1991M05 2015M12 Included observations: 296 after adjustments

![](_page_603_Picture_288.jpeg)

# **Null Hypothesis: VDLEXR has a unit root**

**Exogenous: Constant, Linear Trend**

Bandwidth: 3 (Used-specified) using Bartlett kernel

![](_page_603_Picture_289.jpeg)

\*MacKinnon (1996) one-sided p-values.

![](_page_603_Picture_290.jpeg)

### Phillips-Perron Test Equation Dependent Variable: D(VDLEXR) Method: Least Squares Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments

![](_page_603_Picture_291.jpeg)

# **Null Hypothesis: VDLM2 has a unit root Exogenous: Constant, Linear Trend**

Bandwidth: 7 (Used-specified) using Bartlett kernel

![](_page_604_Picture_270.jpeg)

Phillips-Perron Test Equation Dependent Variable: D(VDLM2) Method: Least Squares Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments

![](_page_604_Picture_271.jpeg)

## **Null Hypothesis: VDLM2 has a unit root Exogenous: Constant**

Bandwidth: 7 (Used-specified) using Bartlett kernel

![](_page_604_Picture_272.jpeg)

Phillips-Perron Test Equation Dependent Variable: D(VDLM2) Method: Least Squares Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments

![](_page_604_Picture_273.jpeg)

![](_page_605_Picture_260.jpeg)

# **Null Hypothesis: D(VDLM2) has a unit root**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 13 (Used-specified) using Bartlett kernel

![](_page_605_Picture_261.jpeg)

### Phillips-Perron Test Equation Dependent Variable: D(VDLM2,2) Method: Least Squares Sample (adjusted): 1991M05 2015M12 Included observations: 296 after adjustments

![](_page_605_Picture_262.jpeg)

# **Null Hypothesis: VDLGDPRICE has a unit root**

# **Exogenous: Constant, Linear Trend**

Bandwidth: 4 (Used-specified) using Bartlett kernel

![](_page_605_Picture_263.jpeg)

\*MacKinnon (1996) one-sided p-values.

![](_page_606_Picture_127.jpeg)

Phillips-Perron Test Equation Dependent Variable: D(VDLGDPRICE) Method: Least Squares Date: 05/16/17 Time: 23:48 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments

![](_page_606_Picture_128.jpeg)

# **Appendix S: ARDL Cointegration Test on Conditional Variances**

## **S 1 ARDL Specification**

**Dependent Variable: VDLDSEGEN** Method: ARDL Date: 05/17/17 Time: 23:09 Sample (adjusted): 1991M03 2015M12 Included observations: 298 after adjustments Maximum dependent lags: 1 (Automatic selection) Model selection method: Akaike info criterion (AIC) Dynamic regressors (7 lags, automatic): VDLIPI VDLINT VDLCPI VDLEXR VDLM2 VDLGDPRICE Fixed regressors: C Number of models evalulated: 262144 Selected Model: ARDL(1, 0, 0, 0, 0, 0, 0) Note: final equation sample is larger than selection sample

![](_page_607_Picture_281.jpeg)

\*Note: p-values and any subsequent tests do not account for model selection

### **S 2 ARDL Bounds Test**

Date: 05/17/17 Time: 23:11 Sample: 1991M03 2015M12 Included observations: 297 Null Hypothesis: No long-run relationships exist

![](_page_607_Picture_282.jpeg)

### Test Equation: **Dependent Variable: D(VDLDSEGEN) Method: Least Squares** Sample (adjusted): 1991M04 2015M12 Included observations: 297 after adjustments

![](_page_608_Picture_389.jpeg)

## **S 3 ARDL Cointegrating And Long Run Form Dependent Variable: VDLDSEGEN**

Selected Model: ARDL(1, 0, 0, 0, 0, 0, 0) Sample: 1991M01 2015M12 Included observations: 298

![](_page_608_Picture_390.jpeg)

 Cointeq = VDLDSEGEN - (3.2256\*VDLIPI - 27.2636\*VDLINT + 55.4220 \*VDLCPI + 4.8936\*VDLEXR - 4.0855\*VDLM2 - 0.0856\*VDLGDPRICE)

![](_page_608_Picture_391.jpeg)

# **S 4 Viability Check of the Model**

## **S 4.1 Correlogram Test**

Sample: 1991M01 2015M12 Included observations: 298 **Q-statistic probabilities adjusted for 1 dynamic regressor**

![](_page_609_Picture_613.jpeg)

\*Probabilities may not be valid for this equation specification.

