UNIVERSITY OF THE WITWATERSRAND

THE STOCK MARKET AS A LEADING INDICATOR OF ECONOMIC ACTIVITY

TIME-SERIES EVIDENCE FROM SOUTH AFRICA

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Declaration

I, Ayesha Bibi Sayed, declare that this research report is my own unaided work. It is submitted in partial fulfilment of the requirements for the degree of Master of Commerce in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at this or any other university.

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ABSTRACT

Several studies have assessed the forward-looking characteristic of share prices and confirmed their resultant capability as leading indicators of economic activity, especially in advanced economies. Contention however exists when evaluating the role of stock markets as leading indicators for less developed countries. This study examines the validity of the stock market as a leading indicator of economic activity in South Africa using quarterly time-series data for the period January 1992 to June 2014. Causality and cointegration between the JSE All Share Index against Real GDP and Real Industrial Production is evaluated by employing Granger-causality tests and the Johansen cointegration procedure. The empirical investigation indicates that unidirectional causality exists between the nominal and real stock indices and economic activity in South Africa, and confirms a long-run relationship between the JSE and GDP and Industrial Production. Therefore, similar to the study by Auret and Golding (2012), in a South African context, the stock market is in fact a leading indicator of economic activity.

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Definition of Terms and Abbreviations

ARMA: Autoregressive moving-average models that describe the dynamics of an individual time-series in terms of its own past values and current lagged disturbances.

CPI: In South Africa, the Consumer Price Index measures the changes in the prices paid by consumers for a basket of goods and services.

Cointegration: Variables are said to be cointegrated of order one if a combination of the non-stationary variables yields a stationary time-series.

GDP: The Gross Domestic Product measures the national income and output for a country's economy. The GDP is equal to the total expenditures for all final goods and services produced within the country in a stipulated period of time.

Industrial Production: In South Africa, industrial production measures the output of businesses integrated in the manufacturing sector of the economy.

IRF: Impulse response functions utilise the estimated VAR's as a system and allow one study the interaction between variables within a VAR. this involves tracing the marginal effect of a shock in one variable and its effect on another.

Kurtosis: measures the peak or flatness of the distribution of the series.

Non-stationarity: A property common in many macroeconomic and financial time-series, where a variable has no clear tendency to return to a constant value or linear trend.

Procyclical: Any economic quantity that is positively correlated with the overall state of the economy is said to by "procyclical".

Skewness: is a measure of asymmetry of the distribution of the series around its mean.

VAR: Vector autoregressive models are multivariate time-series models that employ both lagged independent as well as dependent variables in explaining time-series data.

VDCs: Also known as the forecast error variance decomposition: allows one to decompose the variation in a forecasted variable due to a shock in another variable.

VECM: Vector Error Correction Model allows for the estimation of long term relationships in non-stationary data based on cointegration between the variables in a VAR.

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1 INTRODUCTION

1.1 Background

There is widespread agreement that the stock market contains information about real economic activity and as such that the stock market is a leading indicator for economic growth. Fama (1981) hypothesizes that the negative correlation between stock returns and inflation is not a causal relation, but instead a proxy for a positive relation between stock returns and real activity. Fama (1981) not only confirms that share returns are highly correlated with future real economic activity, but also finds that industrial production is the only real variable indicating a strong relation with stock returns.

Investors have a vested interest in accurately predicting the future real economy as it is believed that large decreases in stock prices are reflective of a future recession, whereas large increases in stock prices suggest future economic growth. Since a firm's profits are directly linked to the behaviour of the real economy, share prices will be affected by expectations about the future economy as well. The impact of economic fundamentals on share prices is further strengthened by reviewing the Efficient Market Hypothesis (henceforth EMH) which was pioneered by Fama (1970). EMH defines an efficient capital market as a market wherein security prices fully reflect all available information in a rapid and unbiased fashion. Efficient capital markets provide unbiased estimates of a share's underlying value and as such fully reflects both the expectations of the economy as well as a security's intrinsic value at any given point in time. The condition of efficient capital markets must hold for shares prices to exhibit their forward-looking ability, and it is this predictive ability that equips the stock market as a leading indicator. According to Castillo-Ponce, Rodríguez-Espinosa and Gaytan-Alfaro (2015), validation of the EMH implies that the stock market series are non-stationary processes and this not only affirms the possibility that the stock market may share common trends with macroeconomic variables, but also allows for the use of cointegration analyses.

According to Stock and Watson (2003) leading indicators tend to perform better than benchmark autoregressive models in forecasting the future path of economic activity. Moolman and Jordan (2005) claim however that in order to perform well as leading indicators, time-series must have a stable relationship with the business cycle, needs to be published in a timely manner , must be final data without any revisions and should be available on a frequent basis.

According to Ikoku (2010) even though stock prices meet these requirements, one needs to examine their relationship to the business cycle or aggregate economic activity in a rigorous manner in order to establish their suitability as a leading indicator.

1.2 Problem Statement

This objective of this study is to measure the relevant information contained in the stock market for forecasting real economic activity. Its primary purpose is to investigate whether or not share prices are leading indicators of economic activity in South Africa, and to explore the causal relationships among nominal and real stock indices, GDP and the Index of Industrial Production in South Africa both in the long-run and short-run.

1.3 Research question

The core research question of this study seeks to test if there is a causal and statistically significant relationship between the stock market (as proxied by the JSE All Share Index) and economic activity (as proxied by GDP and Industrial Production), in both the long-run and short-run. Therefore, the null hypothesis is that the JSE is not a leading indicator of economic activity in South Africa; while the alternative hypothesis is that the JSE is a leading indicator of economic activity in South Africa.

H0: $\alpha = 0$;

HA: $\alpha < 0$

1.4 Importance and benefits of the study

Conducting this study will add to the body of knowledge both in the fields of economics as well as in finance. If causal relationships between the stock market and economic activity can be identified and if such relationships can be explored this will aid in the understanding of how economic growth as well as the performance of the stock market can be anticipated and assessed, consequently impacting financial and economic policies.

Empirical studies that test the relationship between stock returns and economic growth have mainly been confined to advanced economies and developed regions. As South Africa is one of the leading emerging economies in the global market, it is imperative to test not only the relationship between stock prices and economic growth in South Africa, but the direction of this relationship as well.

Similar to the methodology employed by Ikoku (2010) this study evaluates the stock market as a leading indicator of economic activity by empirically testing for causality and cointegration. The sample period of the study is from January 1992 to June 2014 and time-series data is collected on a quarterly basis. Causality is evaluated by utilising the test proposed by Granger (1969) in order to ascertain if changes in GDP and Industrial Production are Granger-caused by the stock market. Cointegration is assessed by the use of the Johansen cointegration procedure. In addition, impulse response functions (IRFs) and Variance Decompositions (VDCs) are computed to additionally examine the short-run dynamics among the variables.

The results of the tests reveal that the stock market does in fact Granger-cause economic activity in South Africa; while no evidence of reverse causality is offered. The Cointegration analysis is also successful in illustrating that a long-run equilibrium relationship exists between the stock market and economic activity in South Africa.

This study is organised as follows, Section 2 presents a review of the theoretical literature and empirical evidence on the co-dependent relationship between financial development and economic growth, as well as on stock prices as leading indicators both in advanced and in emerging economies. Section 3 discusses the sample period and defines the variables to be used in the study. Section 4 discusses the theoretical bases for each of the econometric and statistical tests employed as well as the corresponding results. Section 5 concludes.

2 LITERATURE REVIEW

2.1 Financial development and growth

The significance of the relationship between financial development and economic growth has been widely documented by academics who differ in their opinion in this regard. Schumpeter (1934) painted financial intermediaries as playing a significant role in output growth by channelling savings to the most productive investments. Robinson (1952) however argued that financial development simply follows economic growth which is generated elsewhere. Patrick

(1966) characterised these two alternating relationships as the supply-leading and demand-following hypotheses.

Goldsmith (1969) has been credited with being a pioneer in examining the relationship between stock returns and economic growth. He sought to assess whether financial structure and development exerted a causal influence on economic growth. He was successful in documenting a positive correlation between financial development and the level of economic activity in thirty-five countries over the period 1860 to 1963.

Substantial progress has been made in extending Goldsmith's (1969) analysis of the association between financial development and economic growth. Academics have provided additional empirical evidence on the finance-growth nexus with firm-level, industry-level and cross-country studies all suggesting that the level of financial development exerts a large, positive impact on economic growth. Specifically, firm-level studies (Dermigue-Kunt and Maksimovic 1998), industry level studies (Rajan and Zingales 1998; Wurgler 2000), cross-country studies (King and Levine 1993a, b; Levine and Zervos 1998), and pooled cross-country, time-series studies (Beck, Levine, and Loayza 2000) found that financial development is positively related to economic growth, and that this relationship is not due only to simultaneity bias. Simultaneity bias occurs in econometrics when a variable on the right-hand side of a causal inferential model equation and a variable on the left-hand of the same model equation influence each other at the same time. As macroeconomic variables have a strong contemporaneous relationship with the stock market, simultaneity bias is a common problem encountered in studies that seek to simultaneously analyse the financial development and economic growth nexus.

Results from emerging economies however have been mixed. Harris (1997) argues that the relationship between stock market development and economic growth is at best weak. From a sample of 49 countries (both developed and developing) from 1980 to 1991, he found no evidence to support the notion that the stock market affects economic growth.

El-Wassal (2005) examined the relationship between stock market growth and economic growth for 12 emerging economies between 1980 and 2000. Using monthly data, both the Johansen cointegration and Granger-causality tests were employed. The results revealed a bidirectional relationship between stock market growth indicators and real economic activity for most of the countries examined. El-Wassal (2005) also showed that the emerging stock markets capitalisation had increased 32 times compared against developed stock market's capitalisation which only increased 11 times between 1980 and 2000. This revealed that the expansion of emerging stock market capitalisation was almost three times larger than the expansion of developed stock markets.

Within a unit root and cointegration framework, Ajit and Wang (2013) investigated the impact of stock market development on economic growth in China using quarterly data from 1996 to 2011. Their results indicated a negative relationship between real stock market development and real GDP growth in China in the long run and short run, supporting the argument that the stock market development in developing countries generally does not contribute positively to economic growth.

Recent theoretical literature has sparked an additional debate concerned with analysing the relative advantages of a bank- versus market-based financial system. Market-based systems are found to behave differently to bank-based ones since the concentration of either banks or financial markets affects economic outcomes through different channels. Market-based systems are seen to provide better cross-sectional risk sharing (Allen and Gale, 1997), enhance efficiency by not committing to unprofitable projects (Dewatripont and Maskin, 1995) and are better at financing new technologies in the presence of diversity of opinion (Allen and Gale, 1999). Bank-based systems, on the other hand, are more effective in weak legal systems with poor institutional infrastructure (Rajan and Zingales, 1998), when firms are more prone to post-lending moral hazard (Boot and Thakor, 1997), and when the economy is dominated by smaller firms (Petersen and Rajan, 1995), or at early stages of development (Chakraborty and Ray, 2006).

Arestis, Demetriades and Luintel (2001) investigated quarterly data in a time-series setting for Germany, USA, Japan, England and France in order to examine the relationship between stock market development and economic growth, while controlling for the effects of the banking system and stock market volatility. Their results indicated that although both banks and stock markets may be able to promote economic growth, the effects of the banking system are stronger. Specifically, their empirical results showed that while stock markets may be able to contribute to long-term output growth, their influence is but a fraction of that asserted by the banking system, concluding that bank-based financial systems may be more capable in promoting long-term growth than their capital-market-based counterparts.

Similarly, Peia and Rozbach (2013) differentiated between stock market and banking sector development in their analysis of the empirical relationship between financial and economic development. Using a time-series analysis, they studied the cointegration and causality between finance and growth for 26 countries. The authors found that the causality patterns were dependent on whether a country's financial development stemmed from the stock market or the banking sector. Their empirical results revealed that stock market development tends to cause growth, while a reverse or bi-directional causality was present between banking sector development and output growth. Their paper brought to light evidence that causality patterns differ between market-based and bank-based economies suggesting that financial structure influences the causal direction between financial and economic development.

From an emerging economies perspective, Ndako (2010) examined the causal relationship between stock markets, banks and economic growth in South Africa using quarterly time-series data over the period 1983 to 2007. His paper used Vector Error Correction Model (VECM) based causality tests to establish a link between financial development (represented by both banking and stock market systems) and economic growth. The empirical investigation revealed that in the long-run evidence existed of bidirectional causality between financial development and economic growth using the banking system; while unidirectional causality existed between economic growth and stock markets. In addition, Ndako (2010) computed Impulse Response Functions (IRFs) and Variance Decompositions (VDCs) to examine the short-run dynamics among variables in the system. The IRFs and VDCs indicated that financial development had a short-run impact on economic growth at the immediate year of initial shocks, while the VDCs showed that all the indicators for financial development contained some useful information in predicting the future path of economic growth. Finally Ndako applied Structural Vector Auto regressions (SVAR) to examine the link between financial development and economic growth. The SVAR results revealed negligible evidence that finance promoted economic growth in the long-run.

2.2 Theoretical basis for stock prices as leading indicators of economic activity

Several theories have been put forward that support the role of stock prices as leading indicators of economic activity. Ikoku (2010) outlines four of these as: stock prices as aggregators of expectations, the cost of raising equity capital, the financial accelerator, and the wealth effect.

The standard valuation model defines the value of a share of common stock as the present value of expected future dividends. The Gordon (1959) constant growth model illustrates the relationship between expected dividends, the required return on equities, the anticipated growth rate of earnings and the current price of common stocks. According to Chen, Roll and Ross (1986) any variable that influences either expected dividends or the growth rate of dividends is instrumental in explaining stock prices. Burmeister and Wall (1986) further assert that the level of current dividends is related to measures of the magnitude of current earnings and broad measures of economic output. Therefore, if stock prices depend on expected dividends, and dividends are influenced by the profitability of firms, stock prices should embody expectations held by investors regarding the level of economic activity. This forward-looking characteristic of stock markets is what supports stock prices as leading indicators. Shares prices should decline if investors anticipate a downturn in the economy and rise if acceleration in economic activity is expected instead. According to Stock and Watson (2003) share and other asset prices are leading indicators of economic activity because they are forward-looking economic variables.

An important concept to consider however is how investors form their expectations. Comincioli and Wesleyan (1996) make reference to the adaptive expectations model and the rational expectations model in explaining how investor expectations may be formed. Adaptive expectation models suggest that expectations are developed through past experiences; whereas rational expectation models pose that expectations are formed using all available current information. These models assume to some extent that expectations arise out of experience or historical data. A shift in recent experience then can cause investors to alter their expectations about the future real economy which subsequently causes them to bid the prices of stocks up or down.

According to Pearce (1983) viewing stock prices as aggregators of expectations emphasizes psychological elements. In this context stock prices are not determined by traditional models but instead they move with the general level of optimism or pessimism or what Keynes (1936) calls “spirit animals”. Stock prices begin to rise when individuals believe that the economy is improving and are thus willing to make financial investments in risky assets like common stocks. In this case it is the perceived state of confidence rather than a forecast of higher corporate earnings that moves share prices. If the optimism and pessimism is unfounded then stock prices will be poor leading indicators of economic activity.

According to Maio and Philip (2013) the stock market should provide sophisticated information about the economy since share prices represent the sum of expected future cash flows discounted at the risk-adjusted discount rate. The reasons are two-fold. Firstly, equity earnings and cash flows are naturally correlated with economic activity and the business cycle. Secondly, equity discount rates, which account for equity risk premia, are related to systematic common risk factors which are affected by macroeconomic variables. Therefore, even if one assumes constant discount rates or discount rates uncorrelated with macro variables, current stock prices should be related to future economic activity through the cash-flow channel.

The optimal capital structure of a company usually involves a mix of debt and equity, making the cost of equity capital a significant portion of a firm’s weighted average cost of capital. Given the exceedingly high cost of raising external equity, firms may be more enthusiastic to issue equity when stock prices are higher (Ritter, 1991). If a lower cost of equity reduces the weighted average cost of capital and makes additional capital projects more financially feasible, a positive relationship could develop between stock prices and subsequent economic activity (Baker and Wurglar, 2001). Therefore, the cost of raising equity capital can be suggested as a theoretical basis for the stock market leading economic growth.

The financial accelerator theory is supported by studies by Fazzari, Hubbard and Peterson (1988) and Bernanke, Gertler and Gilchrist (1996) which confirm that rising stock prices lead to an improvement in the balance sheet of firms and households which in turn improves their creditworthiness. The increase in creditworthiness reduces borrowing costs and increases the borrowing capacity of firms and households, stimulating investment spending and current consumption. According to Bernanke *et al.* (1996) the financial accelerator theory suggests that borrowers prone to higher agency costs in credit markets will be burdened even more during economic downturns due to flights to quality, and that this reduction in spending will further worsen the shocks in recessions.

