International Finance and Banking
ISSN 2374-2089
2016, Vol. 3, No. 2

An Empirical Analysis of Macroeconomic Variability on the Ghanaian Stock Market: A Vector Autoregression Approach

Beverly Acquah

School of Economics, University of Surrey, Guildford, Surrey, GU2 7XH, United Kingdom

E-mail: beverlyacquah@yahoo.com

Received: August 12, 2016 Accepted: August 26, 2016 Published: August 29, 2016

doi:10.5296/ifb.v3i2.9821 URL: http://dx.doi.org/10.5296/ifb.v3i2.9821

Abstract

This study investigates the dynamic interrelationships among stock prices and selected macroeconomic indicators namely; economic activity, global commodity price index, inflation and interest rates in Ghana. By employing a Vector Autoregression (VAR) Model, the empirical results reveal that stock prices depreciate with an increase in global commodity prices and interest rates indicating a negative relationship. On the other hand, stock prices appreciate with an increase in inflation and economic activity indicating a positive relationship. Examining stock market variability on the selected macroeconomic variables also showed that inflation and interest rates respond negatively to changes in asset prices while the stock market itself is not found to be a leading indicator for economic activity. The evidence suggests that the listed equities on the GSE are a hedge against inflation in Ghana. Increasing economic activity over time is advantageous for the Ghanaian stock market.

Keywords: Emerging markets, Macroeconomic indicators, Ghana Stock Exchange, Stock prices, VAR model, Impulse response functions, Forecast error variance decompositions

1. Introduction

1.1 Background

According to the World Bank World Development Indicators (WDI), market capitalisation of stock markets around the world totaled USD 43 209 736 million in 2005 and increased to USD 53 163 894 million by 2012. The value of shares traded as a percentage of global GDP was 70.0 in 2012 with 47 520 domestic companies listed on world stock markets in the same year (WDI, 2014). Undoubtedly, stock markets play a very significant role in financial intermediation in any economy be it developed or developing. They serve as an important investment channel that attracts and mobilizes both domestic and foreign capital efficiently. Stock markets provide alternatives to debt financing for firms that may be used to the conventional approach of borrowing from commercial banks. They also play a role in the redistribution of wealth in the economy. By creating the opportunity for both local and foreign investors to purchase shares in a company listed on an Exchange, stock markets help to create wealth for such investors by way of dividend payments and capital gains.

In recognition of these benefits, stock markets have become increasingly popular in emerging economies. They have also developed out of the need to shift from commercial bank-based financial systems to capital-market based since commercial banks have not been quite a reliable medium for providing long-term financing. To this end, capital markets are viewed as better channels with the potential to meet the long-term capital needs of not only the private sector but also governments to promote economic growth and development. For instance, a number of stock markets have emerged over the past decades in Africa; from 5 in 1960, 18 by the end of 2002 to 29 by the end of 2012 due to extensive financial sector reforms undertaken by a number of African countries (Ntim, 2012). Ghana, like other emerging markets in the world attracts attention as a potential hub for investors to gain from investing in the economy including the stock market. The growing interest and the performance of emerging stock markets have been associated with financial liberalization, stock market reform, privatisation and the conduct of sound macroeconomic policies (Anokye & Tweneboah, 2008). Essentially, relationships exist between the macroeconomic fundamentals and stock price behaviour as well as the market's performance as they are all interrelated.

1.2 Overview of the Ghana Stock Exchange

The stock market in Ghana called the Ghana Stock Exchange (GSE), has grown significantly since its establishment in July 1989 as part of the financial and economic reforms carried out in the 1980s aimed at promoting sustainable economic growth and development. As of December 2013, listed companies on the GSE numbered 34; covering sectors including financial, distribution, food and beverage, ICT, manufacturing, agricultural and mining.

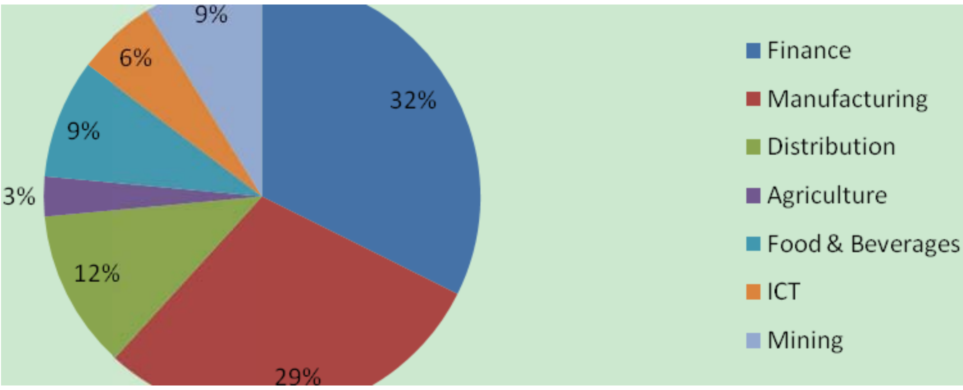

Figure 1. Sectoral composition of listed companies on the GSE

Source: Ghana Stock Exchange.

It started with a market capitalisation of 3.05 million Ghana Cedis and by the year 2010, this increased to 20 116.70 million Ghana Cedis (GSE Market Report, 2013) Successful performance of the stock market in terms of market capitalisation and coverage has been widely attributed to several factors including the macroeconomic environment within which it thrives. Performance of the GSE is mainly monitored by the GSE All Share Index. The GSE was adjudged the sixth, and best emerging stock market in 1993 and 1994 respectively. However, it performed poorly between 1995 and 2000 when interest rates and inflation were high but started recovering following sound macroeconomic policies (Anokye & Tweneboah, 2008).

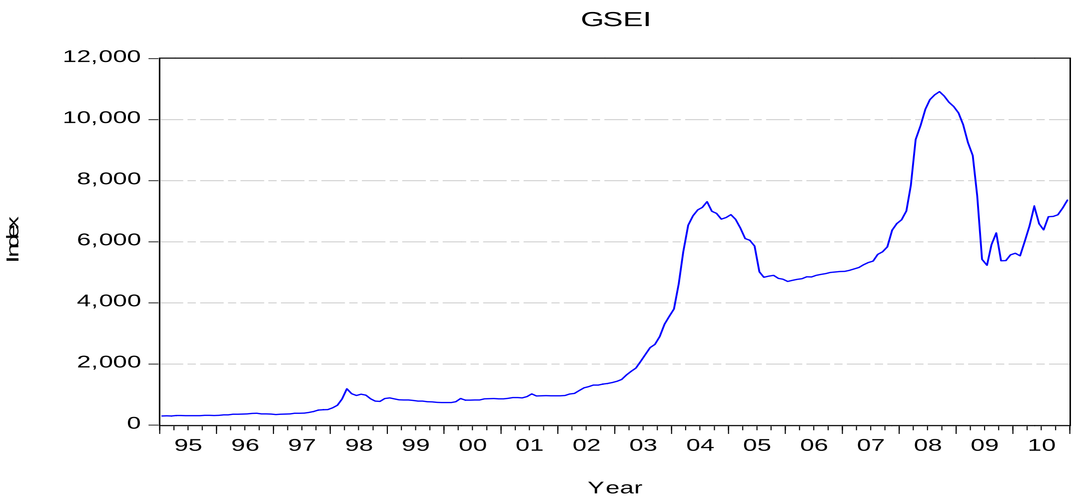

Figure 2. Trend of the GSE Index (1995-2010)

Source: Ghana Stock Exchange.

The GSE Index shot up between 2002 and 2004 and by the close of 2003, topped stock markets in the world market. The GSE became the best performing market in the world at the close of the first quarter of 2004 as reported by (Kyereboah-Coleman & Agyire-Tettey, 2008). This performance was tied to a relatively stable and good macroeconomic environment and a subsequent increase in investor and economic activity but from 2005 to 2006, the plunge in the index was as a result of market corrections due to over valuation of stocks during the 2004 bull runs (Kyereboah-Coleman & Agyire-Tettey, 2008).

According to GSE (2009), one of the most outstanding performances of listed equities on the GSE occurred in 2008 and mainly attributed to excellent operating results of many of the listed companies despite the world economic meltdown and its effects on capital markets. In the later months however, the sharp increase in crude oil prices earlier in the year and the global economic downturn began to affect the Index leading to very thin volumes of stocks traded. The dip in the Index in 2009 was due to the global financial crisis which began to be felt in the last quarter of 2008. The increase in domestic interest ratescausing money market instruments to be relatively more attractive compared to the capital market was also a contributory factor. (GSE, 2009/2010)

1.3 Research Questions

It is evident from the movement of the stock index that macroeconomic variability influences the performance of the market. A wide array of studies has been carried out to establish the dynamic interrelationships among macroeconomic indicators and stock prices, and how these factors influence the operations of the stock market. These include Chen, Roll, & Ross (1986), Lee (1992), Mukherjee & Naka (1995), Kwon & Shin (1999), Maysami & Koh (2000), Hondroyiannis & Papapetrou (2001), Wongbangpo & Sharma (2002), and Ibrahim (2011). Most of the studies have provided empirical proof that the macroeconomic environment in which the stock market operates has a significant impact on its performance. But these studies have largely been focused on developed capital markets such that the stock markets in emerging economies like Ghana have barely been studied. The few studies on Ghana examining the relationships between stock prices and macroeconomic factors include Anokye & Tweneboah (2008), Kyereboah-Coleman & Agyire-Tettey (2008), and Kuwornu (2012) and have mainly focused on interest rate, inflation rate, exchange rate, foreign direct investment and crude oil prices as macroeconomic indicators. None have introduced a variable to capture general economic activity or conditions.

In order to fill in his gap, this research attempts to contribute to existing literature by establishing the dynamic interrelationships among stock prices and selected macroeconomic indicators in Ghana using a Vector Autoregression (VAR) Model. Specifically, it is aimed at answering the following questions:

a. What are the impacts of changing macroeconomic indicators on stock prices?

b. What are the impacts of stock market variability on the Ghanaian economy?

In addition to the commonly used interest and inflation rates, this dissertation includes Gross Domestic Product (GDP) as a measure of economic activity, as well as the global commodity price index which comprises both fuel and non-fuel price indices.

The study is of interest to policy makers and investors at large. Knowledge on the relationships between changing macroeconomic indicators and stock prices would inform economic policies appropriately. For investors, this research would be a useful and valuable source of information that could guide or influence investment decisions on the stock market.

1.4 Organisation of the Research

This study is organised into five sections. After the introduction, the next section presents a literature review, both theoretical and empirical of the existing relationships between macroeconomic factors and the stock market. This is followed by sections 3 and 4 which describe the econometric methodology, and the data and empirical results respectively. Section 5 then presents a summary and recommendations from the research.

2. Literature Review

2.1 Introduction

The interaction between the stock market and the macro economy has been a subject of interest among researchers. A wealth of literature exists on the relationship between several macroeconomic indicators and stock prices (from which stock returns are constructed) using various econometric methods and models and has sometimes, produced mixed results. This chapter seeks to present the current state of knowledge concerning the dynamic relations between macroeconomic indicators and stock prices as has been studied in developed and emerging economies while highlighting what is novel in terms of the contribution this research attempts to make.

2.2 Theoretical Review

In theory, the relationship between macroeconomic variables and stock prices can be traced to the Dividend Discount Model (DDM) developed by Miller & Modigliani (1961). The DDM can be expressed as:

$$P_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t} \tag{2.1}$$

where P_0 is the current price of the asset

r is the required rate of return

D is the dividends

t is the time period

According to the DDM, the determinants of stock prices are the expected future cash flow streams arising from the underlying assets and the required rate of return for investors. Macroeconomic variability therefore influence changes in stock prices because, the two factors namely, expected future cash flow streams and discount rate are quite sensitive to changes in macroeconomic indicators.

