IMPACT OF THE MACROECONOMIC VARIABLES ON ALL SHARE PRICE INDEX: GARCH-X APPROACH

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Declaration

"I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Abstract

This study examines the dynamic impact of macroeconomic variables on all share price index (ASPI) volatility. Data were collected for the period commence from January 2006 to December 2015 using Central Bank annual reports and publications of Colombo stock exchange. Money supply, interest rates, consumer price index, exchange rate, and industrial production index were used as macroeconomic variables of the study. The AR(1)-GARCH (1, 1)-X model was identified as the significant model to model volatility of all share price index series. It was found that the previous all share price index (lag 1) positively and significantly affects the current all share price index implying that the volatility of stock market prices is affected by related news from the previous period (lag 1) more than by past volatility. Negative values of two parameters of the GARCH indicates that shocks to the conditional variance take a short time to die out, so volatility is not persistent. The result further implies that the volatility in interest rate and industrial production index are highly impact for the volatility of all share price index. The Johansen-Juselius cointegration test suggested that macroeconomic variables in the system share a long run relationship. Results imply that, all share price index has significant positive long run relationships with money supply, interest rate & exchange rate while significant negative long run relationships with industrial production index & consumer price index. The results of this study can be utilized for better decision making in share market.

Key words: all share price index, dynamic relationship, macroeconomic variables, volatility

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List of Abbreviations

Abbreviation	Description
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterions
APT	Arbitrage Pricing Theory
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ASPI	All Share Price Index
BSE	Bombay Stock Exchange
CAPM	Capital Asset Price Model
CCPI	Colombo Consumer Price Index
CSE	Colombo Stock Exchange
EGARCH	Exponential GARCH
EMH	Efficient Market Hypothesis
EXR	Exchange Rate
FEVD	Forecast Error Variance Decomposition
FPE	Final Prediction Error
FTSE	Financial Times Stock Exchange
GARCH	Generalized Autoregressive conditional Heteroscedasticity
GCC	Gulf Cooperation Council
GDP	Gross Domestic Production
GNP	Gross National Product
GRT	Granger’s Representation Theorem
HQ	Hannan-Quinn information criterion
IPI	Industrial Production Index
IR	Interest Rate
IRF	Impulse Response Function
LM	Lagrange Multiplier
LN	Natural Log
LR	Lag Range
LTTE	Liberation Tigers of Tamil Eelam
MA	Moving Average

MS	Money Supply
NSE	National Stock Exchange
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
PGARCH	Periodic GARCH
PVM	Present Value Model
S&P	Standard & Poor
SIC	Schwarz Information Criterion
TGARCH	Threshold GARCH
UK	United Kingdom
US	United States
VAR	Variance Autoregressive
VDC	Variance Decomposition
VECM	Vector Error Correction Model
VMA	Vector Moving Average
WTI	Western Texas Intermediate

CHAPTER 01
INTRODUCTION

1.1 Background of the Study

Stock markets play a vital role in the modern economy, because it acts as a mediator between lenders and borrowers. That is, a well-functioning stock market may assist the development process in an economy through two important channels: boosting savings and allowing for a more efficient allocation of resources. Savings are presumed to increase as the stock market provides households with assets that may satisfy their risk preferences and liquidity needs (Leigh, 1997). Also, based upon the idea of the price mechanism, a well-functioning stock market values profitable company's shares more than those of unsuccessful companies. That is, relative share prices in a well-functioning stock market may fundamentally reflect the status of a company compared to the other companies listed in the stock market, i.e., the expected dividend growth and discount rates. Therefore, the price mechanism ensures the efficiency of utilizing economic resources available to the economy in the sense that the cost of capital to the profitable company will be lower compared to the cost that the unsuccessful companies would face (Lamin, 1997).

It is also well established that the volatility of stock prices characterizes the behavior of the stock market (Mandelbrot, 1963; Black, 1976). The most direct definition of volatility is the relative rate at which the price of a security moves up and down within a very short period of time (Taylor, 2007). Typically volatility is calculated by the standard deviation of the price of stock market returns. A highly volatile market means that prices or stock returns have enormous swings over a specific time; i.e., day, week, month or year. In light of this definition, volatility can be considered as a measurement of the uncertainty or the risk that is associated with stock market investment decisions (Taylor, 2007).

Engle and Ng (1993) revealed that the causes of volatility as the arrival of new, unanticipated information that alters expected returns on a stock. Macro factors of an economy can generate this information that causes stock market volatility. Thus, this study attempted to measure the volatility of ASPI and to recognize the most significant macro variable factors that cause the variability.

Excessive volatility may prevent the smooth functioning of financial markets and adversely affect the performance of the economy. Black Monday on October 19, 1987 (Report of the U.S Presidential Task Force on Market Mechanisms, 1988), The Asian Crisis of 1997, the Global Financial Crisis of 2008 and recent Gold market crisis (Mishra, Das and Mishra, 2010) are examples of the stock market's effects on the domestic and global economies. Thus, understanding the dynamic behavior of the stock market is crucial for financial analysts, macroeconomists, and policymakers. Financial analysts and investors are interested in understanding the nature of volatility patterns of financial assets, and what events can alter and determine the persistence of volatility over time (Malik & Hassan, 2004). This type of information is significant to build an accurate volatility model which may help to analyze the risk of holding an asset, and provide indicators for investors to diversify their portfolios. Also, volatility plays a central role in determining investment spending. That is, excessive volatility may cause investors in financial markets to shift their funds towards risk-free assets rather than investing in riskier assets.

The existing economics and finance literature provides a number of theories explaining the link between macroeconomic variables and the stock market (Fama, 1981; Schwert, 1981; Fama, 1990; and Geske and Roll, 1983). Some of these theories are the efficient market hypothesis (EMH) and asset pricing theory. The EMH advocates that stock market prices fully and rationally incorporate all relevant information. Thus, past information is useless in predicting future asset prices. For that reason, new relevant information is only used to explain stock market movements (Fama, 1965). Asset pricing theory such as the arbitrage price theory (APT), and the Present Value Model (PVM) illustrates the dynamic relationship between the stock market and economic activity (Ross, 1976; and Semmler, 2006).

Efficient Market Hypothesis (EMH) and Asset Pricing Theory are silent about which precise events or economic factors likely influence asset prices. This silence opens the door to investigating a wide range of relevant events both at the microeconomic and macroeconomic levels of a stock market. Discounted cash flows of the expected returns or the present value model (PVM) provides a motivation for the selected variables in the majority of related empirical work. PVM simply states that the price of a stock is the present discounted value of the expected future dividends received by the owner (Semmler, 2006, and McMillan, 2010).

With regard to the Sri Lankan economy, little work has been done on the dynamic relationships between the stock market and real economic activity. To the best of my knowledge, there is no published work considering both the short and long run dynamic relationships between the Colombo Stock Exchange behavior and real economic activity.

This study investigates five macroeconomic variables that all have a significant impact on the general index of the Colombo Stock Exchange, specifically the All Share Price Index (ASPI). These five macroeconomic variables include: money supply (M2); a proxy for short term interest rates (IR), 3-month treasury bill rate; the Colombo Consumer Price Index (CCPI); the nominal effective exchange rate (EXR); and Industrial Production Index (IPI). The selection of these variables was based upon the PVM theory, and a previous literature discussed in the Chapter 2.

These variables were selected for two important reasons. First, these variables are commonly used in the literature to examine the theoretical links between stock market and economic activity. Second, these variables are available at a monthly frequency.

1.2 Macroeconomic Variables

1.2.1 Money Supply (MS)

The impact of the money supply on the stock prices has been widely discussed in the economic literature. The money supply may affect the present value of cash flows via its effect on the discount rate. Although a strong relationship between the money supply and the stock market prices has been found, the effect of changes in the money supply on stock market prices is still debated, (Hamburger and Kochin, 1972; and Hashemzadeh and Taylor, 1988).

Tightening the money supply would raise the real interest rate. An increase in the real interest rate will lead to an increase in the discount rate, which decreases the value of the stock. In addition, tightening the money supply will increase the risk premium necessary to compensate an investor for holding the risky asset. As a result, economic activity would slow down, potentially reducing firms' profits. If this is the case, investors would demand a higher risk premium to bear more risk. A higher risk premium makes the stock unattractive, which lowers the price of the stock (Bernanke and Kuttner, 2005)

Inclusion of the money supply in my study may contribute to the existing literature in regards to the relationship between changes in the money supply and share prices in an emerging stock market such as the Colombo stock market. In the absence of a unique measure of the money supply in the Sri Lankan economy, this study will use broad money supply (M2) as a proxy for the money supply which consists of the narrow money supply (M1) components, time deposits and savings deposits.

1.2.2 Short Term Interest Rate (IR)

Economic theory, based on rational expectations, assumes that stock prices are determined in a forward-looking manner such that they are determined by expected future earnings. Monetary policy shocks influence stock prices directly through the discount rate and indirectly through its influence on the degree of uncertainty or risks that an agent may face in the market (Bjornland and Leitemo, 2009). For example, with a negative interest rate shock, i.e., increasing real interest rate, risk and required rate of return of a particular investment increase and profits of a firm tend to decrease, due to increased cost of capital. Ultimately, this may result in a decrease of the stock value.

According to Bernanke (2003), there are two equivalent explanations for why expectations of higher short-term real interest rates should lower stock prices. First, for an investor to value future dividends, they must discount them back to the present time. Since higher interest rates make a given future dividend less valuable in today's currency, the value of that share or stock will decline. Second, higher real interest rates increase the required return on stocks and reduce what investors are willing to pay for these stocks. In other words, higher real interest rates would make other investments, such as bonds, more attractive to investors. This study uses three months Treasury bill rate as a proxy for the local interest rate, to account for fundamental changes in the local economy.

1.2.3 Colombo Consumer Price Index (CCPI)

The dynamic impact of inflation on equity prices is a matter of considerable debate both theoretically and empirically. This debate is motivated partially by the theory that the stock market provides an effective hedge against inflation, (Bodie, 1976). The argument that the stock market serves as a hedge against inflation is based on the fundamental idea of Irving Fisher (1930), and is known as the Fisher Effect. The Fisher Effect states that in the long run, inflation and the nominal interest rate should move one-to-one with expected inflation. This implies that higher inflation will increase the nominal stock market return, but the real stock return remains unchanged. Therefore, investors are fully compensated.

Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976), Fama and Schwert (1977), Firth (1979) and Boudhouch and Richardson (1993) extended the original concept of a Fisher Effect to examine the specific interrelationships between rates of return on common stocks and the expected and unexpected rate of inflation. Firth (1979) and Boudhouch and Richardson (1993), among others, provide support in favor of a positive relationship between inflation and stock market returns. On the other hand, Fama (1981) and Schwert (1981), among others, support a negative correlation between inflation and stock market prices (returns). One reason for why inflation negatively impacts equity prices is the negative correlation between inflation and expected real economic growth so that investors shift their portfolios towards real assets if the expected inflation rate becomes remarkably high (Hatemi-J, 2009).

Given that the empirical evidence this study includes inflation, by means of the CCPI to provide a new insight about the generalized Fisher effect from the perspective of a developing market such as Colombo stock exchange. Therefore, investors may benefit from this study to learn how to allocate their resources more efficiently to protect the purchasing power of their investments, especially during inflationary periods.

1.2.4 Exchange Rate (EXR)

There are different theoretical approaches to understanding the relationship between the exchange rate and stock prices. Among these approaches, Dornbusch and Fischer’s (1980) approach explains the impact of exchange rate fluctuations on the stock market using the current account or the trade balance. This approach advocates that changes in exchange rates affect international competitiveness of the economy, and thus, changes in its trade balance. A depreciation of the domestic currency makes local firms more competitive, i.e., their export is cheaper in international markets, which increases exports. This increase translates into higher incomes of these companies and higher stock prices. The converse is true for an appreciation in domestic currency. While it is obvious that the Dornbusch and Fischer approach suggests a negative relationship between stock prices and exchanges rates with the source of causation being attributed to exchange rates, one may argue that the impact of exchange rate fluctuations on the stock market returns, on a macro and micro scale, dependents on importance of international trade to the local economy and whether the companies listed on the stock market are importing or exporting companies.

Frankel's (1993) portfolio balance approach stresses the role of capital account transactions on determining the relationship between the exchange rate and stock prices. This approach postulates a positive relationship between stock prices and exchange rates, with stock prices being the root cause of the relationship. This conclusion is based on the fact that investors hold domestic and foreign assets, including currencies, in their portfolio. The exchange rate plays a significant role in balancing the demand for assets included in their portfolio. An appreciation of a local stock market would attract capital flows from foreign markets and disposal of foreign assets, causing the local currency to appreciate. The reverse would occur if the local stock market depreciated. In other words, rising (declining) stock prices may lead to an appreciation (depreciation) of the exchange rate of the local currency.

By including the exchange rate (USD Vs. LKR) in this study, we gain a better understanding of how exchange rates affect stock prices within a small open economy such as Sri Lankan economy.

1.2.5 Industrial Production Index (IPI)

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. Fama (1990) and Geske and Roll, (1983) hypothesized a similar positive relationship through the effects of industrial production on expected future cash flows. The productive capacity of an economy indeed depends directly on the accumulation of real assets, which in turn contributes to the ability of firms to generate cash flow. Chen, Roll and Ross’ (1986) findings based on a US stock portfolio, indicated that future growth in industrial production was a significant factor in explaining stock returns. Hence, suggesting a positive relationship between real economic activities and stock prices.

1.3 All Share Price Index (ASPI)

ASPI is the only general price index for the Colombo Stock exchange. ASPI is computed based on the calculation that takes into account traded securities or shares (www.cmic.sec.gov.lk). The ASPI reflects the performance of all listed 297 companies in the Colombo stock market taking into account the shares. Thus, ASPI expected to provide better insight into the overall performance of the Colombo stock market in response to fundamental changes within the Sri Lankan economy.

1.4 GARCH Approach

It is well known that financial time series data, including stock market returns, often exhibit the phenomenon of volatility clustering, meaning that a period of high volatility tends to be followed by periods of high volatility, and periods of low volatility tend to be followed by periods of low volatility. Stock returns also exhibit leptokurtosis, meaning that the distribution of the financial data has heavy tailed, non-normal distributions. In addition, data on stock market returns is expected to show a so called “leverage effect” or asymmetric volatility. This means that the effect of bad news on stock market volatility is greater than the effect induced by good news. Cont (2001) shows how these stylized financial facts invalidate many of the common statistical approaches used to study financial data sets.

While VAR models are commonly used to investigate the interrelationship between stock market behavior and key macroeconomic variables, these models by nature do not account for the stylized facts that characterize financial time series in general and stock market returns in particular (Rydberg, 2000). For that reason, it is motivated to go further and employ GARCH models to account for these stylized facts in order to find the impact of macroeconomic variables on ASPI.

1.5 Objectives of the Study

On view of the above, the objectives of the study are;

- To investigate the macroeconomic determinants of ASPI volatility
- To investigate the dynamic relationship between macroeconomic determinants and ASPI

1.6 Problem Statement

The Sri Lankan authorities were neutral during the crash periods. It can be argued that this neutrality can be explained partially by identifying the problem's causes given that there were no fundamental changes in the Sri Lankan economy associated with or preceding these collapses. Previous studies by Fama (1981, 1990), Geske and Roll (1983), and Chen, Roll, and Ross (1986), and Schwert (1989), indicate a link between increased price volatility in the stock market to the movements of macroeconomic variables. Therefore, it is important to explore the relationship between the Colombo stock market and a set of macroeconomic variables to shed light on the relationship, if any, between real economic activity and the behavior of the stock market in Sri Lanka.

Within this argument, this study is going to be find whether there is a short run or long run dynamic relationship between selected macroeconomic variables and stock market returns.

1.7 Hypotheses Development

Following hypotheses are developed to achieve the two objectives describes in section 1.5. Thus to achieve the first objective, the null and alternative hypotheses are;

H_{0A} There is no any significant influence of the volatility of selected five macroeconomic variables to ASPI volatility

H_{1A} There is a significant influence of the volatility of selected five macroeconomic variables to ASPI volatility

Then to achieve the second objective, null and alternative hypotheses are;

H_{0B} There is no any significant long run / short run relationship between selected five macroeconomic variable and Colombo stock market prices, proxied by the general price index, ASPI

H_{1B} There is a significant long run / short run relationship between selected five macroeconomic variable and Colombo stock market prices, proxied by the general price index, ASPI

1.8 Significance of the Study

This study is expected to add several primary contributions to the existing literature. First, it will extend the literature by examining the relationship of the stock market with a set of macroeconomic variables in a unique emerging market, the Colombo Stock Exchange. Second, this study will apply different econometric methods, which may provide insight for the existing literature if the analysis is sensitive to the methods employed. To the best of my knowledge, this is the first study to estimate a GARCH-X model using data on the Sri Lankan economy. The importance of the GARCH-X model is that it allows for examination of the link between short-run deviations from a long-run co-integrating relationship and volatility. This study is expected to offer some insights for policymakers, shareholders, and portfolio managers. Policymakers are mainly interested in exploring the determinants of the stock market, and how stock market shocks spillover to real economic activity. The efficient market hypothesis (EMH) implies that portfolio diversification benefits from a low correlation between stock market indexes and all relevant information that is publicly available. In that sense, this study is also significant to shareholders and portfolio managers too.

1.9 Chapter Organization

Chapter 02 – Chapter II will review the theoretical background of the efficient market hypothesis (EMH) and asset pricing theory (arbitrage price theory (APT) and related empirical studies which have identified the short run and long run dynamic relationships between share returns and macroeconomic variables as well as studies where they have used GARCH models to measure the stock market volatility.

Chapter 03 – Chapter III will illustrate the econometric methods that are going to be used in this research. It is provided some background on autoregressive conditional heteroscedasticity modeling with the standard GARCH model suggested by Bollerslev (1986) and its GARCH-X suggested by Lee (1994). Then, brief description is provided on the empirical methods of VAR models.