Lastly, the wealth effect theory is explored. The wealth effect is a behavioural economic theory which posits that consumer spending increases significantly when overall portfolio performance is high (Darby, 1987). During a bull market, portfolio values rise, causing portfolio holders to perceive themselves as more affluent and as a result increase their spending. The wealth effect operates under the consumption function, where households consume not only out of earned income but also as a result of perceived increases in the value of their assets, including real estate and equity. According to Janor, Halid and Abdur Rahman (2005) the wealth effect contends that stock prices lead economic activity by either stimulating or failing to stimulate the consumption pattern of investors that will later on influence demand and production of the economy. Otoo (1999) suggests that increasing stock market wealth seems to improve consumer sentiment while raising expectations of higher incomes in the future. According to Ikoku (2010) the operation of the wealth effect was vastly transparent in the United States prior to the global financial crisis with households making use of their rising home values to fund consumption spending. The importance of the wealth effect in determining the role of stock prices as leading indicators however depends crucially on the extent of stock ownership in a country (Paiella, 2007). Empirical evidence favouring the wealth effect in the US outweighs those in several European nations with lower stock-ownership rates (Simone, 2009).

2.3 Empirical evidence on stock prices as leading indicators from advanced economies

Several studies in developed countries have found empirical evidence in favour of stock prices being a reliable indicator of economic activity. Individual indicators were first compiled into a composite index in 1938 by Mitchell and Burns. The variables were chosen to maximise the predictability of the index using econometric procedures and amongst the variables included was the Dow Jones composite index of stock prices as a leading indicator for the US economy. This composite index is still widely accepted today as a guide to predicting future economic activity.

Fama (1981) found that stock prices led all real variables when he examined monthly, quarterly and annual US data over the period 1953 to 1987. He found that there was a negative association between stock returns and inflation and that this negative correlation existed due to the association between inflation and future output. Fama used money-demand theory to demonstrate a strong negative relation between expected inflation and anticipated real activity. Stock returns were shown to be positively related to future real variables. Consequently it is argued that the negative relation between stocks returns and expected inflation is simply a proxy for the positive relation between stock returns and future real variables.

The study by Pearce (1983) also found support in favour of the stock market as an indicator of economic growth. Over the period 1955 to 1983 Pearce analysed quarterly data in Canada, France, Germany, the UK and the US and found that stock prices could lead the direction of the economy. Specifically, he found that stock prices tend to rise midway through a recession.

Huang and Kracaw (1984) examined US quarterly data for the period 1962 to 1978 and found support of the "lagged information hypothesis" as stock prices led GDP by four quarters. Specifically, the results of their tests indicated that changes in the log of real GNP and unemployment rate are Granger-caused by the variation in stock market returns. This result can be interpreted as being supportive of the notion that the arrival of information relevant to production decisions impacts real output and employment gradually over time.

Using a multivariate vector-autoregression (VAR) approach, Lee (1992) investigated causal relations and dynamic interactions among asset returns, real activity and inflation in the post-war United States over the period 1947 to 1987 using monthly data. His study found that share prices Granger-caused industrial production, revealing that share returns help explain real activity Granger-causally.

In their paper, Comincioli and Wesleyan (1996) used formal tests of causality developed by Granger (1969) on quarterly US data for the period 1970 to 1994 to investigate the relationship between the growth rate in stock prices and the growth rate in the economy. Their results indicated a causal relationship between the stock market and the economy confirming that the stock market does help predict the future economy. They found that while stock prices Granger-caused economic activity, no reverse causality was observed.

In her paper on consumer sentiment and stock prices, Otoo (1999) made use of a survey using monthly US data over the period 1980 to 1999 to establish whether an increase in stock prices raised aggregate sentiment because people were wealthier or because movements in stock prices were viewed as an indication of future economic activity and potential labour income growth. Her results were found to be consistent with the view that investors use movements in equity prices as a leading indicator.

Stock and Watson (2003) assessed the usefulness of asset prices as predictors of inflation and output growth for seven countries by analysing the information content of asset prices and other leading indicators. Their results revealed instability in the relationship between stock returns and economic activity. The authors also found that the predictive content of stock returns for future economic activity was also contained in other financial variables such as interest rate spreads.

In his US-based study, Foresti (2007) carried out a Granger-causality analysis between stock market prices and economic growth in order to assess whether there was any potential predictive power between them. His results confirmed that the stock market can be used to predict economic growth, however the reverse is not true, and i.e. growth was not found to be a good indicator for predicting future stock market outcomes.

Maio and Philip (2013) conducted a comprehensive analysis of the forecasting role of stock market indicators for macroeconomic variables. The authors estimated macro factors mainly related to aggregate output, inflation and the housing sector over the period 1964 to 2010. As equity indicators the authors used the log dividend-to-price ratio, log dividend-payout ratio, stock-bond yield gap, stock market variance, stock return dispersion and the value spread. In addition, they used equity risk factors commonly employed in the cross-sectional asset pricing literature—the size, value, and momentum factors from Fama and French (1993) and Carhart (1997), and the liquidity factor used in Pastor and Stambaugh (2003). Their results showed that the contribution of the equity variables in predicting the macro factors increased with the forecasting horizon and was therefore especially relevant at long horizons. The yield gap, the value factor, and especially the dividend-payout ratio were found to be relevant forecasters of future output. The most successful variable in forecasting inflation however was the dividend payout-ratio.

Krchniva (2013) investigated the relationship between stock markets and the economic growth of several developed countries. She used seasonally adjusted quarterly time-series data for seven countries over the period 2000 to 2012. Stock markets were represented by the stock indices of the United States, Japan, Germany, Poland, Hungary, the Czech Republic and the Euro Area. The economic growth of selected countries was reflected by GDP at constant prices. With the use of correlation analysis and Granger-causality tests the author's empirical results supported the contention that stock markets provide forecast ability for real economic activity confirming that stock markets can be used as a predictor of economic efficiency.

Castillo-Ponce, Rodríguez-Espinosa and Gaytan-Alfaro (2015) evaluated the association between stock market development and the aggregate economy for the long-run and short-run for the case of Mexico over the period 1993 to 2011. They considered three different indicators for the Mexican Stock Exchange (MSE) to illustrate the development or deepening of the stock market: stock price index (IPC), value of stocks (Value) and the level of operations (operations). In addition, they constructed two measures of economic activity by dividing Value and Operations by GDP. This transformation was done with the purpose of capturing stock market liquidity relative to the size of the economy. Their empirical analysis revealed that stock market indicators, including the price index, share a common trend with real GDP. Improvements in stock market activity were found to be associated with increases in economic activity, while declines in stock market activity were associated with decreases.

2.4 Empirical evidence on stock prices as leading indicators from emerging economies

Leading indicator studies of emerging markets are found to be less common than studies in advanced economies. Ikoku (2010) suggests that this inadequacy could be attributable to data constraints as quarterly GDP surveys have only recently become customary for less developed nations. He found that that among emerging economies, stock prices tend to become significant leading indicators as the economy develops and financial markets become larger in relation to

GDP. Ikoku also suggested that the focus in leading indicator studies centres around the information content of stock prices in terms of their ability to help predict the direction of economic activity in the near future, and not only on the long-term relationship between financial development and economic growth.

Using quarterly data over the period 1975 to 1991, Leigh (1997) examined the efficiency of the Singapore Stock Exchange and the relationship between the stock market and the overall economy. Granger-causality tests based on the efficiency test results indicated that developments in the stock market appeared to be systematically related to the overall economy in Singapore and could therefore serve as a leading indicator of its behaviour.

Jefferis, Okeahalam and Matome (2001) examined quarterly data for Botswana, South Africa and Zimbabwe to study international stock market linkages in Southern Africa between 1985 and 1996 and found stock prices to be cointegrated with GDP, further supporting stock prices as a leading indicator of economic growth.

According to Mauro (2003) the stock market should be taken into account to forecast output in both developed and developing countries. He also found that this link is stronger for countries with a high market capitalisation to GDP ratio, a large number of listed domestic companies and initial public offerings and English origin of the regulations governing the stock market. His study revealed that the relationship between output growth and lagged stock returns in several countries was fairly significant. In addition, his results confirmed that stock prices in all the nations he examined (Argentina, Chile, Greece, India, Mexico, Korea, Thailand and Zimbabwe) save for India, led GDP for up to four quarters.

In his assessment of monthly data in several Asian markets, Amadja (2005) found that stock prices Granger-caused GDP in Singapore and Thailand while no causality was found in Malaysia and the Philippines. Janor, Halid and Abdul Rahman (2005) also examined the stock market as a predictor of economic activity in Malaysia over the period 1980 to 2004. Their Johansen Cointegration tests as well as their Variance Decompositions confirmed that the stock market can lead changes to economic activity. Additional support in the Asian sphere was put forward by Mun, Siong and Thing (2008) who after analysing annual data over the period 1977 and 2006 found evidence of stock prices Granger-causing GDP in Malaysia, with a lag of up to two years.

Bahadur and Neupane (2006) examined the relationship between the stock market and economic growth in Nepal based on time-series data for the period 1988 to 2005. Using Granger-causality tests their study found empirical evidence of long-run integration and causality of macroeconomic variables and stock market indicators even in a small capital market such as Nepal. The causality had been observed only in real terms but not in nominal variables, depicting that the stock market plays a significant role in determining economic growth. In addition this causality was evident with a lag of 3 to 4 years.

Basdas and Soytas (2009) investigated whether stock returns could trigger economic growth. Their paper not only evaluated the bi-variate relationship between stock returns and economic growth but also accounted for the interest rates and inflation in Turkey between 1997 and 2008. Growth, stock returns and interest rates were transformed into real terms and an unrestricted VAR model was developed. Granger-causality tests were applied to test if innovations in real stock returns could impact real activity and/or interest rates, and in return, if innovations in real growth and/or real interest rates caused changes in stock markets. Empirical results showed that over the study's period causality ran from stock returns to real growth and from interest rates to real growth, while none of the other variables had significant causality test results. The most interesting finding was that empirical results for the period 2002 to 2008 (post the global financial crisis) indicated that the link between real growth and real stock returns had disappeared. The authors attributed this result to the increasing foreign share in the Istanbul Stock Exchange which they argued weakened the link between the stock market and economic growth.

Using quarterly data from 1984 to 2008, Ikoku (2010) examined the causal relationships among stock prices, real GDP and the index of industrial production in Nigeria. The purpose of his paper was to determine whether or not stock prices contained information which could be used to improve predictions of economic activity in Nigeria. Granger-causality tests indicated that the All Share Index of the Nigerian Stock Exchange was a leading indicator of real GDP but had no relationship with the Index of Industrial Production. Furthermore, no causality was found between GDP and the Index of Industrial Production. Johansen cointegration tests also supported a long-run equilibrium relationship between nominal and real stock prices and real GDP in Nigeria.

Paramati and Gupta (2011) investigated empirically the causal nexus between stock market performance and economic growth in India while also examining the short-run and long-run dynamics between them. This was the first study to undertake both the exchanges in India (Bombay Stock Exchange and New Delhi Stock Exchange) and growth variables (GDP and Index of Industrial Production). Their empirical analysis was conducted on both monthly and quarterly series for the time period April 1996 to March 2009. Results of their study provided evidence in favour of the demand-following hypothesis in the short-run. Findings in the study also suggested that economic growth has been playing an important role in determining stock price movements and furthermore that economic growth was also more likely to stimulate and promote stock market performance by adopting appropriate reallocation of resources.

In their analysis of the Peruvian stock market and economy, Lahura and Vega (2014) went beyond the study of empirical causality and attempted to identify the possible causal effects of stock markets on real economic activity. Using annual time-series data for the period 1965 to 2013 they estimated vector autoregressive models (VARs) and identified stock market shocks using long-run restrictions. The historical evolution of the Peruvian stock market prompted the authors to perform their empirical analyses over three sub-samples based on well-known important political and economic events: 1965-1990 covered the initial development of stock markets in Peru, political and economic unstable episodes, and a period of rising inflation that resulted in a hyperinflation era between 1988 and 1990; 1991-2013 which covered the period of structural macroeconomic reforms, macroeconomic stability and low inflation; and 1965-2013 which covered the full sample. The authors used GDP per capita and three financial indicators associated with stock markets, namely, value traded/GDP, stock market capitalisation/GDP and turnover ratio. Their results unveiled that the dynamic relationship between real GDP per capita and the stock market in Peru had altered over time and that the stock market shocks had a short-run causal effect on real GDP per capita only after 1991. In particular, a one-standard deviation shock to value traded/GDP, turnover and capitalisation/GDP increased real GDP per capita after one year by 1%, 1.40% and 1.0% respectively. Their results also revealed that the contribution of stock market shocks to output growth had been small. In conclusion, the authors suggested that policy actions aimed at further developing the Peruvian stock market, for example by promoting a higher participation of both lenders and borrowers, would have a positive impact on the dynamics of economic growth.

The first significant study of this nature to be conducted in a South African context is credited to Auret and Golding (2012), who investigated the information content of equity prices on the Johannesburg Stock Exchange (JSE). The primary focus of their analysis was on the forecasting power of stock prices for real output growth and the overall economy, through the proxy of GDP and industrial production. Their sample period ran from December 1969 to September 2010 and both quarterly and annual data was used. An autoregressive model was used to test whether the cycle of real stock prices could be a useful indicator of the cycle of real economic activity. Their paper found conclusive evidence that the cycle of real stock prices led both the cycle of real GDP and the cycle of real industrial production in South Africa.

2.5 Empirical evidence negating stock prices as leading indicators

Several studies however have contradicted the stock market as a leading economic indicator. Pearce (1983) criticised the stock market for having generated "false signals" regarding the economy. The 1987 stock market crash for instance was an example in which stock prices falsely predicted the direction of the economy. Instead of entering into a recession which many analysts anticipated, the US economy continued to grow until the early 1990s. Barro (1990) contends however that although the stock market did not predict accurately following the crash of October 1987, the errors were not statistically significant. In addition a study by Peek and Rosenberg (1989) indicated that between 1955 and 1986, out of eleven cases in which the S&P 500 declined by more than 7 percent (the smallest pre-recession decline in the S&P500), only six were followed by recessions. Furthermore, Barro (1989) found that stock prices predicted three recessions for the years 1963, 1967 and 1978 that did not materialize.

Burgstaller (2002) examined whether or not stock markets were a leading indicator for real macroeconomic developments in Austria, Japan and the US. He examined monthly data over the period 1976 to 2002. In his study, domestic real activity was represented by industrial production and retail sales. The financial and international variables were the three month interest rate, the effective exchange rate, the inflation rate, an index reflecting oil price developments, a stock price index and industrial production. Granger-causality tests, impulse response functions and variance decompositions led to the conclusion that stock returns did not have predictive content for changes in growth rates of industrial production, gross fixed capital formation or consumption.

Guo (2002) shed further light on why the predictive power of stock market returns on future economic activities might be severely limited. Using quarterly data between 1953 and 2000, Guo (2002) analysed the predictive power of excess stock market returns of the S&P 500 for economic activities by decomposing it into three parts: expected return, shocks to expected future return, and shocks to the expected future dividend. He found that stock prices were not sensitive to dividend news and therefore that the dividend component had little predictive power for GDP and its components. In contrast, he found that the expected return and shocks to expected future returns were strong predictors for economic activities; however their predictive patterns differed substantially, especially over long horizons.

Gan, Lee, Yong and Zhang (2006) examined the New Zealand stock index based on several macroeconomic variables and a sample period covering 1990 to 2003. They found lack of support for the argument that the stock index was a leading indicator of other macroeconomic factors. Their paper showed that most of the variance in the stock index could be explained by the lagged stock index, the interest rates, the money supply and real GDP; whereas the exchange rate, the inflation rate and domestic retail oil price played minor roles after two years.

From an emerging markets perspective, Men and Li (2006) analysed the relationship between both the Shenzen Securities Exchange and Shanghai Securities Exchange against the performance of the Chinese national economy over the period 1995 to 2005. Their empirical results employed cointegration and Granger-causality analyses and negated any long-run equilibrium relationship between GDP and Chinese stock markets. Specifically, there was no Granger-causality relationship between the stock index yield and the GDP growth rate, and the cointegration tests reiterated no link between the Chinese stock exchanges and Chinese GDP. The authors put forward several possible explanations for their results. They argued that the composition of Chinese GDP was inconsistent with the stock market's structure as the private sector instead played a pivotal role in contributing to China's GDP growth rate. They explained further that most of the listed companies in China were state owned enterprises (SOEs) and their reason for listing was simply to reduce their financial distress. Therefore the stock market performance of these listed companies failed to reflect their real economic competency and consequently the stock market indices failed to reflect the true macro-economic outlook of the country. Lastly, they argued that as most Chinese financing was supported by commercial bank loans, this dominant commercial banking industry had weakened the stock market's role. This unbalanced financial structure could therefore be a possible explanation for the lack of influence the stock market had as a leading indicator for economic activity in China.

From the above literature review it can be seen that financial development and economic growth in a country are interrelated. The ability of a stock market to exert a causal influence and significant impact on the aggregate economy is also dependent on the level of development of a country's financial system. Several theories supporting the stock market as a leading indicator of economic activity was also proposed. These illustrated the role of share prices to optimally allocate resources in the economy, reflect expectations and sentiment, as well as the information content of share prices and their ability to be forward-looking and predictive for economies of both advanced and emerging countries. Empirical evidence refuting the stock market as a leading indicator was also presented. These studies often found a lack of continued significant causality between the stock market variables and the macroeconomic variables. This was often attributed to the imbalance and lack of cohesion between financial development and the economy, as well as the ability to explain share price variation predominantly by the share prices' own lagged values. Common to all the empirical studies reviewed however was the use of econometric models in their analyses. Econometric models are equipped to analyse the time-series data found in these studies and to correctly ascertain if significant relationships, free from bias and statistical errors, do indeed exist between the stock market and the economy. In this light the methodology employed in this study will be in line with the above empirical investigations reviewed; and econometric tests in the form of Granger-causality and Johansen cointegration will be used to investigate the information content of share prices, its forecasting ability, and the direction and magnitude of these predictions.