# **S 4.2 Normality Test of the Residuals**

![](_page_609_Figure_7.jpeg)

Histogram - Normality Test

![](_page_610_Picture_393.jpeg)

# **S 4.3 Breusch-Godfrey Serial Correlation LM Test:**

# **S 4.4 Heteroskedasticity Test: Breusch-Pagan-Godfrey**

![](_page_610_Picture_394.jpeg)

Log likelihood 1048.844 Hannan-Quinn criter. -6.934124

### Test Equation: Dependent Variable: RESID^2 Method: Least Squares Sample: 1991M03 2015M12 Included observations: 298

Durbin-Watson stat 1.999454

![](_page_610_Picture_395.jpeg)

# **Appendix T: Ordinary Least Squares Estimation of the Recovery Period**

## **T 1 OLS Estimation Dependent Variable: DLDSEGEN Method: Least Squares** Date: 07/01/17 Time: 17:02

Sample: 2000M01 2009M12 Included observations: 120

![](_page_611_Picture_396.jpeg)

# **T 2 Breusch-Godfrey Serial Correlation LM Test:**

![](_page_611_Picture_397.jpeg)

## Test Equation: Dependent Variable: RESID Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120 Presample missing value lagged residuals set to zero.

![](_page_611_Picture_398.jpeg)
# **T 3 Heteroskedasticity Test: ARCH**



Test Equation: Dependent Variable: RESID^2 Method: Least Squares Date: 07/01/17 Time: 17:03 Sample (adjusted): 2000M02 2009M12 Included observations: 119 after adjustments



# **Appendix U: Optimal Lag Selection for Johansen Cointegration Test**

**Roots of Characteristic Polynomial Endogenous variables: LDSEGEN LIPI** Exogenous variables: C @TREND Lag specification: 1 1 Date: 07/08/17 Time: 16:24



No root lies outside the unit circle. VAR satisfies the stability condition.

# -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

**VAR Lag Order Selection Criteria Endogenous variables: LDSEGEN LIPI**

Exogenous variables: C @TREND Date: 07/08/17 Time: 16:06 Sample: 1991M01 2015M12 Included observations: 285



\* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

#### Inverse Roots of AR Characteristic Polynomial

# **Appendix V: Relationship between Stock Market and the Real Economy in Total Sample Period**

# **V 1 Johansen Cointegration**

Roots of Characteristic Polynomial Sample (adjusted): 1992M04 2015M12 Included observations: 285 after adjustments Trend assumption: Linear deterministic trend (restricted) Series: LDSEGEN LIPI Lags interval (in first differences): 1 to 14 Unrestricted Cointegration Rank Test (Trace)



Trace test indicates no cointegration at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)



Max-eigenvalue test indicates no cointegration at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values





# **V 2 Restricted VAR Model**







No root lies outside the unit circle. VAR satisfies the stability condition.

#### **VAR Lag Order Selection Criteria Endogenous variables: DLDSEGEN DLIPI**

Exogenous variables: C Date: 07/08/17 Time: 16:08 Sample: 1991M01 2015M12 Included observations: 285



\* indicates lag order selected by the criterion

# **V 2.2 Vector Autoregression Estimates**

Date: 07/08/17 Time: 16:09 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments Standard errors in ( ) & t-statistics in [ ]