Another asset pricing model that relates macroeconomic conditions to stock prices is the Arbitrage Pricing Theory (APT) advanced by Ross (1976). This theory of asset pricing postulates that the expected return of an asset is a linear combination of several risk factors from two sources; systematic and unsystematic risk factors. The unsystematic risk is asset-specific and can be eliminated through portfolio diversification while the systematic risk is not diversifiable and can be made up of macroeconomic factors like GDP, inflation and interest rates such that the sensitivity to changes in each factor is represented by a factor-specific beta coefficient. The APT can be expressed in the form:

$$R_i = E(R_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + \ldots + \beta_{ik}F_k + \varepsilon_i \tag{2.2}$$

Where R_i is the rate of return on asset i

E (R_i) is the expected rate of return on the asset i

F_k are macroeconomic factors

β_{ik} is a measure of the sensitivity of the asset i to the macroeconomic factor F_k

ε_i is the unsystematic risk of asset I and is independent of all factors and other error terms.

The multi-factor APT model, was developed as an alternative to the Capital Asset Pricing Model (CAPM) which was flawed with unrealistic and much restrictive assumptions. The APT assumes that markets are efficient in their reflection of asset prices, and is therefore tied to the Efficient Market Hypothesis (EMH). The EMH developed by Fama (1970), states that markets are efficient when asset prices fully reflect all available information. In other words, in an efficient market, asset prices are a representation of the true intrinsic value of the asset, and there are no unexploited profit opportunities. According to Fama, three forms of market efficiency exist depending on the available information set. Weak-form market efficiency states that asset prices are a reflection of all past publicly available information, and technical analysis cannot be used to consistently predict stock prices. Semi strong-form market efficiency states that asset prices are a reflection of both past prices, and all other public information while strong-form market efficiency essentially states that markets are perfect, and asset prices reflect all available information.

2.3 Empirical Review

2.3.1 Evidence from Advanced Countries

Chen, Roll, & Ross (1986) studied the US stock market and selected macroeconomic variables; inflation, term structure, market return, industrial production, consumption, risk premium, inflation and oil prices as a means of testing the APT. They established a strong relationship between stock returns and the macroeconomic factors, and this set the tone for further empirical investigations into these relationships. Hamao (1988) tested the robustness of the Chen, Roll, & Ross (1986) results by employing the APT in an empirical investigation of the Japanese stock market using similar macroeconomic variables. He found that changes in anticipated inflation and unanticipated changes in both the slope of the term structure of interest rates and the risk premia significantly influence the stock market in Japan.

By employing a Vector Error Correction Model (VECM), Mukherjee & Naka (1995) proved a long run relationship between stock prices and six macroeconomic variables: money supply, inflation, interest rate on government bonds, call money rate, exchange rate and industrial production, and found a positive relationship between money supply, exchange rate and stock prices and a negative relationship between stock price and interest rates. On the contrary, Diacogiannis (1986) as well as Poon & Taylor (1991), after replicating the Chen, Ross, & Roll (1986) study on the UK stock market, found that the stock returns do not seem to be influenced by macroeconomic conditions. However, Clare, & Thomas (1994) observed that oil prices and the retail price index are important for stock market returns in the UK. Similar conclusions from the APT model were also reached by Priestley (1996) for the UK stock market.

Using post-war data for the USA, UK, Canada and Germany, Kaul (1990) revealed that in countries where the monetary policy regime remains unchanged, a negative relationship between stock prices and changes in anticipated inflation exists.

The Vector Autoregression (VAR) analysis by Gjerde & Saettem (1999) in Norway confirmed a negative relationship between interest rate, inflation and stock prices and a positive reaction to oil prices and real economic activity. They also found that the stock market shows a delayed response to changes in real economic activity in Norway.

2.3.2 Evidence from Emerging Economies

Indeed, stock markets in developed countries like USA, UK, Japan, Germany and other major economies have been extensively studied and well documented compared to developing or emerging markets in Asia, Latin America and Africa such as the Ghanaian stock market. Kwon & Shin (1999), employing a VECM, established a long run relationship between the Korean stock market and the exchange rate, money supply, production index and trade balance. However, a positive relationship was found between money supply and stock price, but the stock price was not found to be a leading indicator for macroeconomic variables. Similarly, the VECM also used by Maysami & Koh (2000) on the Singapore stock market proved that the stock price is cointegrated with money supply, interest and exchange rates, and changes in price levels. The authors found a negative relationship between stock prices and interest rates, and also between stock prices and the exchange rate, suggesting that the Singapore stock market is exchange and interest rate sensitive.

By employing a Vector Autoregression (VAR) analysis, the study by Achsani & Strohe (2002) in Indonesia confirmed a negative relationship between interest rate, inflation and stock prices and a positive reaction to oil prices and real economic activity as was also found by Gjerde & Saettem (1999) in Norway. Similar results were also obtained by Hondroyiannis & Papapetrou (2001) who established a negative relationship between interest rate and stock price and also between oil price changes and the stock price. They revealed that stock prices do not lead changes in real economic activity which is contrary to Lee (1992), and that oil price changes have a negative impact on macroeconomic activity in Greece. Using monthly data, the relationship between macroeconomic variables and stock markets in Malaysia, Indonesia, Thailand, Singapore and Philippines was explored by Wongbangpo & Sharma

(2002). A negative relationship between stock prices and the interest rate was found for Philippines, Singapore and Thailand, while a positive relationship was found for Malaysia and Indonesia. All five stock indices were negatively related to the consumer price index but positively related to output growth. In studying the effect of macroeconomic variablility on stock market returns for four emerging economies: Brazil, Russia, India and China (BRIC), Gay (2008) employed the Box-Jenkins ARIMA model and revealed no significant relationship between oil price and exchange rate for the stock markets of all four economies. Again, there was no significant relationship between present and past stock market returns, suggesting that BRIC stock markets exhibit weak-form efficiency.

In Croatia, interest rates, oil prices and industrial production marked a positive influence on stock prices, while inflation had a negative relation as observed by Benakovic & Posedel (2010) who estimated a multifactor model. The results of the VAR analysis by Ibrahim (2011) on the stock market in Thailand indicate a positive relationship between the stock market index and real GDP as well as the investment ratio.

2.3.3 Evidence from Africa

Studies on African stock markets have also been carried out over the years. Adjasi, Biekpe, & Osei (2011) examined the relationship between stock prices and exchange rates for seven African countries using a VECM. Cointegration between stock prices and the exchange rate was found for Tunisia, in which the depreciation of the exchange rate reduces stock prices. Stock returns in Kenya, Nigeria, Ghana and Mauritius decline when caused by exchange rate shocks but rise in South Africa and Egypt as depicted by the impulse response functions. Stock price shocks or the exchange rate shocks are more prolonged in Kenya, Nigeria, Ghana and Mauritius than in Egypt and South Africa. On investigating the macroeconomic determinants of stock prices in Namibia, Eita (2012), using a VECM, found economic activity, exchange and interest rates, money supply and inflation to be the main determinants of stock prices. Money supply and economic activity influence stock prices positively while interest and inflation rates exhibit a negative influence.

For the Nigerian Stock market, the macroeconomic factors were found to be cointegrated with stock prices and hence related to stock returns (Soyode, 1993). Using a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, Nkoro & Uko (2013) established that inflation and government expenditure positively influence stock returns significantly, while interest rate has a negative impact on stock prices. However, exchange rate and money supply did not have any significant relationship with stock market returns in Nigeria.

2.3.4 Evidence from Ghana

The impact of macroeconomic indicators on the Ghana Stock Exchange has been studied by Kyereboah-Coleman & Agyire-Tettey (2008). Cointegration and the VECM employed revealed that the inflation rate has a negative effect on the stock market. Contrary to theory, exchange rate losses have no effect on the stock market but are rather beneficial to investors as a result of domestic currency depreciation.

Anokye & Tweneboah (2008) also analysed the dynamic relations between the Ghanaian stock market and macroeconomic factors. Apart from the regular variables like the treasury bill and exchange rates and consumer price index, they introduced inward foreign direct investments as a macroeconomic indicator, and conducted the analysis using quarterly data. They however do not make use of the Ghana Stock Exchange All Share Index but rather include the Databank Stock Index to reflect stock market performance. The cointegration analysis revealed a long run relationship between macroeconomic variables and share prices. Inflation was found to positively correlate with share prices. They also established that interest rate and foreign direct investment are the major determinants of the stock price movements in Ghana. Similar cointegration analysis by Kuwornu (2012) also found a long run equilibrium relationship between the consumer price index, exchange rate, crude oil price and the treasury bill rate. The inflation rate appeared to be the most influential macroeconomic factor affecting the Ghanaian stock market both in the short run and in the long run.

From the above review of the literature, it is evident that different methodologies have been employed and different macroeconomic indicators have been used in estimating relationships between stock prices and these macroeconomic variables across different economies. Like other emerging markets in Africa, Asia and Latin America, the Ghanaian stock market poses as an investment hub for potential investors. However, few empirical studies investigating the relationships between macroeconomic indicators and stock market returns focused on Ghana exist. Due to the paucity of literature relative to the Ghanaian stock market, this dissertation seeks to contribute to existing literature on the relationships between macroeconomic variables and stock prices in Ghana. The African Economic Outlook, 2014 reports that Ghana's economy has maintained commendable growth trajectory with an average annual growth of about 6.0% over the past six years indicating that the economy has over time experienced relative macroeconomic stability in terms of GDP growth. Therefore the country's GDP should have a plausible effect on the movement of stock prices in Ghana. Since the GDP variable has not been included to capture economic activity in any of the previous studies conducted on Ghana, this research aims to provide further empirical evidence by making use of a VAR model and most importantly, including the output (GDP) variable as a measure of economic activity in the model in addition to the commonly used interest and inflation rates to analyse the effects of macroeconomic variability on the stock market.

3. Methodology

3.1 Introduction

This paper seeks to examine the dynamic interactions between stock prices in the Ghanaian stock market and some selected macroeconomic variables. Therefore, this chapter is concerned with the econometric methodology that will be used in determining the interrelationships among selected macroeconomic indicators and stock prices in Ghana.

3.2 Model Specification and Estimation

3.2.1 Unit Root Tests

Many macroeconomic time series tend to be non-stationary around their means or display trending behaviour. A time series is stationary if its mean and variance are constant over time, and the covariance between two values from the series depends only on the length of time separating the two values, and not on the actual time at which the variables are observed. Therefore, stationary series have the property of mean reversion. Nonstationary series on the other hand exhibit a random walk.

To avoid spurious regressions stressed by Granger & Newbold (1974), the time series data will be tested for non-stationarity (the presence of unit root) using the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests. This is because it is important to determine the order of integration of each time series before proceeding with estimation.

For a simple time series, that is, AR (1) model: $y_t = \rho y_{t-1} + e_t$ (3.1)

where e_t is the error term, the test for unit root can be carried out by testing the null hypothesis that ρ=1 against the alternative that ρ<1. By taking differences of (3.1), the Dickey-Fuller test takes the form:

$$\Delta y_t = \gamma y_{t-1} + v_t \tag{3.2}$$

Where v_t is the error term. In this case, the null hypothesis tested is that γ=0 against the alternative that γ<0.

The ADF test is an extension of the Dickey-Fuller test that allows for the possibility of and corrects for autocorrelation in the error term by including lags of order p to capture the full dynamic nature of the process. Three possible forms of the ADF test are:

$$\Delta y_t = \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t \tag{3.3}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t \tag{3.4}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \lambda_t + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t \tag{3.5}$$

(3.3), (3.4) and (3.5) are test equations for nonstationarity without intercept and trend (if the series appears to be wandering around a sample average of zero), with intercept only (if the series appears to be wandering around a non-zero sample avearge), and with both intercept and trend (if the series appears to be fluctuating around a linear trend) respectively based on a visual inspection of the time series plotted on a graph. The null hypothesis tested is that γ=0 against the alternative that γ<0 as in the Dickey-Fuller test.