3 DATA AND MEASUREMENT

Quarterly data for the period January 1992 to June 2014 is used for this study. Consistent with other studies conducted on the JSE, the JSE ALSI is used as the market proxy. The JSE was established in 1887 and is currently the largest stock exchange in Africa. The FTSE/JSE Africa All Shares Index is a market capitalisation-weighted index. According to Bloomberg, companies included in this index make up the top 99% of the total pre free-float market capitalisation of all listed companies on the Johannesburg Stock Exchange. The performance of the JSE has been robust; its market capitalisation is one of the largest in emerging markets reflecting South Africa's inclusion in the major investible global stock market indices (Ndako, 2010). The ALSI is the only stock index with the coverage and vintage necessary to examine the role of the stock market as a leading indicator of economic activity in South Africa. Nominal values of the ALSI is deflated with the Consumer Price Index (CPI) to create another variable, real ALSI (ALSIR). The data is collected from I-Net Bridge and Statistics South Africa.

Gross Domestic Product (GDP) and the Index of Industrial Production (IIP) is used to measure economic activity. While most studies use either GDP or IIP as the measure of economic activity, several studies, including the seminal paper by Fama (1981) use both variables. Tainer (1993) suggests that the Industrial Production Index is procyclical; it rises during economic expansions and drops during a recession and is therefore commonly used as a proxy for the level of real economic activity. In the interest of completeness this paper will make use of both variables to proxy for economic activity in South Africa. GDP growth rate data is obtained from Statistics South Africa. The Index of Industrial Production is obtained from International Financial Statistics through the IMF database. The aggregate Industrial Production Index for South Africa is calculated by the Statistics Department from industrial and manufacturing production indices that are published nationally. The index covers industrial activities in mining, quarrying, manufacturing, and electricity, gas and water. Seasonal dummy variables s2, s3 and s4 are also constructed.

4 ECONOMETRIC METHODOLOGY

The purpose of this paper is to examine causality and cointegration between the JSE and economic activity in South Africa as proxied by GDP and Industrial Production. The research methods employed are therefore in a time-series setting and are econometrically dense. According to Roussea and Wachtel (1988) time-series approaches are better equipped in addressing the issue of causality since each country may have its own causality pattern and unique evolution path over time.

Since most macroeconomic time-series variables are often non-stationary in nature, conventional hypothesis-testing procedures are often unreliable as it is inappropriate to apply the conventional regression techniques to investigate their relationships. Time-series data violate the underlying assumptions of linear regression as residual errors are correlated purely by construction leading to inconsistent coefficient estimates. Moreover, the mean and/or variance of the explanatory variables may change over time leading to invalid regression results. In a bid to avoid the possibility of spurious results, a time-series econometric methodology is employed to examine the data.

Two basic methodological approaches are used to test the stock market as a leading indicator of economic activity in South Africa. The first approach is to test for statistical causality between stock prices and the economy using the test proposed by Granger (1969) to assess whether or not changes in nominal or real stock prices precede changes in economic activity.

The second methodological approach is to determine the usefulness of stock prices in forecasting economic activity both in the short-run and long-run. Here the VAR framework will be adopted to examine the long-run relationship between the stock market and economic growth as well as to evaluate the dynamics and causal relationships among the variables. A structural VAR (SVAR) will also be employed to examine how each variable response is shocked by other variables in the VAR framework through the impulse response functions and variance decompositions.

The VAR framework is adopted for this study as according to Ang and McKibbin (2007) once variables are cointegrated it becomes simpler to distinguish between the short run dynamics and long run causality. The VAR framework also eliminates the problems of endogeneity by treating all variables as potentially endogenous as explained by Sims (1980). Multivariate simultaneous equations models were used extensively for macroeconometric analysis when Sims (1980) advocated vector autoregressive models as alternatives. VAR models are better equipped to describe the dynamic structure of variables observed in macroeconomic time-series and are natural tools for forecasting.

4.1 Descriptive Statistics

Descriptive statistics for the variables' time-series shows that during the sample period, the ALSI had a mean quarterly return of 1.45 percent (median of 1.84 percent); the mean quarterly return for ALSIR was -0.17 percent (median of -0.12 percent); quarterly GDP growth rate was 2.59 percent (median of 2.5 percent); and the mean quarterly IIP growth rate was 0.42 percent (median of 0.80 percent).

	ALSI	ALSIR	GDP	IIP
Mean	0.014451	-0.001690	0.025987	0.004243
Median	0.018424	-0.001227	0.025068	0.007949
Maximum	0.095307	0.089979	0.063122	0.044303
Minimum	-0.072147	-0.102708	-0.001769	-0.085847
Std. Dev.	0.031649	0.035734	0.011271	0.020965
Skewness	-0.158982	-0.090838	0.314343	-1.311911
Kurtosis	3.606118	3.697062	3.540306	7.201618
Jarque-Bera	1.756801	1.945882	2.576915	92.01764
Probability	0.415447	0.377970	0.275696	0.000000
Sum	1.300550	-0.152103	2.338837	0.381909
Sum Sq. Dev.	0.089148	0.113646	0.011306	0.039120
Observations	90	90	90	90

The Jarque-Bera is a test statistic for testing whether a series has a normal distribution. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. Under the null hypothesis of a normal distribution, we reject the null hypothesis of normal distribution at the 1%, 5% and 10% significance levels for IIP. For ALSI, ALSIR and GDP we fail to reject the null hypothesis. It should however be noted that the reliability of the Jacque-Bera test for sample sizes smaller than 100 observations has been called into question. For small samples, the chi-squared approximation has been argued to be overly sensitive, often rejecting the null hypothesis when it is true. In this regard a more superior test for stationarity will be employed using the unit root tests.

Examining the correlation matrix below reveals that ALSI and GDP have a correlation of 0.2021; ALSIR and GDP have a negative correlation of -0.0134; ALSI and IIP have a correlation of 0.289; ALSIR and IIP have a correlation of 0.278 and GDP and IIP have a correlation of 0.457. Correlation however does not necessarily imply causation, and a formal test of causality is employed in the time-series analysis of the variables.

	ALSI	ALSIR	GDP	IIP
ALSI	1.000000	0.966993	0.020653	0.289205
ALSIR	0.966993	1.000000	-0.013364	0.271853
GDP	0.020653	-0.013364	1.000000	0.457070
IIP	0.289205	0.271853	0.457070	1.000000

4.2 Unit root tests

The first step in interrogating the data is to plot the time-series to detect for the existence of trends or seasonality. Unit root tests are also utilised to test for stationarity in the variable's data series. Many economic and financial time-series data exhibit trending behaviour on non-stationarity in the mean, especially time-series related to asset prices and the levels of macroeconomic aggregates like real GDP (Zivot, 2015). Testing for the presence of unit roots in time-series data is a significant precondition in any cointegration analysis and other empirical research using time-series data. The basis for this is embedded in the "spurious regression" problem (Granger and Newbold, 1974) or nonsense regression as labelled by Yule (1926). For a long time it was common practice to estimate equations involving non-stationary variables in macroeconomic models by straightforward linear regression. In an influential paper, Granger and Newbold (1974) pointed out that the regression of an integrated series on another unrelated integrated series may often indicate a statistically significant relationship where none actually exists. The results from their Monte Carlo study revealed that many of the apparently significant relationships between non-stationary variables in existing econometric models were in fact spurious. Statisticians then proposed a simple solution to the "spurious regression" problem that involved specifying economic variables in first differences instead of levels as first differenced variables are usually stationary even if the original variables are not.

Two common trend removal or de-trending procedures are first differencing and time-trend regression. First differencing is appropriate for I (1) time-series and time-trend regression is appropriate for trend stationary I (0) time-series. Unit root tests can be used to determine if trending data should be first differenced or regressed on deterministic functions of time to render the data stationary. Additionally, economic and finance theory often suggests the existence of long-run equilibrium relationships among nonstationary time-series variables. If these variables are I (1), then cointegration techniques can be used to model these long-run relations. Therefore, pre-testing for unit roots is often the first step in cointegration modelling between variables.

Trend models by their very construction are likely to exhibit serial correlation. The preferred unit root test in the presence of serial correlation is the Augmented Dickey Fuller (ADF) test as according to Dickey and Fuller (1979) one can control for serial correlation by "adding lags" (by augmenting). Furthermore, many financial time-series have a more complicated dynamic structure than is captured by simple AR (1) models (which make use of standard unit root tests). Said and Dickey (1984) augment the basic autoregressive unit root test to accommodate general ARMA (p,q) models with unknown orders and their test is referred to as the Augmented Dickey Fuller (ADF) test. The ADF test is used to test the stationarity of the variables in this series. It tests the null hypothesis that a time-series y(t) is I(1) against the alternative that it is I(0), assuming that the dynamics in the data have an ARMA structure. The ADF test is a regression of the first difference of the variable on its lagged level as we as additional lags of the first difference. The ADF statistic used in the test is a negative number, and the more negative it is, the stronger the rejection of the hypothesis that there is a unit root and therefore that the variable is stationary.

The null hypotheses for each of the variables is that the series contains a unit root, and the (one-sided) alternative is that the series is stationary:

H0: $\alpha = 0$;

HA: $\alpha < 0$

Recording and comparing the t-statistic to a table of critical values for the Dickey-Fuller distribution will allow one to reject the null hypothesis that the series is I(1) in favour of the alternative that it is I(0) for all t-statistics more negative than their relevant critical values.
Determination of the appropriate truncation lag, *p*, is an important practical issue for the implementation of the ADF test as revealed in studies by Schwert (1989) as well as Campbell and Perron (1981) amongst others. If *p* is too small then the remaining serial correlation in the errors will bias the test. Alternatively, if *p* is too large then the power of the test will suffer. Instead of using the automatic based Schwartz criterion, the lag length selection in this study is based on the frequency of the data (4 for quarterly).

Table 1				
Augmented Dickey-Fuller Unit Root Tests				
ADF Tests – Levels				
Null Hypothesis: Variable has a unit root				
Without Trend				
Variable:	**ALSI**	**ALSIR**	**GDP**	**IIP**
ADF test statistics:	-4.888603	-4.856806	-3.396664	-4.711138
1% Level	-3.509281	-3.509281	-3.509281	-3.509281
5% Level	-2.895924	-2.895924	-2.895924	-2.895924
10% Level	-2.585172	-2.585172	-2.585172	-2.585172
MacKinnon prob-values:	0.0001	0.0001	0.0137	0.0002

Table 1 summarizes the ADF test statistics and MacKinnon (1996) one-sided p-values for the ADF tests on the levels of the variables ALSI, ALSIR, GDP and IIP; with only a constant and no trend in the equations. As all p-values are less than 0.05 we reject the null hypothesis of a unit root in favour of the alternative. According to the ADF test here all variables are stationary.

Table 2				
Augmented Dickey-Fuller Unit Root Tests				
ADF Tests – Levels				
Null Hypothesis: Variable has a unit root				
With Trend				
Variable:	**ALSI**	**ALSIR**	**GDP**	**IIP**
ADF test statistics:	-4.857196	-4.870000	-4.135365	-4.827030
1% Level	-4.069631	-4.069631	-4.069631	-4.069631
5% Level	-3.463547	-3.463547	-3.463547	-3.463547
10% Level	-3.158207	-3.158207	-3.158207	-3.158207
MacKinnon prob-values:	0.0008	0.0008	0.0083	0.0009

Table 2 summarizes the results of the ADF tests on the levels of the variables, with a constant and a linear trend in the equation. As all p-values are less than 0.05 we reject the null hypothesis of a unit root in favour of the alternative. According to the ADF test here, all variables are stationary.

In summary, the unit root tests revealed that all series in the study are I(0) , i.e. that all the variables have stationary series.

4.3 VAR Estimation

The vector autoregression is commonly used for forecasting systems of interrelated time-series and for analysing the dynamic impact of random disturbances on the system of variables. Fry and Pagan (2007) cite three major uses of VARs in macroeconometric research. Firstly they can quantify impulse responses to macroeconomic shocks. Secondly, they can be used to measure the degree of uncertainty about the impulse responses from them. Lastly, they can be used to examine the contribution of different shocks to business cycles and forecast errors through variance decompositions.

The first step to the VAR estimation process is selecting an appropriate lag order. In choosing the lag order of the VAR for the variables ALSI, GDP and IIP VAR is estimated four times using lag orders 4, 3, 2 and 1. The full sample of endogenous variables are used and seasonal dummies s2, s3 and s4 are added as exogenous variables. Information criteria can be used for model selection such as determining the lag length of the VAR; the smaller the value of the information criteria, the "better" the model. One can also use a likelihood ratio (LR) test to test the appropriate lag length. To carry out the LR test, the VAR needs to be estimated twice, each with different lags. The LR test statistic is then computed and is asymptotically distributed chi-squared with degrees of freedom equal to the number of restrictions under the test.

Table 3

Vector Autoregression Estimates

ALSI, GDP & IIP

Akaike Information Criteria VAR(4)	-15.18
Akaike Information Criteria VAR(3)	-15.20
Akaike Information Criteria VAR(2)	-15.08
Akaike Information Criteria VAR(1)	-15.06

In comparing the Akaike Information Criteria from the different options of lag orders summarised in Table 3 above, it is clear that a lag order of 3 is more favourable as the VAR(3) has the smallest Akaike Information Criteria of -15.20 compared to the VAR(1) (AIC is -15.06), the VAR (2) (AIC is -15.08) and VAR (4) (AIC is -15.18).

Table 4 **Vector Autoregression Estimates** **ALSIR, GDP & IIP**	
Akaike Information Criteria VAR(4)	-14.96
Akaike Information Criteria VAR(3)	-14.99
Akaike Information Criteria VAR(2)	-14.86
Akaike Information Criteria VAR(1)	-14.84

For the sample where the endogenous variables are ALSIR, GDP and IIP, a lag order of 3 is also preferred as the VAR(3) has the smallest Akaike Information Criteria of -14.99 compared to the VAR(1) (AIC is -14.84), the VAR (2) (AIC is -14.86) and VAR (4) (AIC is -14.96) as summarised in Table 4 above.

4.4 Impulse Response Functions

Structural VAR analysis attempts to investigate structural economic hypotheses with the use of VAR models. Impulse response analysis and variance decompositions are the tools which have been proposed for disentangling the relations between the variables in a VAR model. An impulse response function traces the effect of a one standard deviation shock to one of the innovations on current and future values of the endogenous variables. A shock to the i-th variable directly affects the i-th variable, and is also transmitted to all of the other endogenous variables through the dynamic structure of the VAR. Impulse response functions of a dynamic system is its output when presented with a brief input signal, called an impulse. An impulse response therefore refers to the reaction of any dynamic system in response to some external change.

According to Lu and Xin (2010) if a VAR is written in vector MA (∞) form as $y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} \ldots$, then the matrix Ψ_s has the interpretation $\Psi_s = \partial y_{t+s} / \partial \varepsilon 1t$, that is the row 1 column j-th variable's innovation at date (ε_{jt}) for the value of the i-th variable at time $_t + s(y_{it+s})$, holding all other innovations at all dates constant. $\partial yt{+}s/\partial \varepsilon 1t$ as a function of s is called the impulse response function. It describes the response of y_{it+s} to a one-time impulse in y_{jt} with all other variables dates t or earlier held constant.

One important limitation of the Cholesky method, which was employed in this study, is that results from IRFs and VDCs depend on the Cholesky ordering. The Cholesky option imposes an ordering of the variables in the VAR and attributes all of the effect of any common component to the variable that comes first in the VAR system. However, if one particular ordering is "reasonable" then at least one of the orthogonalized shocks can be interpreted as a structural or primitive shock, i.e. a shock whose true origin could be known conditional on the VAR specification (Lahura and Vega, 2014). Variables that are not caused by any other variables in the system should be placed first in the list of ordering. Therefore in computing the IRFs and VDCs for this study the variables ALSI and ALSIR are placed first.

The impulse response function of a VAR is to analyse dynamic effects of the system when the model received the impulse. In both of the VAR (3) models, there are three variables: ALSI, GDP and IIP, and ALSIR, GDP and IIP.