#### **Dependent Variable: DLDSEGEN**

**Method: Least Squares (Gauss-Newton / Marquardt steps)**

Date: 07/08/17 Time: 16:09

Sample (adjusted): 1992M03 2015M12

Included observations: 286 after adjustments

DLDSEGEN = C(1)\*DLDSEGEN(-1) + C(2)\*DLDSEGEN(-2) + C(3) \*DLDSEGEN(-3) + C(4)\*DLDSEGEN(-4) + C(5)\*DLDSEGEN(-5) + C(6) \*DLDSEGEN(-6) + C(7)\*DLDSEGEN(-7) + C(8)\*DLDSEGEN(-8) + C(9) \*DLDSEGEN(-9) + C(10)\*DLDSEGEN(-10) + C(11)\*DLDSEGEN(-11) +  $C(12)^*$ DLDSEGEN(-12) + C(13)\*DLDSEGEN(-13) + C(14)\*DLIPI(-1) +  $C(15)^*$ DLIPI(-2) +  $C(16)^*$ DLIPI(-3) +  $C(17)^*$ DLIPI(-4) +  $C(18)^*$ DLIPI(-5) + C(19)\*DLIPI(-6) + C(20)\*DLIPI(-7) + C(21)\*DLIPI(-8) + C(22)\*DLIPI( -9) + C(23)\*DLIPI(-10) + C(24)\*DLIPI(-11) + C(25)\*DLIPI(-12) + C(26)  $*$ DLIPI(-13) + C(27)



#### **Wald Test:**

Equation: Untitled



Null Hypothesis: C(14)=C(15)=C(16)=C(17)=C(18)=C(19)=  $C(20)=C(21)=C(22)=C(23)=C(24)=C(25)=C(26)=0$ 

Null Hypothesis Summary:



Restrictions are linear in coefficients.

#### **Dependent Variable: DLIPI**

#### **Method: Least Squares (Gauss-Newton / Marquardt steps)**

Date: 07/08/17 Time: 16:32 Sample (adjusted): 1992M03 2015M12 Included observations: 286 after adjustments DLIPI = C(28)\*DLDSEGEN(-1) + C(29)\*DLDSEGEN(-2) + C(30) \*DLDSEGEN(-3) + C(31)\*DLDSEGEN(-4) + C(32)\*DLDSEGEN(-5) + C(33)\*DLDSEGEN(-6) + C(34)\*DLDSEGEN(-7) + C(35)\*DLDSEGEN( -8) + C(36)\*DLDSEGEN(-9) + C(37)\*DLDSEGEN(-10) + C(38) \*DLDSEGEN(-11) + C(39)\*DLDSEGEN(-12) + C(40)\*DLDSEGEN(-13) + C(41)\*DLIPI(-1) + C(42)\*DLIPI(-2) + C(43)\*DLIPI(-3) + C(44)\*DLIPI( -4) + C(45)\*DLIPI(-5) + C(46)\*DLIPI(-6) + C(47)\*DLIPI(-7) + C(48) \*DLIPI(-8) + C(49)\*DLIPI(-9) + C(50)\*DLIPI(-10) + C(51)\*DLIPI(-11) +  $C(52)^*$ DLIPI(-12) +  $C(53)^*$ DLIPI(-13) +  $C(54)$ 





#### **Wald Test:**

Equation: Untitled



Null Hypothesis: C(28)=C(29)=C(30)=C(31)=C(32)=C(33)=  $C(34)=C(35)=C(36)=C(37)=C(38)=C(39)=C(40)=0$ 

Null Hypothesis Summary:



Restrictions are linear in coefficients.

#### **V 2.3 Pairwise Granger Causality Tests**

Date: 07/08/17 Time: 20:45 Sample: 1991M01 2015M12 Lags: 12



#### **V 3 ARDL Approach**

#### **V 3.1 ARDL Cointegration Test**

Dependent Variable: LDSEGEN Method: ARDL Sample (adjusted): 1991M07 2015M12 Included observations: 294 after adjustments



#### Dependent lags: 2 (Fixed) Dynamic regressors (6 lags, fixed): LIPI Fixed regressors: C @TREND

\*Note: p-values and any subsequent tests do not account for model selection

# **V 3.2 ARDL Bounds Test**

Date: 12/06/17 Time: 10:48 Sample: 1991M07 2015M12 Included observations: 294 Null Hypothesis: No long-run relationships exist



Test Equation:

Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 1991M07 2015M12 Included observations: 294