Chapter 04 – Chapter IV presents the behavior of selected variables and the descriptive statistics which were calculated on original data collected. Development of ARCH / GARCH models are discussed in details.

Chapter 05 – Chapter V analyze the short run and long run relationships between ASPI and selected macroeconomic variables. Johansen-Juselius Cointegration Test, Causality Test, Impulse Response Function Analysis and Forecast Error Variance Decompositions analysis are used for that purpose.

Chapter 06 – Chapter VI conclude the research by providing some recommendations to the stake holders of the Colombo Stock Exchange.

Chapter 2

Literature Review

The existing economics and finance literature provides a number of theories explaining the link between macroeconomic variables and the stock market. The efficient market hypothesis (EMH) and asset pricing theory are the key aspects for the consideration in this regard. In asset pricing theory, arbitrage price theory (APT) and the Present Value Model (PVM), explain the dynamic relationship between the stock market and economic activity. Therefore, in this chapter, the study carried out to the above are extensively reviewed.

2.1 Theory of Efficient Market Hypothesis (EMH)

The basic idea underlying the EMH developed by Fama (1965, 1970) is that asset prices promptly reflect all available information such that abnormal profits cannot be produced regardless of the investment strategies utilized. Formally, the EMH can be explained using the following equation:

$$\Omega t{*}=\Omega t \qquad (2.1)$$

Where $\Omega t*$ represents a set of relevant information available to the investors, at time *"t"* and Ωt is the set of information used to price assets, at time *"t"*. The equivalence of these two sides implies that the EMH is true, and the market is efficient. Fama (1970) distinguished between three forms of market efficiency based upon the level of information used by the market: weak form, semi-strong, and strong form market efficiency.

Weak Form

The weak form of the EMH stresses that asset prices today incorporate all relevant past information, i.e., past asset prices, security dividends, and trading volume. Knowing the past behavior of stock prices provides no indication of future stock prices. In other words, the EMH theory hypothesizes that asset prices evolve according to a random walk. Thus, asset prices cannot be predicted, and investors cannot beat the market.

Semi-strong Form

The semi-strong form of the EMH states that current asset prices fully reflect all available public information. Public information includes not only information about an asset’s past price, but also includes all information related to the company's performance, expectations regarding macroeconomic factors, and any other relevant public information such as GDP, the money supply, interest rates, and the exchange rate.

Strong Form

In addition to relevant past information and public information, the strong form of the EMH requires that asset prices fully incorporate more than past and public information. In particular, the strong form of the EMH declares that asset prices reflect private information, i.e. insider information, related to the assets of a specific company.

2.2 Implementation of EMH

The implications of the EMH are broad (Alshogeathri, 2011). From an investor’s perspective, participants in the stock market should not be able to generate an abnormal profit regardless of the level of information they may possess. In the world of a perfect capital market, investors cannot consistently beat the market. This is consistent with the financial idea that the maximum price that investors are willing to pay is the current value of future cash flows. The current value of a future cash flows is usually evaluate by a discount rate, which represents the degree of uncertainty associated with the investment, considering all relevant available information (Timmermann and Granger, 2004).

From an economic standpoint, an efficient stock market will assist with the efficient allocation of economic resources. For instance, if the shares of a financially poor company are not priced correctly, new savings will not be used within the financially poor industry. In the world of the EMH, the level of asset price fluctuations, or volatility, fairly reflects underlying economic fundamentals. Along these lines, Levich (2001) argues that policymaker’s interventions may disrupt the market, and cause it to be inefficient. In the literature, the three forms of the EMH are usually used as guidelines rather than strict facts (Fama, 1991). Also, most empirical studies have examined the EMH in its weak or semi-strong forms, partly because the strong form is difficult to measure, and there is a high cost associated with acquiring private information (Timmermann and Granger, 2004).

2.3 Arbitrage Price Theory (APT)

The theory of asset pricing, in general, demonstrates how assets are priced given the associated risks. The Arbitrage Price Theory (APT) suggested by Ross (1976) has been an influential form of asset price theory. APT is a general form of Sharpe's (1964) capital asset price model (CAPM). While the CAPM suggests that asset prices or expected returns are driven by a single common factor, the APT advocates that they are driven by multiple macroeconomic factors. Mathematically APT can be expressed as:

$$R_{it} = r_{if} + \beta_i X_t + \varepsilon_t \qquad (2.2)$$

Where;

R_{it} = the return of the stock i at time t

r_{if} = the risk free interest rate or the expected return at time t

X_t = a vector of the predetermined economic factors or the systematic risks

β_i = the sensitivity of the stock to each economic factor included in X_t

ε_t = the error term of time t or unsystematic risk or the premium for risk associated with assets at time t

Interestingly, APT does not specify the type or the number of macroeconomic factors for researchers to include in their study. For example, although Chen, Roll & Ross (1986) examined the effect of four factors including inflation, gross national product (GNP), investor confidence, and the shifts in the yield curve, they suggested that the APT should not be limited to these factors. Therefore, there is a large number of empirical studies that have considered different macroeconomic factors, depending on the stock market they studied (Fama, 1981 and 1990; Geske and Roll, 1983; and Chen, Roll, and Ross, 1986). Also, analysts face the challenge of identifying significant factors in explaining fluctuations of individual stock markets (Chen, Roll and Ross, 1986).

2.4 Related Empirical Studies

During the last three decades, numerous studies have examined the dynamic relationships between stock market behavior and economic activity, particularly for developed stock markets such as the U.S., United Kingdom (UK), Germany, and Japan. Examples of pioneering studies are Fama (1981, 1990), Geske and Roll (1983), and Chen, Roll, and Ross (1986). However, studies in this area are different in terms of their hypotheses and the methods used. Several studies investigated the predictability of stock returns for real economic activity. Examples of these studies are Estrella and Hardouvelis (1991), Estrella and Mishkin (1996), and Domain and Louton (1997). A large body of research focuses on the integration of stock markets across economies (Arshanapalli and Doukas, 1993; Becker, Finnerty and Friedman, 1995; Jeon and Chiang, 1991; Kasa, 1992; and Longin and Solnik, 1995). Another dimension in previous studies examined the short and long run relationship between stock prices and macroeconomic and financial variables such as inflation, the interest rate, and output. Within this group of studies, some studies examined macroeconomic factors that affect stock prices, while others examined factors that determine stock return volatility (Semmler, 2006).

Due to vast number of studies by various authors in various aspects, it is not feasible to review such works. However, this study is most closely related to studies in the last dimension which examined the short run and long run relationship and stock price volatility. Therefore past studies related to; (a) developed economies, (b) developing economies and (c) studies that include more than one economy are reviewed.

2.4.1 Studies Related to Developed Economies

Hashemzadeh and Taylor (1988) examined the relationships between the S&P 500, the money supply (M1), and the return on U.S. Treasury bills. They conducted Granger-Sims's causality tests (1969; 1972) using weekly U.S. data covering the week ending January 2, 1980 to July 4, 1986, and found a feedback relationship between M1 and the S&P 500. The relationship between the S&P 500 and the U.S. Treasury bills was not conclusive, and the causality relationship appeared to start with the U.S. Treasury bills and move to stock prices, not the other direction. Hashemzadeh and Taylor also concluded that U.S. Treasury bills and M1 are not highly successful in predicting U.S. stock prices. This finding implies that U.S. stock prices incorporate all information available in the stock market.

Malliaris and Urrutia (1991) examined the linkage between industrial production (IP), the money supply (M1), and the S&P 500, using U.S. monthly data from January 1970 to June 1989. Based on the Granger causality tests, the authors concluded that: (i) there is a causal relationship between M1 and the S&P 500 where M1 seems to lead the S&P 500, and (ii) the S&P 500 appears to affect IP. These findings confirmed that the stock return's fluctuations were a leading indicator of future real economic activity. However, the causal relationships among IP, M1, and the S&P 500 were not statistically significant. Using the same data set as Malliaris and Urrutia (1991), Darrat and Dickens (1999) examined multivariate co-integration and error-correction models. Consistent with conventional wisdom, but contradicting Malliaris and Urrutia's (1991) findings, Darrat and Dickens found strong evidence that IP, M1, and the S&P 500 were integrated and found causal interrelationships between these variables. Darrat and Dickens' results indicated that the stock market was a key leading indicator of monetary policy and real economic activity. These interrelationships were strengthened when inflation and interest rates were included in the model.

Abdullah and Hayworth (1993) used seven macroeconomic variables to explain fluctuations of monthly stock returns in the U.S. stock market using a vector auto regressions, Granger causality tests, and impulse response analysis. The macroeconomic variables were M1, budget deficits, trade deficits, inflation, IP, short-term interest rates, and the S&P 500. The results indicated that money growth, budget deficits, trade deficits, inflation, and both short-term and long-term interest rates Granger-cause stock returns. Additionally, stock returns were positively related to inflation and money growth, but, consistent with economic theory, stock returns were negatively related to budget deficits, trade deficits, and both short-term and long-term interest rates.

Dhakal, Kandil, and Sharma (1993) explored the links between five macroeconomic variables: money supply, short-term interest rate, price level, real output, and share prices in the U.S. stock market from 1973 to 1991. It was argued that this study was of particular interest to policymakers to understand share market volatility. The results of the VAR estimation indicated that changes in the money supply have direct significant impacts on share price changes, and indirect impacts on share prices through the effect on the interest rate and the inflation rate. The results also suggested that share price volatility causes real output fluctuations, which is a relationship that monetary policy had not previously considered. Same time Serletis (1993) analyzed the relationships between eight different measures of the money supply and the S&P 500 using monthly data from January 1970 to May 1988. Serletis concluded that the U.S. stock market satisfied the efficient market hypothesis (EMH) since the S&P 500 did not co-integrate with any of the eight money supplies during the sample period.

Sadorsky (1999) investigated the impact of the price of oil shocks, IP, and the interest rate on U.S. stock market returns using monthly data from January 1947 to April 1996. Results from the VAR approach suggested that positive oil shocks depress real stock returns, while stock returns have a positive impact on interest rates and IP. Also, this study showed evidence that the effect of the price of oil on U.S. stock market returns was not constant over time, compared to the effect of interest rate changes, and that oil price movements explain a large portion of the forecast error variance in real stock returns, particularly after 1986.

Ratanapakorn and Sharma (2007) investigated the long and short run relationships between the S&P 500 and six macroeconomic variables using monthly data from January 1975 to April 1999. The study observed that the stock prices were negatively related to the long-term interest rate, but were positively related to the money supply, IP, inflation, the exchange rate, and the short-term interest rate. The inconsistent results of the effect of long and short run interest rate on the S&P 500 suggested that the long-term interest rate was behaving more like the S&P 500 than the short-term interest rate. This result coincides with the findings from Abdullah and Hayworth (1993). Also, each macroeconomic variable included in the study Granger caused stock prices in the long run but not in the short run. Results from the variance decomposition also support the finding that the S&P 500 is exogenous in relation to the other macroeconomic variables in the study. That is, even after 24 months, 87% of the S&P 500 variance was explained by its own shocks.

Thornton (1993) investigated the lead-lag relationships between stock prices in the UK, namely the Financial Times Stock Exchange 100 index (FTSE 100), and real

GDP and two definitions of the money supply - the monetary base (M0) and the broadest definition of the money supply (M5) - using quarterly data from 1963 to 1990. The results of Granger causality tests suggested that: (i) stock prices tend to lead M5; (ii) stock prices tend to lead real GDP; (iii) there were feedback effects between M0 and M5 volatility and stock price volatility; and (iv) real GDP tends to lead stock price volatility. Thornton suggested that the causal relationship among real and monetary variables in the UK was not statistically significant in contrast to the literature on the US economy. After five years time, Thornton (1998) utilized the Johansen co-integration test and Granger-causality tests to observe the long and short run dynamic relationships between real M1, real income, interest rates, and real stock prices in Germany for 1960 to 1989. The results of the study indicated that: (i) real stock prices have a significant and positive wealth effect on the long-run demand for M1; and (ii) there was a unidirectional Granger-causality effect from interest rates to real stock prices.

Abdullah (1998) employed Sims (1980) forecast error variance decompositions to analyze the effects of six macroeconomic variable changes on UK stock returns, proxied by the London share price index. The macroeconomic variables were M1, budget deficits and surpluses, IP, the consumer price index (CPI), and a long term interest rate. The results suggested that money growth variability accounts for 22.82% and 19.53% of the variance in interests' rates and stock returns, respectively. Therefore, money growth variability contributed to the uncertainty associated with returns on investments in stocks and other financial assets. The other variables included in the model were statistically significant in explaining the variance of UK stock returns.

Mukherjee and Naka (1995) employed Johansen's (1991) vector error correction model (VECM) to examine the impact of six macroeconomic variables on the Japanese stock market. The six variables were the exchange rate, inflation, the money supply, IP, the long-term government bond rate, the call money rate, and the Tokyo Stock Exchange index. The results indicated that these variables were integrated with stock prices for the whole sample period spanning from January 1971 to December 1990, and for two additional sub-periods examined. Using the same methods Gan, Lee, Yong and Zhang (2006) were going to determine whether the New Zealand

Stock Index is a leading indicator for a set of seven macroeconomic variables that include M1, the short term interest rate, the long term interest rate, the inflation rate, the CPI, exchange rates, GDP, and the domestic retail the price of oil. This analysis was conducted using monthly data spanning from January 1990 to January 2003. Evidence from the study suggested that a long run relationship exists between New Zealand's stock index and all seven examined macroeconomic variables. Based on the sample period used in the study, the New Zealand stock index was predicted by M1, interest rate, and real GDP during the sample period. In addition, the New Zealand stock index was not a leading indicator of New Zealand's economy.

Chaudhuri and Smiles (2004) utilized Johansen and Juselius (1990) methodology, impulse response function analysis and forecast error variance decomposition analysis to examine the relationship between the Australian real stock price index and real measures of aggregate economic activity, including the most broad money supply (M3), GDP, private personal consumption expenditures, and the world oil price index. The analysis used quarterly data from 1960 to 1998. The study showed evidence of a long-run relationship between all variables. Also, the error correction mechanism indicated that real returns are, in general, related to changes in real macroeconomic variables along with deviations from the observed long-run relationships. However, IRF and VDC analyses revealed weak evidence for the relationship between the Australian real stock price index and all variables included in the analysis.

Darrat (1990) employed Akaike's final prediction error (FPE) criteria in conjunction with multivariate Granger causality tests to examine whether changes in Canadian stock returns are predicted by several economic variables including the money base, interest rates, interest rate volatility, real income, inflation, exchange rates, and fiscal deficits. The empirical study used monthly data from January 1972 to February 1987. Results indicated that current stock prices in Canada fully incorporate all available information from monetary policy instruments, and that stock returns are Granger-caused by lagged changes in fiscal deficits. This conclusion held even when interest rates, interest rate volatility, real income, inflation, monetary policy, and exchange rates are excluded from the estimation. Under the assumption of constant expected stock returns, such findings appear inconsistent with the stock market efficiency hypothesis.

Maysami, Howe and Hamzah (2004) used monthly data from January 1989 to December 2001 to examine the relationship between Singapore's composite stock index, three Singapore sector indexes (the finance index, the property index, and the hotel index), and a set of macroeconomic variables. These variables are the CPI, IP, proxies for long and short-run interest rates, the money supply (M2), and exchange rates. Based on the results of Johansen's co-integration test, the Singapore stock market and property index showed a significant long-run relationship with all macroeconomic variables included in the analysis. On the other hand, the finance sector index indicated a significant relationship with all macroeconomic variables included in the analysis with the exception of real economic activity, and the money supply. Also, the hotel index showed no significant relationship with the money supply and short and long term interest rates but significant relationships with all macroeconomic variables included in the analysis. These results questioned the efficiency of Singapore's market in the sense that stock prices do not incorporate all information available in the market promptly.

Gjerde and Saettem (1999) used a VAR model and monthly data from 1974 to 1994 to investigate the relationship between stock market returns and a set of macroeconomic variables in the small open economy of Norway. The set of variables consisted of interest rates, inflation, IP, consumption, the OECD industrial production index, the foreign exchange rate, and the price of oil. Consistent with Humpe and Macmillan's (2009) findings about the U.S. and Japanese stock markets, Gjerde and Saettem established several significant links between stock market returns and the investigated macroeconomic variables. In particular, changes in the real interest rate affected both stock returns and inflation, and the stock market responded significantly to the price of oil changes. The stock market also displayed a delayed response to changes in domestic real activity. For instance, after two years, the industrial production shock only explained 8% of the variance of real stock returns while innovations in real stock returns contributed only 1% to the variance of changes in IP. On the other hand, there was no evidence that real economic activity responded to real stock return shocks. This finding may be attributed to the difference in size and type of companies listed on developed stock markets compared to companies in the domestic industry. That is, if most companies listed on the stock exchange are large exporting companies while the industrial production index contains a substantial amount of small companies, then stock market should not lead industrial production.

Hondroyiannis and Papapetrou (2001) investigated the dynamic relationships in the Greek economy between stock returns and a set of macroeconomic indicators consisting of IP, interest rates, exchange rates, real foreign stock returns as represented by the S&P 500, and real oil prices. They used a multivariate vector autoregressive VAR model to examine monthly data from January 1984 to September 1999. Results from their study suggested that stock returns did not lead changes in real economic activity, and macroeconomic activity and foreign stock market changes only partially explained stock market movements. The price of oil changes, however, explained stock price movements and had a negative impact on macroeconomic activity. For the same country, in 2006, Patra and Poshakwale, applied different econometric approaches and used monthly data from 1990 to 1999 to examine the short and long run equilibrium relationship between the price index and a set of macroeconomic variables including the money supply, inflation, the exchange rate, and trading volume. Based on the results from these different techniques, all of the investigated variables except the exchange rate consistently exhibit both short and long run relationships with stock prices. These findings suggested that the Greek stock market was informationally inefficient during this time period.