Figure 1: Impulse response functions – ALSI, GDP and IIP

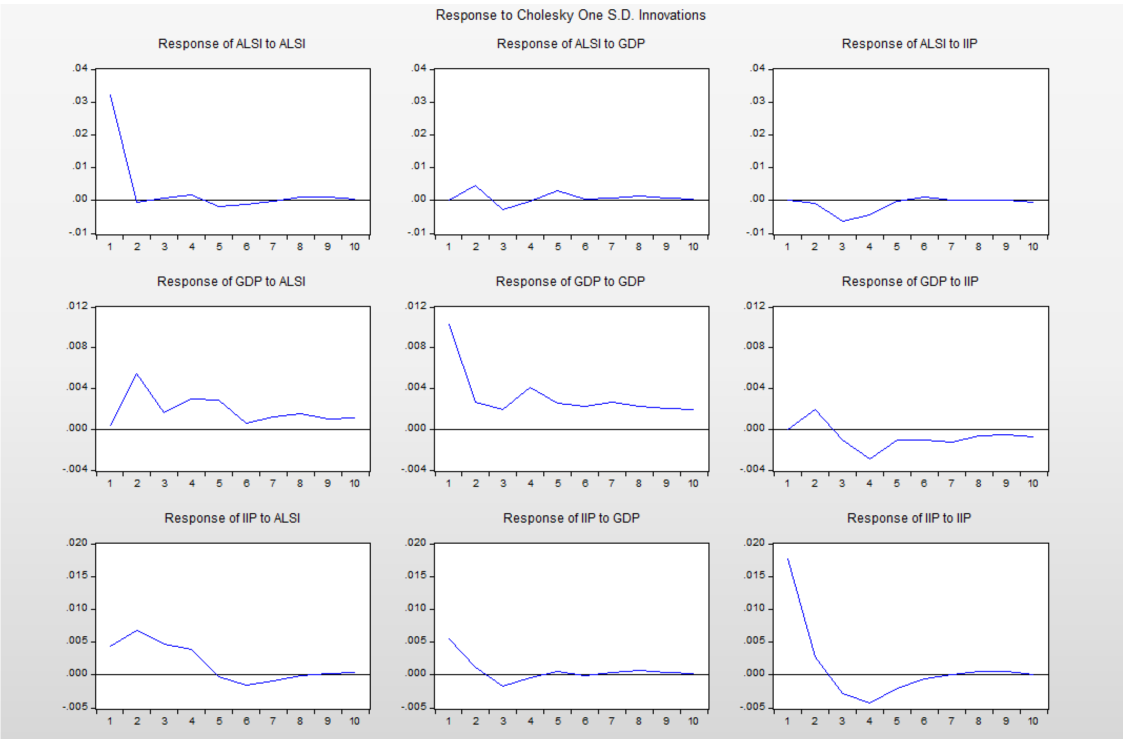
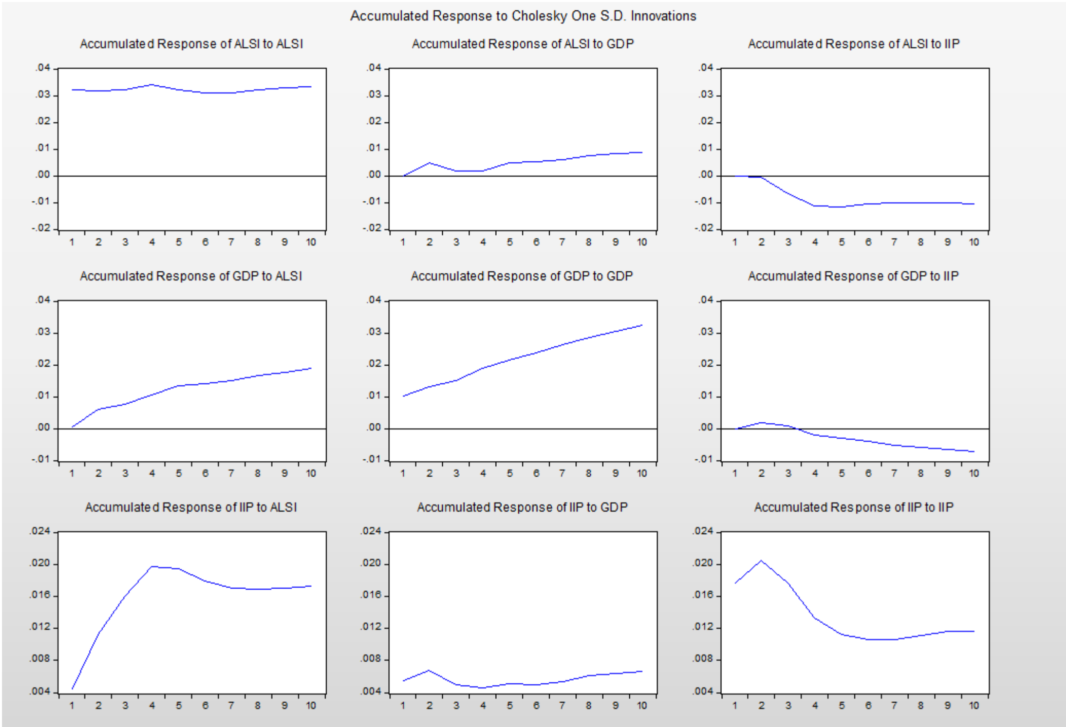


Figure 2 Accumulated Impulse response functions ALSI, GDP and IIP



Interpreting the IRFs from Figures 1 and 2 above it is clear that when the impulse is the JSE ALSI a positive shock to GDP can be seen in the second quarter, followed by a negative decrease in the third quarter, followed by another increase in the fifth quarter, with the response dissipating close to zero after that. When the impulse is ALSI and the response is IIP, a negative effect can be seen in the first few quarters, especially at the third quarter, and then the effect dissipates to zero. If the stock market is meant to be a leading indicator of economic activity, the IRFs above illustrate that a shock to the JSE impacts GDP positively, while having a predominantly negative effect on Industrial Production. A shock to ALSI when the impulse is GDP seems to have a significant positive effect. A shock to ALSI when the impulse is IIP also seem to have a significant impact with the shock decreasing and then dying out from the fifth quarter. This finding contradicts the notion that the stock market leads economic activity as the IRFs show that shocks to GDP and IIP instead have a significant and positive impact on the stock market. Finally, the response of IIP to GDP is negligible with a clear negative shock at the second to third quarter however. The impact of GDP to IIP seems to be positive at the second quarter, followed by a strong decrease which then dies out from the fifth quarter.

Figure 3: Impulse response functions – ALSIR, GDP and IIP

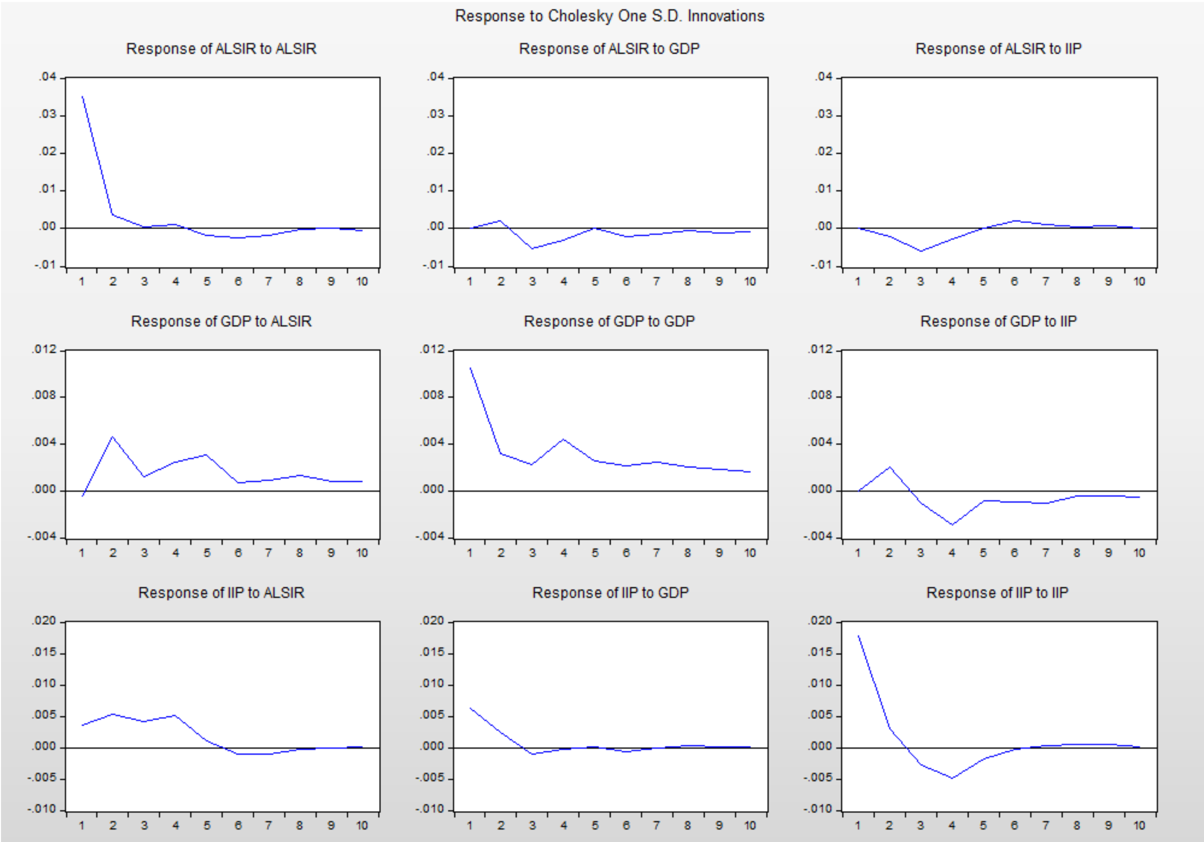
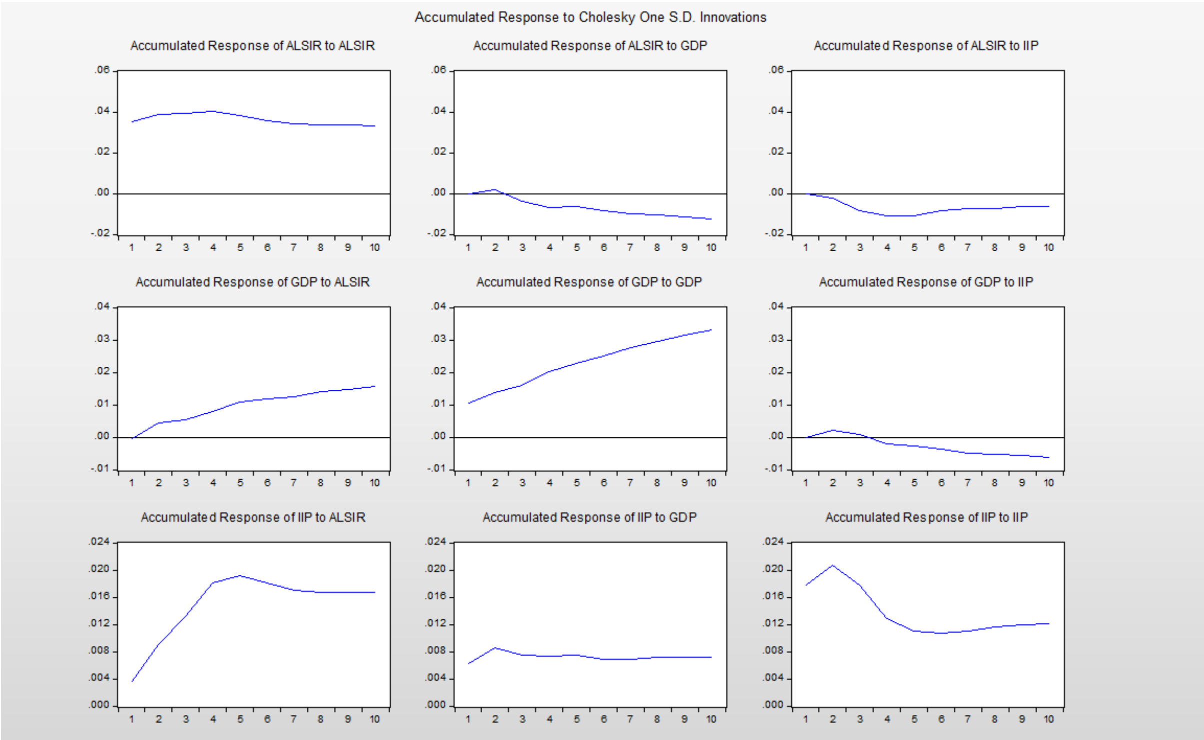


Figure 4: Impulse response function – Accumulated responses of ALSIR, GDP and IIP



Interpreting the IRFs from Figures 3 and 4 above it is clear that the response from ALSIR to GDP as well as from ALSIR to IIP both have an overwhelmingly negative effect, particularly from the third quarters. The effect on ALSIR by both GDP and IIP seem to be significant and mainly positive. When the market proxy is the real stock market, the impact on the economic activity variables appear to be principally negative. The results from the IRFs also indicate that shocks to economic activity variables have a significant and positive impact on the stock market, especially when the variable ALSIR is used as the market proxy. Evaluating the dynamic behaviour between the variables from a structural VAR approach exposes an interconnected relationship between the financial and economic variables instead of just a unidirectional one.

4.5 Variance Decomposition

Variance decomposition provides another method of depicting the system dynamics. Impulse response functions trace the effects of a shock to an endogenous variable on the variables in the VAR. By contrast, variance decomposition decomposes variation in an endogenous variable into the component shocks to the endogenous variables in the VAR. The variance decomposition gives information about the relative importance of each random innovation to the variables in the VAR. Variance decomposition breaks down the variance of the forecast error for each variable into components. Each variable is thus explained as a linear combination of its own current innovations and lagged innovations of all the other variables in the system. Similar to IRFs, the ordering is important.

According to Stock and Watson (2001) the forecast error decomposition is the percentage of the variance of the error made in forecasting a variable due to a specific shock at a given horizon and thus can be seen as a partial R^2 for the forecast error by forecast horizon

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Figure 5: Variance Decomposition – ALSI, GDP and IIP

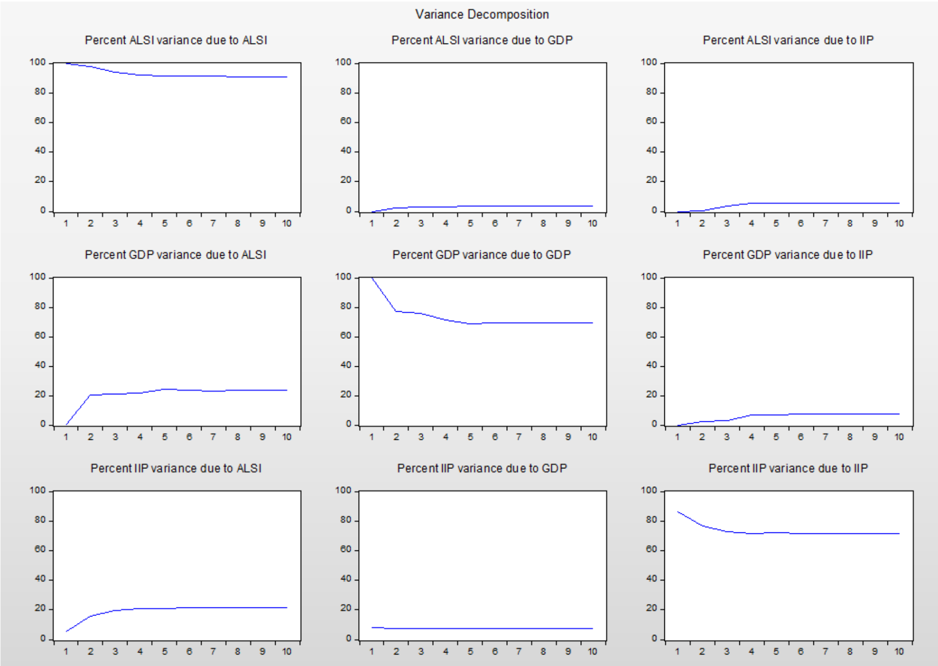
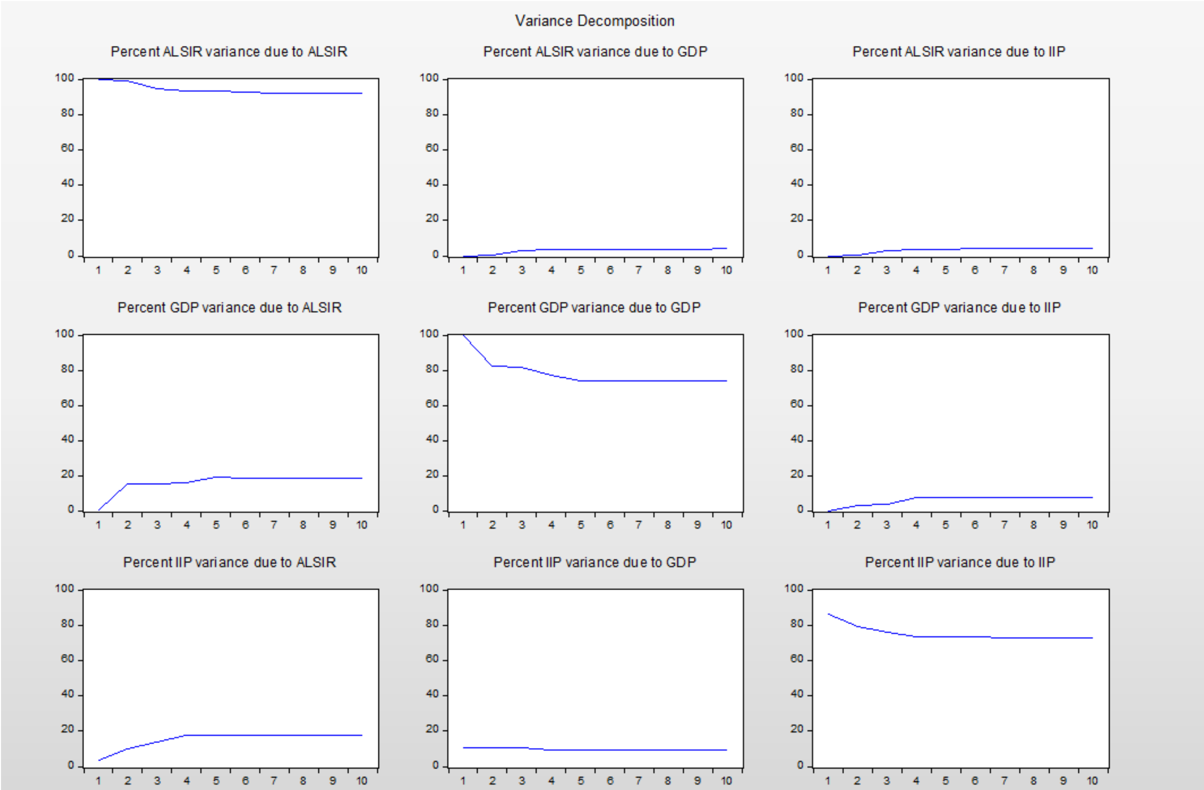


Figure 6: Variance Decomposition – ALSIR, GDP, IIP



According to the Variance Decomposition between ALSI and GDP and ALSI and IIP it is clear that the contribution of a shock to GDP and IIP contributes significantly to their own variance over time. In addition, the variance of GDP and IIP is considerably explained by both ALSI and ALSIR. The findings indicate that the stock market has a significant effect on the dynamic behaviour of the economic activity variables, i.e. GDP and Industrial Production.