On the other hand, the PP test corrects for any autocorrelation and heteroskedasticity in the error term by modifying the Dickey-Fuller test statistics. The PP test statistics can be seen as Dickey-Fuller statistics made robust to autocorrelation by using the Newey-West (1987) heteroskedasticity- and autocorrelation-consistent (HAC) covariance matrix estimator. This is one advantage of the PP test over the ADF test, hence this study will rely on the results of the PP test.

For both tests, the null hypotheses to be tested is that the series is non-stationary, that is, there exists a unit root, against the alternative hypotheses of stationarity (absence of a unit root).

3.2.2 VAR Model

Following Lee (1992), Gjerde & Saettem (1999), and Hondroyiannis & Papapetrou (2001), the Vector Autoregression (VAR) methodology will be employed. The following vector autoregression of order p will then be considered;

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \quad (3.6)$$

Where y_t is a (5 x 1) vector of endogenous variables included in the VAR,

c = $(c_1,\ldots,c_5)$ is the (5 x 1) vector of intercept terms,

$\phi$is the (5 x 5) matrix of coefficients for i=1,2,…,p,

ε_t= $(\varepsilon_{1t},\ldots,\varepsilon_{5t})$ is the (5 x 5) vector of white noise processes, and,

p = optimal lag length that prevents error terms in the VAR from being serially correlated.

The VAR model provides a framework where each variable is regressed on its own lags and the lags of the other variables (Dekker et al., 2001). VAR models examine the lead-lag relationships among the variables in the model and also allows for innovation accounting, that is, impulse response functions and variance decomposition to be used as bases for inferences. Thus the VAR framework provides a systematic way to capture important dynamics or features in multivariate time series.

The existence of unit roots in the variables presents three options for estimating the VAR: in levels (with non-stationary variables), in first-differences (with stationary variables) or with an error correction term. Since the objective of a VAR analysis is to determine the interrelationships between variables and not to determine the parameter estimates or draw inferences about intercepts or linear combinations of coefficients, Sims (1980) and Sims, Stock, & Watson (1990) recommend against differencing even if the variables are not stationary, that is, contain a unit root as noted by Enders (2010). Differencing to achieve stationarity introduces distortions into the data. That is, it throws away important details on the co-movements in the time series such as the possibility of cointegrating relationships.

Again, Sims, Stock, & Watson (1990) argue that the estimated coefficients of the VAR are consistent and the asymptotic distribution of individual estimated parameters is standard even when the variables are nonstationary in levels and there are some variables that form a cointegrating relationshipas noted by Basher, Haug, & Sadorsky (2012). This argument is also supported by Wendel (1992). Also, the impulse response functions of an estimated VAR in levels with nonstationary variables are consistent estimators of their true impulse response functions only in the short run and medium run (Basher, Haug, & Sadorsky (2012). To this end, it is suggested that it is still considerable to estimate a VAR in levels despite the presence of unit roots in the variables. The residuals from the estimated VAR in levels are then tested for unit root to ensure that the nonstationarity is eliminated, in effect; checking the rationality of the stationarity assumption so that the results from the VAR still hold and inferences are valid.

3.2.3 Cointegration Test

Comovements among nonstationary variables can be established through cointegration analysis. Cointegration exists when a linear combination of nonstationary or I(1) variables is stationary or I(0). This means that when cointegrating relationships are found between variables, then they share similar stochastic trends; hence a long run relationship exists between them. The Johansen (1991) maximum likelihood method will be employed in testing for the possibility of a cointegrating relationship between the nonstationary series.

Assuming a VAR of order p:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + Bx_t + \epsilon_t \tag{3.7}$$

written in matrix form as:

$$y_t = \sum_{i=1}^{p} \phi_i \, y_{t-i} + Bx_t + \varepsilon_t \tag{3.8}$$

Where y_t is a k-vector of nonstationary I(1) variables

x_t is a d-vector of deterministic variables variables

ϕ_i and B are matrices of coefficients

ϵ_t is a vector of independent and identically distributed innovations.

(3.8) can be rewritten as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + Bx_t + \epsilon_t \tag{3.9}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$

If the coefficient matrix Π has reduced rank, that is r<k, then k x r matrices α and β exists each with rank r such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is I(0). This is according to Granger's representation theorem. The number of cointegrating relations or linear combinations is given by r while the cointegration vector is given by each column of β. If Π has a rank of zero, (r = 0) then the variables in y_t are not cointegrated and linear combinations will still be nonstationary I(1). If r = k such that Π has a full rank, then there are k cointegrating vectors and all the variables in (3.9) are stationary I(0). There will be r possible stationary linear combinations or relationshipsin y_t if the rank is 0<1< k.

The order or rank of cointegration which is r is determined from the trace statistic (λ_{trace}) and the maximum eigenvalue statistic (λ_{max}). The trace statistic tests the null hypothesis of r cointegrating relations against the alternative of k cointegrating relations, where k is the number of endogenous variables, for r = 0,1,…,k - 1. On the other hand, the maximum eigenvalue statistic tests the null hypothesis of r cointegrating relations against the alternative of r + 1 cointegrating relations. (EViews 8 Users Guide II, 2013)

3.2.4 Lag Length Selection

Standard lag order selection criteria will be used as a guide in determining the optimal number of lags to be employed in estimating the VAR for the analysis such that the residuals are not serially correlated. The choice of the lag order selection criterion has significant implications for the accuracy of the VAR impulse response functions as suggested by Ivanov & Kilian (2005)

3.2.5 VAR Identification

Following Sims (1980), the VAR (p) to be estimated will be identified by Cholesky decomposition; such that the shocks are or thogonalised (have uncorrelated error terms) and have a unit variance and the resulting residual covariance matrix is diagonal. This imposes a recursive structure of shocks in the VAR.

Assuming a simple bivariate VAR (1) system:

$$y_t = a_{10} - a_{12}z_t + \rho_{11}y_{t-1} + \rho_{12}z_{t-1} + \varepsilon_{yt} \tag{3.10}$$

$$z_t = a_{20} - a_{21}y_t + \rho_{21}y_{t-1} + \rho_{22}z_{t-1} + \varepsilon_{zt} \tag{3.11}$$

where ε_{yt} and ε_{zt} are white noise processes and $\{\varepsilon_{yt}\}$ and $\{\varepsilon_{zt}\}$ are uncorrelated white noise processes.

Imposing a recursive structure on the above system implies imposing a restriction such that the coefficient of y_t which is $a_{21}$is zero for example. Rewriting (3.10) and (3.11) with the imposed restriction then becomes:

$$y_t = a_{10} - a_{12}z_t + \rho_{11}y_{t-1} + \rho_{12}z_{t-1} + \varepsilon_{yt} \tag{3.12}$$

$$z_t = a_{20} + \rho_{21}y_{t-1} + \rho_{22}z_{t-1} + \varepsilon_{zt} \tag{3.13}$$

When a_{21} is zero, it means that z_t has a contemporaneous effect on y_t but y_t affects the $\{z_t\}$ sequence with period of one lag. This kind of restriction (a_{21}= 0) also means that $\mathbf{A}^{-1}$can be expressed as: $\mathbf{A}^{-1} = \begin{bmatrix} 1 & -a_{12} \\ 0 & 1 \end{bmatrix}$

Multiplying (3.12) and (3.13) by $\mathbf{A}^{-1}$ gives:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} 1 & -a_{12} \\ 0 & 1 \end{bmatrix}\begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} 1 & -a_{12} \\ 0 & 1 \end{bmatrix}\begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & -a_{12} \\ 0 & 1 \end{bmatrix}\begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{3.14}$$

It follows from estimation of the system that $e_{1t} = \varepsilon_{yt} - a_{12}\varepsilon_{zt}$ and$e_{2t} = \varepsilon_{zt}$. Hence, var (e_1) $= \sigma_y^2 + a_{12}^2\sigma_z^2$; *var* $(e_2) = \sigma_z^2$; *and cov* $(e_1, e_2) = -\ a_{12}^2\sigma_z^2$

From (3.14), the imposed restriction shows that the contemporaneous value of y_t is affected by both ε_{yt} and ε_{zt} shocks while the contemporaneous value of z_t is affected by ε_{zt} shocks only. The values of the residuals such as e_{2t} observed after estimation of the system are solely attributed to shocks from the z_t sequence. When the residuals in the VAR system are decomposed in this manner, then the VAR is identified by Cholesky decomposition; the resulting residual covariance matrix has symmetric correlations and unit variance.

The results from the estimated VAR (p) depend largely on the order of variables in the system. Thus, a pre-specified causal ordering of the variables is needed (Ibrahim, 2011)

A variable ordered first in the VAR system is viewed to respond to other variables with lags while a variable ordered second responds contemporaneously to the first-ordered variable and with lags to the remaining variables. However, a variable ordered last is most endogenous since it reacts contemporaneously to other variables in the VAR system (Ibrahim, 2011). This means that each variable depends on only those above it in the vector y_t from (3.6)

Based on the above, the ordering of the variables for this study is LGCPI, LGDP, LGSEI, LINF and LIR. This causal ordering infers that: (i) LGCPI does not respond contemporaneously to shocks of other model variables, (ii) LGDP is affected contemporaneously by LGCPI, but it does not respond contemporaneously to LGSEI, LINF and LIR innovations, (iii) LGSEI is affected contemporaneously by LGCPI and LGDP, but it does not respond contemporaneously to the LINF and LIR innovations, (iv) LINF is affected by LGCPI, LGDP and LGSEI, but does not respond contemporaneously to the LIR innovations, and (v) LIR is affected contemporaneously by all innovations in the system. Hence, LGCPI is not contemporaneously affected by any other shocks in the system apart from its own shocks because it is determined outside the model.

The rationale for this causal ordering is given as follows: LGCPI is determined by global market conditions other than conditions in the Ghanaian economy; consequently it is ordered in a way such that it influences all the other variables in the model but does not respond to contemporaneous changes from other variables in the system. LGSEI is a reflection of LGDP and is therefore ordered after LGDP. LIR is ordered last because monetary authorities set the future interest rate based on current inflation using the Taylor rule. Hence, the current interest rate is a reflection of previous inflation.

3.2.6 Innovation Accounting

Innovation accounting comprises impulse response functions and forecast error variance decompositions. Impulse response functions capture the direct and indirect effects by tracing out the time paths of the effects of a shock in a chosen variable on each of the other variables in the model so that the extent to which an exogenous shock affects the variables can be determined (Obben et al., 2007). Typically, impulse responses reveal the dynamic interactions that exist between endogenous variables in the VAR (p) model.

Forecast error variance decomposition separates the variation in an endogenous variable into contributions explained by the component innovations in the VAR. It is the percentage of the variance of the error made in forecasting a variable due to a particular innovation at a given time period. Thus, it provides information about the relative importance of each innovation in affecting the variables in the VAR.

3.2.7 Residual Diagnostics

The residuals from the estimated VAR model will then be subjected to serial correlation, normality and heteroskedasticity tests to verify whether the model is acceptable or not.

4. Data and Empirical Results

4.1 Introduction

This chapter presents the data used and the empirical findings from the research. After testing for the presence of unit root in each of the variables, a cointegration analysis is carried out before estimation of the VAR model in levels. Impulse response functions and variance error decompositions are generated. Residual diagnostics tests conclude this chapter.

4.2 Data Description

The study uses monthly time series for the period January 1995 to December 2010 consisting of 192 observations for each variable. Hence, the number of observations for each variable is sufficient in order to be confident about the reliability of results from the VAR analysis since time series models such as VAR tend to require much data.