Rahman and Mustafa (2008) studied the long-run and short-run dynamic effects of the broad money supply (M2) and the price of oil on the S&P 500 the using monthly data from January 1974 to April 2006. The results provided support in favor of the three variables being co-integrated. The vector error-correction model revealed no causal relationships in the long run although feedback relationships existed in the short run. Also, the results indicated that the current volatility of the U.S. stock market was fueled by its past volatility, and negative monetary and oil price shocks initially depressed the U.S. stock market.

Another stream of research examined the impact of economic factors on stock return volatility. The studies usually consider the conditional variance process in financial data. This type of study was motivated primarily by the introduction of the autoregressive conditional heteroscedasticity (ARCH) model by Engle (1982), its generalized form, the GARCH model, developed by Bollerslev (1986).

One of the pioneer studies in this area was conducted by Schwert (1989), in which he analyzed the relationships between the U.S. stock market volatility and real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity using monthly data from 1857 to 1987. He concluded that macroeconomic volatility, as measured by changes in real output and inflation, did not help to predict stock and bond return volatility. However, Schwert provided evidence that the volatility of financial assets helped to predict future macroeconomic volatility. This finding supported his claim that the prices of speculative assets should react quickly to new information about economic events.

As cited in Alshogeathri (2011), Kapital (1998) adopted Lee's (1994) GARCH-X model to investigate volatility in the U.S. stock market and the effect of short-run deviations between stock prices and a set of macroeconomic fundamentals such as the money supply, the exchange rate, income, consumer prices, and real oil prices. This study used monthly data from January 1978 to December 1996. Based on his findings, the macroeconomic variables had a significant and positive effect on the volatility of the U.S. stock market. Also, the GARCH-X model was found to outperform the standard GARCH model in that regard.

Liljeblom and Stenius (1997) analyzed whether changes in stock market volatility attributed to time-varying volatility of a set of macroeconomic variables in Finland's economy. Macroeconomic variables included in the analysis were industrial production, the money supply (M2), the CPI, and a trade variable represented by the export price index divided by the import price index. They examined a 71 year time period from 1920 to 1991. With the exception of the growth of stock market trading volume, the authors concluded that the VAR estimates indicated predictive power in both directions: from stock market volatility to macroeconomic volatility and from macroeconomic volatility to stock market volatility.

Léon (2008) investigated the effects of interest rate volatility on stock market return volatility in the Korean economy using weekly return data from January 31, 1992 to October 16, 1998. Léon estimated two GARCH (1,1) models: one without interest rates, and another one with interest rates in both the conditional mean and variance. Consistent with results for the U.S. market, Léon found that the conditional market returns have a significantly negative relationship with the interest rates. Also, the conditional variance had a positive, but insignificant relationship with the interest rates compared to the findings documented in the U.S. market. Results from Léon's study indicated that interest rates have strong predictive power for stock returns in Korea, but weak predictive power for volatility. Based on these findings, investors in the Korean stock market should adjust their portfolios in response to changes in monetary policy.

2.4.2 Studies Related to Developing Economies

Ibrahim (1999) studied the dynamic relationships between Malaysian stock prices and seven macroeconomic variables, including the narrow and broad money supplies (M1 & M2), IP, the CPI, domestic credit, foreign reserves, and the exchange rate. Co-integration and Granger causality tests with monthly data from January 1977 to June 1996 were used. The results revealed that the Malaysian stock market is informationally inefficient with respect to consumer prices, official reserves, and the domestic credit aggregates. This study also provided evidence that stock prices are Granger-caused by changes in official reserves and exchange rates in the short run. With respect to M2 and Malaysian stock price were co-integrated, and there was no long-run relationship between stock prices and M1.

Maghayereh (2003) used Johansen's (1990) methodology to analyze the link between the Jordanian capital market index and a set of macroeconomic variables: M1, interest rates, domestic exports, foreign reserves, inflation, and IP. The cointegration test and the vector error correction model indicated that the Jordanian stock price index was cointegrated with all the macroeconomic variables under consideration. Thus, all the variables were significant in predicting changes in stock prices, which suggests that the Jordanian capital market violated the theory of market efficiency from January 1987 to December 2000.

Gunasekarage, Pisdtasalasai and Power (2004) examined the relationship between a set of macroeconomic variables and the stock market index in the Sri Lanka. The money supply, the Treasury bill rate as a proxy for the short term interest rate, the CPI as a measure of inflation, and the exchange rate were the macroeconomic variables. The Johansen cointegration approach, IRFs analysis, and FEVD analysis using monthly data from 1985 to 2001 yielded three results. First, the lagged values of the money supply and the Treasury bill rate had a significant influence on the stock market. Second, the All Share Price Index did not have any influence on the money supply, but it did influence the Treasury bill rate. Finally, both VDC and IRF explained only a little of the forecast variance error for the market index, and these effects did not persist for long period.

Ibrahim (2006) evaluated the relationship between bank loans and stock prices in Malaysia using quarterly data from January 1978 to February 1998, using in a VAR framework. The VAR model included four other variables as well, namely interest rates, output, the exchange rate, and the price level. The results revealed that bank loans reacted positively to an increase in stock prices, but the converse is not true. Similarly, bank loans appeared to accommodate an expansion in real output, but had no influence on real economic activity. The impulse response function suggested that bank loans played no significant role in transmitting stock market shocks to the real sector. Ibrahim interpreted these results as an indication that the health of the banking sector may significantly depend on stock market stability. Consequently, stimulating bank loans may be an inefficient way to boost stock market activities and expand real activities.

Muradoglu, Metin and Argac (2001) examined the long-run relationship between Turkish stock market returns and three monetary variables, the overnight interest rate, the money supply, and the foreign exchange rate, during the period from 1988 to 1995. The three monetary variables were found to not be cointegrated with stock prices during the sample period and also during the sub-sample period from 1988 to 1989. However, all three monetary variables were cointegrated with stock prices in the sub-period from 1990 to 1995. These findings suggested that the results of the analysis were sensitive to the examined period. Using quarterly data, Ahmed (2008) investigated the nature of the long and short run relationships between Indian stock prices and a set of macroeconomic variables over the period March 1995 to March 2007. These variables were the money supply, interest rates, IP, exports, foreign direct investment, exchange rates, the primary stock index of the National Stock Exchange (NSE) in India, and the Bombay Stock Exchange (BSE) index. Johansen's (1990) approach, the causality test of Toda and Yamamoto (1995), FEVD analysis, and IRFs analysis were used. Findings from the study revealed that a long run relationship between stock prices and money supply existed. However, the same relationship did not exist for the interest rate with stock prices. With respect to the short run analysis, the stock market index was discovered to not be affected by money supply movements, but the interest rate was. Therefore, the interest rate appeared to lead stock prices in the short run.

Hasan and Javed (2009) explored the long-term relationship between Pakistan equity prices and monetary variables from June 1998 to June 2008. The monetary variables included the money supply, Treasury bill rate, foreign exchange rates, and the CPI. The Johansen-Juselius (1990) cointegration test provided evidence of a long run relationship between the equity market and the monetary variables. Unidirectional Granger causality was found between the monetary variables and the equity market. Impulse response analysis indicated that the interest rate shock and the exchange rate shocks both have a negative impact on equity returns, whereas the money supply has a positive impact on the equity market. With respect to inflation, Hasan and Javed found little impact on returns in the equity market. Also, FEVD analysis suggested that interest rate, exchange rate, and money supply shocks were important sources of volatility for equity returns. For example, monetary shocks explained about 4% to 16% of the variation in the Pakistani equity market returns. For that reason they suggested that policymakers be careful in designing monetary policy since it has a direct impact on both cash inflows into the capital market and on capital market stability.

Zafar, Urooj and Durrani (2008) investigated the effects of changes in the interest rate proxied by the 90-day T-bill rate on the volatility of Karachi stock returns. Similar to Léon’s (2008) approach, Zafar et al. estimated two distinct GARCH (1,1) models; one without interest rates and the other with interest rates to estimate the conditional mean and variance for monthly data for the period from January 2002 to June 2006. For both models, the conditional market returns and variance parameters were very similar to each other. In particular, conditional market returns had a negative significant relationship with interest rates, indicating that it was easy to predict the stock returns by analyzing interest rates. However, the conditional variance had an insignificant negative relationship with interest rates and was a weak predictor for its volatility. These results, in general, demonstrated that when interest rates increase, people tend to deposit their savings in bank accounts rather than investing in the stock market. That is, higher interest rates reduce the profitability of firms, and hence, stock prices go down. Accordingly, Zafar et al. suggested that policymakers should carefully consider these relationships when intervene the stock market and overall investments policy in the economy.

In Sri Lanka, Peiris and Peiris (2011) examined the volatility of different sectors in Colombo Stock Exchange (CSE) and the effect of macro-economic factors on the volatility by fitting Autoregressive Conditional Heteroscedasticity (ARCH) and the Generalized ARCH (GARCH) using monthly time series data of 20 sectors in CSE for the period 2005-2010. Their results showed that sixteen out of twenty sectors in CSE had a significance volatile and both ARCH and GARCH terms on the fitted models for individual sectors were significant. The volatility of composite stock returns of volatile sectors was regressed against Narrow Money Supply (M1), Broad Money Supply (M2), Inflation (I) and Interest Rate (IR). Then they found that inflation and interest rate were the two significantly influencing macroeconomic factors on the stock market volatility of emerging Economy of Sri Lanka. Same time, again for the Sri Lankan data, Peiris and Dayarathna (2012) using same macroeconomic factors with other two factors (Crude Oil Prices and Exchange Rate), examined the influence of the market volatility in high and low volatility regimes. Monthly stock returns of 20 sectors from 2007 to 2010 were used for their investigation. The Iterated Cumulative Sums of Squares (ICSS) algorithm was applied in splitting the original series into high volatile and low volatile periods. Generalized Autoregressive Conditional Heteroscedasticity (GARCH), Exponential GARCH (EGARCH), Threshold GARCH (TGARCH) and GARCH Regression were the econometric models employed for the empirical analysis. Their results showed that 16 out of 20 sectors in CSE significantly volatile. In the low volatility regime, all most all of the macroeconomic factors except Crude Oil Prices significantly influence the stock market volatility. However, none of these macroeconomic factors are significant in the high volatility regime.

2.4.3 Studies of Multiple Countries

Unlike the studies above, other studies have emphasized comparisons of developing economies, of developed economies, or of developing against developed economies. These studies examined how market structure may affect the nature of the short and long run relationships between stock returns and real economic activity. One of the most recent studies in this area of research was by Wong, Khan & Du (2006). Their study examined the long and short equilibrium relationships between the major stock index in Singapore, U.S. stock markets, and two macroeconomic variables, the money supply (M1), and the short term interest rate. In their analysis, they used monthly data from 1982 to 2002 and conducted a Johansen-Juselius (1990) cointegration test, fractional cointegration tests, and Granger causality tests. They analyzed the whole sample period and two sub periods to account for the short-run dynamics of the relationship among the represented variables. The results indicated that Singapore's stock prices generally displayed a long-run equilibrium relationship with the interest rate and M1, but similar results did not hold true for the U.S. economy. Also, systematic causal relationships among the underlying variables were revealed, which suggests that the stock market performance might be a good measure of monetary policy adjustment in these two countries.

Within the framework of a standard discounted value model, Humpe and Macmillan (2009) compared U.S. and Japanese stock price behavior with a number of macroeconomic variables over the period January 1965 to June 2005. Based on cointegration analysis, there was evidence of a single cointegration vector between U.S. stock prices, IP, inflation, and the long-term interest rate. The coefficients from the cointegrating vector, normalized on the stock price, suggested that the U.S. stock price was influenced positively, as expected, by IP, and negatively by inflation and the long-term interest rate. The money supply (M1) did not have a significant influence over the U.S. stock price. With respect to the Japanese stock price, two cointegrating vectors were found. The first vector, which was normalized on the stock price, provided evidence that Japanese stock prices were positively related to IP, but negatively related to the money supply (M1). The second vector, normalized on IP, suggested that IP is negatively related to the interest rate and the rate of inflation. The difference in behavior between the two stock markets may be attributed to Japan's slump after 1990 and its consequent liquidity trap of the late 1990s and early 21st century.

Hammoudeh and Choi (2006) examined the dynamic relationships of three global factors, the price of oil, the S&P 500, and the U.S. T-bill rate, with the Gulf Cooperation Council's (GCC) stock markets. A VECM model as well as IRFs and VDC analyses were used in the study with weekly data from February 15, 1994 to December 28, 2004. Based on the results, the U.S. T-bill rate had a direct influence on some of the GCC markets. The S&P 500 and the Western Texas Intermediate (WTI), or the Brent oil price, did not have such a direct impact, which implies that local factors such as liquidity and profitability may be more important for explaining the behavior of GCC markets than the international factors. In contrast, the impulse response analysis suggested that the S&P 500 shocks had positive impacts on all GCC markets over a 20-week forecast horizon, suggesting that the GCC stock markets rose with the U.S. markets. From the results, there was no definite consensus on the impact of the T-bill rate. Additionally, most of the GCC markets were benefiting from positive oil shocks. The FVDC analysis indicated that the largest portion of total variations in the GCC index returns was attributed to their own domestic or other GCC shocks over the forecast horizon with only two exceptions: the Oman's and Saudi stock markets where the price of oil explained about 30% and 19% of the variations of the market, respectively.

Errunza and Hogan (1998) investigated whether macroeconomic variability can explain time variation in seven European stock markets compared to the U.S. stock market. Macroeconomic variables included IP as a proxy for real activity, and money supply and inflation as proxies for monetary factors. Different techniques including various GARCH models, a VAR model, and ordinary least squares (OLS) two step procedure were used in this study. Along with monthly data from January 1959 to March 1993; Errunza and Hogan found that the time variation in the seven European stock markets was significantly affected by the past variability of monetary and real macroeconomic factors, which contradicts the results commonly documented for the U.S. economy.

Najand and Rahman (1991) used the GARCH model to examine the effect of the volatility of macroeconomic variables on stock return volatility for the U.S., Germany, UK, and Canada. The macroeconomic variables included in the analysis were the actual volatility of real output, the interest rate, inflation, and monetary base. From their empirical analyses of 309 monthly observations between January 1962 and September 1987, Najand and Rahman provided support for existing relationships between the volatility of stock returns and the volatility of macroeconomic variables. But Fang (2002) investigated the impact of currency depreciation on stock returns and its volatility in the five Far East Asian economies of Hong Kong, Singapore, South Korea, Taiwan, and Thailand during the Asian crisis (1997-1999). Based on the GARCH model, this study provided strong evidence indicating that currency depreciation adversely affected stock returns and/or increased market volatility during the Asian crisis. From his finding, Fang suggested that international investors and fund managers planning to invest in Far East markets should evaluate the stability of foreign exchange markets before taking action.

Another comprehensive study conducted by Muradoglu, Taskin and Bigan (2000) considered 19 emerging markets from all over the world. The study investigated possible causality relationships between the 19 emerging stock markets returns and other macroeconomic variables; i.e., exchange rates, interest rates, inflation, and IP using monthly data from 1976 to 1997. The results revealed that the relationship between stock returns and the macroeconomic variables mainly depend on the size of the stock markets and their integration with world markets.

2.5 Summary of Chapter 02

The purpose of reviewing the previous literature is to identify the present situation of the research problem in the research context as well as to identify the literature gap between previous studies and this study. Most of the studies carried out by different authors (Darrat and Dickens, 1999; Serletis, 1993; Ratanapakorn and Sharma, 2007; Thornton, 1998; Chaudhuri and Smiles, 2004; Maysami, Howe and Hamzah, 2004; Patra and Poshakwale, 2006; Hasan and Javed, 2009) have focused on long run or short run relationship between stock returns and macroeconomic variables. Some other researches (Hashemzadeh and Taylor, 1988; Thornton, 1993; Malliaris and Urrutia, 1991; Darrat, 1990) have discussed the causal relationship between stock returns and macroeconomic variables. The statistical methods used in many studies are GARCH models, impulse response function and forecast error variance decomposition analysis. There is no published work considering both the short and long run dynamic relationships between the Colombo Stock Exchange behavior and real economic activity. Nevertheless, the result acquired from this review is immensely useful for this study.

Chapter 3
Materials & Methods

This chapter presents the statistical and econometric methods that are used in this study and the type of secondary data used. Some background on autoregressive conditional heteroskedasticity (ARCH) modeling is provided along with the standard GARCH models suggested by Bollerslev (1986) and GARCH-X suggested by Lee (1994). Also, a brief description is given on the empirical methods such as vector autoregressive (VAR) models, the Johansen-Juselius (1990) test, causality tests, impulse response functions (IRFs), and forecast error variance decompositions (FEVD).

3.1. Secondary Data

Monthly frequency data on all share price index (ASPI), money supply (MS), interest rate (IR), exchange rate (EXR), Colombo Consumer Price Index (CCPI) and industrial production index (IPI) were collected for the period from January, 2006 to December, 2015 from Data Library of Colombo Stock Exchange and annual reports of Central Bank of Sri Lanka. Data are given in Appendix A.

3.2. ARCH / GARCH Models

Given the three stylized facts that characterize financial time series, i.e., volatility clustering, leptokurtosis, and a leverage effect, the assumption of homoscedasticity of errors is often not met (Rachev, et al., 2007). In other words $V(\mathcal{E}_t)$ does depends on time and then it is assumed $V(\mathcal{E}_t) = h^2_t$, thus, ARCH / GARCH models are introduced to model h^2_t.

3.2.1 Conditional Mean Equation

Estimating the mean equation is the first step in the ARCH / GARCH modeling. The conditional mean equation can be anything, but in practice, the typical form of the mean equation adapted in the literature is the ARMA (p,q) process (Alexander, 2007) based on the observed time series, $\{R_t\}$.