Tables 5 and 6 below display a separate variance decomposition for each endogenous variable. The second column, labelled "S.E.", contains the forecast error of the variable at the given forecast horizon. The source of this forecast error is the variation in the current and future values of the innovations to each endogenous variable in the VAR. The remaining columns give the percentage of the forecast variance due to each innovation, with each row adding up to 100. As with the impulse responses, the variance decomposition based on the Cholesky factor can change dramatically if you alter the ordering of the variables in the VAR.

Table 5

Variance Decomposition - ALSI, GDP & IIP

Variance Decomposition of ALSI:

Period	S.E.	ALSI	GDP	IIP
1	0.032036	100.0000	0.000000	0.000000
2	0.032380	97.89844	2.051828	0.049729
3	0.033094	93.75453	2.712824	3.532642
4	0.033439	92.07658	2.657613	5.265804
5	0.033623	91.31999	3.465875	5.214136
6	0.033665	91.20968	3.477408	5.312915
7	0.033674	91.16089	3.525878	5.313236
8	0.033722	91.00084	3.700913	5.298243
9	0.033741	90.97479	3.731236	5.293978
10	0.033751	90.93985	3.752876	5.307272

Variance Decomposition of GDP:

Period	S.E.	ALSI	GDP	IIP
1	0.010331	0.172767	99.82723	0.000000
2	0.012118	20.27262	77.30971	2.417671
3	0.012415	20.95708	75.96981	3.073115
4	0.013715	21.75418	71.34571	6.900106
5	0.014270	24.11001	69.00257	6.887418
6	0.014502	23.53457	69.24402	7.221407
7	0.014843	23.15396	69.19140	7.654635
8	0.015094	23.37678	69.06432	7.558905
9	0.015268	23.24805	69.23674	7.515205
10	0.015443	23.26914	69.17462	7.556242

Variance Decomposition of IIP:

Period	S.E.	ALSI	GDP	IIP
1	0.019037	5.408572	8.319158	86.27227
2	0.020428	15.69639	7.575275	76.72833
3	0.021227	19.48593	7.677558	72.83652
4	0.022006	21.15356	7.184962	71.66148
5	0.022106	20.98225	7.181869	71.83588
6	0.022164	21.32252	7.145998	71.53148
7	0.022189	21.46387	7.164610	71.37152
8	0.022206	21.43648	7.244798	71.31872
9	0.022214	21.42601	7.257444	71.31655
10	0.022217	21.43934	7.265670	71.29499

Cholesky Ordering: ALSI GDP IIP

Table 6

Variance Decomposition - ALSIR, GDP & IIP

Variance Decomposition of ALSIR:

Period	S.E.	ALSIR	GDP	IIP
1	0.034925	100.0000	0.000000	0.000000
2	0.035244	99.28891	0.287151	0.423941
3	0.036167	94.29390	2.573311	3.132791
4	0.036424	93.05130	3.268635	3.680069
5	0.036470	93.06372	3.260736	3.675548
6	0.036667	92.48351	3.533050	3.983437
7	0.036755	92.26884	3.687783	4.043381
8	0.036763	92.24085	3.703158	4.055994
9	0.036782	92.14223	3.780945	4.076826
10	0.036800	92.07340	3.852239	4.074364

Variance Decomposition of GDP:

Period	S.E.	ALSIR	GDP	IIP
1	0.010521	0.200327	99.79967	0.000000
2	0.012103	15.01546	82.28343	2.701113
3	0.012415	15.26086	81.46300	3.276131
4	0.013721	15.75400	76.91150	7.334495
5	0.014303	18.96710	73.90460	7.128292
6	0.014516	18.66647	74.00768	7.325856
7	0.014790	18.34444	74.10243	7.553121
8	0.014990	18.64868	73.90514	7.446185
9	0.015128	18.59197	73.99480	7.413234
10	0.015255	18.58749	73.97727	7.435245

Variance Decomposition of IIP:

Period	S.E.	ALSIR	GDP	IIP
1	0.019113	3.544253	10.50707	85.94868
2	0.020192	10.14929	10.77502	79.07570
3	0.020840	13.52187	10.37195	76.10618
4	0.021999	17.32458	9.316711	73.35870
5	0.022109	17.40497	9.232418	73.36261
6	0.022144	17.58465	9.277725	73.13762
7	0.022176	17.80311	9.251283	72.94560
8	0.022186	17.80457	9.260126	72.93531
9	0.022190	17.79816	9.256955	72.94488
10	0.022190	17.79830	9.257051	72.94465

Cholesky Ordering: ALSIR GDP IIP

In addressing the implementation of SVARs, Fernandez - Villaverde and Rubio - Ramirez (2005) contend that in the hands of skilful researchers SVARs contributed to the understanding of aggregate fluctuations while clarifying the importance of different economic shocks. However they also argue three limitations as well. Firstly, that economic shocks recovered from an SVAR do not resemble the shocks measured by other mechanisms, such as market expectations embodied in future prices. Secondly, that the shocks recovered from an SVAR may reflect variables omitted from the model. Lastly, that the results of several SVAR studies are sensitive to the identification of restrictions. Related to this drawback Uhlig (2005) argues that many of the identification schemes are the product of a specification search in which academics search for “reasonable” results. If an identification scheme matches the conventional wisdom employed it is deemed successful while if it does not it is termed a puzzle.

In line with the proposed objective of the study to investigate the stock market as a leading indicator, it is apparent from the above results that shocks to the stock market translate into meaningful shocks in both GDP as well as in Industrial Production.

4.6 Granger-causality tests

Granger (1969) proposed a time-series data based approach to determine causality where the definition of causality is closely related to predictability. In the Granger-sense *x* is a cause of *y* if it is useful in forecasting *y*, or equivalently if the coefficients on the lagged *x*'s are statistically significant. In this context "useful" alludes to *x* being able to increase the accuracy of the prediction of *y* with respect to a forecast, given only past values of *y*. Granger-causality measures precedence and information content but does not by itself indicate causality in the more common use of the term. Therefore the Granger (1969) approach to the question of whether *x* causes *y* is to ascertain how much of the current *y* can be explained by past values of *y* and subsequently to evaluate whether adding lagged values of *x* can improve the explanation. In picking the lag length during execution of the test it is advisable to select more rather than fewer lags, since the theory is embedded in terms of the relevance of all past information. A lag length that corresponds to reasonable beliefs about the longest time over which one of the variables could predict the others should be chosen.

It is worthwhile to mention that the Granger-causality tests are actually tests of precedence and do not imply that changes in share prices cause changes in economic activity in the conventional sense. Evaluating the difference between "true causality" and "predictive causality" is instrumental in explaining this distinction. True causality in the conventional sense is defined as the agency that connects one process (the cause) with another (the effect), where the former is understood to be partly responsible for the latter. Diebold (2001) asserts however, that the Granger-causality test, despite its name, is only a test for predictive causality, not true causation. A time-series is said to Granger-cause another series if it has incremental predictive power when forecasting it (Gelper and Croux, 2007).

The JSE ALSI as well as the growth rate of real values of the JSE All Share Index (ALSIR) are used as indicators for stock prices, while changes in economic activity is proxied by the growth rate of GDP and then by Industrial Production

Several hypotheses about the relationship between the stock market and economic activity are formulated:

1. Unidirectional Granger-causality from ALSIR/ALSI to GDP/IIP. In this case Stock Prices increase the prediction of the economy, but not vice versa.

2. Unidirectional Granger-causality from GDP/IIP to ALSI/ALSIR. In this case the growth rate of the economy increases the prediction of the Stock Prices, but not vice versa.
3. Bidirectional or feedback causality. In this case the growth rate of the economy increases the prediction of the Stock Prices and vice versa.
4. Independence between GDP/IIP and ALSI/ALSIR. In this case there is no Granger-causality in any direction.

Similar to Ikoku (2010), Granger-causality tests are conducted on the following bivariate regressions, using 1 to 10 quarterly lags, *l*.

$$ALSI_t = \alpha_0 + \alpha_1 ALSI_{t-1} + \ldots + \alpha_l ALSI_{t-l} + \beta_1 GDP_{t-1} + \ldots + \beta_l GDP_{t-l} + \varepsilon_t \quad (1)$$

$$GDP_t = \alpha_0 + \alpha_1\, GDP_{t-1} + \ldots + \alpha_l GDP_{t-l} + \beta_1 ALSI_{t-1} + \ldots + \beta_l ALSI_{t-l} + \mu_t \quad (2)$$

$$ALSI_t = \alpha_0 + \alpha_1 ALSI_{t-1} + \ldots + \alpha_l ALSI_{t-l} + \beta_1 IIP_{t-1} + \ldots + \beta_l IIP_{t-l} + \varepsilon_t \quad (3)$$

$$IIP_t = \alpha_0 + \alpha_1\, IIP_{t-1} + \ldots + \alpha_l IIP_{t-l} + \beta_1 ALSI_{t-1} + \ldots + \beta_l ALSI_{t-l} + \mu_t \quad (4)$$

$$ALSIR_t = \alpha_0 + \alpha_1 ALSIR_{t-1} + \ldots + \alpha_l ALSIR_{t-l} + \beta_1 GDP_{t-1} + \ldots + \beta_l GDP_{t-l} + \varepsilon_t \quad (5)$$

$$GDP_t = \alpha_0 + \alpha_1\, GDP_{t-1} + \ldots + \alpha_l GDP_{t-l} + \beta_1 ALSIR_{t-1} + \ldots + \beta_l ALSIR_{t-l} + \mu_t \quad (6)$$

$$ALSIR_t = \alpha_0 + \alpha_1 ALSIR_{t-1} + \ldots + \alpha_l ALSIR_{t-l} + \beta_1 IIP_{t-1} + \ldots + \beta_l IIP_{t-l} + \varepsilon_t \quad (7)$$

$$IIP_t = \alpha_0 + \alpha_1\, IIP_{t-1} + \ldots + \alpha_l IIP_{t-l} + \beta_1 ALSIR_{t-1} + \ldots + \beta_l ALSIR_{t-l} + \mu_t \quad (8)$$

The noteworthy null hypotheses are as follows: GDP does not Granger-cause ALSI (1), ALSI does not Granger-cause GDP in equation (2), IIP does not Granger-cause ALSI (3), ALSI does not Granger-cause IIP (4), GDP does not Granger-cause ALSIR (5), ALSIR does not Granger-cause GDP in equation (6), IIP does not Granger-cause ALSIR (7), ALSIR does not Granger-cause IIP (8). F-tests are conducted with the joint hypothesis that β_1 though β_{10} are zero.

Table 7: Pairwise Granger-causality tests – ALSI, ALSIR, GDP, IIP									
No. of Lags	1 From ALSI to GDP	2 From GDP to ALSI	3 From ALSI to IIP	4 From IIP to ALSI	5 From ALSIR to GDP	6 From GDP to ALSIR	7 From ALSIR to IIP	8 From IIP to ALSIR	9 Test Result
1	0.0008	0.8798	0.0146	0.9738	0.0039	0.3956	0.0187	0.4001	ALSI/ALSIR causes GDP; ALSI/ALSIR causes IIP
2	0.0041	0.1699	0.0186	0.1172	0.0171	0.0703	0.0337	0.1302	ALSI/ALSIR causes GDP; ALSI/ALSIR causes IIP
3	0.0005	0.1486	0.0070	0.1385	0.0023	0.0622	0.0151	0.1726	ALSI/ALSIR causes GDP; ALSI/ALSIR causes IIP
4	0.0008	0.1994	0.0034	0.1293	0.0036	0.0993	0.0049	0.2022	ALSI/ALSIR causes GDP; ALSI/ALSIR causes IIP
5	0.0007	0.5192	0.0117	0.1663	0.0032	0.3208	0.0177	0.1694	ALSI/ALSIR causes GDP; ALSI/ALSIR causes IIP
6	0.0010	0.4607	0.0119	0.0954	0.0039	0.3451	0.0203	0.1630	ALSI/ALSIR causes GDP; ALSI/ALSIR causes IIP
7	0.0011	0.7177	0.0308	0.1512	0.0013	0.5733	0.0326	0.2011	ALSI/ALSIR causes GDP; ALSI/ALSIR causes IIP
8	0.0013	0.2495	0.0607	0.2720	0.0017	0.2209	0.0590	0.2310	ALSI/ALSIR causes GDP
9	0.0023	0.3444	0.0796	0.3897	0.0022	0.3744	0.0921	0.3814	ALSI/ALSIR causes GDP
10	0.0031	0.4401	0.1041	0.5443	0.0034	0.4002	0.1317	0.5202	ALSI/ALSIR causes GDP

1/ The numbers are p-values for the null hypothesis "ALSI does not cause GDP"; 5/ The numbers are p-values for the null hypothesis "ALSIR does not cause GDP"

2/The numbers are p-values for the null hypothesis "GDP does not cause ALSI"; 6/The numbers are p-values for the null hypothesis "GDP does not cause ALSIR"

3/The numbers are p-values for the null hypothesis "ALSI does not cause IIP"; 7/The numbers are p-values for the null hypothesis "ALSIR does not cause IIP"

4/The numbers are p-values for the null hypothesis "IIP does not cause ALSI"; 8/The numbers are p-values for the null hypothesis "IIP does not cause ALSIR"

9/The test result is based on a 5% significance level.

Table 7 above summarises the pairwise Granger-causality tests. In each of the 10 lags we reject the null hypothesis that ALSI does not Granger-cause GDP in favour of the alternative; as well as rejecting the null hypothesis that ALSIR does not Granger-cause GDP in favour of the alternative. Unidirectional causality exists between the JSE ALSI, in both its nominal and real form, and GDP. The nominal and real stock indices therefore are able to increase the accuracy of the prediction of GDP with respect to a forecast.

For lags 1 to 7 we reject the null hypothesis that ALSI does not Granger-cause IIP and that ALSIR does not Granger-cause IIP. For lags 8 through to 10 however we fail to reject these null hypotheses. Unidirectional causality exists between the JSE ALSI, in both its nominal and real form, and the Index of Industrial Production for lags I through to 7. Weak causality exists between the stock market and Industrial Production for lags 8 to 10. The tests also verifies no bidirectional causality between the variables at any of the lags.

Furthermore, and more importantly, the tests also demonstrated that the stock market is not led by any of the economic activity variables. This finding contradicts much of the literature concerned with empirically validating that stock returns and aggregate real activity are correlated, such that macroeconomic variables have been found to have explanatory power for future stock returns. Prior empirical investigations have been successful in proving macroeconomic variables to have statistically significant and causal relationship with the stock market. For instance, Fama (1990) and Geske and Roll (1983) found that economic activity, represented by Industrial Production, affected stock prices positively. In addition, Chen *et al.* (1986) used macroeconomic variables to explain stock returns in the US. A possible explanation is that many of these earlier studies could have documented spurious regressions.

4.7 Cointegration

Cointegration analysis helps clarify the long-run relationship between integrated variables. The Johansen procedure will be used to test if the variables in the study are cointegrated. Based on this test one will be able to determine if there is a long run equilibrium relationship between the stock market index and real economic activity in South Africa.

Running the Johansen Cointegration test will allow one to confirm if the variables are cointegrated and to determine subsequently the number of cointegrating equations. If it is established that the variables are cointegrated then a restricted VAR model in the form of a Vector Error Correction Model can be developed.

Cointegration will be tested using the Johansen (1991, 1995) VAR-based methodology.

Consider a VAR of order *p*:

$y_t = A_1 y_{t-1} + \dots + A p y_{t-p} + B x_t + \varepsilon_t$

where y_t is a *k*-vector of nonstationary I(1) variables, x_t is a *d*-vector of deterministic variables, and ε_t is a vector of innovations.