Table 1. Data description and source

Variable	Concept	Description	Units	Source
LGSEI	Logarithm of the Ghana Stock Exchange Index	Ghana Stock Exchange All Share Index (1990=77.65 points)	Index number	Ghana Stock Exchange
LGDP	Logarithm of Gross Domestic Product	Gross Domestic Product	Local Currency Units (million Ghana Cedis)	Ghana Statistical Service
LINF	Logarithm of Inflation Rate	Inflation Rate	Percentage per annum	Bank of Ghana
LIR	Logarithm of 91-day Treasury Bill Rate	91-day Treasury Bill Rate	Percentage per annum	Bank of Ghana
LGCPI	Logarithm of Global Commodity Price Index	Global Commodity Price Index (2005=100)	Index number	IMF Database

As shown in Table 1, data on the stock market index was sourced from the GSE while global commodity price index data was obtained from the International Monetary Fund (IMF) online database. Interest and inflation rates were obtained from the Bank of Ghana. The source for the annual GDP data was the Ghana Statistical Service. It was interpolated to obtain monthly series using the “cubic-match last” method which assigns each value of the annual series to the last month in the year associated with the period, and then places all interim points on a “natural” cubic spline (a 3rd-degree piecewise polynomial) that connects all the points across each space (Chamberlain, 2010; EIA, 2010 and EViews 8 Users Guide I, 2013). Since the variables have different scales of magnitudes which make graphical comparisons quite difficult, all variables are transformed by their logarithms in order to smooth the data.

4.3 Descriptive Statistics of Variables

Table 2 presents the summary statistics of the variables. All the variables exhibit a positive mean.

Table 2. Descriptive statistics of variables

Statistic/Variable	LGCPI	LGDP	LGSEI	LINF	LIR
Mean	1.902909	3.719792	3.274372	1.304729	1.387549
Median	1.808005	3.694143	3.150718	1.255273	1.416641
Maximum	2.341909	4.663164	4.038281	1.850033	1.680607
Minimum	1.622318	2.731490	2.471878	0.933487	0.982271
Std. Dev.	0.181958	0.559230	0.510088	0.227540	0.230152
Skewness	0.577107	0.092134	-0.086136	0.647436	-0.391582
Kurtosis	2.072347	1.793823	1.495308	2.689528	1.865666
Jarque-Bera	17.54201	11.91053	18.35021	14.18470	15.20047
Probability	0.000155	0.002592	0.000104	0.000831	0.000500
Sum	365.3586	714.2000	628.6794	250.5081	266.4095
Sum Sq. Dev.	6.323762	59.73300	49.69630	9.888908	10.11727
Observations	192	192	192	192	192

LGCPI has the lowest standard deviation of 0.181958 compared to the other variables although LGDP displays more volatility than LGSEI over the period. Again LGDP has the highest range from 2.731490 to 4.663164 while LIR has the lowest maximum and minimum values. In terms of skewness, LGCPI, LGDP and LINF are right-skewed while LGSEI, and LIR are left-skewed. The value for kurtosis for each variable is less than the benchmark of 3 for normal distribution, which implies that the variables have distributions with thinner tails, hence platykurtic. On the whole, the variables are not normally distributed as confirmed by the J-B statistics.

4.4 Variable Description and Justification

Ghana Stock Exchange All Share Index: This is the main stock index of the GSE and it is calculated from the values of each of the market's listings. The Index captures overall stock market performance, which informs investors in taking investment decisions.

Gross Domestic Product (GDP): This is a measure of national output that reflects general economic conditions or activity. Growth in GDP is largely seen to be a driver of stock market performance. In general, income levels and corporate earnings and profits rise when the economy is booming. There is the tendency for an increase in stock market activity and performance as investor ability to buy or demand shares increases causing an upward movement in share prices. Similarly, it is also theorised that a larger, more efficient stock market also boosts economic growth (Levine & Zervos, 1996). Hence a positive relationship is hypothesised between stock market and GDP.

Interest Rate: Interest rates affect stock prices through firm investment. Higher interest rates lead to high borrowing costs as firms lose huge sums of money in the form of interest payments which lead to a decline in corporate earnings and profits.

This translates into lower dividend payments to investors and a decrease in share prices. A decrease in interest rates however is likely to increase economic activity, increasing firm revenue and profits. The increase in firm profits will lead to an increase in dividends paid, and hence cause an increase in stock prices. It is important to note that if financial markets expect a change in interest rates, then according to the EMH, stock prices would reflect the expected change in interest rates, and hence would not react to any changes.

In this study, the 91-day Government of Ghana Treasury Bill rate is used as a proxy for the interest rate. This Treasury bill is one of the most actively traded money market instruments in Ghana. Investing in Treasury bills is viewed as an opportunity cost for holding shares. In general, an increase in interest rates increases the opportunity cost of holding money. Investors substitute their holdings on stocks or shares by transferring their investments from the stock market into the money market, triggering a decrease in stock prices due to the decline in its demand. The decrease in stock prices may cause the stock index to decline. Higher Treasury bill rates attract investors to buy more interest-bearing government securities, thus Treasury bills and stocks are in competition for the resources of an investor. A negative relationship between stock market returns and the interest rate is therefore expected.

Inflation Rate: The rate of inflation is used as a measure of inflation in the analysis. Higher inflation rates increase costs of living and shift resources from investments to consumption leading to a decline in the demand for stocks, and hence a fall in the volume of stocks traded in the market. Monetary policy also reacts to the rise in the inflation rate with tightening of economic policies, which results in an increase in the nominal risk-free rate as well as the discount rate. The overall effect is adecrease in the present value of cash flows. Rising inflation also affects corporate revenues which tend to have a negative impact on dividends. Stocks depreciate in value as a result of the decrease in expected stock returns. The relationship between stock prices and the inflation rate is hypothesized to be negative.

Global Commodity Price Index: This index includes both fuel and non-fuel price indices in the international commodity market. An increase in global commodity prices negatively affects productivity of firms and hence, profitability of equities on the stock market and national production on the whole.

In general, with the exception of the global commodity price index, the rest of the variables are the common indicators for measuring macroeconomic and stock market performance in Ghana which influenced their selection for inclusion in this study. Again, they are chosen based on their interdependence and interrelationship and also due to data availability.

4.5 Unit Root Test Results

The study employs both the ADF and PP unit root tests. The lag length for the ADF test is determined by the Schwarz Information Criterion. For the PP test, the Newey-West bandwidth is chosen.

Table 3. ADF unit root test results

Augmented Dickey-Fuller (ADF) Test					
Variables	Level/First Difference/Second Difference	With Intercept	With Trend and Intercept	Adjusted t- statistic (p value)	Conclusion
LGSEI	Level	-	x	-2.172157 (0.5019)	I(1)
	First Difference	-	-	-5.083463*** (0.0000)	
LGDP	Level	-	x	-2.843861 (0.1836)	I(2)
	First Difference	x	-	-2.209429 (0.2037)	
	Second Difference	-	-	-3.851049*** (0.0001)	
LINF	Level	-	x	-2.181845 (0.4965)	I(1)
	First Difference	-	-	-11.14228*** (0.0000)	
LIR	Level	-	x	-2.277729 (0.4436)	I(1)
	First Difference	-	-	-8.582967*** (0.0000)	
LGCPI	Level	-	x	-2.448769 (0.3534)	I(1)
	First Difference	-	-	-9.365099*** (0.0000)	

Table 4. PP Unit root test results

Philips-Perron (PP) Test					
Variables	Level/First Difference	With Intercept	With Trend and Intercept	Adjusted t-statistic (p value)	Conclusion
LGSEI	Level	-	-	1.859636 (0.9850)	I(1)
	First Difference	-	-	-8.163787*** (0.0000)	
LGDP	Level	x	-	-0.582751 (0.8703)	I(1)
	First Difference	x	-	-3.143223** (0.0251)	
LINF	Level	-	x	-2.551963 (0.3030)	
	First Difference	-	-	-11.56078*** (0.0000)	I(1)
LIR	Level	-	-	-0.908122 (0.3217)	I(1)
	First Difference	-	-	-8.896289*** (0.0000)	
LGCPI	Level	-	x	-2.384817 (0.3863)	I(1)
	First Difference	-	-	-9.553137*** (0.0000)	

From both tests, the null hypothesis of a unit root fails to be rejected at 5% significance level. This indicates that all the variables have a unit root as shown in Table 3 and Table 4. LGDP is made stationary at 1% significance level after second differencing using the ADF test but made stationary at 5% significance level after first differencing using the PP test, while LGSEI, LGCPI, LINF and LIR become stationary at 1% significance level after first differencing.

For both tests, *denotes significance at 10% significance level, ** denotes significance at 5% significance level and ***denotes significance at 1% significance level. The p values are shown in parantheses. The symbol (x) indicates inclusion in the test equation and (-)indicates exclusion from test equation.

The results of the PP test are chosen over the ADF test since it corrects for both autocorrelation and heteroskedasticity in the error term as explained in the previous chapter. All the variables are therefore non-stationary and are integrated of order one. The null hypothesis of nonstationarity is strongly rejected at 5% significance level for all the variables after first differencing.

Both unit root tests on LGSEI show that stock prices follow a random walk. This gives a hint that the Ghanaian stock market exhibits weak form-efficiency according to the EMH; share prices reflect all historic publicly available information only. Excess returns for investors could only be made as and when stocks are consistently overvalued as was the case during the bull runs in 2004. This result is consistent with results from previous studies on the GSE by Mensah, Pomaa-Berko, & Adom (2012), and Ayentimi, Mensah, & Naa-Idar (2013).

The presence of unit root in all variables leads to a cointegration analysis of the series.

4.6 Cointegration Test Results

Since the variables are nonstationary and are integrated of the same order, the Johansen Cointegration test described in the previous chapter is carried out to determine a possible long run relationship so that a VAR in levels can still be estimated despite the presence of unit root. Table 5 reports the Johansen Cointegration test results and is presented.

Table 5. Johansen cointegration test results

Date: 09/01/14 Time: 21:10					
Sample (adjusted): 1995M06 2010M12					
Included observations: 187 after adjustments					
Trend assumption: Linear deterministic trend					
Series: LGCPI LGDP LGSEI LINF LIR					
Lags interval (in first differences): 1 to 4					
Unrestricted Cointegration Rank Test (Trace)					
Hypothesized		Trace	0.05		
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**	
None *	0.178385	72.31355	69.81889	0.0312	
At most 1	0.090456	35.57126	47.85613	0.4182	
At most 2	0.058092	17.84137	29.79707	0.5778	
At most 3	0.034361	6.649779	15.49471	0.6187	
At most 4	0.000595	0.111354	3.841466	0.7386	
Trace test indicates 1 cointegratingeqn(s) at the 0.05 level					
* denotes rejection of the hypothesis at the 0.05 level					
**MacKinnon-Haug-Michelis (1999) p-values					
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)					
Hypothesized		Max-Eigen	0.05		
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**	
None *	0.178385	36.74228	33.87687	0.0221	
At most 1	0.090456	17.72989	27.58434	0.5177	
At most 2	0.058092	11.19159	21.13162	0.6281	
At most 3	0.034361	6.538425	14.26460	0.5451	
At most 4	0.000595	0.111354	3.841466	0.7386	
Max-eigenvalue test indicates 1 cointegratingeqn(s) at the 0.05 level					
* denotes rejection of the hypothesis at the 0.05 level					
**MacKinnon-Haug-Michelis (1999) p-values					
Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):					
LGCPI	LGDP	LGSEI	LINF	LIR	
5.584842	-4.170881	7.075891	-7.394573	16.34876	
-12.10545	5.473027	-1.003806	6.461213	-2.423984	