In this study, $\{R_t\}$ in the daily return series of a market index is calculated as $\{R_t\} = log\ (P_t) - log\ (P_{t-1})$. In ARMA (p,q), p and q are the order of autoregressive and moving average processes respectively. Depending on the values of p and q, it can be distinguished four different forms of the mean equation. First, when p and q are equal to zero, we have a random walk model. This model implies that stock prices cannot be predicted using their past values. Second, when p and q are greater than zero the mean equation is an ARMA (p,q) process. Third, the mean equation is a pure autoregressive process, AR (p), when $p>0$ and $q = 0$, and a pure moving average process, MA (q), when $p = 0$ and $q>0$. Then in general $\{R_t\}$ can be expressed as;

$$R_t = \mu + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j} + \varepsilon_t \tag{3.1}$$

Where; μ is the grand mean. R_{t-i} and ε_{t-j} are the autoregressive and moving average components, and α_i and γ_j are the coefficients of these two components respectively. In developing ARMA model, it is first necessary to make the $\{R_t\}$ is stationary. Depending on the pattern of Sample Autocorrelation Function (SACF) and Sample Partial Autocorrelation Function (SPACF) of the stationary series of $\{R_t\}$, the relevant parsimonious models are considered. The Schwarz Information Criterion (SIC), and the Akaike Information Criterions (AIC), are generally used to determine to select the best fitted model for the data. Alexander (2007) reports that when a large number of parameters are included in the model, they may affect convergence of the conditional mean so it is difficult to maximize the likelihood function.

3.2.2 ARCH (q) model

Engle (1982) developed the autoregressive conditional heteroskedasticity (ARCH) model for the variance of error series. The ARCH model is designed to account for a time-varying variance that usually is associated with high frequency financial and economic data. Toward this goal, Engle (1982) suggested that the conditional variance equation needs to be modeled as a linear function of the past q squared innovations and the corresponding equation is shown in equation (3.2),

$$h_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 \tag{3.2}$$

ω & α_i are non-negative parameters to ensure that the conditional variance is positive, and ε_t^2 is the square error obtained from the mean equation. However, empirical work has shown evidence that the ARCH (p) model fits financial time series well only with a large number of lags (Fan and Yao, 2003). This weakness led to extensions of the ARCH model in a number of directions, driven by either economic or statistical considerations (Fan and Yao, 2003).

Bollerslev (1986) developed a fundamental extension to the ARCH (p) model known in the literature as generalized autoregressive conditional heteroskedasticity (GARCH) model. This extension was an attempt to overcome the need for a large number of lags usually required by the ARCH (p) process to correctly model the high persistence of variance associated with financial and economic data. Bollerslev (1986) achieved this objective using a technique that allows the conditional variance to be modeled as an ARMA process such that the conditional variance is determined by the innovations and its own lags (Fan and Yao, 2003).

3.2.3 GARCH (p,q) model

The conditional variance equation is the fundamental contribution of the GARCH (p,q) model, and can be written in the following form:

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{i-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2, \tag{3.3}$$

Where $h_t^2 = V(\varepsilon_t)$ and

$$\omega > 0\,,\ \alpha_i,\ \beta_j \geq 0 \ \rightarrow\ h_t^2 \geq 0,\ i = 1, \ldots p, \text{and}\ j = 1, \ldots .\, q$$

The conditional variance of the GARCH model defined in equation (3.3) as a function of three terms. The first term is the mean of yesterday's forecast, ω. The second term is the lag of the squared residuals obtained from the mean equation, $\varepsilon^2{}_{i-1}$, or the ARCH terms. The ARCH terms represent the news (information) about volatility from the previous period that has a weighted impact, which declines gradually, while never reaching zero, on the current conditional volatility. The third term is the GARCH term, h^2_{t-j}, measuring the impact of last period's forecast variance. It is important to note that these three parameters (ω, α_i's, and β_j's) are restricted to be non-negative to ensure positive values for the conditional variance or $h_t^2 \geq 0$ (Enders, 2004).

3.2.4 Properties of GARCH (p,q) model

The size of the parameters α_i and β_j determines the short-run dynamics of the volatility of the data, and the sum of the estimated α_i and β_j determines the persistence of volatility to a particular shock. A large positive value of α_i indicates strong volatility clustering is present in the time series of interest. A large value of β_j indicates that the impact of the shocks to the conditional variance lasts for a long time before dying out, so volatility is persistent (Alexander, 2007). The GARCH (p,q) model is covariance stationary if and only if $\alpha_i + \beta_j < 1$ (Nelson, 1990). In this case, the unconditional variance of the errors is $h_t^2 = \omega / 1 - \Sigma\ (\alpha_i + \beta_j)$, where n is equal to the lag order of q and p. One advantage of the GARCH (p,q) model over the ARCH (p) process is that good news corresponds to negative shocks ($\varepsilon^2_{i-1}<0$) since it reduces the conditional volatility, while bad news corresponds to positive shocks ($\varepsilon^2_{i-1}>0$) since it increases conditional volatility. Thus, in Bollerslev's GARCH model, the sign of the shock is irrelevant. The magnitude of the positive or negative shocks is the only factor that matters for conditional volatility.

3.3 Different versions of GARCH

A large number of extensions to the standard GARCH model have been suggested either to overcome the asymmetries problem and/or to account for different local or international shocks that may affect the behavior of specific stock markets. The Exponential GARCH model (EGARCH) suggested by Nelson (1991), the Glosten-Jagannathan-Runkle GARCH model (GJR-GARCH) suggested by Glosten, Jagannathan, and Runkle (1993), and the periodic GARCH model (PGARCH) developed by Ding, Granger, and Engle (1993) are commonly used to account for the asymmetric phenomenon that characterizes financial time series data.

Some other extensions to the standard GARCH model advocate adding an explanatory variable in the GARCH conditional mean equation, conditional variance equation, or both. The GARCH-M model introduced by Engle, Lilien and Robins (1987) is an example of the first extension. This extension seeks to examine the risk-return tradeoffs suggested in finance theory by adding the variance of the return as an independent variable to the conditional mean equation. For example a higher perceived risk should be correlated with a higher return on average. The second type of extension to the standard GARCH model is the GARCH-X model suggested by Lee (1994).

For this study, the GARCH-X model is of interest as it examines the impact of the short-run deviation on the long run equilibrium within cointegrated series. Lee (1994) extends the standard GARCH model by adding error correction terms obtained from the cointegration model to the conditional variance equation. According to Lee, the GARCH-X model is useful for examining how the short-run disequilibrium affects uncertainty in predicting cointegrated series. According to Lee, examining the behavior of the variance over time as a function of the disequilibrium is reasonable when one expects increased volatility due to shocks to the system. Mathematically the GARCH-X model can be expressed as follows (Lee, 1994):

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{i-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 + \lambda_n Z_{t-1}^2, \qquad (3.4)$$

$$\omega > 0\ ,\ \alpha_i\ ,\ \beta_j\ ,\ \lambda_n \geq 0 \ \rightarrow\ h_t^2 \geq 0,\ i = 1, \dots p, \text{and } j = 1, \dots .\, q.$$

The new feature of this model over the other GARCH models is the addition of the lagged squared error correction terms obtained from the long-run cointegration model, $Z^2{}_{t-1}$. These terms account for the short-run deviation of the conditional variance. The parameter λ_n measures the effect of short-run deviations from the long-run relationship of the selected variables. A large positive value of the parameter λ_n indicates that the deviation of stock market returns from the group of macroeconomic variables gets larger over time. The implication of this is that the stock market becomes more volatile and harder to predict.

3.4 Evaluation of GARCH models

The robustness of the GARCH models can be evaluated using a number of in-sample and out-sample diagnostics. Consistent with the goal of this study, it is used some in-sample diagnostics to assess the performance of the estimated GARCH models. These diagnostics include the Ljung-Box (1978) test statistics, (p) and $Q^2(p)$. These tests examine the null hypothesis of no autocorrelation and homoscedasticity in the estimated residuals, and squared standardized residuals, or $\varepsilon_t/\sqrt{h_t}$, up to a specific lag, respectively. Also, Engle's (1982) LM statistic is used to test the null hypothesis of no remaining ARCH effects up to a specific order. In fact, if the GARCH model is specified correctly, then the estimated standardized residuals should behave like white noise, i.e., they should not display serial correlation, conditional heteroskedasticity, or any other type of nonlinear dependence. Furthermore, since GARCH models can be treated as ARMA models for squared residuals, traditional model selection criteria, such as the AIC, the SIC, and maximized log-likelihood value can be used to assess the most appropriate model.

3.5 VAR Models

Many economic time series data, such as consumption and income, stock prices and dividends show theoretical long-run relationships. It is also widely accepted that these time series data evolve over time such that their mean and variance are not constant (Nelson and Plosser, 1982). Relying on such non-stationary time series data may lead macroeconomists to wrongly conclude that two variables are related when in reality they are not. This phenomenon is well known in the literature as spurious regression (Stock and Watson, 2006).

That is, if Y_t and X_t are non-stationary time series data and $Y_t \sim \mathrm{I}(1)$, then a "spurious" relationship between these two variables may exist unless the linear combination of the two variables, $Y_t - \beta X_t$, is stationary. The typical method to analyze a non-stationary process is to either detrend or difference the data depending on the type of trend (Maddala, 2001). Granger's Representation Theorem – GRT introduced an effective method to analyze non-stationary processes without losing valuable long run information as with differencing or de-trending techniques. This method is well known in literature by the cointegration.

The idea of the cointegration test is simple. Suppose Y_t and X_t are integrated of order one that is $Y_t \sim I(1)$ and $X_t \sim I(1)$. Then Y_t and X_t are said to be cointegrated if and only if $Y_t - \beta X_t = Z_t$ obtained from the long run relationship regression is integrated of order zero that is $Z_t \sim I(0)$. Therefore, if the cointegration condition is met, then Y_t and X_t move together in the long run such that they cannot drift arbitrarily far apart from each other as time goes on (Maddala, 2001). In this context, according to GRT, the short term disequilibrium relationship between two cointegrated time series can be expressed in the error correction form which may be seen as a force pushing the residual errors back towards the equilibrium (Maddala, 2001).

Two typical methods recommended to examine the long run relationships among variables are; (1) Engle and Granger (1987) cointegration test and (2) Johansen-Juselius (1990) cointegration test. The first is suitable for bivariate analysis, while the second is convenient to use when there are more than two variables. In this study, Johansen-Juselius (1990) cointegration test is used.

3.6 Various Statistical Tests related to Time Series Modelling

3.6.1 Johansen-Juselius (1990) Cointegration Test

The Johansen-Juselius (1990) cointegration test is a statistical method for testing for cointegration. The Johansen-Juselius approach is based on a VAR model of order p to examine the long run relationships that may exist among representative variables. For that reason, the Johansen-Juselius approach overcomes some drawbacks associated with the two-step Engle-Granger (1987) method. The Johansen-Juselius approach does not require the choice of dependent and independent variables. All variables entering the VAR models are treated as endogenous variables. Also, the Johansen-Juselius approach is a one step calculation; free from carrying forward any bias introduced in the first step as in the case of the two-step Engle-Granger methodology (1987). Finally, if multiple cointegrating vectors exist, the use of the Engle-Granger method may simply produce a complex linear combination of all distinct cointegrating vectors. The Johansen-Juselius approach can be expressed mathematically in the following general form:

$$Y_t = \mu + A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \cdots + A_p Y_{t-p} + \varepsilon_t \qquad (3.5)$$

Where Y_t is a vector containing p variables, all of which are integrated of order one and the subscript t denotes the time period. μ is an $(nx1)$ vector of constants, A_p is an $(n \times n)$ matrix of coefficients where ρ is the maximum lag included in the model, and ε_t is an $(n\ x1)$ vector of error terms.

This can be written in the form of the error correction model assuming cointegration of order p. Enders (2004) shows how to rewrite above equation as:

$$\Delta Y_t = \mu + (A_1 - I)\ Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \cdots + A_p Y_{t-p} + \varepsilon_t, \qquad (3.6)$$

Where $(A_1 + A_2 + \cdots + A_{p-1-I})$ represents the dynamics of the model in the short run. In above equation, $(A_1 + A_2 + \cdots + A_{p-I})$ represents the long run relationship among the variables included in the vector Y, and I is the identity vector. The key idea of the Johansen-Juselius approach is to determine the rank of the matrix $(A_1 + A_2 + \cdots + A_{p-I})$, which represents the number of independent cointegration vectors. In other words, how many error correction terms belong in the model.

3.6.2 Granger Causality Tests

It is essential to consider the relationship among the variables of interest in the short run. That is, it requires to investigate the short run linkages among the variables by performing Granger causality tests. It is also known as causality test. Causality tests can be conducted in two different ways depending on the results of the long run analysis (Granger, 1969). It is suitable for analyzing the short-run relationship if no cointegration exists among the variables. On the other hand, when the variables of interest are cointegrated, the standard causality test is misspecified and the error correction strategy suggested by Engle and Granger (1987) should be used (Enders, 2004).

This test examines whether including lags of one variable have predictive power for another variable. This test implies that X causes Y if Y can be better forecast by including past values of X in the model rather than using only Y's past values. It should be noted that the concept of causality in the Granger test does not mean that changes in one variable cause changes in another variable, as the term is used in the context of policy discussions. The causality test only tests whether predictability exist among the variables of interest.

Thus, this test is based on a VAR models in differences is appropriate when the long-run analysis indicates there is no long-run relationship between variables that are integrated of the same order, i.e., X and Y ~ I(1). As in Enders (2004), the Granger test begins with the estimation of a VAR model in differences:

$$\Delta X_t = \delta_i + \sum_{i=1}^{p} a_i \, \Delta X_{t-i} + \sum_{j=1}^{p} \beta_j \, \Delta Y_{t-j} + u_{1t} \tag{3.8}$$

$$\Delta Y_t = \gamma_i + \sum_{i=1}^{p} c_i \, \Delta Y_{t-i} + \sum_{j=1}^{p} d_j \, \Delta X_{t-j} + u_{2t} \tag{3.9}$$

Where ΔX_t and ΔY_t are the first difference of the time series under investigation, δ_i and γ_i are constants, and u_{1t} and u_{2t} are white noise error terms. Furthermore, the subscripts t and p denote time periods and the number of lags used in the model.

3.7 The Error Correction Model

Engle and Granger (1987) argue that the Granger test is misspecified and may lead to spurious causality among the variables if they are cointegrated. In other words, the Granger test is valid only when there is no long-run equilibrium relationship among the examined variables. To overcome this drawback of the Granger test, Engle and Granger suggest including error terms in equations. These error terms capture the long run and short run relationships among variables that are cointegrated in their levels. More precisely, in a two variable setting where X and Y are integrated of order one or $I{\sim}(1)$, the error correction model (ECM) can be formulated as:

$$\Delta X_t = \delta_i + \sum_{i=1}^{p} a_i \, \Delta X_{t-i} + \sum_{i=1}^{p} \beta_i \, \Delta Y_{t-i} + \gamma_1 \hat{\varepsilon}_{1t-1} + v_{1t} \tag{3.10}$$

$$\Delta Y_t = \lambda_i + \sum_{i=1}^{p} d_i \, \Delta X_{t-i} + \sum_{i=1}^{p} c_i \, \Delta Y_{t-i} + \gamma_2 \hat{\varepsilon}_{2t-1} + v_{2t} \tag{3.11}$$

Where $\hat{\varepsilon}_{1t-1}$ and $\hat{\varepsilon}_{2t-1}$ are the error correction terms obtained from the long run model lagged once, which can be interpreted as the deviation of X and Y from their long run equilibrium values, respectively. Including the error correction terms represents the short-run dynamics necessary to reach the long run equilibrium and opens a channel to detect Granger causality (Granger,1988).

γ_i capture the long run causal relationships among the variables in the system, and it is expected to be negative and most likely have an absolute value of less than one. When the $\gamma_i's$ are not statistically significant, the system of equations suggests that the variables of the system are independent in the context of prediction. When γ_1 is statistically significant, while γ_2 is not, the system suggests a unidirectional causality from $Y\ to\ X$, meaning that Y drives X toward long run equilibrium but not the other way around. However, the opposite implication will be observed when γ_2 significant and γ_{i} is not. Indeed, if both coefficients $\gamma_1$and γ_2 are significant, then this suggests feedback causal relationships in the system or bidirectional Granger causality relationships. β_j measures the short run impact of changes in X on Y, d_j measures the short run impact of changes in Y on X, and v_{it} is the standard error term.

3.8 Impulse Response Functions

The impulse response function (IRF) is one of the essential tools for interpreting VAR model results. The IRF allows researchers to examine the current and future behavior of a variable that following a shock to another variable within the system. The IRF is a useful tool for determining the magnitude, direction, and the length of time that the variables in the system are affected by a shock to another variable. To estimate IRFs, some practical issues need to be considered. The VAR model needs to be transformed into the vector moving average (VMA) representation. In the case of a VAR model with two variables included, the form of the IRFs can be written as shown in Enders (2004):

$$\begin{bmatrix} Y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{Y} \\ \bar{Z} \end{bmatrix} + \sum_{i=0}^{\infty} \frac{A^i}{1 - b_{12}b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{Y_{t-i}} \\ \varepsilon_{Z_{t-i}} \end{bmatrix}$$

$$\begin{bmatrix} Y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{Y} \\ \bar{Z} \end{bmatrix} + \textstyle\sum_{i=0}^{\infty} \begin{bmatrix} \theta_{11}^i & \theta_{12}^i \\ \theta_{21}^i & \theta_{22}^i \end{bmatrix}^i \begin{bmatrix} \varepsilon_{Y_{t-i}} \\ \varepsilon_{Z_{t-i}} \end{bmatrix}, \qquad \text{and}$$

$$X_t = \mu + \sum_{i=0}^{\infty} \theta_i \varepsilon_{t-i} \tag{3.12}$$

Where, θ_i is the IRFs of disturbances. Therefore, the IRF is found by reading off the coefficients in the moving average representation of the process. If the innovations ε_{t-i} are contemporaneously uncorrelated, the interpretation of the impulse response is straightforward. For example, the i^{th} innovation of ε_t is simply a shock to the i^{th} endogenous variable in the system (Enders, 2004).