The Johansen procedure defines two statistics: the trace statistic and the maximum eigenvalue statistic. The trace statistic tests the null hypothesis that the number of independent cointegrating vectors is less than r against the alternative that it is greater than (r+1). The test is used iteratively, starting with a null of r = 0 and then repeated for r=1, r-2, until one fails to reject. The maximum eigenvalue statistic tests the null hypothesis that the number of cointegrating vectors is r against the alternative that it is (r+1) and is also used iteratively.

When conducted the Johansen cointegration test the series used may have nonzero means and deterministic trends as well as stochastic trends. Likewise, the cointegrating equations may have intercepts and deterministic trends. The distribution of the test statistic used for cointegration does not have the standard χ^2 distribution and is dependent on the assumptions made with regard to deterministic trends. Therefore in order to compute the test an assumption needs to be made regarding the underlying trend in the data. For this test it is assumed that the level data have linear trends but the cointegrating equations have only intercepts as the trends in the series are presumed to be stochastic. Furthermore, lag intervals 1 3 is chosen in employing the tests. The critical values for the test are computed using MacKinnon-Haug-Michelis (1999) p-values.

The Johansen test requires that the variables used are nonstationary and integrated of the same order. Following the results of the unit root tests previously conducted, and assuming for ease of practical application that all the variables have a unit root and are cointegrated, the cointegration test will be evaluated between the variables ALSI, GDP and IIP, and then between ALSIR, GDP and IIP, using level data.

Table 8: Johansen Cointegration Test – ALSI, GDP and IIP			
Trace Test			
Hypothesized # of CE's	Statistic	0.05 Critical Value	Prob.**
None*	69.05	29.80	0.0000
At most 1*	36.66	15.49	0.0000
At most 2*	16.10	3.84	0.0001
Maximum Eigenvalue Test			
Hypothesized # of CE's	Statistic	0.05 Critical Value	Prob.**
None*	32.39	21.13	0.0009
At most 1*	20.56	14.26	0.0045
At most 2*	16.10	3.84	0.0001
Normalized Cointegrating Coefficients (Standard Error in Parenthesis)			
ALSI	GDP	IIP	
1.0000	-0.773769 (0.57877)	-1.281970 (0.31358)	
*Denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug Michelis (1999) p-values			

To determine the number of cointegrating relationships, r, subject to the assumptions made about the trend in the series, one can proceed sequentially from r = 0 to r=k-1 until one fails to reject.

In interpreting the results of the Johansen Test between ALSI, GDP and IIP, the trace statistics are first examined. The null hypothesis of none is first assessed where the null hypothesis is of no cointegration, i.e. the number of cointegrated equations is zero. The p-value here is 0.000 which is less than 5%, therefore we can reject the null hypothesis in favour of the alternative. In addition, the trace statistic is 69.05 and is greater than the critical value is 29.80 confirming the rejection of the null hypothesis.

The second null hypothesis of "At most 1" (r=1) is also examined. Here the null hypothesis is that there is at most 1 cointegrating equation. Here the p-value is 0.0000 and as it is less than 5%, the null hypothesis is rejected. In addition, the trace statistic is 36.66 and is greater than the critical value 15.49, reiterating the rejection of the null hypothesis.

The third null hypothesis of "At most 2" (r=2) is also examined. Here the null hypothesis is that there is at most 2 cointegrating equations. Here the p-value is 0.0001 and as it is less than 5%, the null hypothesis is rejected. In addition, the trace statistic is 16.10 and is greater than the critical value 3.84, reiterating that we reject the null hypothesis in favour of the alternative.

The maximum eigenvalue results reiterate the finding that a cointegrating relationship does indeed exist between our variables.

The Johansen procedure indicates that ALSI, GDP and IIP are cointegrated. One can therefore conclude that a long-run relationship exists between the nominal stock market index and economic activity in South Africa.

Table 9 Johansen Cointegration Test – ALSIR, GDP and IIP			
Trace Test			
Hypothesized # of CE's	Statistic	0.05 Critical Value	Prob.**
None*	68.75	29.80	0.0000
At most 1*	36.55	15.49	0.0000
At most 2*	15.85	3.84	0.0001
Maximum Eigenvalue Test			
Hypothesized # of CE's	Statistic	0.05 Critical Value	Prob.**
None*	32.20	21.13	0.0009
At most 1*	20.70	14.26	0.0042
At most 2*	15.85	3.84	0.0001
Normalized Cointegrating Coefficients (Standard Error in Parenthesis)			
ALSIR	GDP	IIP	
1.0000	-0.162187 (0.78613)	-1.902064 (0.42280)	
*Denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug Michelis (1999) p-values			

The Johansen Cointegration Test is repeated using the endogenous variables ALSIR, GDP and IIP with the results summarised in Table 9 above. The null hypothesis in the trace test of none is first assessed where the null hypothesis is of no cointegration, i.e. the number of cointegrated equations is zero. The p-value here is 0.000 which is less than 5%, therefore we can reject the null hypothesis. In addition, the trace statistic is 68.75 and is greater than the critical value of 29.80, confirming the rejection of the null hypothesis.

The second null hypothesis of "At most 1" (r=1) is also examined. Here the null hypothesis is that there is at most 1 cointegrating equation. Here the p-value is 0.0000 and as it is less than 5% and the null hypothesis is rejected. In addition, the trace statistic is 36.55 and is greater than the critical value 15.49, reiterating the rejection of the null hypothesis.

The third null hypothesis of "At most 2" (r=2) is also examined. Here the null hypothesis is that there is at most 2 cointegrating equations. Here the p-value is 0.0001 and as it is less than

5% and the null hypothesis is rejected. In addition, the trace statistic is 15.85 and is greater than the critical value 3.84, reiterating the rejection of the null hypothesis.

Examining the maximum eigenvalue reinforces our finding that a significant long-run relationship exists between ALSIR and GDP and IIP.

The Johansen procedure indicates that the ALSIR, GDP and IIP are cointegrated. One can therefore conclude that a long-run relationship exists between the real stock market index and economic activity in South Africa.

4.8 Vector error correction model

Initially the lag order of the VAR was selected using an unrestricted VAR. An unrestricted VAR does not assume the presence of cointegration. Running the Johansen Cointegration Test established that the variables are indeed cointegrated while also confirming the number of cointegrating relationships.

Now that cointegration between the variables has been confirmed, a restricted VAR model in the form of a Vector Error Correction Model (VECM) can be established. A vector error correction (VEC) model is a restricted VAR that has cointegration restrictions built into the specification, enabling its use with nonstationary series that are known to be integrated. The VEC specification restricts the long-run behaviour of the endogenous variables to converge to their cointegrating relationships while allowing a wide range of short-run dynamics. The cointegration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments.

Traditionally vector autoregressive models were designed for stationary variables without time trends. Trending behaviour can be captured by including deterministic polynomial terms (Luetkepohl, 2011). In the 1980s the discovery of the significance of stochastic trends in economic variables and the development of the concept of cointegration by Granger (1981), Engle and Granger (1987), Johansen (1995), amongst others, showed that stochastic trends can also be captured by VAR models. If trends exist between some of the variables it may be desirable to separate the long-run relations from the short-run dynamics of the generation process of a set of variables. Vector error correction models offer a convenient framework for separating long-run and short-run components of the data generating process (DGP).

Each column of the β matrix in vector error correction analyses gives an estimate of a cointegrating vector. The cointegrating vector is not identified unless some arbitrary normalization is imposed. Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary, or I(0), linear combination exists, the non-stationary (with a unit root) time-series are said to be cointegrated. The stationary linear combination is called the cointegration equation and may be interpreted as a long-run equilibrium relationship between the variables.

According to Sims (1980) once the variables in the VAR are cointegrated, the VECM representation of a dynamic system is obtained by a simple rearrangement of the vector autoregressive model. The number of cointegrating ranks chosen for the VEC model for the variables GDP, ALSI and IIP is 1. If one looks at the cointegrating equation in the long run it is given by:

GDP = 1.672ALSI – 2.274IIP

The number of cointegrating ranks chosen for the VEC model for the variables GDP, ALSIR and IIP is 1. If one looks at the cointegrating equation in the long run it is given by:

GDP = -2.411ALSIR + 4.523IIP

The no. of cointegrating ranks chosen for the VEC model for the variables IIP, ALSI and GDP is 1. If one looks at the cointegrating equation in the long run it is given by:

IIP = 0.735ALSI – 0.44GDP

The no. of cointegrating ranks chosen for the VEC model for the variables IIP, ALSIR and GDP is 1. If one looks at the cointegrating equation in the long run it is given by:

IIP = 0.533ALSIR + 0.221GDP

Similar to the study by De Brouwer and Ericsson (1998), a restriction is imposed to test *linear homogeneity* amongst the variables. The homogeneity restriction $\Upsilon + \delta = 1$ tests whether the coefficients sum to 1 and if there is unit homogeneity in the variables.

Testing the restriction on GDP, ALSI and IIP, the sum of the coefficients are close to unity and we fail to reject the restriction of long-run homogeneity with a p-value of 0.838.

With long run unit homogeneity imposed the cointegrating equation becomes:

GDP = 2.269ALSI – 3.269IIP

Testing the long-run homogeneity restriction on GDP, ALSIR and IIP, the sum of the coefficients are close to unity and we fail to reject the restriction of long-run homogeneity with a p-value of 0.375.

With long run unit homogeneity imposed the cointegrating equation becomes:

GDP = 1.686ALSIR – 2.686IIP

Testing the long-run homogeneity restriction on IIP, ALSI and GDP, the sum of the coefficients are close to unity and we fail to reject the restriction of long-run homogeneity with a p-value of 0.194.

With long run unit homogeneity imposed the cointegrating equation becomes:

IIP = 0.869ALSI – 1.869IIP

Testing the long-run homogeneity restriction on IIP, ALSI and GDP, the sum of the coefficients are close to unity and we fail to reject the restriction of long-run homogeneity with a p-value of 0.071.

With long run unit homogeneity imposed the cointegrating equation becomes:

IIP = 0.5398ALSIR – 1.5398IIP

The results from the long-run homogeneity tests also imply a significant long-run relationship between the stock market and economic activity in South Africa.

<u>Weak exogeneity</u> of the variables is tested next. The concept of exogeneity has been analysed and elaborated in an influential article by Engle, Hendry and Richard (1983). Whether or not a variable is exogenous depends upon whether or not that variable can be taken as "given" without losing information. Valid exogeneity assumptions may permit simpler modelling strategies; while invalid exogeneity assumptions may lead to inconsistent inferences and result in misleading forecasts and policy simulations (Ericsson, 1991). The statistic for testing the

weak exogeneity of a given variable tests whether or not the corresponding row of α is 0. The coefficients in α measure how the process adjusts to disequilibrium errors. The hypothesis of weak exogeneity is the hypothesis that some rows of α is zero. If that row is 0, disequilibrium in the cointegrating relationship does not feedback onto the associated variable. Weak exogeneity implies that the cointegrating vector and the feedback coefficients enter only the GDP or IIP equations, so inferences about those parameters can be conducted from a conditional model of the GDP or IIP alone, without loss of information. Therefore, weak exogeneity permits a much simpler modelling strategy – namely, a single equation analysis rather than a system one.

To test the speed of adjustment and weak exogeneity of ALSI and ALSIR, the restriction B (1, 1) =1, A (2, 1) =0 is imposed. ALSI and ALSIR are found to be weakly exogenous in describing the long-run relationship between the stock market and economic activity in South Africa, with p-values of 0.9640 and 0.5950 respectively. This finding implies that the stock market does not display any error-correcting behaviour and as such any short-term changes in the JSE is not updated into reactions in GDP and Industrial Production.

5 CONCLUSION

Following a plethora of studies which examined the interrelation among the development of financial markets and economic growth, several studies sought to examine the direction and magnitude of the relationship between the stock market and economic activity given this interrelation. Much debate ensued regarding the predictive ability of stock markets and the information content reflected in share prices with empirical support presented for studies both supporting the stock market as a leading indicator, as well as those refuting it. As the analysis of stock markets on the aggregate economy for emerging countries is scarce, the objective of the study was to ascertain whether or not the stock market, as proxied by the nominal and real stock indices in South Africa, is a leading indicator of economic activity, as proxied by the growth rates of real GDP and Industrial Production.

Granger-causality tests were employed to test the predictive ability of the stock market in forecasting economic growth. The Granger-causality tests indicated that causality does indeed exist between the stock market and economic activity in South Africa. The tests demonstrated that statistically significant unidirectional causal relationships exist between the nominal and real stock indices and the economic activity variables. This suggests that both the ALSI and ALSIR could be useful in forecasting GDP and Industrial Production. The tests also verified no bidirectional causality between the variables, and more importantly, that the stock market is never led by any of the macroeconomic variables.

Vector autoregressive models were also estimated and impulse response functions and variance decompositions were computed to examine the short-run dynamics among the variables in the system. The results showed that a shock to the ALSI has a positive initial impact on GDP while having a predominantly negative impact on Industrial Production. When ALSIR was used as the market proxy, its impulse had a negative impact on both GDP and Industrial Production. While the Granger-causality tests may have shown no causality from the economic activity variables to the stock market; shocks to the stock market, whether nominal or real, by GDP and IIP were found to be significant and positive. In addition, the variance decomposition analysis revealed that the variance of both GDP and Industrial Production was largely explained by the stock market.

The cointegration tests were used to investigate the long-run relationship between the JSE and GDP and Industrial Production. The Johansen cointegration test revealed that a statistically significant long-run equilibrium relationship exists between the stock market and real economic output. Specifically there was a positive relationship from ALSI to GDP and Industrial Production as well as from ALSIR to GDP and Industrial Production. The findings from this study therefore indicated that the financial sector plays a significant role in the South African economy.

Testing the speed of adjustment and weak exogeneity however had less favourable results in the context of finding the stock market to be a leading indicator, as both ALSI and ALSIR were found to be weakly exogenous. According to Hendry (2004) however, both exogeneity and causality play different roles in modelling, forecasting and policy analysis. Hendry (2004) asserts that exogeneity is neither necessary nor sufficient for causality in the data generating process, and as such a variable can be exogenous for the parameters of interest in a given system and still be causal. In addition, this was the only evidence that was contrary to the previous findings.

In summary, while the Granger-causality tests confirmed a unidirectional causal relationship between the JSE and economic activity in South Africa, the long-run and short-run dynamics of the variables revealed often contradictory results. The variance decomposition showed that much of the variation in GDP and Industrial Production was explained by the stock market, however imposing restrictions onto the vector error correction model indicated that the stock market variables were in fact weakly exogenous.

Finding evidence in favour of the stock market as a leading indicator also has implications for the level of financial development in South Africa. According to Shaw (1973) less developed countries are characterised by financial repression which may impede economic growth, and thus rapid economic development in these countries can only be achieved when the financial sector is liberalised. South Africa’s financial system has undergone significant restructuring in the past two decades in line with market-based liberalisation reforms. This financial liberalisation in South Africa has led not only to an increase in the role of the stock market in the financial system, but has also improved the proficiency of this system. This superior level of efficiency in the country’s financial infrastructure is reiterated by the finding that the stock market is in fact a leading indicator of economic activity.

An interesting extension of this paper could be to replicate the methodology in order to investigate the information content of the yield curve in South Africa as a leading indicator. This is embedded in the premise that South Africa together with the U.S., UK and Japan have both the stock market and the yield curve included in their composite indices of leading economic indicators.

Another avenue for future research could be to concurrently evaluate both the stock market and the banking sector as leading indicators in order to determine which of the two would be superior in forecasting economic growth. Or alternatively, if the use of both leading indicators, as compliments and not substitutes, could lead to improved economic growth forecasts. According to Stiglitz (1985) the banking sector performs better in forecasting economic growth when compared with the stock market, especially when considering resource allocation. In addition, Blackburn, Bose and Capasso (2005) have found that both the stock market and the banking sector are necessary in promoting economic growth.