-9.965162	2.479780	-0.242033	-3.479772	-1.008047	
-1.939935	-3.967527	4.908653	2.732632	-3.527448	
-3.859342	-1.465182	0.856656	-0.512830	0.125048	
Unrestricted Adjustment Coefficients (alpha):					
D(LGCPI)	-0.004570	0.002211	0.002779	0.001086	-7.04E-05
D(LGDP)	-8.77E-06	-6.41E-07	-4.16E-06	5.58E-06	1.12E-06
D(LGSEI)	-0.004418	0.000572	-0.000870	-0.003672	0.000154
D(LINF)	0.001962	-0.006370	0.006946	-0.001030	0.000396
D(LIR)	-0.005175	-0.005034	-0.001427	0.000492	-0.000219
1 Cointegrating Equation(s):		Log likelihood	3257.314		
Normalized cointegrating coefficients (standard error in parentheses)					
LGCPI	LGDP	LGSEI	LINF	LIR	
1.000000	-0.746822	1.266981	-1.324043	2.927346	
	(0.18185)	(0.25067)	(0.28378)	(0.44685)	
Adjustment coefficients (standard error in parentheses)					
D(LGCPI)	-0.025525				
	(0.00785)				
D(LGDP)	-4.90E-05				
	(2.6E-05)				
D(LGSEI)	-0.024672				
	(0.01009)				
D(LINF)	0.010958				
	(0.01734)				
D(LIR)	-0.028902				
	(0.00998)				
2 Cointegrating Equation(s):		Log likelihood	3266.179		
Normalized cointegrating coefficients (standard error in parentheses)					
LGCPI	LGDP	LGSEI	LINF	LIR	
1.000000	0.000000	-1.733542	0.678653	-3.983411	
		(0.32328)	(0.62505)	(0.99755)	
0.000000	1.000000	-4.017724	2.681625	-9.253556	
		(0.57464)	(1.11103)	(1.77316)	
Adjustment coefficients (standard error in parentheses)					
D(LGCPI)	-0.052285	0.031161			
	(0.01859)	(0.00960)			
D(LGDP)	-4.12E-05	3.31E-05			
	(6.3E-05)	(3.2E-05)			
D(LGSEI)	-0.031597	0.021557			
	(0.02408)	(0.01243)			
D(LINF)	0.088065	-0.043045			
	(0.04087)	(0.02109)			
D(LIR)	0.032032	-0.005964			

	(0.02323)	(0.01199)			
3 Cointegrating Equation(s):		Log likelihood	3271.775		
Normalized cointegrating coefficients (standard error in parentheses)					
LGCPI	LGDP	LGSEI	LINF	LIR	
1.000000	0.000000	0.000000	1.451274	0.091497	
			(0.66283)	(0.63662)	
0.000000	1.000000	0.000000	4.472283	0.190608	
			(1.73963)	(1.67084)	
0.000000	0.000000	1.000000	0.445689	2.350625	
			(0.58014)	(0.55719)	
Adjustment coefficients (standard error in parentheses)					
D(LGCPI)	-0.079980	0.038053	-0.035231		
	(0.02293)	(0.01008)	(0.00985)		
D(LGDP)	2.02E-07	2.28E-05	-6.04E-05		
	(7.8E-05)	(3.4E-05)	(3.4E-05)		
D(LGSEI)	-0.022925	0.019399	-0.031622		
	(0.03005)	(0.01320)	(0.01291)		
D(LINF)	0.018848	-0.025821	0.018597		
	(0.05022)	(0.02207)	(0.02158)		
D(LIR)	0.046253	-0.009503	-0.031220		
	(0.02895)	(0.01272)	(0.01244)		
4 Cointegrating Equation(s):		Log likelihood	3275.044		
Normalized cointegrating coefficients (standard error in parentheses)					
LGCPI	LGDP	LGSEI	LINF	LIR	
1.000000	0.000000	0.000000	0.000000	1.063322	
				(0.20569)	
0.000000	1.000000	0.000000	0.000000	3.185408	
				(0.54072)	
0.000000	0.000000	1.000000	0.000000	2.649075	
				(0.27345)	
0.000000	0.000000	0.000000	1.000000	-0.669636	
Adjustment coefficients (standard error in parentheses)					
D(LGCPI)	-0.082087	0.033745	-0.029901	0.041375	
	(0.02304)	(0.01144)	(0.01193)	(0.01481)	
D(LGDP)	-1.06E-05	6.41E-07	-3.30E-05	9.04E-05	
	(7.8E-05)	(3.9E-05)	(4.1E-05)	(5.0E-05)	
D(LGSEI)	-0.015803	0.033966	-0.049645	0.029358	
	(0.02987)	(0.01483)	(0.01546)	(0.01920)	
D(LINF)	0.020846	-0.021734	0.013540	-0.082650	
	(0.05054)	(0.02510)	(0.02616)	(0.03249)	
D(LIR)	0.045298	-0.011455	-0.028805	0.012055	
	(0.02914)	(0.01447)	(0.01508)	(0.01873)	

From the table, since the corresponding p values from the trace and maximum eigenvalue statistics are 0.0312 and 0.0221 respectively and are less than the 5% significance level, the null hypothesis that there is no cointegration (r = 0) is strongly rejected in favour of the alternative. Hence, the series are cointegrated at 5% significance level as reported at the bottom of the output by both the trace and maximum eigenvalue tests which indicate one cointegrating equation. These lend continuity in the modeling process. Thus, estimating a VAR in levels is still in order without differencing as explained in the previous chapter.

4.7 Lag Length Selection

The optimal lag length that prevents the residuals in the VAR from being serially correlated is determined by the lag order selection criteria, but to a large extent, combined with some form of judgement that addresses the ultimate purpose of estimating the VAR. From table 6, the AIC indicates 5 lags, while both SC and HQ indicate 4 lags. Although all the information criteria penalize a model with more parameters, the SC involves a stricter penalty than the AIC so it is more likely to choose the more parsimonious model than the AIC. The AIC is therefore inconsistent and overestimates the true lag length with positive probability (Lütkepohl & Kärtzig, 2004). Hence, based on the Schwarz Information Criterion, a VAR (4) model is estimated to examine the dynamic interactions among the variables in the system. These are reported in the appendix in detail.

Table 6. VAR lag order selection criteria

VAR Lag Order Selection Criteria						
Endogenous variables: LGCPI LGDP LGSEI LINF LIR						
Exogenous variables: C						
Date: 08/25/14 Time: 21:28						
Sample: 1995M01 2010M12						
Included observations: 180						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	351.1370	NA	1.47e-08	-3.845967	-3.757273	-3.810005
1	2284.144	3737.148	9.13e-18	-25.04605	-24.51389	-24.83028
2	2632.625	654.3701	2.51e-19	-28.64028	-27.66466	-28.24471
3	2991.400	653.7663	6.16e-21	-32.34889	-30.92979	-31.77350
4	3115.171	218.6631	2.06e-21	-33.44635	-31.58379*	-32.69116*
5	3145.751	52.32605	1.95e-21*	-33.50835*	-31.20232	-32.57336
6	3155.931	16.85269	2.31e-21	-33.34368	-30.59419	-32.22888
7	3189.934	54.40526	2.11e-21	-33.44371	-30.25076	-32.14911
8	3206.455	25.51566	2.35e-21	-33.34950	-29.71308	-31.87509
9	3226.543	29.90797	2.53e-21	-33.29492	-29.21503	-31.64070
10	3248.882	32.02016	2.66e-21	-33.26536	-28.74200	-31.43133
11	3264.401	21.38112	3.04e-21	-33.16001	-28.19319	-31.14618
12	3296.617	42.59720*	2.90e-21	-33.24019	-27.82990	-31.04655

* indicates lag order selected by the criterion					
LR: sequential modified LR test statistic (each test at 5% level)					
FPE: Final prediction error					
AIC: Akaike information criterion					
SC: Schwarz information criterion					
HQ: Hannan-Quinn information criterion					

To show that the variables in the VAR are stationary, the AR roots table is examined. From Table 7, all the modulus are less than one, which means the VAR stability condition is satisfied and the VAR system is stationary (i.e., all inverse roots of the AR characteristic polynomial lie inside the unit circle). The stability of the VAR system implies that the shocks are transient and die out over time.

Table 7. AR roots table

Roots of Characteristic Polynomial	
Endogenous variables: LGCPI LGDP LGSEI LINF LIR	
Exogenous variables: C	
Lag specification: 1 4	
Date: 08/20/14 Time: 15:09	
Root	Modulus
0.999492	0.999492
0.939035 - 0.223189i	0.965194
0.939035 + 0.223189i	0.965194
0.939622 - 0.048092i	0.940852
0.939622 + 0.048092i	0.940852
0.912392 - 0.159289i	0.926193
0.912392 + 0.159289i	0.926193
0.922930	0.922930
0.732840	0.732840
0.654311 - 0.064018i	0.657435
0.654311 + 0.064018i	0.657435
-0.045038 - 0.603878i	0.605556
-0.045038 + 0.603878i	0.605556
-0.309451 - 0.489331i	0.578969
-0.309451 + 0.489331i	0.578969
-0.175854 - 0.377037i	0.416031
-0.175854 + 0.377037i	0.416031
-0.351594	0.351594
0.304442 - 0.144121i	0.336832
0.304442 + 0.144121i	0.336832
No root lies outside the unit circle.	
VAR satisfies the stability condition.	

4.8 Impulse Response Functions

From the estimated VAR, impulse response functions are generated over a 36-month horizon. Figure 3 shows responses of LGSEI to a Cholesky one standard deviation shock in LGCPI, LGDP, LINF and LIR with two standard error confidence bands. The dotted lines represent the two standard error bands. These generated impulse response functions aid in determining what the impacts of changing macroeconomic indicators are on stock market returns.

From Figure 3, a positive shock in the stock price variable (LGSEI) has a positive effect on itself. It is observed that an innovation in LGCPI has a negative effect on LGSEI. Throughout the period it remains below its pre-shock level. This implies that an increase in global commodity prices which includes both fuel- crude oil (petroleum), natural gas, coal- and non-fuel commodities (food and beverages, industrial inputs consisting of agricultural raw materials and metals) negatively affects stock prices. Almost all of the 33 companies listed on the GSE during the period being studied face a rise in production costs when commodity prices increase. This translates into a decline in production levels and a reduction in earnings and profits and hence, dividends paid out to shareholders. It ultimately affects patronage of stocks on the market through a reduction which leads to a decrease in stock prices and the overall market performance as measured by the stock index.

The immediate impact of the LGDP shock on the LGSEI is negative for the first 13 months. This suggests that the increase in economic output or activity is not convincing enough to draw potential investors onto the GSE as firms constantly battle with rising production costs even when GDP is increasing which affects profits and dividends negatively. This suggests that it may take some time for potential investors to make decisions based on the apparent increase in GDP. This is evident from the impulse response function as it recovers and rises above its pre-shock level thereafter indicating a positive response over the period. This implies that an increase in economic activity over time is advantageous for stock prices and returns as the market experiences a positive effect. This supports evidence found by Hondroyiannis & Papapetrou (2001), Ibrahim (2011), Eita (2012) and Nkoro & Uko (2013).