However, the residuals generated by the VAR models are usually contemporaneously correlated. This is because in a VAR model only lagged endogenous variables are admitted on the right-hand side of each equation (in addition to a constant term), and hence all the contemporaneous shocks which impact on X_t are forced to feed through the residuals, u_{it} (Kuszczak and Murray, 1986). While this may not cause a problem in the estimation of the VAR model, the impulse responses and variance decompositions derived from the initial estimates of the VAR model could be affected such that any adjustment to the order in which the variables are entered in the system could produce different results (Kuszczak and Murray, 1986). Thus, there is a need to impose some restrictions when estimating the VAR model to identify the IRFs. In this regard, a common approach is the Cholesky decomposition, which was originally applied by Sims (1980).

3.9 Forecast Error Variance Decompositions

For any variable, short run variations are due to its own shocks, but over time other shocks contribute to these changes as well. Forecast error variance decomposition (FEVD) is a method available to examine this interesting phenomenon. In fact, while the IRFs analyze the dynamic behavior of the target variables due to unanticipated shocks within a VAR model, variance decompositions determine the relative importance of each innovation to the variables in the system. That is, variance decompositions can be considered similar to R^2 values associated with the dependent variables in different horizons of shocks. Enders (2010) show how to write FEVD to conditionally calculate n-period forecast error X_{t+n} considering the VMA representation of VAR presented in equation as:

$$X_{t+n} - E_t X_{t+n} = \mu + \sum_{i=0}^{\mathrm{n}-1} \theta_i \varepsilon_{t+\mathrm{n}-i} \qquad (3.13)$$

However, it is typical for a variable to explain almost all of its forecast error variance at a short horizon and smaller proportions at longer horizons (Enders, 2010). From this stand point FEVD is useful to assess the Granger causal relationships among variables when the variance decomposition results imply that one variable explains a high portion of the forecast error variance of another variable.

Chapter 4

Development of GARCH model

The first part of this chapter presents the behavior of selected variables and their distribution using descriptive statistics. Remaining of this chapter comprises details of the development of GARCH models and related statistical analysis along with interpretation of results.

4.1 Behavior of Selected Variables

The temporal variability of selected six variables; All Share Price Index (ASPI), money supply (M2); a proxy for short term interest rates (IR), 3-month treasury bill rate; the Colombo Consumer Price Index (CCPI); the nominal effective exchange rate (EXR); and Industrial Production Index (IPI) are shown in figures 4.1 to 4.6 respectively.

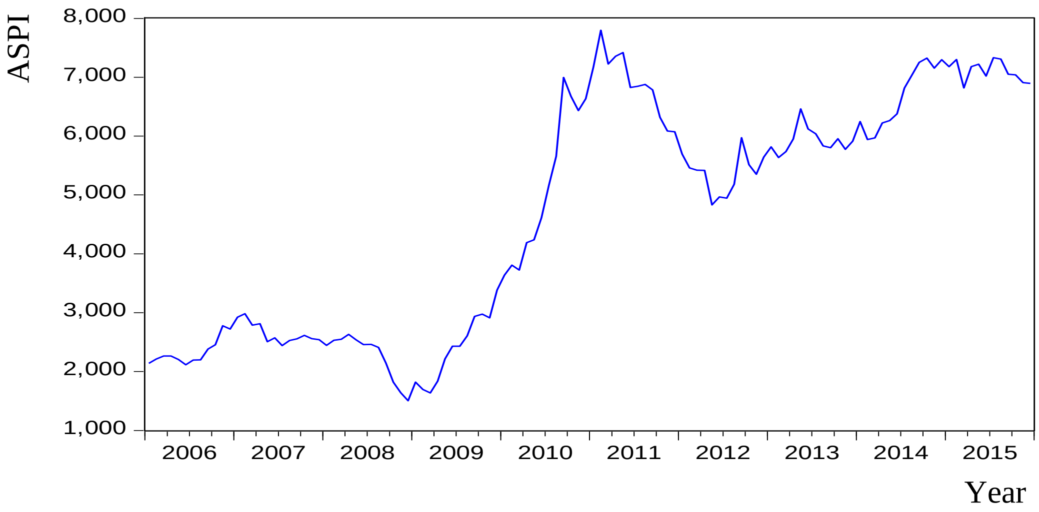

Figure 4.1 Monthly closing price of ASPI (units)

It should be noted that from middle of 2008 to middle of 2010 there is high increase in market price of shares, basically because of the victory of war by defeating LTTE terrorists (Figure 4.1). That abnormal situation was remained until end of 2012. After that, there has been a slight increasing trend in share prices. Because of unstable economic situation in 2008 due to terrible war situation in the country, the index comes to the lowest of 1503 in December 2008. The ASPI gets the highest value (7798) in February 2011 ever marked so far. Based on the pattern of ASPI over the years, it would be better to consider three separate scenarios; (i) Jan 2006 to Dec

2008, (ii) Jan 2009 to Feb 2011, (iii) March 2011 to Dec 2015. However, in this study, data are analyzed ignoring the three scenarios. The temporal trends of MS, IR, EXR, IPI and CPI are shown in Figure 4.2 to Figure 4.6 respectively.

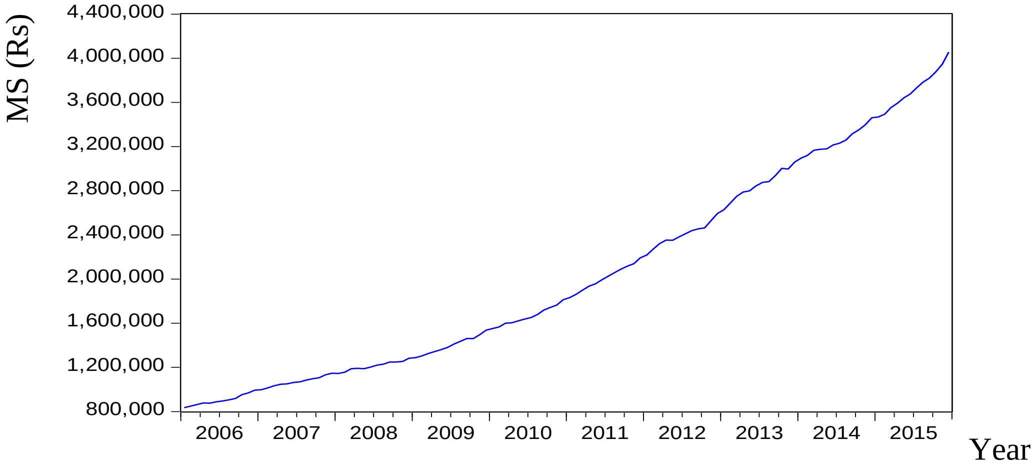

Figure 4.2 Month end Money Supply (MS)

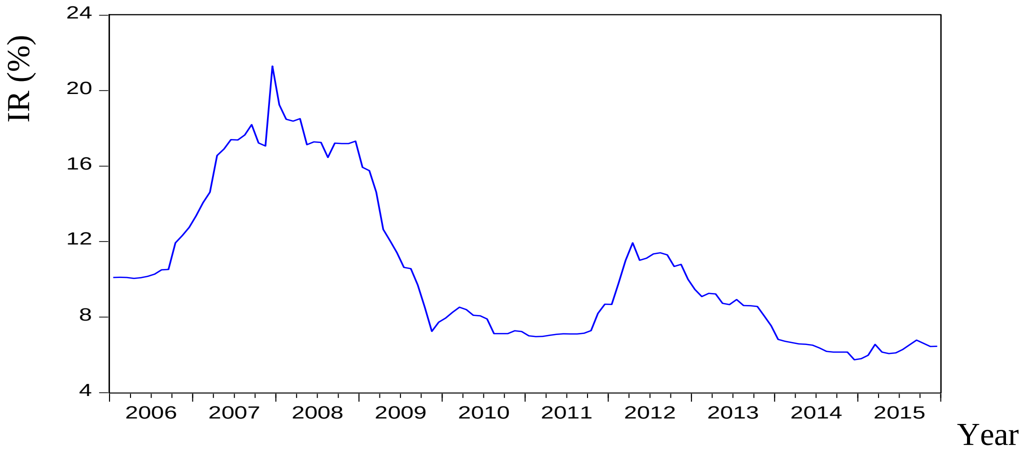

Figure 4.3 Three months Treasury bill rate (IR)

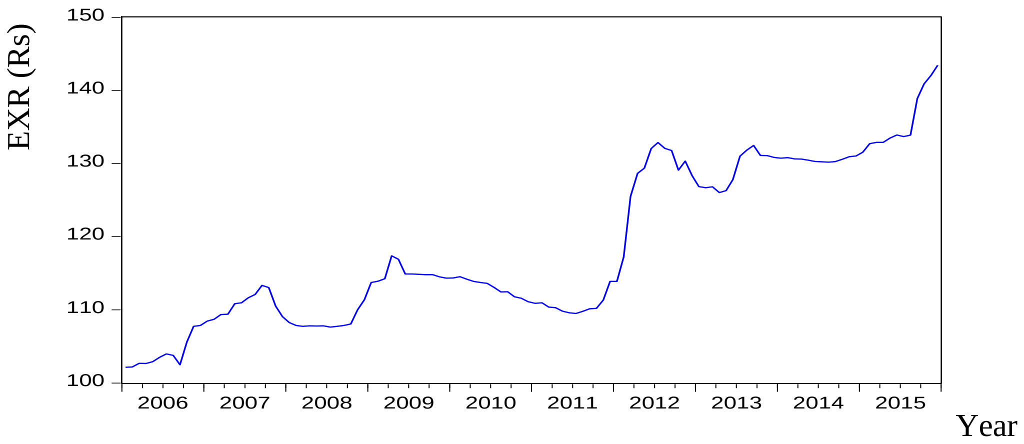

Figure 4.4 Month end Exchange rate (EXR)

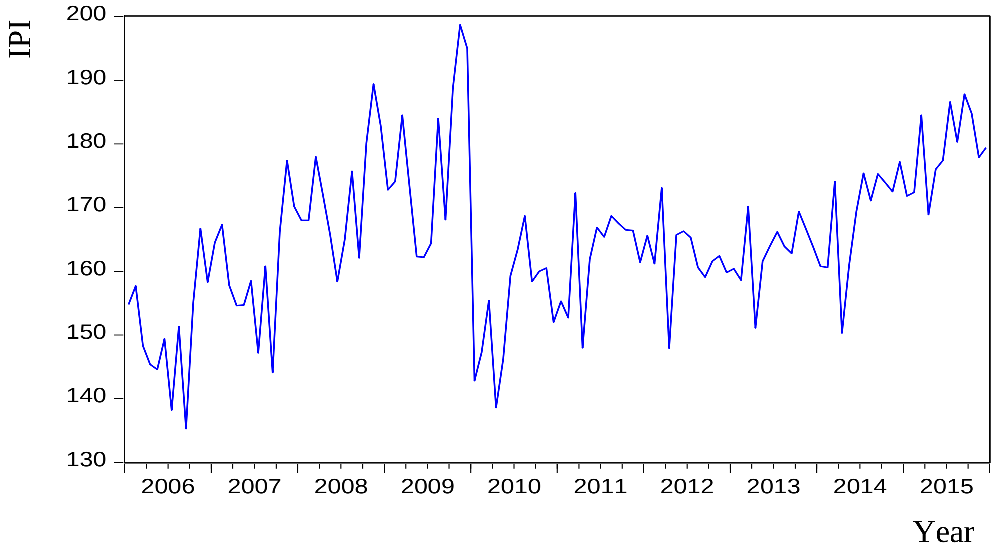

Figure 4.5 Monthly closing value of Industrial Production Index (IPI)

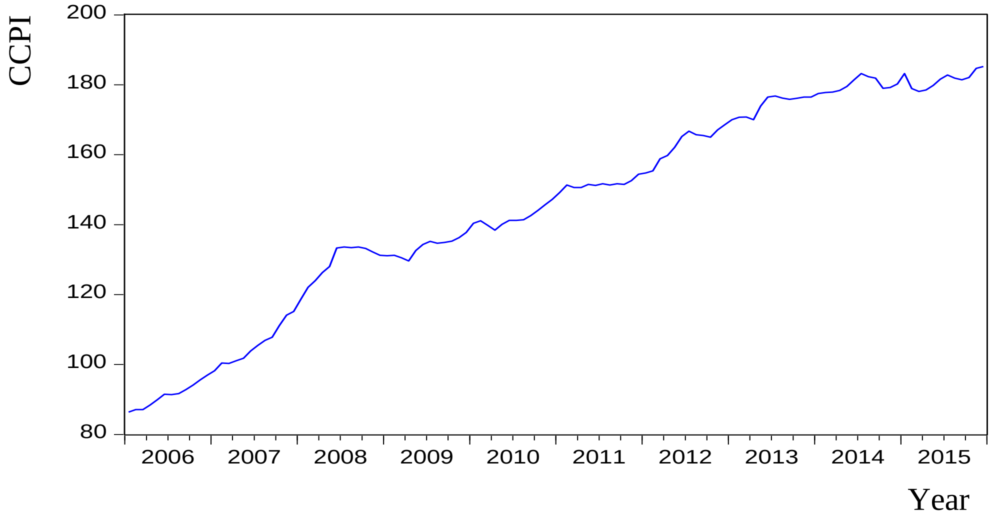

Figure 4.6 Monthly closing value of Colombo Consumer Price Index (CCPI)

The behavior of money supply shows continuous linear increasing trend over time (Figure 4.2). According to Figure 4.3, three months Treasury bill rate has been fluctuating within the sample period and it clearly shows volatile situation during 2007 to 2009. Furthermore, it can be seen that IR has been decreasing since 2012. Exchange rate is also fluctuating during the sample period (Figure 4.4). In Sri Lanka we have floating exchange rate where the price is depend totally on the demand and supply of the dollars. Until 2011 Sri Lanka had controlled floating rate where the Central Bank of Sri Lanka involved in controlling the exchange rate. Therefore from 2011, it can be seen increasing trend in dollar rate because of uncontrolled floating situation. Industrial production index shows increasing trend in values as well as seasonal pattern in the sample period (Figure 4.5). According to Figure 4.6 Consumer price index also has continues linear increasing trend throughout the sample period. It is similar to the trend in money supply.

4.2 Descriptive Statistics

Table 4.1 summarizes the basic statistical features of the data series under consideration, including the mean, median, the minimum and maximum values, standard deviation, coefficient of variance, kurtosis, skewness, AD test and the range for the data.

Table 4.1 Useful Statistical Indicators of the Macroeconomic Variables

Variable	ASPI	MS (Rs)	IR (%)	EXR (Rs)	IPI	CPI
Mean	4675.00	2047721.00	10.38	118.46	132.87	145.12
StDev	2017.00	933616.00	4.04	10.95	28.98	29.67
CV	43.14	45.59	38.93	9.25	21.81	20.45
Minimum	1503.00	834273.00	5.74	102.15	85.00	86.40
Median	5385.00	1822517.00	9.01	114.05	121.10	148.20
Maximum	7798.00	4057191.00	21.30	143.45	198.70	185.20
Range	6295.00	3222918.00	15.56	41.30	113.70	98.80
Skewness	-0.11	0.48	0.90	0.40	0.49	-0.43
Kurtosis	-1.64	-1.06	-0.42	-1.23	-1.07	-0.92
AD Test	6.80	1.95	2.99	5.63	3.44	3.56

ASPI, MS, IR, IPI and CPI show huge variances which is because of higher range between minimum and maximum values. The coefficient of variation (CV), also known as relative standard deviation (RSD), is a standardized measure of dispersion of a probability distribution. Higher values of CVs in ASPI (43.14), MS (45.59), IR (38.93), IPI (21.81) and CPI (20.45) imply higher variability. Higher standard deviations can be seen in ASPI and MS which indicate the higher volatile condition than other variables. IR and EXR show the lower standard deviation because of low volatility in those variables. That is because of fixed rate in interest as well as controlled exchange rate by the Central Bank of Sri Lanka.

Normality of the data sets was checked using Skewness, Kurtosis and AD test. Normality tests are used to determine if a data set is well-modeled by a normal distribution and to compute how likely it is for a random variable underlying the data set to be normally distributed. According to the values of AD test, each variable has non normal distribution because of p-value is less than 0.05. There is no reason to assume that all economic time series are, even after a suitable transformation, marginally, or at least conditionally, normally distributed in general.

Two numerical measures of shape, skewness and excess kurtosis, can be used to test for normality. If either of these values is not close to zero, then your data set is not normally distributed. As a general rule of thumb, if skewness is between -0.5 and 0.5, the distribution is approximately symmetric. All the skewness values are within that range. Therefore it can be argue that data sets are approximately symmetric.

4.3 Association among Six Macroeconomic Variables

Correlation coefficient is one of the most common and most useful statistical indicators to describe the association among variables. That shows the strengths of the linearity. The correlation coefficient between ASPI and MS ($r = 0.84$, $p = 0.000$), ASPI and EXR ($r = 0.66$, $p = 0.000$), and ASPI and CPI ($r = 0.83$, $p = 0.000$) indicated that correlation between these variables are significantly different from zero. Also it should be noted that correlation is positive and MS, EXR and CPI are positively influence to ASPI.