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7 APPENDICES

Appendix 1 - Unit root tests

Null Hypothesis: ALSI has a unit root
Exogenous: Constant
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.888603	0.0001
Test critical values:	1% level	-3.509281	
	5% level	-2.895924	
	10% level	-2.585172	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ALSI)
Method: Least Squares
Date: 03/26/16 Time: 10:11
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALSI(-1)	-1.259788	0.257699	-4.888603	0.0000
D(ALSI(-1))	0.214534	0.229576	0.934480	0.3529
D(ALSI(-2))	0.191812	0.196330	0.976989	0.3316
D(ALSI(-3))	0.190592	0.157359	1.211190	0.2294
D(ALSI(-4))	0.199818	0.108861	1.835541	0.0702
C	0.018644	0.005100	3.655349	0.0005

R-squared	0.544514	Mean dependent var	-7.61E-05
Adjusted R-squared	0.515686	S.D. dependent var	0.046340
S.E. of regression	0.032249	Akaike info criterion	-3.962660
Sum squared resid	0.082162	Schwarz criterion	-3.790238
Log likelihood	174.4131	Hannan-Quinn criter.	-3.893307
F-statistic	18.88822	Durbin-Watson stat	1.989381
Prob(F-statistic)	0.000000		

Null Hypothesis: ALSIR has a unit root
Exogenous: Constant
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.856806	0.0001
Test critical values:	1% level	-3.509281	
	5% level	-2.895924	
	10% level	-2.585172	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ALSIR)
Method: Least Squares
Date: 03/26/16 Time: 10:13
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALSIR(-1)	-1.095380	0.225535	-4.856806	0.0000
D(ALSIR(-1))	0.187473	0.202705	0.924857	0.3579
D(ALSIR(-2))	0.178418	0.175306	1.017752	0.3119
D(ALSIR(-3))	0.181787	0.145003	1.253679	0.2137
D(ALSIR(-4))	0.224654	0.107480	2.090185	0.0398
C	-0.001056	0.003915	-0.269819	0.7880

R-squared	0.485859	Mean dependent var	-7.75E-05
Adjusted R-squared	0.453318	S.D. dependent var	0.048625
S.E. of regression	0.035952	Akaike info criterion	-3.745276
Sum squared resid	0.102113	Schwarz criterion	-3.572854
Log likelihood	165.1742	Hannan-Quinn criter.	-3.675923
F-statistic	14.93087	Durbin-Watson stat	1.985407
Prob(F-statistic)	0.000000		

Null Hypothesis: GDP has a unit root
Exogenous: Constant
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.396664	0.0137
Test critical values:	1% level	-3.509281	
	5% level	-2.895924	
	10% level	-2.585172	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP)
Method: Least Squares
Date: 03/26/16 Time: 10:15
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP(-1)	-0.740481	0.218002	-3.396664	0.0011
D(GDP(-1))	-0.070539	0.193116	-0.365266	0.7159
D(GDP(-2))	-0.100265	0.177927	-0.563517	0.5747
D(GDP(-3))	0.104497	0.148547	0.703462	0.4838
D(GDP(-4))	-0.101076	0.116778	-0.865534	0.3894
C	0.018961	0.005886	3.221526	0.0019

R-squared	0.456948	Mean dependent var	-0.000466
Adjusted R-squared	0.422577	S.D. dependent var	0.014850
S.E. of regression	0.011284	Akaike info criterion	-6.062844
Sum squared resid	0.010059	Schwarz criterion	-5.890422
Log likelihood	263.6709	Hannan-Quinn criter.	-5.993491
F-statistic	13.29481	Durbin-Watson stat	1.934445
Prob(F-statistic)	0.000000		

Null Hypothesis: IIP has a unit root
Exogenous: Constant
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.711138	0.0002
Test critical values:	1% level	-3.509281	
	5% level	-2.895924	
	10% level	-2.585172	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IIP)
Method: Least Squares
Date: 03/26/16 Time: 10:19
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IIP(-1)	-0.932398	0.197913	-4.711138	0.0000
D(IIP(-1))	0.338126	0.176653	1.914069	0.0592
D(IIP(-2))	0.187049	0.149469	1.251419	0.2145
D(IIP(-3))	0.061078	0.124804	0.489389	0.6259
D(IIP(-4))	0.130786	0.106463	1.228460	0.2229
C	0.004149	0.002268	1.828959	0.0712

R-squared	0.365215	Mean dependent var	-5.64E-05
Adjusted R-squared	0.325038	S.D. dependent var	0.023388
S.E. of regression	0.019215	Akaike info criterion	-4.998315
Sum squared resid	0.029167	Schwarz criterion	-4.825893
Log likelihood	218.4284	Hannan-Quinn criter.	-4.928962
F-statistic	9.090308	Durbin-Watson stat	1.982185
Prob(F-statistic)	0.000001		

Null Hypothesis: GDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.135365	0.0083
Test critical values:	1% level	-4.069631	
	5% level	-3.463547	
	10% level	-3.158207	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP)
Method: Least Squares
Date: 03/26/16 Time: 10:28
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP(-1)	-0.998382	0.241425	-4.135365	0.0001
D(GDP(-1))	0.123641	0.207089	0.597042	0.5522
D(GDP(-2))	0.048504	0.185636	0.261285	0.7946
D(GDP(-3))	0.198602	0.150752	1.317403	0.1916
D(GDP(-4))	-0.045145	0.116548	-0.387348	0.6996
C	0.031628	0.008033	3.937253	0.0002
@TREND("1992Q1")	-0.000125	5.53E-05	-2.253744	0.0270

R-squared	0.490149	Mean dependent var	-0.000466
Adjusted R-squared	0.450930	S.D. dependent var	0.014850
S.E. of regression	0.011004	Akaike info criterion	-6.102402
Sum squared resid	0.009444	Schwarz criterion	-5.901243
Log likelihood	266.3521	Hannan-Quinn criter.	-6.021490
F-statistic	12.49766	Durbin-Watson stat	1.935710
Prob(F-statistic)	0.000000		

Null Hypothesis: IIP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.827030	0.0009
Test critical values:	1% level	-4.069631	
	5% level	-3.463547	
	10% level	-3.158207	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IIP)
Method: Least Squares
Date: 03/26/16 Time: 10:29
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IIP(-1)	-0.977344	0.202473	-4.827030	0.0000
D(IIP(-1))	0.372190	0.179571	2.072660	0.0415
D(IIP(-2))	0.210111	0.151027	1.391215	0.1681
D(IIP(-3))	0.076134	0.125576	0.606277	0.5461
D(IIP(-4))	0.141642	0.106918	1.324773	0.1891
C	0.008607	0.004848	1.775314	0.0797
@TREND("1992Q1")	-9.05E-05	8.70E-05	-1.040368	0.3014

R-squared	0.373903	Mean dependent var	-5.64E-05
Adjusted R-squared	0.325741	S.D. dependent var	0.023388
S.E. of regression	0.019205	Akaike info criterion	-4.988567
Sum squared resid	0.028768	Schwarz criterion	-4.787407
Log likelihood	219.0141	Hannan-Quinn criter.	-4.907655
F-statistic	7.763549	Durbin-Watson stat	1.986420
Prob(F-statistic)	0.000001		

Null Hypothesis: ALSI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.857196	0.0008
Test critical values:	1% level	-4.069631	
	5% level	-3.463547	
	10% level	-3.158207	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ALSI)
Method: Least Squares
Date: 03/26/16 Time: 10:24
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALSI(-1)	-1.259762	0.259360	-4.857196	0.0000
D(ALSI(-1))	0.214528	0.231044	0.928515	0.3560
D(ALSI(-2))	0.191825	0.197589	0.970829	0.3346
D(ALSI(-3))	0.190594	0.158364	1.203513	0.2324
D(ALSI(-4))	0.199824	0.109558	1.823911	0.0720
C	0.018580	0.008511	2.183225	0.0320
@TREND("1992Q1")	1.34E-06	0.000144	0.009320	0.9926

R-squared	0.544515	Mean dependent var	-7.61E-05
Adjusted R-squared	0.509477	S.D. dependent var	0.046340
S.E. of regression	0.032455	Akaike info criterion	-3.939132
Sum squared resid	0.082162	Schwarz criterion	-3.737972
Log likelihood	174.4131	Hannan-Quinn criter.	-3.858220
F-statistic	15.54097	Durbin-Watson stat	1.989424
Prob(F-statistic)	0.000000		

Null Hypothesis: ALSIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.870000	0.0008
Test critical values:	1% level	-4.069631	
	5% level	-3.463547	
	10% level	-3.158207	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ALSIR)
Method: Least Squares
Date: 03/26/16 Time: 10:27
Sample (adjusted): 1993Q2 2014Q2
Included observations: 85 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALSIR(-1)	-1.110966	0.228124	-4.870000	0.0000
D(ALSIR(-1))	0.200916	0.204917	0.980476	0.3299
D(ALSIR(-2))	0.189925	0.177195	1.071839	0.2871
D(ALSIR(-3))	0.189529	0.146247	1.295948	0.1988
D(ALSIR(-4))	0.229127	0.108221	2.117208	0.0374
C	-0.005417	0.008561	-0.632748	0.5287
@TREND("1992Q1")	9.22E-05	0.000161	0.573407	0.5680

R-squared	0.488017	Mean dependent var	-7.75E-05
Adjusted R-squared	0.448634	S.D. dependent var	0.048625
S.E. of regression	0.036106	Akaike info criterion	-3.725953
Sum squared resid	0.101684	Schwarz criterion	-3.524794
Log likelihood	165.3530	Hannan-Quinn criter.	-3.645041
F-statistic	12.39148	Durbin-Watson stat	1.989220
Prob(F-statistic)	0.000000		

Appendix 2: **Vector Autoregression Estimates**

VAR (4): ALSI, GDP, IIP

R-squared	0.132685	0.318908	0.352425
Adj. R-squared	-0.038335	0.184608	0.224734
Sum sq. resids	0.074827	0.007612	0.023065
S.E. equation	0.032464	0.010355	0.018024
F-statistic	0.775844	2.374592	2.759983
Log likelihood	180.9888	279.2608	231.5937
Akaike AIC	-3.860204	-6.145599	-5.037062
Schwarz SC	-3.432121	-5.717515	-4.608978
Mean dependent	0.015146	0.025941	0.004466
S.D. dependent	0.031859	0.011467	0.020470
Determinant resid covariance (dof adj.)	3.21E-11		
Determinant resid covariance	1.81E-11		
Log likelihood	697.6161		
Akaike information criterion	-15.17712		
Schwarz criterion	-13.89287		

VAR (3): ALSI, GDP, IIP

R-squared	0.108193	0.290698	0.269057
Adj. R-squared	-0.022605	0.186667	0.161852
Sum sq. resids	0.076971	0.008004	0.027181
S.E. equation	0.032036	0.010331	0.019037
F-statistic	0.827174	2.794344	2.509740
Log likelihood	182.3678	280.8278	227.6468
Akaike AIC	-3.916502	-6.179949	-4.957397
Schwarz SC	-3.576376	-5.839824	-4.617272
Mean dependent	0.015079	0.026061	0.004924
S.D. dependent	0.031679	0.011455	0.020794
Determinant resid covariance (dof adj.)	3.42E-11		
Determinant resid covariance	2.19E-11		
Log likelihood	697.3409		
Akaike information criterion	-15.20324		
Schwarz criterion	-14.18286		

VAR (2): ALSI, GDP, IIP

R-squared	0.089926	0.099653	0.217987
Adj. R-squared	-0.002234	0.008479	0.138796
Sum sq. resids	0.081130	0.010166	0.030374
S.E. equation	0.032046	0.011344	0.019608
F-statistic	0.975763	1.092996	2.752668
Log likelihood	182.6511	274.0397	225.8803
Akaike AIC	-3.946617	-6.023630	-4.929097
Schwarz SC	-3.693253	-5.770266	-4.675733
Mean dependent	0.014470	0.026033	0.004459
S.D. dependent	0.032011	0.011392	0.021129
Determinant resid covariance (dof adj.)	4.25E-11		
Determinant resid covariance	3.07E-11		
Log likelihood	690.4356		
Akaike information criterion	-15.07808		
Schwarz criterion	-14.31799		

VAR (1): ALSI, GDP, IIP

R-squared	0.027019	-0.013924	0.174127
Adj. R-squared	-0.031594	-0.075004	0.124375
Sum sq. resids	0.086739	0.011463	0.032302
S.E. equation	0.032327	0.011752	0.019728
F-statistic	0.460978	-0.227968	3.499931
Log likelihood	182.2549	272.3124	226.2102
Akaike AIC	-3.960785	-5.984549	-4.948543
Schwarz SC	-3.793012	-5.816776	-4.780770
Mean dependent	0.014460	0.025989	0.004273
S.D. dependent	0.031828	0.011335	0.021082
Determinant resid covariance (dof adj.)	4.74E-11		
Determinant resid covariance	3.85E-11		
Log likelihood	688.3244		
Akaike information criterion	-15.06347		
Schwarz criterion	-14.56015		

VAR (4): ALSIR, GDP, IIP

R-squared	0.179899	0.302483	0.341851
Adj. R-squared	0.018188	0.164944	0.212076
Sum sq. resids	0.089278	0.007796	0.023442
S.E. equation	0.035460	0.010479	0.018170
F-statistic	1.112475	2.199255	2.634171
Log likelihood	173.3961	278.2361	230.8973
Akaike AIC	-3.683631	-6.121770	-5.020867
Schwarz SC	-3.255547	-5.693686	-4.592783
Mean dependent	-0.000554	0.025941	0.004466
S.D. dependent	0.035787	0.011467	0.020470

Determinant resid covariance (dof adj.)	3.99E-11
Determinant resid covariance	2.25E-11
Log likelihood	688.2116
Akaike information criterion	-14.95841
Schwarz criterion	-13.67416

VAR (3): ALSIR, GDP, IIP

R-squared	0.159734	0.264374	0.263197
Adj. R-squared	0.036494	0.156482	0.155132
Sum sq. resids	0.091484	0.008301	0.027399
S.E. equation	0.034925	0.010521	0.019113
F-statistic	1.296127	2.450357	2.435551
Log likelihood	174.8536	279.2426	227.2994
Akaike AIC	-3.743760	-6.143508	-4.949412
Schwarz SC	-3.403635	-5.803383	-4.609287
Mean dependent	-0.000595	0.026061	0.004924
S.D. dependent	0.035581	0.011455	0.020794

Determinant resid covariance (dof adj.)	4.23E-11
Determinant resid covariance	2.71E-11
Log likelihood	688.0696
Akaike information criterion	-14.99011
Schwarz criterion	-13.96973

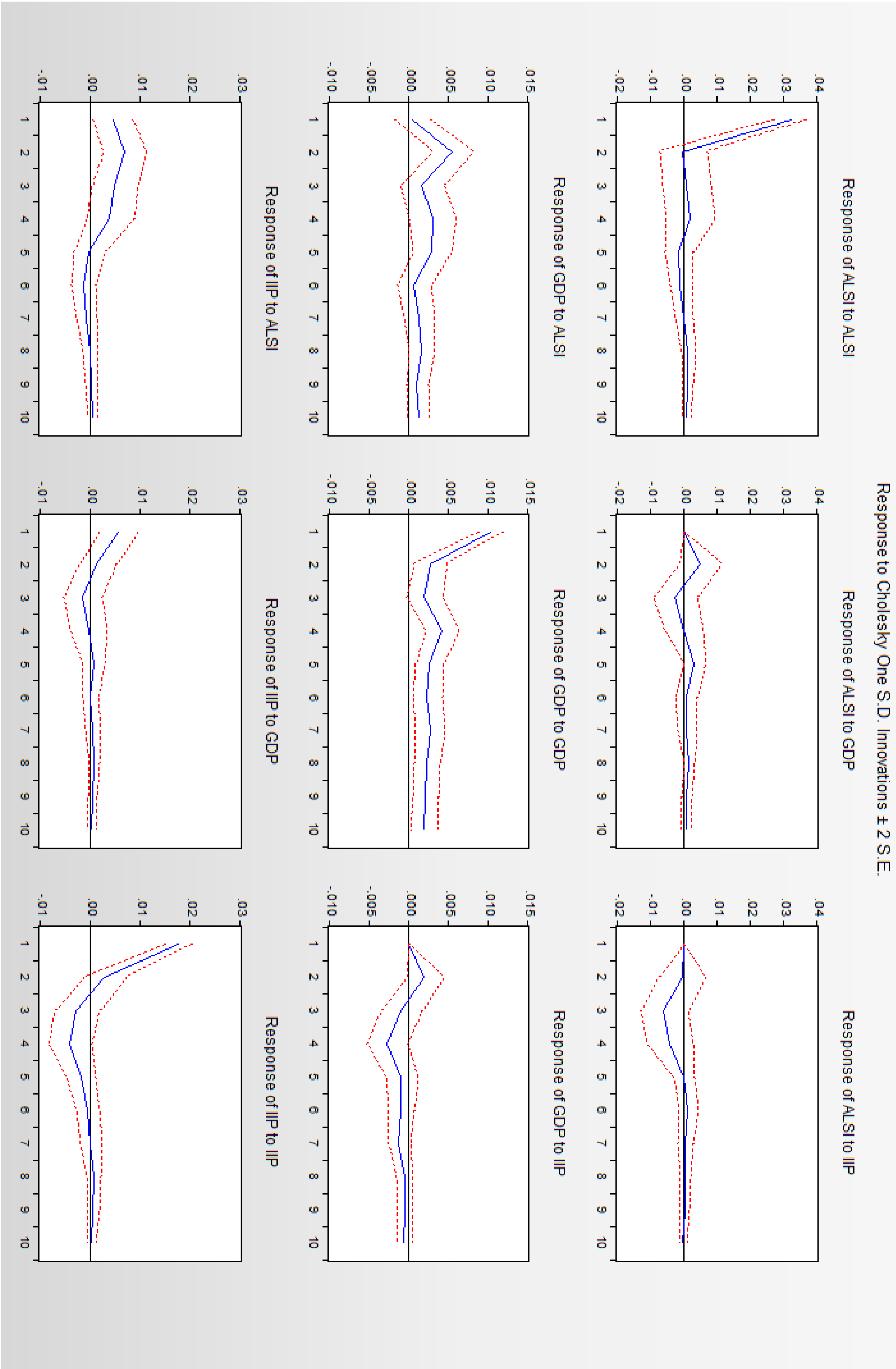
VAR (2): ALSIR, GDP, IIP

R-squared	0.147351	0.066404	0.206973
Adj. R-squared	0.061007	-0.028137	0.126666
Sum sq. resids	0.096494	0.010541	0.030801
S.E. equation	0.034949	0.011551	0.019746
F-statistic	1.706551	0.702382	2.577285
Log likelihood	175.0204	272.4441	225.2649
Akaike AIC	-3.773190	-5.987366	-4.915111
Schwarz SC	-3.519826	-5.734002	-4.661747
Mean dependent	-0.001344	0.026033	0.004459
S.D. dependent	0.036067	0.011392	0.021129
Determinant resid covariance (dof adj.)	5.28E-11		
Determinant resid covariance	3.82E-11		
Log likelihood	680.8581		
Akaike information criterion	-14.86041		
Schwarz criterion	-14.10032		