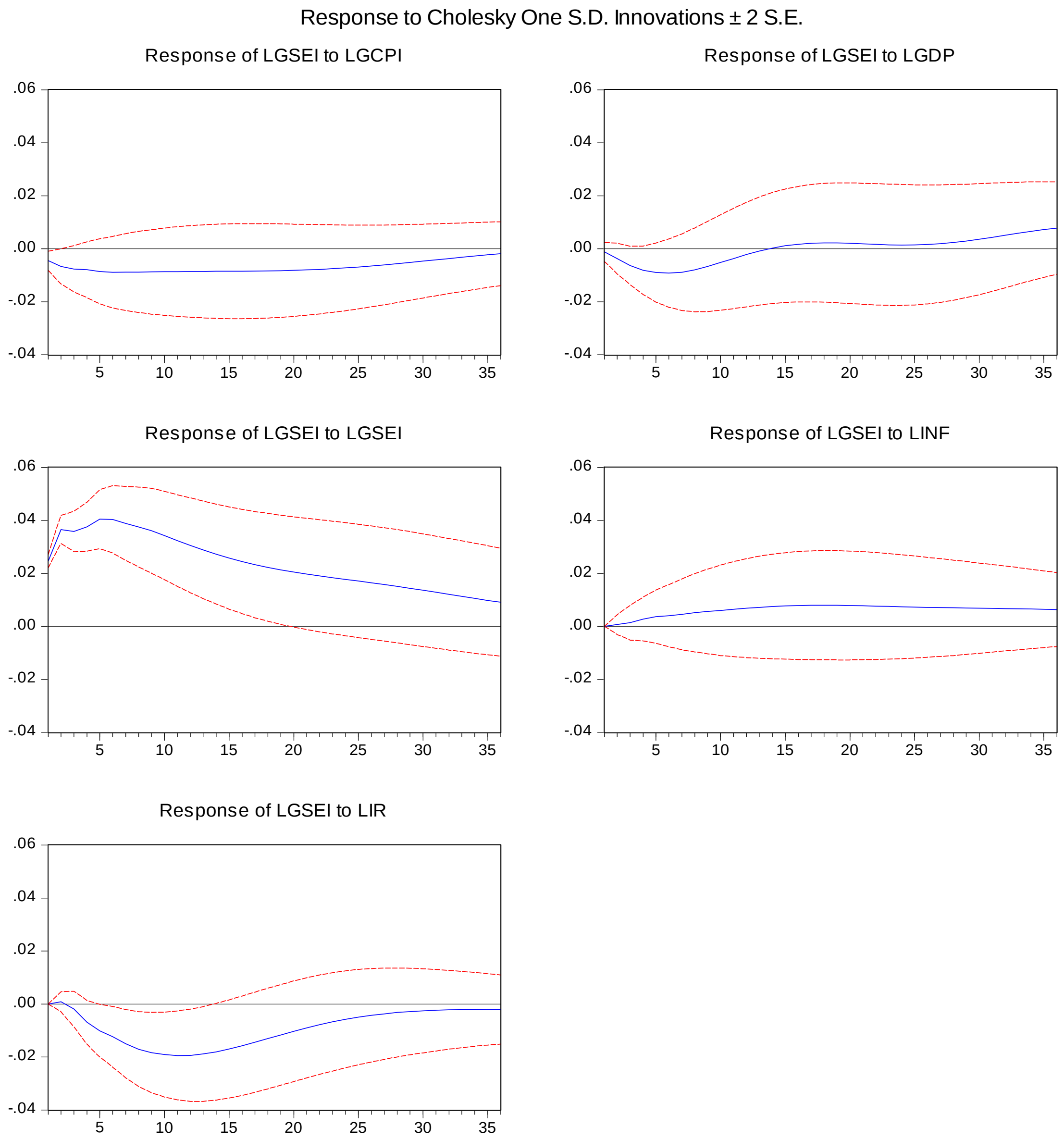

Figure 3. Impulse response functions of LGSEI to LGCPI, LGDP, LGSEI, LINF and LIR shocks

LGSEI responds positively to an innovation in LINF over the period. This contradicts the findings of Fama (1981), Kaul (1990), and Kyereboah-Coleman & Agyire-Tettey (2008). The positive impact that occurs suggests that inflationary pressures in the economy drive up stock prices as well as stock market returns because a higher return is expected when inflation rises. This implies that the equities listed on the GSE serve as a full hedge against inflation. This provides evidence in support of the results of Choudhry (2001), Ibrahim & Aziz (2003) and Maysami, Howe, & Hamzah (2004).

A shock in LIR causes the stock index to decline below its pre-shock level for the entire period indicating a negative relationship between the interest rate and stock prices which provides support to the substitution effect claim: that high interest rates cause investors to increase investments in less risky assets with higher returns which leads to a fall in investment in the stock market and hence a depreciation in stock prices. In Ghana, between 1995 and 2010 and even till date, government borrowing as a means of gross public debt financing has been quite frequent. The government sells securities like bonds and Treasury bills with attractive rates to mobilise capital to finance its debt. As interest rates on treasury bills increase, the private sector is crowed out and stock market investments reduce due to the fact that the money and capital markets are alternative investment opportunities. The negative relationship is line with the findings of Mukherjee & Naka (1995), Gjerde & Saettem (1999), Maysami & Koh (2000), Achsani & Strohe (2002), Anokye & Tweneboah (2008), Kyereboah-Coleman & Agyire-Tettey (2008) and Kuwornu (2012).

It can also be observed that the impulse responses to the shocks in figure 3 and 4 do not dissipate as the shocks appear to have a permanent effect. Lütkepohl (1991) notes that this maybe a reflection of the nonstationarity of the variables.

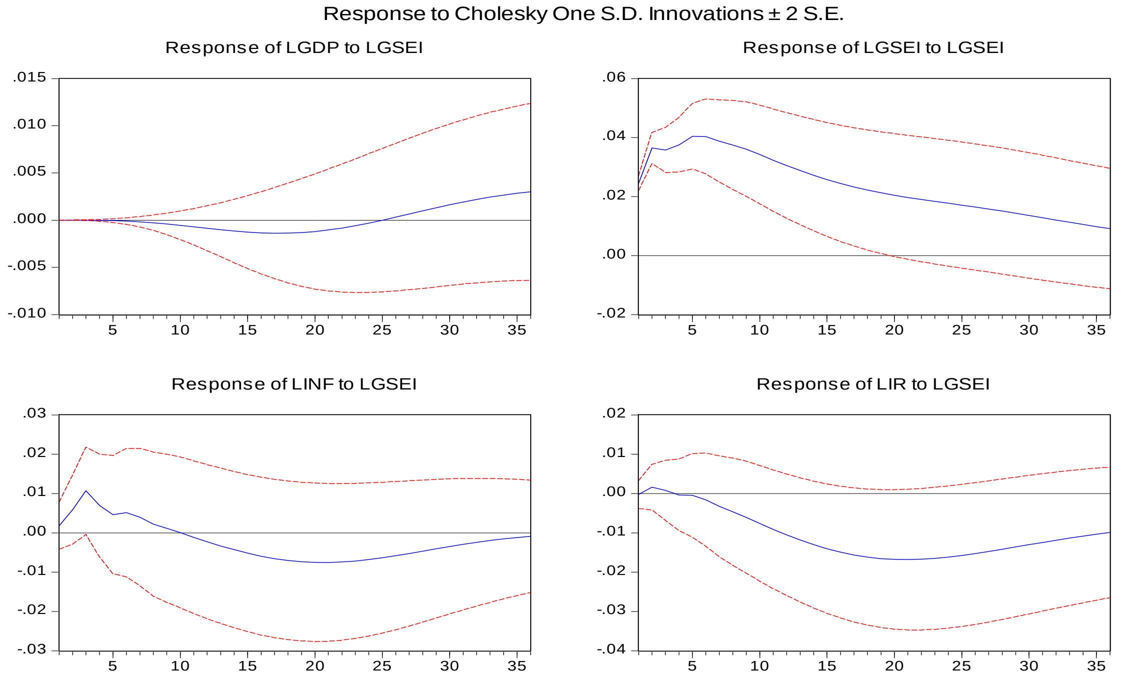

Figure 4. Impulse response functions of LGDP, LGSEI, LINF and LIR to LGSEI shocks

Figure 4 shows responses of LGDP, LGSEI, LINF, and LIR to a Cholesky one standard deviation shock in LGSEI with two standard error confidence bands. These impulse response functions depict the different impacts that stock market variability has on the Ghanaian economy.

In general, LIR and LINF respond negatively to a positive innovation in the LGSEI for the most part of the period with some positive responses in the first 5 and 10 months respectively.

International Finance and Banking
ISSN 2374-2089
2016, Vol. 3, No. 2

This implies that as stock prices rise, investment on the market becomes attractive. Hence, investors reduce their holdings of money market instruments like treasury bills and increase their holdings in stocks. It is observed that LGDP does not respond immediately to a positive shock in LGSEI until approximately after 8 months when it begins to decline implying a negative response up till the 25th month. After this, it rises above its pre-shock level, indicating a positive response to the LGSEI innovation. This implies that a rise in stock prices does not by definition translate into increased levels of economic activity. Hence, the stock market is not found to be a leading indicator for economic activity. This is contrary to Lee (1992) but is consistent with the findings of Hondroyiannis & Papapetrou (2001). The stock index however reacts positively to its own innovations over the entire period.

Therefore, it can be observed that dynamic interactions exist in the macro economy and it is evident that all the macroeconomic variables; both local and global have important relationships with stock market movement in Ghana. The stock market however, does not lead changes in domestic economic activity.

4.9 Forecast Error Variance Decompositions

Table 8 shows the variance decompositions for a 36-month period of LGDP, LGSEI, LINF and LIR in the VAR (4) model respectively where the first column represents the forecast period. The standard errors (S.E.) are also reported. The last five columns are percentage values which represents the contributions of innovations to the variations of each variable in the VAR. The sum of the values in each row is 100%. See appendix for variance decompositions of LGCPI in Table 9.

Table 8. Forecast error variance decompositions

Variance decompositions of LGSEI

Period	S.E	LGCPI	LGDP	LGSEI	LINF	LIR
1	0.025007	3.315672	0.240202	96.44413	0.000000	0.000000
6	0.094158	3.832187	3.276133	88.96475	0.437656	3.489275
12	0.138191	4.177179	2.748668	79.83720	1.258105	11.97885
18	0.159279	4.855042	2.124472	75.33753	2.338922	15.34404
24	0.169870	5.552470	1.934045	74.12134	3.283666	15.10848
30	0.175805	5.860119	1.917439	73.82874	4.020758	14.37294
36	0.179483	5.803852	2.563689	73.09460	4.659624	13.87823

Variance decompositions of LGDP

Period	S.E	LGCPI	LGDP	LGSEI	LINF	LIR
1	6.97E-05	0.641947	99.35805	0.000000	0.000000	0.000000
6	0.003715	0.808495	97.97881	0.096376	1.107639	0.008684
12	0.019319	1.356534	96.25756	0.488385	1.873336	0.024187
18	0.040339	1.892208	95.39000	0.699139	1.953391	0.065263

24	0.055348	2.293239	95.13035	0.548365	1.702243	0.325805
30	0.063612	2.352094	94.38031	0.560513	1.416431	1.290650
36	0.070614	2.079365	92.56778	1.228582	1.204739	2.919536

Variance decompositions of LINF

Period	S.E	LGCPI	LGDP	LGSEI	LINF	LIR
1	0.041200	0.567316	0.060014	0.193197	99.17947	0.000000
6	0.116090	0.929189	0.063811	1.852663	86.68660	10.46774
12	0.154821	1.251164	0.238959	1.160692	80.60657	16.74262
18	0.165111	3.196378	0.781853	1.693003	77.98744	16.34133
24	0.169239	4.541112	1.710845	2.722038	74.90302	16.12299
30	0.171824	4.697233	2.531630	3.151487	72.69276	16.92689
36	0.172538	4.666245	2.637450	3.200288	72.13924	17.35677

Variance decompositions of LIR

Period	S.E	LGCPI	LGDP	LGSEI	LINF	LIR
1	0.024518	0.389673	0.088079	0.008573	0.207054	99.30662
6	0.084321	0.332880	6.126090	0.086998	4.430486	89.02355
12	0.121093	1.382711	16.41758	2.227569	6.699035	73.27310
18	0.138412	3.468415	21.63722	8.148598	5.859812	60.88596
24	0.149027	4.703878	22.90810	14.45632	5.120018	52.81168
30	0.155110	4.993410	22.63719	18.55390	5.043566	48.77193
36	0.158089	5.029931	21.92878	20.84783	5.148907	47.04456

Table 9. Variance decompositions of LGCPI

Period	S.E	LGCPI	LGDP	LGSEI	LINF	LIR
1	0.019001	100.0000	0.000000	0.000000	0.000000	0.000000
6	0.053057	92.00399	0.117950	1.217828	3.102086	3.558146
12	0.071422	67.62056	2.338070	5.154759	6.064059	18.82255
18	0.079324	56.65598	5.545369	5.950914	5.833573	26.01416
24	0.082082	52.95305	8.201149	5.758060	5.502041	27.58570
30	0.086040	48.25905	14.46782	6.194841	5.139881	25.93840
36	0.091074	43.07853	22.11170	6.454475	4.906636	23.44866

As expected, from Table 8, the share of the fluctuations in LGSEI, LGDP, LINF, and LIR are caused by its own innovations although the contributions of these shocks decline over time, compared with the shocks to the other variables.