The correlation coefficient between ASPI and IR ($r = -0.79$, $p = 0.000$), and ASPI and IPI ($r = -0.78$, $p = 0.000$) also indicated that correlation between these variables are significantly different from zero. Also it should be noted that correlation is negative and IR and IPI are negatively influence to ASPI. Further, It can be confirmed with 95% confidence that the correlation among variables are significant different from zero. These results support the inclusion of these macroeconomic variables in our analysis. The correlation matrix among six macroeconomic variables is shown in table 4.2

Table 4.2 Correlation Matrix among Six Macroeconomic Variables

	ASPI	MS	IR	EXR	IPI
MS	0.840				
	(0.000)				
IR	-0.790	-0.674			
	(0.000)	(0.000)			
EXR	0.662	0.929	-0.501		
	(0.000)	(0.000)	(0.000)		
IPI	-0.779	-0.573	0.675	-0.467	
	(0.000)	(0.000)	(0.000)	(0.000)	
CPI	0.830	0.934	-0.622	0.878	-0.605
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Parenthesis indicates p-value for the significance of the correlation coefficients

4.4 Autocorrelation Function (ACF) of LNASPI

First step in estimating an ARCH / GARCH model is to determine the dynamics of the conditional mean. To find an adequate model for the conditional mean equation, autocorrelation function (ACF) and partial autocorrelation function (PACF) were used. The data were transformed to natural log (LN) to reduce the heteroskedasticity of the variables. In fact, this is common practice in analyzing financial time series. The plot of ACF of log series (LNASPI) is shown in Figure 4.7.

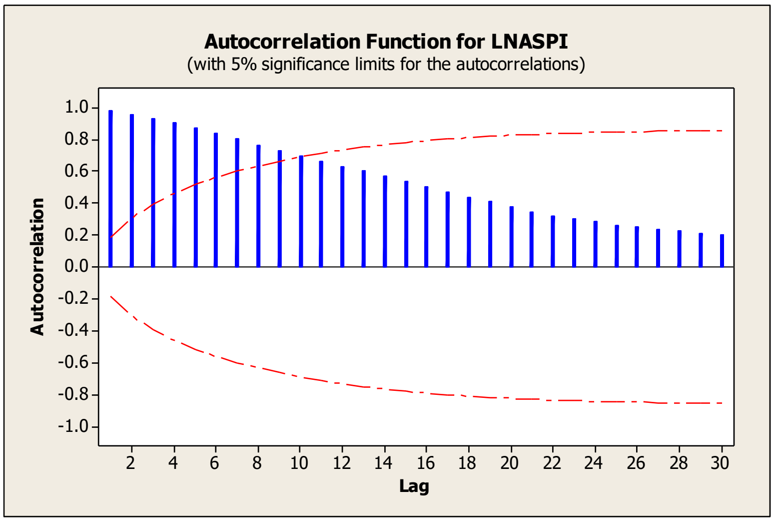

Figure 4.7 Plot of ACF for LNASPI

The ACF plotted in Figure 4.7 for the original series of LNASPI shows the linear decreasing of autocorrelations, and first few autocorrelations are significantly different from zero. That implies the series is not stationary. Augmented Dicky Fuller test also used to check the stationary of the original series. Table 4.3 shows the results of ADF analysis.

Table 4.3 ADF Test Results for LNASPI

	t-Statistic	Probability
Augmented Dickey-Fuller test statistic	-0.99856	0.7523
Test critical values:		
1% level	-3.486064	
5% level	-2.885863	
10% level	-2.579818	

Results in Table 4.3 shows that the original ASPI series is not stationary, because p-value (0.7523) is more than 0.05. Therefore, first difference of original series was used for the plot of ACF. Figure 4.8 shows the plot of ACF for first difference of LNASPI.

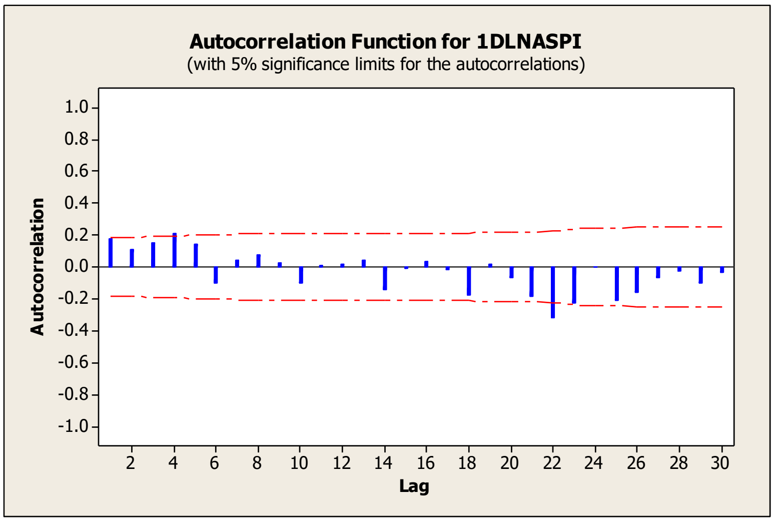

Figure 4.8 Plot of ACF for First Difference of LNASPI

Spike no 1 and 4 are significantly different from zero and other autocorrelations are around zero within the boundaries of two standard errors. It can’t be clearly identify the stationary of the series and which model is appropriate for further estimations. Therefore, Augmented Dickey fuller test is also used to check the stationary of the first difference of original series.

Table 4.4 ADF Test Results for First Difference of LNASPI

	t-Statistic	Probability
Augmented Dickey-Fuller test statistic	-9.054161	0.0000
Test critical values:		
1% level	-3.486551	
5% level	-2.886074	
10% level	-2.579931	

Results are in Table 4.4 clearly shows that first difference of original series is stationary because p-value of ADF test statistic (p = 0.000) is statistically significant and the t-statistic value is higher than the critical values of all the levels.

In time series analysis, the partial autocorrelation function (PACF) plays an important role in data analyses, particularly in identifying the order of an autoregressive model. The plot of PACF in Figure 4.9 shows the first lag falls significantly within the boundaries of two standard errors.

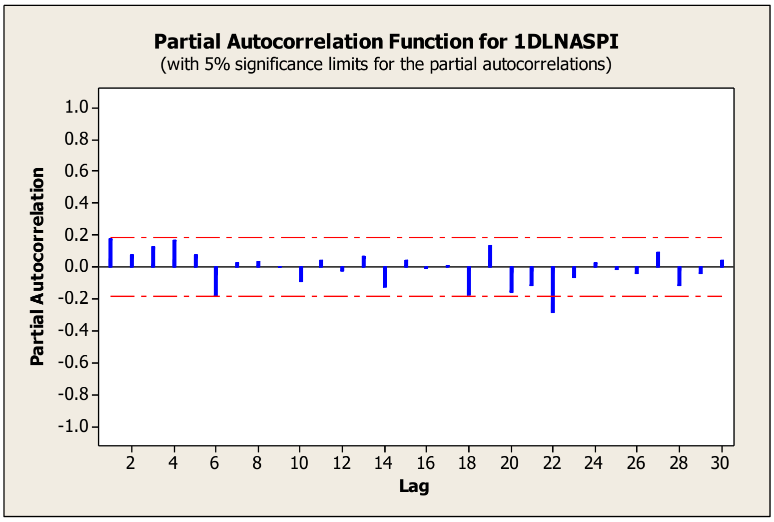

Figure 4.9 Plot of PACF for First Difference of LNASPI

The PACF of the stationary series was considered to decide few parsimonious models. By comparing theoretical ACF and PACF with the Sample ACF (Figure 4.7), ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1) models were considered as parsimonious models. The significance of the parameters of each model is shown in Table 4.5.

Table 4.5 Summary of Output of Different Models

Model	θ_1	Φ_1	Constant
ARIMA (1,1,0)	Significant (0.006)		Not Significant (0.162)
ARIMA (0,1,1)		Not Significant (0.098)	Not Significant (0.144)
ARIMA (1,1,1)	Significant (0.000)	Not Significant (0.063)	Not Significant (0.345)

Results in Table 4.5 indicate the parameters of the ARIMA (1,1,1) and ARIMA (0,1,1) are not significant confirming these two models are not suitable. The AR parameter of the ARIMA (1,1,0) is significant (p = 0.006) confirming AR (1) model is significant. Thus, it can be concluded that out of three parsimonious models the most suitable model is ARIMA (1,1,0). Also Box-Pierce statistics at lag 12 and 36 also insignificant providing evidences for the randomness of the errors. However, it should be noted that Box-Pierce statistic is significant at lag 24.

It was found using Box-Pierce statistics that the errors of the model is random. Also it was found that mean of the errors are not significantly different from zero. In fact, the plot of residuals of ARIMA (1,1,0) model is shown in Figure 4.10. Therefore, this model satisfies the primary statistical diagnostics to conduct the impact of a set of macroeconomic variable volatility on the conditional variance of the ASPI.

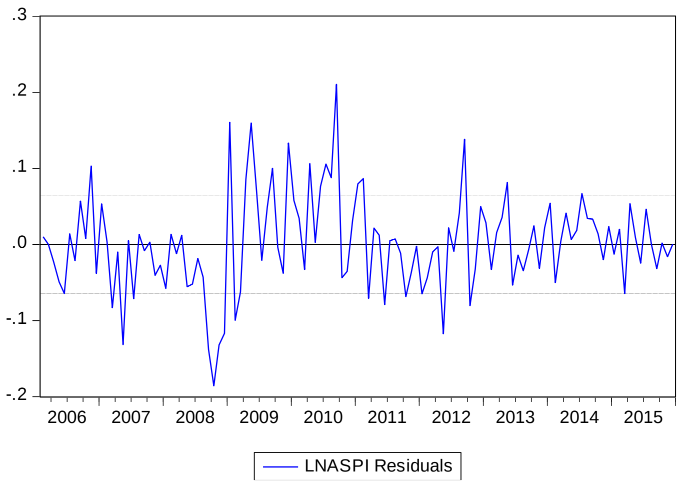

Figure 4.10 Estimated Residuals of the ARIMA (1,1,0) model

The ARCH-LM test for heteroskedasticity of errors confirmed that errors are significantly deviated from constant variance (Table 4.6). Furthermore, correlogram of the squared residuals (Table 4.7) indicates ACF of first few laps are insignificant. It is now clear based on the above analysis, it is necessary to go for ARCH/GARCH models to model the variance of the residual series of the mean equation.

Table 4.6 Heteroskedasticity Test for the Estimated Residuals of the AR (1) Model

Order	F-statistic	Probability	Obs*R-squared	Prob. Chi-Square
1	27.9506	0.0000	22.9118	0.0000
2	16.6040	0.0000	26.3935	0.0000
3	13.0042	0.0000	29.9674	0.0000

Table 4.7 Residual Diagnostic Fits for AR(1)

Order	Q-Stat ^2	Probability
1	0.0026	0.959
3	0.9948	0.803
6	16.307	0.012
9	17.973	0.035
12	23.576	0.023
24	40.907	0.017
36	58.736	0.010

Table 4.8 shows the results for the estimated model from which the P-value associated with the AR(1) coefficient is statistically significant. This result implies that ASPI has a relatively short memory, which may be reasonable since the stock market should react to information faster than other markets like goods markets.

Table 4.8 Estimated Optimal AR (1) Model

Variable	Coefficient	Probability	
C	5177.669		0.1677
AR(1)	0.851606		0.0000
R-squared	0.961501	Mean dependent var	4695.893
Adjusted R-squared	0.961172	S.D. dependent var	2011.56
S.E. of regression	396.3744	Akaike info criterion	16.62939
Sum squared resid	18382179	Schwarz criterion	16.72281
Log likelihood	-985.4487	Hannan-Quinn criter.	16.66732
Durbin-Watson stat	0.803223		

4.5 Estimation of Variance Equation

Results in Table 4.11 show that all the key parameters in the variance equation (ω, α_1, and β_1) are highly significant ($p < 0.05$). Thus, it can be conclude that LNASPI can be modeled by AR (1) GARCH (1,1).

Table 4.9 and Table 4.10 contains the diagnostic tests on the residuals generated from the AR(1)-GARCH(1,1) model. The Ljung-Box Q-statistics suggest no serial correlation on the standardized residuals obtained from the model up to 36th order at the 5% significance level. Also, the Q2-statistic test cannot effectively reject the null hypothesis of no autocorrelation of the squared standardized residuals obtained from the AR(1)-GARCH(1,1) model up to 36 lags at the 5% significance level. These results are also confirmed by the fact that the estimated standard AR(1)-GARCH(1,1) model successfully produced residuals that are free from ARCH effects based on the ARCH-LM test up to order 12 either by the F-statistic or by Chi-squared tests. These findings support the adequacy of the standard GARCH (1,1) model as a benchmark to describe the dynamic behavior of the ASPI with the volatility of the macroeconomic variables in the system during the sample time period.

Table 4.9 Residual Diagnostic Fits for AR(1) GARCH(1,1)

Order	Q-Stat	Probability
1	0.0763	
3	6.0218	0.049
6	11.034	0.051
9	15.813	0.045
12	18.647	0.068
24	32.661	0.087
36	48.026	0.070

Q-Stat ^2	Probability
0.5768	0.448
2.7199	0.437
3.0644	0.801
4.0727	0.907
5.0543	0.956
9.2105	0.997
15.609	0.999

Table 4.10 ARCH-LM Test results for AR(1) GARCH(1,1) Model

	AR (1) GARCH (1,1)			
Orders	F-statistic	Probability	Obs*R-squared	Prob. Chi-Square
1	0.55197	0.45900	0.55883	0.45470
3	0.73037	0.53600	2.22580	0.52690
6	0.40823	0.87220	2.55216	0.86260
9	0.34108	0.95900	3.27611	0.95230
12	0.32788	0.98240	4.29870	0.97740

Table 4.11 Estimates of the AR (1)-GARCH (1,1) Model

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Probability
μ	5288.462	803.743	6.5798	0.0000
θ_1	0.957	0.019	50.9358	0.0000
Variance Equation				
ω	2608001	536963	4.856943	0.0000
α_1	-0.969008	0.20559	-4.713401	0.0000
β_1	-0.997527	0.00137	-726.5829	0.0000
R-squared	0.979659	Mean dependent var		4695.89
Adjusted R-squared	0.979486	S.D. dependent var		2011.56
S.E. of regression	288.1128	Akaike info criterion		15.6451
Sum squared resid	9712051	Schwarz criterion		15.7619
Log likelihood	-925.8848	Hannan-Quinn criter.		15.6925
Durbin-Watson stat	1.68601			

Results in Table 4.11 shows that both parameters are negative (α_1 = -0.969 and β_1 = -0.997). The sum of the ARCH and GARCH coefficients is less than one, i.e., $\alpha_1+\beta_1$= -1.97, which implies that the conditional variance of ε_t or $h_t^2=\omega/1\text{-}(\alpha_1+\beta_1)<1$ is stationary. Also, α_1 is greater than β_1, indicating that the volatility of stock market prices is affected by related news from the previous period more than by past volatility.

A standardized GARCH model is good to measure the volatility of financial time series. However, as described in chapter 02, many authors have shown that the use of these models tends to produce bias in predictions of volatility. Furthermore, many authors have claimed that GARCH (1,1) model alone does not help to estimate volatility of cross-sectional market volatility. In such situation, GARCH-X model has been suggested as a suitable model. A different version of GARCH-X models was introduced by Apergis (1998) to investigate how short-run deviations from the relationship between stock prices and certain macroeconomic fundamentals affect stock market volatility. In the Apergis model, the squared past error-correction term which represents the short run deviations is added to the GARCH conditional volatility. GARCH-X models may be considered a simplified version of Connor and Linton (2001). Thus, GARCH-X (1,1) model is developed.

4.6 AR (1)-GARCH-X (1,1) Model

The analysis proceeds to estimate an AR (1)-GARCH (1,1)-X model as suggested by Lee (1994). The AR (1)-GARCH (1,1)-X model links the volatility of ASPI to the deviation from equilibrium, represented by the magnitude of the volatility of each macroeconomic variable. This task is accomplished by adding the independent variables into the variance equation.

Table 4.12 present the estimated results of the AR (1)-GARCH (1,1)-X model. The mean equation of the GARCH-X model implies that the previous ASPI positively and significantly affect the current ASPI since the p-value on θ_1 is zero.

Table 4.12 Estimated results of AR (1)-GARCH (1,1)-X model

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Probability
μ	8.502373	0.15582	54.56644	0.0000
θ_1	0.981735	0.00874	112.3007	0.0000
Variance Equation				
ω	0.196466	0.04039	4.864773	0.0000
α_1	0.376644	0.13086	2.878199	0.0040
β_1	-0.404314	0.11658	-3.468283	0.0005
λ_1	-0.003470	0.00852	-0.407148	0.6839
λ_2	-0.005350	0.00358	-1.494423	0.0951
λ_3	-0.009963	0.01593	-0.625376	0.5317
λ_4	-0.006006	0.00344	-1.748338	0.0804
λ_5	-0.010353	0.01191	-0.868955	0.3849
R-squared	0.983038	Mean dependent var		8.34484
Adjusted R-squared	0.982893	S.D. dependent var		0.49223
S.E. of regression	0.06438	Akaike info criterion		-2.62296
Sum squared resid	0.484933	Schwarz criterion		-2.38942
Log likelihood	166.0663	Hannan-Quinn criter.		-2.52813
Durbin-Watson stat	1.615529			

The estimated parameters α_1 is positive and β_1 negative in the variance equation of the AR (1)-GARCH (1,1)-X model and statistically significant. ω is positive and statistically significant. The ARCH effect, α_1, is more than the GARCH effect, β_1, which implies that the volatility of stock market prices is affected by related news from the previous period more than by past volatility. Also, a negative GARCH coefficient β_1=-0.404 indicates that shocks to the conditional variance take a short time to die out, so volatility is not persistent. λ_2 and λ_5 are statistically significant at 90% confident level which implies that the volatility in interest rate and industrial production index are highly impact for the volatility of ASPI.

Money supply, exchange rate and consumer price index are not statistically significant with GARCH terms at any significance level (P-values > 0.05 and 0.1). Hence, the above results indicate that out of the five macroeconomic variables considered with this study, only interest rate and industrial production index were found to be significantly influence the volatility of ASPI.