#### **V 3.3 ARDL Cointegrating And Long Run Form**

ARDL Cointegrating And Long Run Form Dependent Variable: LDSEGEN Selected Model: ARDL(2, 6) Date: 12/06/17 Time: 10:48 Sample: 1991M01 2015M12 Included observations: 294



#### **V 3.4 VECM and Significance Test of the Coefficients**

#### **Estimation Command:**

========================= LS DLDSEGEN DLDSEGEN(-1) DLIPI DLIPI(-1) DLIPI(-2) DLIPI(-3) DLIPI(-4) DLIPI(-5) C @TREND LIPI(-1) LDSEGEN(-1)

#### **Estimation Equation:** =========================

DLDSEGEN = C(1)\*DLDSEGEN(-1) + C(2)\*DLIPI + C(3)\*DLIPI(-1) + C(4)\*DLIPI(-2) + C(5)\*DLIPI(-3) +  $C(6)^*$ DLIPI(-4) +  $C(7)^*$ DLIPI(-5) +  $C(8)$  +  $C(9)^*$  @TREND +  $C(10)^*$ LIPI(-1) +  $C(11)^*$ LDSEGEN(-1) **Substituted Coefficients:**

========================= DLDSEGEN = 0.177291163235\*DLDSEGEN(-1) + 0.0224460457385\*DLIPI - 0.00508828517343\*DLIPI(-1) - 0.0190895973861\*DLIPI(-2) - 0.0414553211349\*DLIPI(-3) - 0.0176542641602\*DLIPI(-4) + 0.107511890654\*DLIPI(-5) - 0.261960381682 - 0.000298754664635\*@TREND + 0.0957331994438\*LIPI(-1) - 0.0348428384748\*LDSEGEN(-1) **Wald Test:** Equation: Untitled





Restrictions are linear in coefficients.

# **V 3.4 Viability Check of the Model**

**Breusch-Godfrey Serial Correlation LM Test:**



Test Equation: Dependent Variable: RESID

Method: Least Squares

Sample: 1991M07 2015M12

Included observations: 294

Presample missing value lagged residuals set to zero.



#### **Heteroskedasticity Test: Breusch-Pagan-Godfrey**



Test Equation: Dependent Variable: RESID^2 Method: Least Squares Date: 12/06/17 Time: 11:39 Sample: 1991M07 2015M12 Included observations: 294





**Histogram - Normality Test**

# **Appendix W: Relationships Between Stock Market and Real Economy in Different Periods**

# **W 1 For Bubble Period**

#### **W 1.1 ARDL Cointegration Test**

Dependent Variable: LDSEGEN Method: ARDL Sample: 1992M03 1996M11 Included observations: 57 Dependent lags: 4 (Fixed) Dynamic regressors (1 lag, fixed): LIPI Fixed regressors: C @TREND



\*Note: p-values and any subsequent tests do not account for model selection.

#### **W 1.2 ARDL Bounds Test**

Date: 12/06/17 Time: 11:47 Sample: 1992M03 1996M11 Included observations: 57 Null Hypothesis: No long-run relationships exist



Test Equation: Dependent Variable: D(LDSEGEN) Method: Least Squares Date: 12/06/17 Time: 11:47 Sample: 1992M03 1996M11 Included observations: 57



# **W 1.3 ARDL Cointegrating And Long Run Form**

Dependent Variable: LDSEGEN Selected Model: ARDL(4, 1) Date: 12/06/17 Time: 11:47 Sample: 1992M03 1996M11 Included observations: 57



Cointeq = LDSEGEN - (-1.4642\*LIPI + 0.0497\*@TREND )



# **W 1.4 Viability Check of the Model**

# **W 1.4.1 Breusch-Godfrey Serial Correlation LM Test:**



Test Equation:

Dependent Variable: RESID Method: Least Squares Date: 12/06/17 Time: 12:03 Sample: 1992M03 1996M11 Included observations: 57 Presample missing value lagged residuals set to zero.