In the first month, LGSEI is mainly influenced by its own innovations, LGCPI and LGDP only. The variation in LGSEI accounted for by shocks in LGCPI and LINF continues to increase over time. After six months, LIR explains nearly 3.5% of the forecast error variance of LGSEI through to the end of the period when LIR and LINF explain a total of approximately 19% of the variation in the stock index. LIR seems to be the most important factor that explains movement in equity prices accounting for about 13.9% at the end of 36 months. The proportion of the error variance accounted for by LGDP to LGSEI is relatively smaller than the proportions explained by each of the other variables in the system, while LIR contributes the largest proportion. It can therefore be observed that the Ghanaian stock market is least responsive to shocks in economic activity but most responsive to monetary shocks.

The fluctuations in LGDP are chiefly caused by its own shocks and LGCPI only in the first month. Over time, only the variation in LGDP accounted for by shocks in LIR increases consistently. The proportion of the error variance accounted for by LINF to LGDP is relatively smaller compared to the proportions explained by each of the other variables in the system, while LIR contributes the largest proportion over the period. The variation in LGDP is significantly explained by LIR which accounts for about 3% of the forecast error variance of Ghana's GDP at the end of 36 months. However, LGCPI, LINF and LGSEI jointly explain about 4.5%. The huge proportion of the variation in GDP is still left unexplained; perhaps, attributable to other factors.

The share of variation in LINF in the first month is predominantly caused by its own shocks and shocks in LGCPI, LGDP and LGSEI only. At the end of twelve months, LIR largely accounts for about 16.7% of the forecast error variance in LINF compared to the other variables in the system. The interest rate still contributes the largest proportion to the forecast error variance of LINF at the end of the 36-month period which is approximately 17.4%, while LGDP accounts for the smallest proportion in the forecast error variance of LINF throughout the entire forecast period.

Like all the other variables LIR is also mainly influenced by its own innovations which decline over time. LGDP seems to be the most significant factor that explains movement in the interest rate accounting for approximately 22% at the end of 36 months followed closely by LGSEI which contributes about 21%.

LIR contributes the largest proportions to the forecast error variance in LGSEI, LGDP and LINF, while LGDP accounts for the largest proportion of the forecast error variance in LIR. The interest rate is therefore a key macroeconomic indicator which provides the most information about the relative importance of each shock in affecting the variables in the VAR.

4.10 Residual Unit Root Tests

Table 10 presents a summary of the group unit root test to confirm stationarity of the residuals after estimating the VAR in levels even in the presence of unit root.

Table 10. Group unit root test on residuals

Group unit root test: Summary				
Series: RESID_LGCPI, RESID_LGDP, RESID_LGSEI, RESID_LINF,				
RESID_LIR				
Date: 08/21/14 Time: 16:43				
Sample: 1995M01 2010M12				
Exogenous variables: Individual effects, individual linear trends				
Automatic selection of maximum lags				
Automatic lag length selection based on SIC: 0 to 12				
Newey-West automatic bandwidth selection and Bartlett kernel				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-38.3011	0.0000	5	923
Breitung t-stat	-18.1648	0.0000	5	918
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-27.7164	0.0000	5	923
ADF-Fisher Chi-square	405.438	0.0000	5	923
PP-Fisher Chi-square	457.186	0.0000	5	935
** Probabilities for Fisher tests are computed using an asymptotic Chi				
-square distribution. All other tests assume asymptotic normality.				

The p values of all the unit root tests are 0.0000 and are smaller than any common significance level (1%, 5% and 10%); hence the null of unit root is strongly rejected and it can be concluded that the residuals of the VAR are stationary. The nonstationarity in the residuals is therefore in the process of estimating the VAR in levels. Hence the inferences drawn from the estimated VAR in levels still hold and are not spurious.

4.11 Residual Diagnostic Tests

The residuals from the estimated VAR model are subjected to serial correlation, normality and heteroskedasticity tests to verify whether the model is acceptable or not. The corresponding tables are reported in the appendix.

Table 11 shows that the VAR has been identified by Cholesky decomposition. It can be observed that the resulting covariance matrix from the estimated VAR (4) is diagonal; the correlation is symmetric and the diagonal elements (variance) are unity.

Table 11. VAR residual cross correlations

VAR Residual Cross-Correlations					
Ordered by: variables					
Date: 08/20/14 Time: 15:14					
Sample: 1995M01 2010M12					
Included observations: 188					
	LGCPI	LGDP	LGSEI	LINF	LIR
LGCPI	1.000000	0.080122	-0.182090	0.075320	-0.062424
LGDP	0.080122	1.000000	-0.063442	0.030454	0.024581
LGSEI	-0.182090	-0.063442	1.000000	0.028250	0.000819
LINF	0.075320	0.030454	0.028250	1.000000	-0.049698
LIR	-0.062424	0.024581	0.000819	-0.049698	1.000000

The results of the residual serial correlation LM test are presented in Table 12. A VAR of order 4 ensures a strong rejection of the null hypothesis of no serial correlation at that lag since the p value of 0.4940 is greater than any common significance level (1%, 5% and 10%). There is no evidence of serial correlation in the residuals of the model.

Table 12. VAR residual serial correlation LM test results

VAR Residual Serial Correlation LM Tests		
Null Hypothesis: no serial correlation at lag order h		
Date: 08/20/14 Time: 15:08		
Sample: 1995M01 2010M12		
Included observations: 188		
Lags	LM-Stat	Prob
1	52.86691	0.0009
2	34.42390	0.0992
3	22.81922	0.5881
4	24.44091	0.4940
5	13.29438	0.9727
6	54.55055	0.0006
7	27.57263	0.3279
8	25.99128	0.4081
9	27.07357	0.3522
10	26.38031	0.3875
11	46.38093	0.0058
12	138.7485	0.0000
Probs from chi-square with 25 df.		

From Table 13, the null of homoscedasticity or no heteroskedasticity is not rejected as the p value of 0.1273 is larger than any common significance level (1%, 5% and 10%).

Table 13. Residual heteroskedasticity test results

VAR Residual Heteroskedasticity Tests: Includes Cross Terms					
Date: 08/20/14 Time: 15:16					
Sample: 1995M01 2010M12					
Included observations: 188					
Joint test:					
Chi-sq	df	Prob.			
2783.892	2700	0.1273			
Individual components:					
Dependent	R-squared	F(180,7)	Prob.	Chi-sq(180)	Prob.
res1*res1	0.990185	3.923199	0.0299	186.1547	0.3610
res2*res2	0.993871	6.305980	0.0074	186.8477	0.3477
res3*res3	0.997127	13.49522	0.0007	187.4598	0.3362
res4*res4	0.988468	3.333316	0.0469	185.8319	0.3672
res5*res5	0.996677	11.66308	0.0010	187.3752	0.3378
res2*res1	0.995141	7.964743	0.0036	187.0865	0.3432
res3*res1	0.984370	2.449254	0.1037	185.0616	0.3823
res3*res2	0.992491	5.139888	0.0137	186.5883	0.3527
res4*res1	0.982295	2.157629	0.1400	184.6715	0.3901
res4*res2	0.986153	2.769556	0.0763	185.3967	0.3757
res4*res3	0.970934	1.299043	0.3866	182.5355	0.4332
res5*res1	0.990993	4.278515	0.0234	186.3066	0.3581
res5*res2	0.992264	4.988211	0.0150	186.5457	0.3535
res5*res3	0.993485	5.929971	0.0089	186.7751	0.3491
res5*res4	0.986177	2.774410	0.0760	185.4012	0.3756

The Normality test relies on the skewness and kurtosis of the estimated residuals. The null hypothesis to be tested is that the residuals are multivariate normal against the alternative that the residuals are not multivariate normal. From Table 14, since the joint p values are all 0.0000 and smaller than any common significance level (1%, 5% and 10%), the null is strongly rejected in favour of the alternative. This is to be expected as stock price series typically have fat tails.

Table 14. VAR residual normality test results

VAR Residual Normality Tests				
Orthogonalization: Cholesky (Lutkepohl)				
Null Hypothesis: residuals are multivariate normal				
Date: 08/22/14 Time: 22:50				
Sample: 1995M01 2010M12				
Included observations: 188				
Component	Skewness	Chi-sq	df	Prob.
1	-0.502552	7.913487	1	0.0049
2	-2.122254	141.1241	1	0.0000
3	-0.623324	12.17402	1	0.0005
4	1.309606	53.73878	1	0.0000
5	-0.483725	7.331685	1	0.0068
Joint		222.2821	5	0.0000
Component	Kurtosis	Chi-sq	df	Prob.
1	3.424616	1.412337	1	0.2347
2	30.83818	6070.552	1	0.0000
3	8.987972	280.8705	1	0.0000
4	13.43198	852.4716	1	0.0000
5	9.784912	360.6077	1	0.0000
Joint		7565.915	5	0.0000
Component	Jarque-Bera	df	Prob.	
1	9.325824	2	0.0094	
2	6211.676	2	0.0000	
3	293.0446	2	0.0000	
4	906.2104	2	0.0000	
5	367.9394	2	0.0000	
Joint	7788.197	10	0.0000	

Although the estimated VAR (4) model does not pass the Normality test, it passes all other necessary diagnostic tests (serial correlation and heteroskedasticity). Therefore, the estimated VAR (4) model is reliable and valid.

5. Conclusion

5.1 Summary

Over the past years, many studies have been conducted on the impact of changing macroeconomic indicators on stock prices with a great focus on developed stock markets. Capital markets in emerging economies like Ghana have not been studied extensively. By employing a VAR model and monthly data from January 1995 to December 2010, this paper attempted to fill the gap by establishing the relationships between stock prices and macroeconomic factors such as the commonly used interest and inflation rates and, economic activity captured by GDP which has never been included in studies focused on Ghana.

5.2 Main Findings and Recommendations

Stock prices depreciate with an increase in global commodity prices and interest rates indicating a negative relationship. On the other hand, stock prices appreciate with an increase in inflation and economic activity indicating a positive relationship. Examining stock market variability on the selected macroeconomic variables also showed that inflation and interest rates respond negatively to changes in asset prices while the stock market itself is not found to be a leading indicator for economic activity. From the variance decomposition, the stock index is least responsive to shocks in economic activity but most responsive to monetary shocks. The interest rate contributes the largest proportions to the forecast error variance in LGSEI, LGDP and LINF, while LGDP accounts for the largest proportion of the forecast error variance in LIR. The interest rate is therefore a key macroeconomic indicator which provides the most information about the relative importance of each shock in affecting the variables in the VAR. The findings imply that investors should pay particular attention to interest rates rather than economic output and global commodity prices as they explain the least proportion of variation in stock prices. In the same vein, Treasury bill rates should be prevented from increasing so as to attract investment in the stock market. Similarly, monetary policy should be aimed at keeping interest rates low to encourage investments by firms. This would potentially increase earnings and profits and boost economic output. Dividends paid would also increase and cause share prices to appreciate resulting in an increase of the performance of the index. A good stock market performance is likely to draw more investors (both domestic and foreign) and firms to the Exchange for business ultimately promoting economic growth and development.

All unit root tests carried out on stock prices on the GSE showed that they follow a random walk. This gives a hint that the stock market exhibits weak-form efficiency. Policy makers therefore need to ensure that information is allowed to disseminate quickly within the economy in order to improve the level of efficiency of the stock market. Policies should be targeted at enhancing disclosure requirements by firms so that all investors are better informed, and also to improve and sustain the financial literacy of the general public.

5.3 Suggestions for Further Research

A possible extension of this study is to account for structural breaks in the data series. Alternative identification schemes for the VAR model is also left to be explored in future research.

References

Achsani, N., & Strohe H. G. (2002). *Stock market returns and macroeconomic factors, evidence from Jakarta stock exchange of Indonesia 1990-2001*. (Universitat Potsdam, Wirtschaftsund Sozialwissenchaftliche Fakulttitat, Discussion Paper).