Table 4.13 Residual Diagnostic Fits for AR(1)-GARCH(1,1)-X

Order	Q-Stat	Probability
1	0.0492	
3	8.6963	0.013
6	10.503	0.062
9	15.528	0.050
12	22.230	0.023
24	31.421	0.113
36	41.172	0.219

Q-Stat ^2	Probability
1.0396	0.308
3.9732	0.264
5.4080	0.493
6.8368	0.654
8.4585	0.748
12.201	0.978
15.347	0.999

In terms of the adequacy of the estimated AR(1)-GARCH(1,1)-X model, the Ljung-Box Q-statistics (Table 4.13) suggest no serial correlation of the standardized residuals obtained from the AR(1)-GARCH(1,1)-X model up to order 36. Also, the Q^2 test cannot reject the null hypothesis of no autocorrelation of the standardized residuals squared obtained from the model up to 36th order. According to the ARCH-LM test (Table 4.14) using either the F-statistic or Chi-squared statistic up to order 12, results are confirmed by the fact that the estimated standard AR(1)-GARCH(1,1)-X model successfully produced residuals that are free of ARCH effects.

Table 4.14 ARCH-LM Test results for AR(1) GARCH(1,1)-X Model

	AR (1) GARCH (1,1) X			
Orders	F-statistic	Probability	Obs. R-squared	Prob. Chi-Square
1	0.998074	0.3199	1.006621	0.3157
3	1.035638	0.3797	3.131020	0.3719
6	0.697975	0.6518	4.294729	0.6369
9	0.492138	0.8768	4.665515	0.8624
12	0.390416	0.9640	5.079736	0.9553

4.7 Hypothesis testing

Hypothesis (H_A) was developed to test the influence of macroeconomic variables on ASPI volatility. According to the above results, it can be said that the null hypothesis (H_0) is rejected for the interest rate and industrial production index because these two macroeconomic variables were influenced on ASPI volatility. Therefore it is accepted the alternative hypothesis for those two variables; “There is a significant influence of the volatility of selected five macroeconomic variables to ASPI volatility”.

4.8 Summary of Chapter 04

This chapter showed the development of ARCH/GARCH models for the measurement of ASPI volatility. After considering the behavior of original LNASPI series, stationary of the data series was achieved for first difference of LNASPI. ARIMA (1,1,0) was used as the best model for the mean equation and GARCH (1,1) model was found as significant model for the variance equation. The results showed that the volatility of stock market prices is affected by related news from the previous period more than by past volatility. GARCH-X model was used to measure the cross-sectional market volatility between ASPI and selected macroeconomic variables. Results of GARCH-X showed that the volatility in interest rate (IR) and industrial production index (IPI) are highly impact for the volatility of ASPI from the selected five macroeconomic variables. Ljung-Box Q-statistics confirmed that there is no serial correlation of the standardized residuals and ARCH-LM test confirmed that there is no ARCH effect of residuals.

CHAPTER 05

Study of Long run / Short run Relationship

In this chapter, dynamic relationship of the macroeconomic variables was investigated using short run and long run analysis. To test the long run relationship, Johansen-Juselius Cointegration Test was used. For the short run relationship a causality test, Impulse Response Function (IRF) analysis and Forecast Error Variance Decompositions (FEVD) analysis were used.

5.1 Stationary Process

To examine whether all variables in the model are integrated of the same order, the augmented Dickey-Fuller (1979) (ADF) unit root test was carried out.

Table 5.1 ADF Unit Root Test for all Variables

Variables	Augmented Dickey Fuller			
	Level		First Difference	
	Constant	Constant & Linear trend	Constant	Constant & Linear trend
	Test Statistics			
ASPI	-0.878058	-1.457896	-9.964197*	-9.923255*
MS	7.982476	0.711692	-1.464659	-3.954777**
IR	-0.685744	-1.881986	-9.858486*	-9.888145*
EXR	-0.289864	-3.094219	-6.921855*	-6.938608*
IPI	-2.680606	-3.331847***	-13.57534*	-13.52261*
CPI	-2.007397	-1.660434	-7.980614*	-8.223808*
	Critical Values			
1 percent	-3.486551	-4.039075	-3.486551	-4.037668
5 percent	-2.886074	-3.449020	-2.886074	-3.448348
10 percent	-2.579931	-3.149720	-2.579931	-3.149326

Note: * Indicates stationary at 1% level, ** indicates stationary at 5% level and *** indicates stationary at 10% level

Results showed in Table 5.1, rejected for any of the series in their levels since ADF statistics for all variables are not less than the critical values at any significance level, i.e., 1%, 5%, and 10%. Therefore, it can be conclude that all series are non-stationary in levels. Applying the same test to their first differences shows that the null hypothesis of a unit root is rejected in all cases even at a 1% significance level except MS. Constant with linear trend of first difference has the test statistic value more than the 5% significant level. Therefore MS is also stationary in first difference. Thus, it can be concluded that all series are stationary at first difference.

5.2 Long Run Analysis

5.2.1 Selection of Optimal Lag lengths

Before moving to the long run analysis through cointegration test, it should be decided the optimum lag length to the VAR system. Five criteria are used as log likelihood, Schwarz criteria (SC), Akaike information criteria (AIC), final prediction error criteria (FPE), and Hannan-Quinn information criterion (HQ) for this purpose. It will be preceded the analysis using nine lags suggested by the sequential modified (LR) test.

Table 5.2 Optimum lag length for VAR system

Lag	Log Likelihood	LR	FPE	AIC	SC	HQ
0	-3886.90	NA	8.20E+23	72.0908	72.23977	72.15117
1	-2843.77	1951.040	6.52E+15	53.4402	54.48325*	53.86312*
2	-2803.08	71.583	6.02e+15*	53.3534	55.29045	54.13878
3	-2775.73	45.073	7.17E+15	53.5136	56.34473	54.66151
4	-2747.34	43.645	8.50E+15	53.6544	57.37959	55.16483
5	-2722.26	35.759	1.09E+16	53.8567	58.47589	55.72960
6	-2699.35	30.122	1.50E+16	54.0991	59.61234	56.33451
7	-2672.99	31.725	1.99E+16	54.2777	60.68497	56.87559
8	-2630.98	45.905	2.07E+16	54.1663	61.46762	57.12670
9	-2578.71	51.303*	1.87E+16	53.8649	62.06034	57.18788
10	-2539.67	33.976	2.32E+16	53.8087	62.89816	57.49416
11	-2508.31	23.813	3.63E+16	53.8946	63.87806	57.94251
12	-2437.02	46.207	3.07E+16	53.2410*	64.11858	57.65149

Table 5.3 Residual Serial Correlation LM Tests for the VAR

Lags	LM-Stat	Probability
1	34.42747	0.5435
2	37.76665	0.3885
3	39.40018	0.3203
4	20.16014	0.9847
5	46.82708	0.1068
6	43.29861	0.1879

Lags	LM-Stat	Probability
7	31.80234	0.6685
8	37.07321	0.4193
9	54.98300	0.0223*
10	30.13803	0.7430
11	23.51242	0.9459
12	44.39331	0.1590

The p-values associated with the Lagrange multiplier (LM) tests strongly indicate the absence of serial correlation in the estimated residuals generated from the VAR(9) models up to p=12 (Table 5.3). This is further confirmed by LR test selection. Figure 5.1 shows the estimated residuals of the VAR (9) model. This provides visual evidence to support the adequacy of the VAR (9) model to explore the long relationship among the macroeconomic variables.

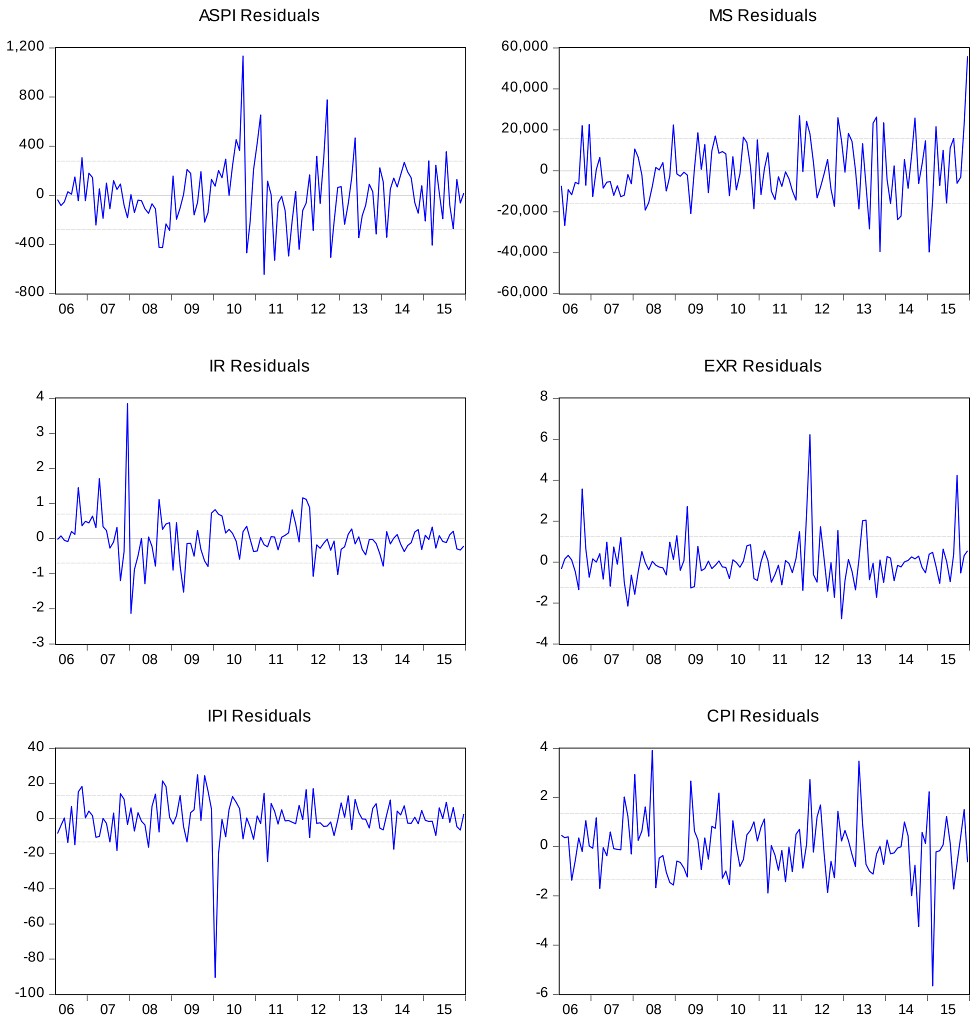

Figure 5.1 The Estimated Residuals of the VAR model

Optimum lag length implies that the time period which take to react ASPI on macroeconomic changes. As an example, a change in money supply will impact to the ASPI changes after nine months of that change. Normally most of the information on macroeconomic changes goes to the general public once a month, quarterly semiannually or yearly. Therefore, immediate reaction can't be expect in stock market. Monthly data were used for this research. Therefore time difference for action and reaction will be 9 months. Lag length 9 can be justify on those reasons.

Colombo stock exchange is not a perfect efficient market. The investors reactions can't be expect as soon as the time where information reach to the general public. Sometimes some information reach to the general public once a year. Therefore lag nine is considerable for some macroeconomic data. Information on money supply, interest rate, consumer price index, industrial production index, etc. published by the Central Bank of Sri Lanka from their publications. There may be a long time gap between the actual situation and the date where information come to the market. Therefore reaction time of the investors may be nine months.

5.2.2 Results of the Johansen-Juselius Cointegration Test

The analysis proceeds to examine the long run and short run relationships between ASPI and the rest of the macroeconomic variables in the system assuming a linear trend in the VAR and the cointegrating relationship only has an intercept. Table 5.4 present detailed results of cointegration tests for the model including the trace test and the max-eigenvalue test at the 5% significance level. Both max-eigenvalue statistic and the trace statistics are significant at 10% level, although, only the P value of the max-eigen statistic at most 4 is close to 0.05. Thus, it can be concluded that the max-eigenvalue tests support four cointegrating vector at the 5% significance level, while trace tests suggest the same four cointegrating vectors at the 5% significance level. The major finding from these two tests is the macroeconomic variables in the system share a long run relationship.

Table 5.4 Johansen-Juselius Cointegration Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability**
None *	0.487573	193.6931	95.75366	0.0000
At most 1 *	0.369402	120.1475	69.81889	0.0000
At most 2 *	0.250483	69.4280	47.85613	0.0002
At most 3 *	0.194544	37.7120	29.79707	0.0050
At most 4	0.117679	13.9139	15.49471	0.0853
At most 5	0.001289	0.1419	3.84146	0.7064

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability**
None *	0.487573	73.54561	40.07757	0.0000
At most 1 *	0.369402	50.71951	33.87687	0.0002
At most 2 *	0.250483	31.71590	27.58434	0.0139
At most 3 *	0.194544	23.79815	21.13162	0.0206
At most 4	0.117679	13.77198	14.26460	0.0597
At most 5	0.001289	0.141924	3.841466	0.7064

Note; * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values

Equation (5.1) presents these findings, which indicate, in general, that all variables included in the system are statistically significantly contributing to the long run relationships between ASPI and the rest of macroeconomic variables in the system.

$$\begin{array}{lllllll} ASPI & = 0.0013\,MS & +\,337.8\,IR & +\,59.5\,EXR & -\,21.95\,IPI & -\,95.22\,CPI & \\ & (0.00057) & (51.7806) & (27.3992) & (6.30402) & (12.2903) & \end{array} \quad (5.1)$$

Results in equation (5.1) implies that there are significant positive long run relationships between ASPI and MS, IR & EXR while there are significant negative long run relationships between ASPI and IPI & CPI.

The existing literature evidence on the positive relationship between ASPI and MS (Hamburger and Kochin, 1972; and Hashemzadeh and Taylor, 1988). Equation (5.1) shows a positive long run relationship between ASPI and IR. But it is totally contradict with the previous findings of Abdullah and Hayworth (1993), Maghayereh (2003), Gjerde and Saettem (1999), Gunasekarage et al. (2004), Hondroyiannis and Papapetrou (2001), Ratanapakorn and Sharma (2007), Sadorsky (1999), Humpe and Macmillan (2009) where they have found negative relationship. Equation (5.1) shows a positive long run relationship between the exchange rate (EXR) and ASPI. Gunasekarage et al. (2004) find similar results for the stock market in Sri Lanka, and Ratanapakorn and Sharma (2007), and Maysami et al. (2004) find a positive relationship for the stock market in the U.S. and Singapore, respectively.

There is a negative long run relationship between industrial production index and ASPI in this study. Some of the previous researchers have found the same results while there may some other researches which have found a positive relationship as well. Equation (5.1) also indicates a statistically significant negative relationship between ASPI and the Consumer Price Index. This result is in line with Fama (1981), Schwert (1981), Maghayereh (2003), Mukherjee and Naka (1995), and Gjerde and Saettem (1999), who all found a negative correlation between inflation and stock prices.

5.3 Short Run Analysis

Causality tests, impulse response analysis, and forecast error variance decompositions are used to analyze the short run dynamic behavior of the selected macroeconomic variables.

5.3.1 Causality Test

Table 5.5 shows the results of pairwise Granger causality test. Money supply, Interest rate, exchange rate and industrial production index have one way causality while consumer price index has no causal relationship with ASPI. Money supply, exchange rate and industrial production index have significant impact on ASPI but interest rate has other way relationship. According to the results, interest rate will not granger cause with ASPI but ASPI will granger cause with interest rate. Consumer price index doesn't have any short run causal relationship, but it has long run cointegration with ASPI.

Table 5.5 Pairwise Granger Causality Test

Null Hypothesis:	Obs	F-Statistic	Probability
MS does not Granger Cause ASPI	118	1.65091	0.1965
ASPI does not Granger Cause MS		3.10462	0.0487
IR does not Granger Cause ASPI	118	5.70215	0.0044
ASPI does not Granger Cause IR		1.39614	0.2518
EXR does not Granger Cause ASPI	118	1.77474	0.1742
ASPI does not Granger Cause EXR		6.03883	0.0032
IPI does not Granger Cause ASPI	118	1.37147	0.2579
ASPI does not Granger Cause IPI		2.47507	0.0887
CPI does not Granger Cause ASPI	118	0.72364	0.4872
ASPI does not Granger Cause CPI		0.15078	0.8602

Despite the importance of conducting causality tests, a causality test, by definition, does not determine the strength of the relationships between the variables nor does it describe the relationship between these variables over time. For that reason, the response of ASPI is examined to shocks to the some macroeconomic shocks. Impulse response functions and forecast error variance decompositions are used to estimate the responses.

5.3.2 Impulse Response Function Analysis

Impulse response functions track the response of a variable over time after a shock to the VAR system. The persistence of a shock indicates how quickly the system returns to equilibrium. In order to examine to what extent innovations in each of the five macroeconomic variables can explain the movements in the ASPI, it was estimated the IRFs. This will allow to determine the magnitude, direction, and length of time that the ASPI is affected by a shock of a variable in the system, holding all other variables constant.

Figure 5.2 displays the estimated impulse response functions with 95% confidence bands represented by dotted lines. That is, all panels in Figure 5.2 show the response of ASPI to a transitory shock associated with each macroeconomic variable in the VAR system. The IRFs indicate that there is a statistically significant short run relationship between ASPI and four macroeconomic variables except money supply. This implies that the IRFs indicate that there are contemporaneous effects of the macroeconomic variable shocks on the stock market.