#### **W 1.4.2 Heteroskedasticity Test: Breusch-Pagan-Godfrey**



Test Equation:

Dependent Variable: RESID^2 Method: Least Squares Date: 12/06/17 Time: 12:03 Sample: 1992M03 1996M11 Included observations: 57





#### **W 1.4.3 Histogram - Normality Test**



#### **W 1.5 Pairwise Granger Causality Tests**

Sample: 1992M03 1996M11



#### **W 2 For Meltdown Period**

#### **W 2.1 ARDL Cointegration Test**

Dependent Variable: LDSEGEN Method: ARDL Sample: 1996M11 1999M12 Included observations: 38 Dependent lags: 2 (Fixed) Dynamic regressors (2 lags, fixed): LIPI Fixed regressors: C @TREND



\*Note: p-values and any subsequent tests do not account for model seletion

#### **W 2.2 ARDL Bounds Test**

Date: 12/06/17 Time: 12:13 Sample: 1996M11 1999M12 Included observations: 38 Null Hypothesis: No long-run relationships exist



Test Equation:

Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38



# **W 2.3 ARDL Cointegrating And Long Run Form**

Dependent Variable: LDSEGEN Selected Model: ARDL(2, 2) Sample: 1996M11 1999M12 Included observations: 38





#### **W 2.4 VECM and Significance Test of the Coefficients**

#### **Estimation Command:**

========================= LS DLDSEGEN DLDSEGEN(-1) DLIPI DLIPI(-1) C @TREND LIPI(-1) LDSEGEN(-1) **Estimation Equation:** =========================

DLDSEGEN = C(1)\*DLDSEGEN(-1) + C(2)\*DLIPI + C(3)\*DLIPI(-1) + C(4) + C(5)\*@TREND + C(6)\*LIPI(-1)  $+ C(7)^*LDSEGEN(-1)$ 

#### **Substituted Coefficients:**

========================= DLDSEGEN = 0.196977452605\*DLDSEGEN(-1) + 0.0338692830994\*DLIPI + 0.179203364017\*DLIPI(-1) + 1.63507842812 - 0.00442529593509\*@TREND - 0.025665655881\*LIPI(-1) - 0.202839300566\*LDSEGEN(- 1)

Wald Test: Equation: Untitled



Restrictions are linear in coefficients.

#### **W 2.5 Viability Check of the Model**

#### **W 2.5.1 Breusch-Godfrey Serial Correlation LM Test:**



Test Equation: Dependent Variable: RESID Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38 Presample missing value lagged residuals set to zero.





# **W 2.5.2 Heteroskedasticity Test: Breusch-Pagan-Godfrey**



Test Equation:

Dependent Variable: RESID^2 Method: Least Squares Sample: 1996M11 1999M12 Included observations: 38







# **W 2.6 Pairwise Granger Causality Tests**

Date: 12/06/17 Time: 13:06 Sample: 1996M11 1999M12 Lags: 12



# **W 3 For Recovery Period**

# **W 3.1 ARDL Cointegration Test**

Dependent Variable: LDSEGEN Method: ARDL Sample: 2000M01 2009M12 Included observations: 120 Dependent lags: 10 (Fixed) Dynamic regressors (12 lags, fixed): LIPI Fixed regressors: C @TREND



\*Note: p-values and any subsequent tests do not account for model selection

#### **W 3.2 ARDL Bounds Test**

Date: 12/06/17 Time: 12:19 Sample: 2000M01 2009M12 Included observations: 120 Null Hypothesis: No long-run relationships exist



Critical Value Bounds



Test Equation:

Dependent Variable: D(LDSEGEN) Method: Least Squares Sample: 2000M01 2009M12 Included observations: 120





#### **W 3.3 ARDL Cointegrating And Long Run Form**

Dependent Variable: LDSEGEN Selected Model: ARDL(10, 12) Sample: 2000M01 2009M12 Included observations: 120



Cointeq = LDSEGEN - (3.3651\*LIPI -0.0065\*@TREND )