Adam, A. M., & Tweneboah, G. (2008). *Macroeconomic factors and stock market movement:*

evidence from Ghana. (MRPA Working Paper No. 11256).

Adjasi, C., Biekpe, N., & Osei, K. (2011). Stock prices and exchange rate dynamics in selected African countries: a bivariate analysis. *African Journal of Economic and Management Studies, 2*, 143-164. http://dx.doi.org/10.1108/20400701111165623

African Development Bank. (2014). African Economic Outlook. [Online] Available: http://www.afdb.org/en/countries/west-africa/ghana/ghana-economic-outlook/

Agyire-Tettey K., & Kyereboah-Coleman, A. (2008). Impact of macroeconomic indicators on stock market performance: the case of the Ghana stock exchange. *Journal of Risk Finance, 9*, 365-378. http://dx.doi.org/10.1108/15265940810895025

Ayentimi, D. T., Mensah, A., E, & Naa-Idar, F. (2013).Stock market efficiency of Ghana stock exchange: an objective analysis. *International Journal of Management, Economics and Social Sciences, 2*, 54-75.

Basher, S. A., Haug, A., A., & Sardosky, P. (2012). Oil prices, exchange rates and emerging markets. *Energy Economics, 34*, 227-240. http://dx.doi.org/10.1016/j.eneco.2011.10.005

Benakovic, D., & Posedel, P. (2010). Do macroeconomic factors matter for stock returns? Evidence from estimating a multifactor model on the Croatian market. *Business Systems Research, 1*(1), 1-50. http://dx.doi.org/10.2478/v10305-012-0023-z

Bjørnland, H. C., & Leitemo, K. (2009). Identifying the interdependence between US monetary policy and the stock market. *Journal of Monetary Economics, 56*, 275-282. http://dx.doi.org/10.1016/j.jmoneco.2008.12.001

Chamberlain, A. (2010). How economists convert quarterly data to monthly: cubic spline interpolation. [Online] Available: http://columbiaeconomics.com/2010/01/20/how-economists-convert-quarterly-data-into-monthly-cubic-spline-interpolation/comment-page-1/

Chen, N. F., Roll, R., & Ross, S. (1986). Economic forces and the stock market. *The Journal of Business, 59*, 383-403. http://dx.doi.org/10.1086/296344

Choudry, T. (2001). Inflation and rates of return on stocks: evidence from high inflation countries. *Journal of International Financial Markets, 11*(1), 75-96. http://dx.doi.org/10.1016/S1042-4431(00)00037-8

Clare, A. D., & Thomas, S. H. (1994). Macroeconomic factors, the APT, and the UK stock market. *Journal of Business, Finance and Accounting, 21*, 309-330. http://dx.doi.org/10.1111/j.1468-5957.1994.tb00322.x

Databank. (2004). *African Stock Markets Consolidate Gains*. Accra: Databank.

Dekker, A., Sen, K., & Young, M. R. (2001). Equity market linkages in the Asia Pacific region: a comparison of the orthogonalised and generalised VAR approaches. *Global Finance Journal, 12*(1), 1-33. http://dx.doi.org/10.1016/S1044-0283(01)00025-4

Diacogiannis, G. P. (1986). Arbitrage Pricing Model: a critical examination of its empirical applicability for the London stock exchange. *Journal of Business, Finance and Accounting, 13*, 498-504. http://dx.doi.org/10.1111/j.1468-5957.1986.tb00513.x

Eita, J. H. (2012). Modelling macroeconomic determinants of stock price: evidence from Namibia. *The Journal of Applied Business Research, 28*, 871-884. http://dx.doi.org/10.19030/jabr.v28i5.7230

Enders, W. (2010). *Applied econometric time series* (3rd ed.). Hoboken, NJ: John Wiley & Sons.

Engle R. F., & Granger C. W. J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica, 55*, 251-276. http://dx.doi.org/10.2307/1913236

EViews 8 Users Guide I. (2013). [Online] Available: https://remote.bus.brocku.ca/files/Published_Resources/EViews_8/EViews%208%20Users%20Guide%20I.pdf

EViews 8 Users Guide II. (2013). [Online] Available: https://remote.bus.brocku.ca/files/Published_Resources/EViews_8/EViews%208%20Users%20Guide%20II.pdf

Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance, 25*, 383-417. http://dx.doi.org/10.2307/2325486

Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *American Economic Review, 71*, 545-565.

Fisher, I. (1930). The theory of interest, as determined by impatience to spend income and opportunity to invest it. [Online] Available: http://files.libertyfund.org/files/1416/Fisher_0219.pdf

Gay, R. D. (2008). Effect of macroeconomic variables on stock market returns for four emerging economies: Brazil, Russia, India and China. *International Business & Economics Research Journal, 7*, 1-8.

Geske, R., & Roll, R. (1983). The fiscal and monetary linkage between stock returns and inflation. *The Journal of Finance, 38*(1), 1-33. http://dx.doi.org/10.1111/j.1540-6261.1983.tb03623.x

Ghana Stock Exchange. (2009). GSE Report. [Online] Available: http://www.gse.com.gh

Ghana Stock Exchange. (2010). GSE Report. [Online] Available: http://www.gse.com.gh

Ghana Stock Exchange. (2013). GSE Market Report. [Online] Available: http://www.gse.com.gh

Gjerde, Ø., & Sættem, F. (1999).Causal relations among stock returns and macroeconomic variables in a small, open economy. *Journal of International Financial Markets, Institutions and Money, 9*(1), 61-74. http://dx.doi.org/10.1016/S1042-4431(98)00036-5

Hamao, Y. (1988). An empirical examination of the arbitrage pricing theory: using Japanese data. *Japan and the World Economy, 1*(1), 45-61. http://dx.doi.org/10.1016/0922-1425(88)90005-9

Hondroyiannis, G., & Papapetrou, E. (2001). Macroeconomic influences on the stock market. *Journal of Economics and Finance*, *25*(1), 33-49. http://dx.doi.org/10.1007/BF02759685

Ibrahim, M. H. (2011). Stock market development and macroeconomic performance in Thailand. *Inzinerine Ekonomika-Engineering Economics, 22*, 230-240. http://dx.doi.org/10.5755/j01.ee.22.3.513

Ibrahim, M. H., & Aziz, H. (2003). Macroeconomic variables and the Malaysian equity market: a view through rolling subsamples. *Journal of Economic Studies, 30*(1), 6-27. http://dx.doi.org/10.1108/01443580310455241

Johansen, S. (1991). Estimations and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models. *Econometrica, 59*, 1551-1580. http://dx.doi.org/10.2307/2938278

Kuwornu, J. K. M., & Owusu-Nantwi, V. (2011a). Effect of macroeconomic variables on the Ghanaian stock market returns. *Agris on-line Papers in Economics and Informatics, 4*, 15-26. [Online] Available: http://online.agris.cz/files/2012/agris_on-line_2012_2_kuwornu.pdf

Kuwornu, J. K. M., & Owusu-Nantwi, V. (2011b). Macroeconomic variables and stock market returns: full information maximum likelihood estimation. *Research Journal in Finance and Accounting, 2*, 49-63.

Kwon, C. S., & Shin, T. S. (1999). Co-integration and causality between macroeconomic variables and stock returns. *Global Finance Journal, 10*(1), 71-81. http://dx.doi.org/10.1016/S1044-0283(99)00006-X

Lee, B. S. (1992). Causal relations among stock returns, interest rates, real activity, and inflation. *The Journal of Finance, 47*, 1591-1603. http://dx.doi.org/10.1111/j.1540-6261.1992.tb04673.x

Levine, R., & Zervos S. (1996). Stock market development and long-run growth. *World Bank Economic Review*, *10*, 323-339. http://dx.doi.org/10.1093/wber/10.2.323

Lütkepohl, H. (1991). *New Introduction to Multiple Time Series Analysis*. Berlin: Springer-Verlag. http://dx.doi.org/10.1007/978-3-662-02691-5

Lütkepohl, H., & Kärtzig, M. (2004). *Applied Time Series Econometrics*. New York: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511606885

Maysami, R. C., & Koh, T. S. (2000). A vector error correction model of the Singapore stock market. *International Review of Economics and Finance, 9*(1), 79-96. http://dx.doi.org/10.1016/S1059-0560(99)00042-8

Maysami, R. C., Howe, L. C., & Hamzah, M. A. (2004). Relationship between macroeconomic variables and stock market indices: cointegration evidence from stock exchange of Singapore's all-s sector indices. *Jurnal Pengurusan, 24*, 47-77.

Mensah, J. T., Pomaa-Berko, M., & Adom, P. K. (2012). *Does automation improve stock market efficiency? Evidence from Ghana.* (MPRA Paper No. 43642).

Miller, M. H., & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *The Journal of Business, 34*, 411-433. http://dx.doi.org/10.1086/294442

Mukherjee, T. K., & Naka, A. (1995). Dynamic relations between macroeconomic variables and the Japanese stock market: an application of the vector error correction model. *The Journal of Financial Research, 18,* 223-237. http://dx.doi.org/10.1111/j.1475-6803.1995.tb00563.x

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55,* 703-708. http://dx.doi.org/10.2307/1913610

Nkoro, E., & Uko K., A. (2013). A generalized autoregressive conditional heteroskedasticity model of the impact of macroeconomic factors on stock returns: empirical evidence from the Nigerian stock market. *International Journal of Financial Research, 4,* 38-51. http://dx.doi.org/10.5430/ijfr.v4n4p38

Ntim, C. G. (2012). Why African stock markets should formally harmonise and integrate their operations. *African Review of Economics and Finance, 4*(1), 53-72.

Obben, J., Pech, A., & Shakur, S. (2007). *Analysis of the relationship between the share market performance and exchange rates in New Zealand: a cointegrating VAR approach.* (Working paper). [Online] Available: http://www.business.otago.ac.nz/econ/events/NZESG/Papers/S5_Obben.pdf

Poon, S., & Taylor, S. J. (1991). Macroeconomic factors and the UK stock market. *Journal of Business and Accounting, 18*, 619-636. http://dx.doi.org/10.1111/j.1468-5957.1991.tb00229.x

Priestley, R. (1996). Arbitrage pricing theory, macroeconomic and financial factors and expectations generating processes. *Journal of Banking and Finance, 20*, 869-890. http://dx.doi.org/10.1016/0378-4266(95)00035-6

Ross S. A. (1976). The arbitrage theory of capital pricing. *Journal of Economic Theory, 13,* 341-360. http://dx.doi.org/10.1016/0022-0531(76)90046-6

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica, 48*(1), 1-48. http://dx.doi.org/10.2307/1912017

Sims, C. A., Stock, J. H., & Watson, M. W. (1990). Inference in linear time series models with some unit roots. *Econometrica, 58*(1), 113-144. http://dx.doi.org/10.2307/2938337

Soyode (1993).Nigerian capital market and macroeconomic variables: an empirical analysis. *Nigerian Journal of Monetary Economics, 3.*

US Energy Information Administration, EIA. (2010). Short-term energy outlook model documentation: macro bridge procedure to update regional macroeconomic forecasts with national macroeconomic forecasts. [Online] Available: http://www.eia.gov/forecasts/steo/documentation/macro_bridge.pdf

Wendel J. (1992). Estimating VAR models under nonstationarity and cointegration: alternative approaches for forecasting cattle prices. *Applied Economics*, *24*, 207-217. http://dx.doi.org/10.1080/00036849200000119

Wongbangpo, P., & Sharma, S. C. (2002). Stock market and macroeconomic fundamental dynamic interactions: ASEAN-5 countries. *Journal of Asian Economics*, *13*(1), 27-51. http://dx.doi.org/10.1016/S1049-0078(01)00111-7

World Bank. (2014). World Development Indicators. Retrieved from World Development Indicators Online (WDI) database.

Copyright Disclaimer