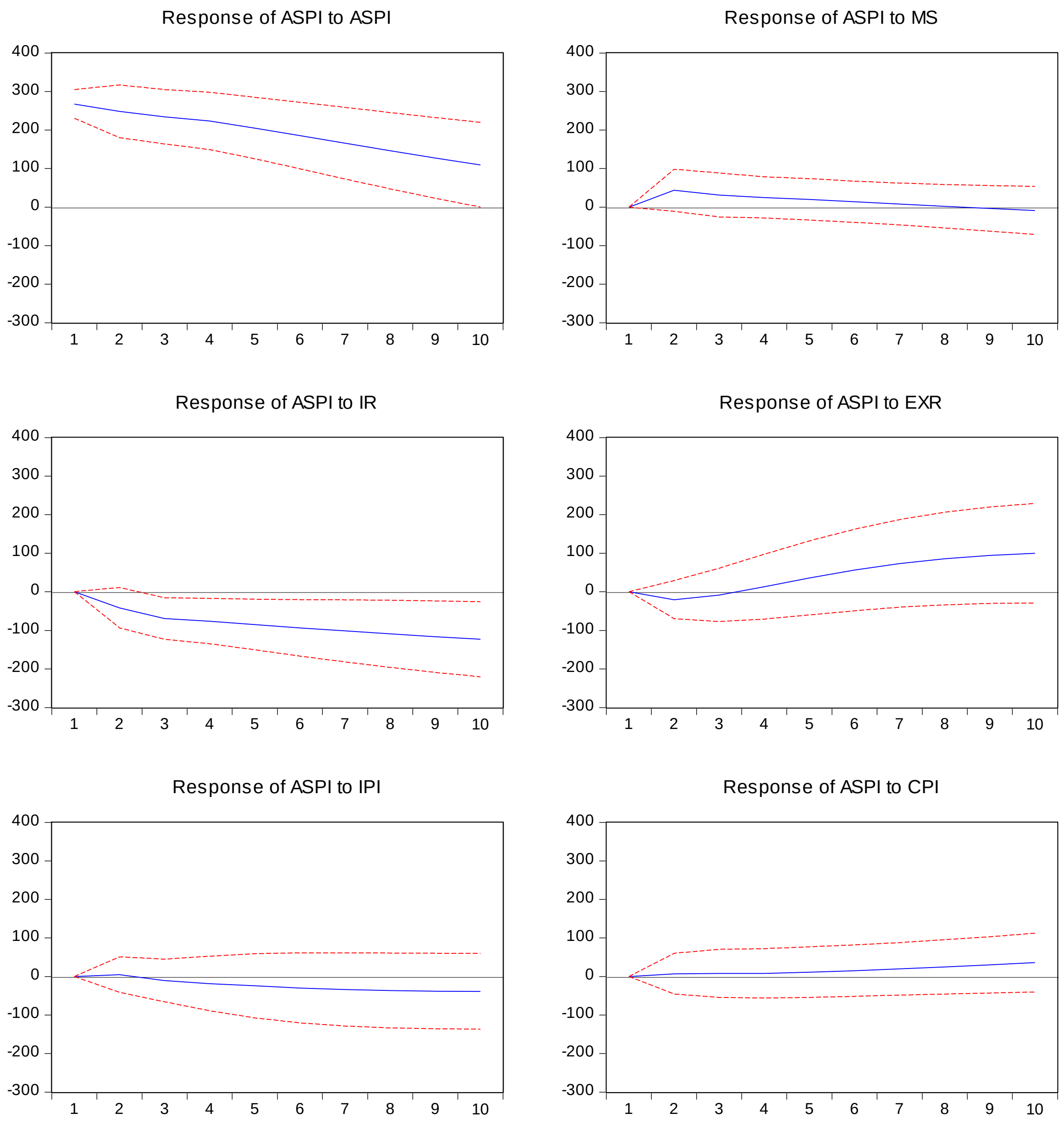

Figure 5.2 Impulse Response Functions of the ASPI to Cholesky One S.D. Innovations

5.3.3 Forecast Error Variance Decompositions (FEVD)

FEVDs indicate the relative importance of each structural shock to the variables in the system. In this study, FEVDs determine the percentage of variation in the forecast error of the ASPI that is due to its own shocks versus shocks to other macroeconomic variables in the system.

Table 5.6 Variance Decomposition

Period	S.E.	ASPI	MS	IR	EXR	IPI	CPI
1	278.7121	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	409.2752	97.22760	1.411724	0.987454	0.195242	0.139580	0.038398
3	507.3956	94.77675	1.035704	2.031270	1.006653	1.065665	0.083957
4	600.1772	92.63650	0.748683	3.130508	2.165151	1.099846	0.219307
5	684.5138	91.15633	0.575781	3.707245	3.081019	1.226738	0.252888
6	759.2727	89.86461	0.469104	4.229071	3.821674	1.354211	0.261329
7	825.9913	88.67842	0.413396	4.711855	4.459304	1.487104	0.249925
8	886.8284	87.59517	0.392339	5.148036	5.039801	1.595989	0.228661
9	942.3772	86.58865	0.398025	5.533396	5.564009	1.711220	0.204698
10	993.4309	85.60859	0.427915	5.902658	6.050524	1.826065	0.184249

Table 5.6 reports the FEVDs for the ASPI over 10 months period using the same identification restrictions that were used for the IRF analysis. The magnitude of the contribution of the variables in the system change dramatically over 10 months which implies that these variables have a significant effect on the stock market.

5.4 Hypothesis testing

The trace test and the max-eigenvalue test in Johansen-Juselius Cointegration Test found that the macroeconomic variables in the system share a long run relationship. The IRFs indicate that there is a statistically significant short run relationship between ASPI and four macroeconomic variables except money supply. The fitted null hypothesis (H_{0B}) of "there is no any significant long run / short run relationship between selected five macroeconomic variable and Colombo stock market prices, proxied by the general price index, ASPI" was rejected by accepting alternative one.

5.5 Summary of Chapter 05

In this chapter, long run and short run relationships between ASPI and selected five macroeconomic variables were checked. Johansen-Juselius cointegration test was used to identify the long run relationship and results implied that there are significant positive long run relationships between ASPI and MS, IR & EXR while there are significant negative long run relationships between ASPI and IPI & CPI. For the short run analysis, Granger causality test, impulse response analysis and variance decomposition analysis were used. Causality test showed that Money supply, Interest rate, exchange rate and industrial production index have one way causality while consumer price index has no causal relationship with ASPI. IRFs indicated a statistically significant short run relationship between ASPI and four macroeconomic variables except money supply. Variance decomposition analysis was finalized indicating variables have a significant effect on the stock market.

CHAPTER 06

CONCLUSIONS, RECOMMENDATIONS AND SUGGESTIONS

Two objectives of this study were; (i) to investigate the macroeconomic determinants of ASPI volatility and (ii) to observe whether a set of macroeconomic factors contribute to the long and short run behavior of the Colombo stock exchange. The macroeconomic variables used were; money supply (MS), interest rates (IR), the consumer price index (CPI), exchange rate (EXR), and industrial production index (IPI). The conclusion, recommendations and suggestions based on the study are given below.

6.1 Conclusions

With respect to the impact of the volatility of macroeconomic variables on ASPI volatility, it was found that a GARCH(1,1) model was adequate to model the volatility of ASPI with the conditional mean equation being modeled as an AR(1) process. That is, GARCH(1,1) model succeeded in capturing the autocorrelation in the volatility of ASPI.

The estimated results of the AR(1)-GARCH (1,1)-X model indicated that the previous ASPI (lag 1) positively and significantly affect the current ASPI. Further this implies that the volatility of stock market prices is affected by related news from the previous period (lag 1) more than by past volatility. Also, a negative GARCH coefficient indicates that shocks to the conditional variance take a short time to die out, so volatility is not persistent. The result of GARCH regression implies that the volatility in IR and IPI are highly impact for the volatility of ASPI.

For the long run analysis, the Johansen-Juselius cointegration test suggested that macroeconomic variables in the system share a long run relationship. Results implies that ASPI has significant positive long run relationships with MS, IR & EXR while ASPI has significant negative long run relationships with IPI & CPI.

To examine whether all variables in the model are integrated of the same order, unit root test is used. Results showed that all series are non-stationary in levels but stationary in first difference.

Granger causality test showed that MS, IR, EXR and IPI have one way causality while CCPI have no causal relationship with ASPI. The response of ASPI is examined to shocks to the some macroeconomic shocks using impulse response functions (IRF) and forecast error variance decompositions. The IRFs indicate that there is a statistically significant short run relationship between ASPI and four macroeconomic variables except money supply. This implies that the IRFs indicate that there are contemporaneous effects of the macroeconomic variable shocks on the stock market. Error variance decomposition also confirms that the selected variables have a significant effect on the stock market.

6.2 Recommendations

The prediction of stock market returns may become difficult as the volatility of macroeconomic variables increases in the short run. In other words, the more volatile the macroeconomic variables are, the more difficult it is to predict stock market returns. Therefore, investors should be keen on price fluctuations when they make economic decisions.

Investors in the stock market should look at the systematic risks revealed by the money supply, interest rates, exchange rates, consumer price index, and industrial production index when structuring portfolios and diversification strategies.

Financial regulators and policymakers may need to take these macroeconomic variables into account when formulating economic and financial policies.

6.3 Suggestions for Future Studies

The following suggestions are given for future studies.

- It is necessary to enhance the understanding about the dynamic relationship between economic activities and the behavior of the stock market in other developing countries as such studies could compare the behavior of the Sri Lankan stock market against the other countries.
- It is necessary to study the impact of other macroeconomic variables such as GDP or oil price which are more important as economic indicators.
- Further, it is better if such studies can continue very frequently, because financial data are changing day by day.

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Appendix A

Raw data collected from Jan 2006 to Dec 2015

Year	Month	ASPI	MS	IR	EXR	IPI	CPI
2006	January	2139.0	834273	10.10	102.15	154.8	86.4
2006	February	2212.7	849000	10.11	102.19	157.7	87.1
2006	March	2264.4	862732	10.10	102.68	148.3	87.1
2006	April	2263.4	878328	10.05	102.66	145.4	88.4
2006	May	2203.8	876162	10.09	102.90	144.6	89.9
2006	June	2114.4	887778	10.16	103.51	149.4	91.5
2006	July	2196.0	895241	10.28	103.98	138.2	91.4
2006	August	2200.0	906552	10.51	103.78	151.3	91.7
2006	September	2383.4	919003	10.53	102.49	135.3	92.8
2006	October	2454.3	952857	11.93	105.59	155.1	94.1
2006	November	2777.7	968095	12.32	107.74	166.7	95.6
2006	December	2722.4	993264	12.76	107.87	158.3	97.0
2007	January	2924.3	996575	13.37	108.46	164.5	98.2
2007	February	2982.9	1013891	14.06	108.70	167.3	100.4
2007	March	2789.8	1032542	14.62	109.34	157.8	100.3
2007	April	2811.3	1046388	16.56	109.40	154.6	101.1
2007	May	2508.3	1050538	16.91	110.85	154.7	101.8
2007	June	2572.2	1063012	17.40	110.97	158.5	103.9
2007	July	2442.1	1068052	17.38	111.66	147.2	105.5
2007	August	2526.6	1085288	17.65	112.11	160.8	106.9
2007	September	2556.6	1097655	18.20	113.34	144.1	107.8
2007	October	2615.2	1106357	17.23	113.06	166.2	111.1
2007	November	2560.2	1132313	17.07	110.51	177.4	114.1
2007	December	2541.0	1147742	21.30	109.08	170.2	115.2
2008	January	2446.1	1144361	19.25	108.25	168.0	118.7
2008	February	2530.9	1155185	18.48	107.87	168.0	122.1
2008	March	2550.5	1188569	18.39	107.73	178.0	124.0
2008	April	2633.0	1192361	18.51	107.81	172.0	126.3
2008	May	2538.4	1187327	17.14	107.79	165.7	128.0
2008	June	2457.8	1201992	17.29	107.82	158.4	133.3
2008	July	2463.4	1220612	17.26	107.65	165.0	133.6
2008	August	2408.6	1229068	16.46	107.75	175.7	133.4
2008	September	2142.3	1248642	17.22	107.87	162.1	133.6
2008	October	1821.5	1249205	17.20	108.07	180.1	133.2
2008	November	1639.9	1253312	17.20	110.01	189.4	132.2
2008	December	1503.0	1282194	17.33	111.39	182.8	131.2
2009	January	1821.2	1288162	15.94	113.74	172.8	131.1
2009	February	1694.1	1304602	15.76	113.92	174.1	131.2
2009	March	1638.1	1324704	14.62	114.26	184.5	130.5
2009	April	1838.5	1343535	12.65	117.37	173.3	129.6
2009	May	2216.0	1360260	12.04	116.92	162.3	132.6
2009	June	2432.2	1380978	11.41	114.90	162.2	134.3
2009	July	2432.2	1411698	10.64	114.91	164.4	135.2

2009	August	2607.7	1435550	10.57	114.86	184.0	134.7
2009	September	2938.6	1461339	9.70	114.80	168.1	134.9
2009	October	2976.9	1461345	8.50	114.80	188.7	135.3
2009	November	2913.4	1497004	7.25	114.51	198.7	136.3
2009	December	3385.6	1536755	7.73	114.35	195.0	137.8
2010	January	3636.4	1551744	7.95	114.35	89.2	140.4
2010	February	3807.9	1565387	8.26	114.54	93.7	141.1
2010	March	3724.6	1600964	8.52	114.18	101.8	139.8
2010	April	4188.9	1603310	8.40	113.88	85.0	138.4
2010	May	4237.2	1622304	8.10	113.74	92.6	140.1
2010	June	4612.5	1637897	8.07	113.61	105.7	141.2
2010	July	5161.2	1650967	7.90	113.06	109.8	141.2
2010	August	5658.0	1679210	7.13	112.45	115.1	141.4
2010	September	6997.2	1718989	7.13	112.47	104.8	142.6
2010	October	6678.1	1742357	7.13	111.79	106.4	144.1
2010	November	6434.9	1763574	7.28	111.58	106.9	145.7
2010	December	6635.9	1813000	7.24	111.10	98.4	147.2
2011	January	7174.9	1832034	7.01	110.90	101.7	149.2
2011	February	7798.0	1863092	6.97	110.96	99.1	151.3
2011	March	7226.1	1899804	6.98	110.36	118.7	150.6
2011	April	7357.0	1935747	7.04	110.29	94.4	150.6
2011	May	7418.1	1957064	7.09	109.82	108.3	151.5
2011	June	6825.9	1992455	7.12	109.59	113.3	151.2
2011	July	6845.4	2025945	7.11	109.50	111.8	151.7
2011	August	6879.3	2059413	7.11	109.80	115.1	151.3
2011	September	6783.6	2091127	7.15	110.14	113.9	151.7
2011	October	6319.3	2116658	7.29	110.19	112.9	151.5
2011	November	6087.4	2139728	8.20	111.33	112.8	152.6
2011	December	6074.4	2192603	8.68	113.90	107.8	154.4
2012	January	5693.9	2216986	8.67	113.90	112.0	154.8
2012	February	5458.1	2270720	9.81	117.23	107.6	155.4
2012	March	5420.2	2321171	11.00	125.52	119.5	158.8
2012	April	5419.2	2353485	11.93	128.66	94.3	159.8
2012	May	4832.2	2351370	11.01	129.38	112.1	162.1
2012	June	4965.8	2381343	11.12	132.04	112.7	165.2
2012	July	4944.9	2410233	11.35	132.87	111.7	166.7
2012	August	5180.2	2439377	11.41	132.07	107.0	165.7
2012	September	5972.0	2455010	11.30	131.78	105.5	165.5
2012	October	5513.6	2463316	10.68	129.11	108.0	165.0
2012	November	5351.3	2529841	10.79	130.33	108.8	167.1
2012	December	5643.0	2593185	10.00	128.35	106.2	168.6
2013	January	5816.9	2627394	9.47	126.85	106.8	170.0
2013	February	5635.9	2688230	9.09	126.70	105.0	170.7
2013	March	5735.7	2749442	9.26	126.82	116.6	170.8
2013	April	5953.2	2788337	9.23	126.03	97.5	170.0
2013	May	6463.1	2799417	8.73	126.31	108.0	173.9
2013	June	6121.0	2843835	8.66	127.81	110.3	176.5
2013	July	6037.2	2875610	8.93	131.01	112.6	176.8

2013	August	5834.0	2883490	8.61	131.83	110.3	176.2
2013	September	5803.3	2937208	8.60	132.47	109.2	175.8
2013	October	5954.6	3002427	8.56	131.10	115.8	176.1
2013	November	5775.1	2997741	8.06	131.08	113.0	176.5
2013	December	5912.8	3058793	7.54	130.83	110.2	176.5
2014	January	6248.1	3094570	6.82	130.73	107.2	177.5
2014	February	5940.3	3120241	6.72	130.82	107.0	177.8
2014	March	5968.3	3165810	6.65	130.63	120.5	177.9
2014	April	6223.7	3175119	6.58	130.62	96.7	178.4
2014	May	6263.5	3178773	6.56	130.46	107.4	179.5
2014	June	6378.6	3214316	6.51	130.29	115.8	181.4
2014	July	6813.9	3230604	6.36	130.24	121.8	183.2
2014	August	7034.1	3259844	6.19	130.19	117.5	182.3
2014	September	7252.1	3316760	6.15	130.26	121.7	181.9
2014	October	7326.8	3351268	6.15	130.60	120.3	179.0
2014	November	7153.9	3398549	6.15	130.94	118.9	179.2
2014	December	7299.0	3460558	5.74	131.02	123.6	180.2
2015	January	7180.1	3467556	5.80	131.55	118.2	183.2
2015	February	7301.3	3492559	5.98	132.73	118.8	178.9
2015	March	6820.3	3553629	6.55	132.90	130.9	178.1
2015	April	7179.0	3593405	6.15	132.90	115.3	178.5
2015	May	7220.3	3641271	6.07	133.50	122.4	179.8
2015	June	7020.8	3677478	6.11	133.90	123.8	181.6
2015	July	7332.1	3732238	6.28	133.69	133.0	182.8
2015	August	7306.9	3783870	6.53	133.88	126.7	181.9
2015	September	7050.9	3821803	6.78	138.88	134.2	181.4
2015	October	7042.1	3877693	6.61	140.89	131.2	182.1
2015	November	6909.2	3945701	6.44	142.02	124.3	184.7
2015	December	6894.5	4057191	6.45	143.45	125.8	185.2