#### **W 3.4 VECM and Significance Test of the Coefficients**

#### **Estimation Command:**

=========================

LS DLDSEGEN DLDSEGEN(-1) DLDSEGEN(-2) DLDSEGEN(-3) DLDSEGEN(-4) DLDSEGEN(-5) DLDSEGEN(-6) DLDSEGEN(-7) DLDSEGEN(-8) DLDSEGEN(-9) DLIPI DLIPI(-1) DLIPI(-2) DLIPI(-3) DLIPI(-4) DLIPI(-5) DLIPI(-6) DLIPI(-7) DLIPI(-8) DLIPI(-9) DLIPI(-10) DLIPI(-11) C @TREND LIPI(-1) LDSEGEN(-1) **Estimation Equation:**

=========================

DLDSEGEN = C(1)\*DLDSEGEN(-1) + C(2)\*DLDSEGEN(-2) + C(3)\*DLDSEGEN(-3) + C(4)\*DLDSEGEN(-4) + C(5)\*DLDSEGEN(-5) + C(6)\*DLDSEGEN(-6) + C(7)\*DLDSEGEN(-7) + C(8)\*DLDSEGEN(-8) +

C(9)\*DLDSEGEN(-9) + C(10)\*DLIPI + C(11)\*DLIPI(-1) + C(12)\*DLIPI(-2) + C(13)\*DLIPI(-3) + C(14)\*DLIPI(- 4) + C(15)\*DLIPI(-5) + C(16)\*DLIPI(-6) + C(17)\*DLIPI(-7) + C(18)\*DLIPI(-8) + C(19)\*DLIPI(-9) + C(20)\*DLIPI(-10) + C(21)\*DLIPI(-11) + C(22) + C(23)\*@TREND + C(24)\*LIPI(-1) + C(25)\*LDSEGEN(-1) **Substituted Coefficients:**

========================= DLDSEGEN = 0.208526896603\*DLDSEGEN(-1) + 0.00954662201785\*DLDSEGEN(-2) + 0.248998489995\*DLDSEGEN(-3) + 0.0701692232607\*DLDSEGEN(-4) + 0.294291505081\*DLDSEGEN(-5) + 0.0718256305352\*DLDSEGEN(-6) + 0.0570623411242\*DLDSEGEN(-7) - 0.293759972497\*DLDSEGEN(-8) + 0.277448480854\*DLDSEGEN(-9) - 0.0706260197846\*DLIPI - 0.251618461476\*DLIPI(-1) - 0.320472823988\*DLIPI(-2) - 0.157604607292\*DLIPI(-3) - 0.343323624262\*DLIPI(-4) - 0.0323809359605\*DLIPI(-5) - 0.235335953458\*DLIPI(-6) - 0.126587840723\*DLIPI(-7) - 0.307193240059\*DLIPI(-8) - 0.195842313495\*DLIPI(-9) - 0.215649901049\*DLIPI(-10) - 0.0115333120635\*DLIPI(-11) - 1.413650351 - 0.000806793642913\*@TREND + 0.416077339512\*LIPI(-1) - 0.123643770463\*LDSEGEN(-1)

#### **Wald Test:**

Equation: Untitled



Null Hypothesis: C(10)=C(11)=C(12)=C(13)=C(14)=C(15)=  $C(16)=C(17)=C(18)=C(19)=C(20)=C(21)=0$ 

Null Hypothesis Summary:



Restrictions are linear in coefficients.

#### **W 3.5 Viability Check of the Model**

#### **W 3.5.1 Breusch-Godfrey Serial Correlation LM Test:**



Test Equation: Dependent Variable: RESID Method: Least Squares Date: 12/06/17 Time: 23:58 Sample: 2000M01 2009M12 Included observations: 120 Presample missing value lagged residuals set to zero.





# **W 3.5.2 Heteroskedasticity Test: Breusch-Pagan-Godfrey**



Test Equation: Dependent Variable: RESID^2 Method: Least Squares Date: 12/06/17 Time: 23:59 Sample: 2000M01 2009M12 Included observations: 120





# **W 3.5.3 Histogram - Normality Test**



# **W 3.6 Pairwise Granger Causality Tests**

Date: 12/06/17 Time: 12:31 Sample: 2000M01 2009M12 Lags: 12