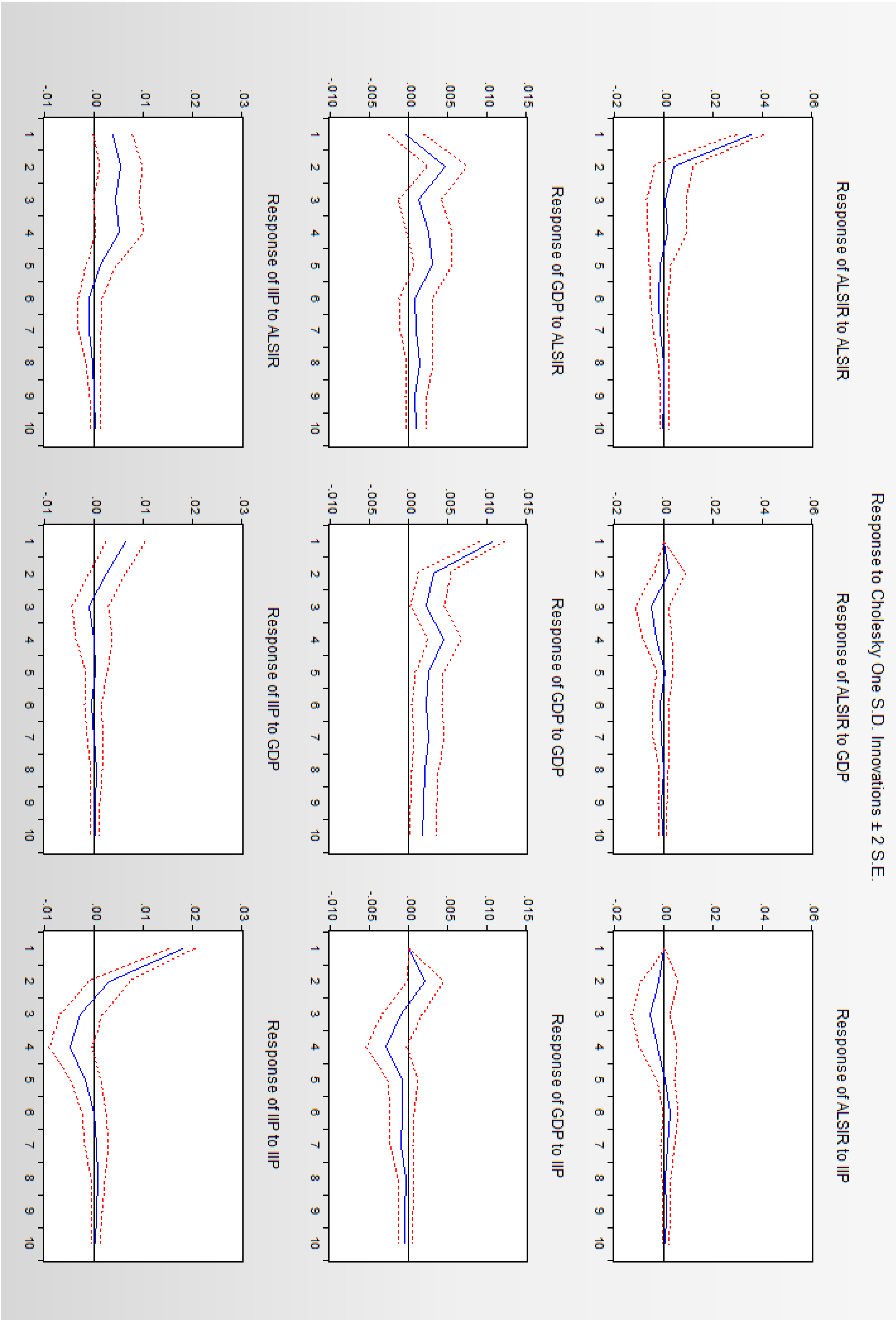
VAR (1): ALSIR, GDP, IIP

R-squared	0.098889	-0.085456	0.170680
Adj. R-squared	0.044605	-0.150845	0.120721
Sum sq. resids	0.102164	0.012272	0.032437
S.E. equation	0.035084	0.012159	0.019769
F-statistic	1.821696	-1.306886	3.416395
Log likelihood	174.9709	269.2788	226.0248
Akaike AIC	-3.797099	-5.916377	-4.944379
Schwarz SC	-3.629326	-5.748604	-4.776605
Mean dependent	-0.001506	0.025989	0.004273
S.D. dependent	0.035894	0.011335	0.021082
Determinant resid covariance (dof adj.)	5.95E-11		
Determinant resid covariance	4.83E-11		
Log likelihood	678.1886		
Akaike information criterion	-14.83570		
Schwarz criterion	-14.33238		

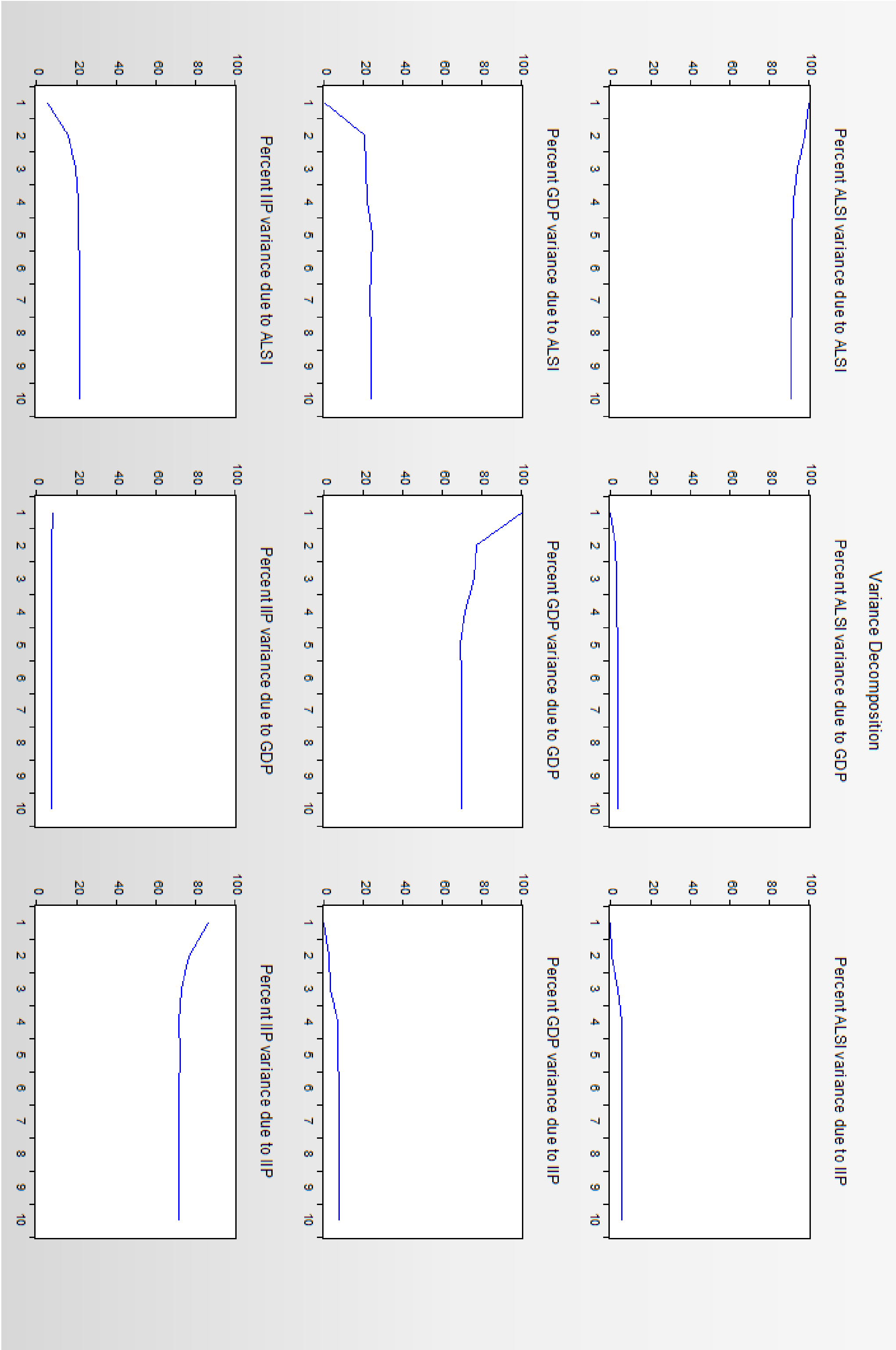
Appendix 3: Impulse Response Functions – Cholesky Decomposition
ALSI, GDP, IIP



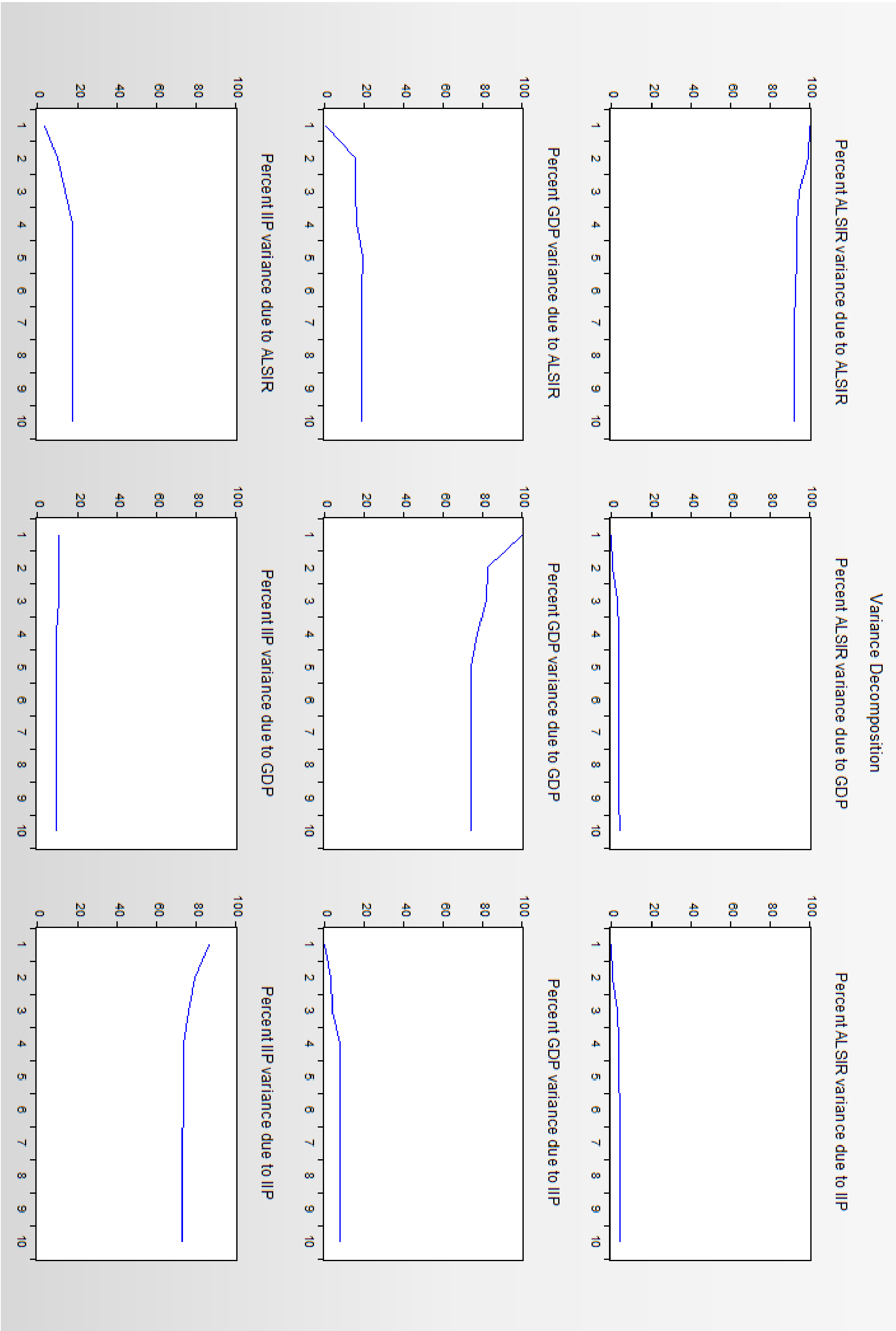
ALSIR, GDP, IIP



Appendix 4: <u>Variance Decomposition</u>
<u>ALSI, GDP, IIP</u>



<u>ALSIR, GDP, IIP</u>



Variance Decomposition of ALSI:

Period	S.E.	ALSI	GDP	IIP
1	0.032036	100.0000	0.000000	0.000000
2	0.032380	97.89844	2.051828	0.049729
3	0.033094	93.75453	2.712824	3.532642
4	0.033439	92.07658	2.657613	5.265804
5	0.033623	91.31999	3.465875	5.214136
6	0.033665	91.20968	3.477408	5.312915
7	0.033674	91.16089	3.525878	5.313236
8	0.033722	91.00084	3.700913	5.298243
9	0.033741	90.97479	3.731236	5.293978
10	0.033751	90.93985	3.752876	5.307272

Variance Decomposition of GDP:

Period	S.E.	ALSI	GDP	IIP
1	0.010331	0.172767	99.82723	0.000000
2	0.012118	20.27262	77.30971	2.417671
3	0.012415	20.95708	75.96981	3.073115
4	0.013715	21.75418	71.34571	6.900106
5	0.014270	24.11001	69.00257	6.887418
6	0.014502	23.53457	69.24402	7.221407
7	0.014843	23.15396	69.19140	7.654635
8	0.015094	23.37678	69.06432	7.558905
9	0.015268	23.24805	69.23674	7.515205
10	0.015443	23.26914	69.17462	7.556242

Variance Decomposition of IIP:

Period	S.E.	ALSI	GDP	IIP
1	0.019037	5.408572	8.319158	86.27227
2	0.020428	15.69639	7.575275	76.72833
3	0.021227	19.48593	7.677558	72.83652
4	0.022006	21.15356	7.184962	71.66148
5	0.022106	20.98225	7.181869	71.83588
6	0.022164	21.32252	7.145998	71.53148
7	0.022189	21.46387	7.164610	71.37152
8	0.022206	21.43648	7.244798	71.31872
9	0.022214	21.42601	7.257444	71.31655
10	0.022217	21.43934	7.265670	71.29499

Cholesky Ordering: ALSI GDP IIP

Variance Decomposition of ALSIR:

Period	S.E.	ALSIR	GDP	IIP
1	0.034925	100.0000	0.000000	0.000000
2	0.035244	99.28891	0.287151	0.423941
3	0.036167	94.29390	2.573311	3.132791
4	0.036424	93.05130	3.268635	3.680069
5	0.036470	93.06372	3.260736	3.675548
6	0.036667	92.48351	3.533050	3.983437
7	0.036755	92.26884	3.687783	4.043381
8	0.036763	92.24085	3.703158	4.055994
9	0.036782	92.14223	3.780945	4.076826
10	0.036800	92.07340	3.852239	4.074364

Variance Decomposition of GDP:

Period	S.E.	ALSIR	GDP	IIP
1	0.010521	0.200327	99.79967	0.000000
2	0.012103	15.01546	82.28343	2.701113
3	0.012415	15.26086	81.46300	3.276131
4	0.013721	15.75400	76.91150	7.334495
5	0.014303	18.96710	73.90460	7.128292
6	0.014516	18.66647	74.00768	7.325856
7	0.014790	18.34444	74.10243	7.553121
8	0.014990	18.64868	73.90514	7.446185
9	0.015128	18.59197	73.99480	7.413234
10	0.015255	18.58749	73.97727	7.435245

Variance Decomposition of IIP:

Period	S.E.	ALSIR	GDP	IIP
1	0.019113	3.544253	10.50707	85.94868
2	0.020192	10.14929	10.77502	79.07570
3	0.020840	13.52187	10.37195	76.10618
4	0.021999	17.32458	9.316711	73.35870
5	0.022109	17.40497	9.232418	73.36261
6	0.022144	17.58465	9.277725	73.13762
7	0.022176	17.80311	9.251283	72.94560
8	0.022186	17.80457	9.260126	72.93531
9	0.022190	17.79816	9.256955	72.94488
10	0.022190	17.79830	9.257051	72.94465

Cholesky Ordering: ALSIR GDP IIP

Appendix 5: Granger-causality tests

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 15:43
Sample: 1992Q1 2014Q2
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	89	12.7003	0.0006
ALSI does not Granger Cause ALSIR		19.2166	3.E-05
GDP does not Granger Cause ALSI	89	0.02299	0.8798
ALSI does not Granger Cause GDP		12.0954	0.0008
IIP does not Granger Cause ALSI	89	0.00109	0.9738
ALSI does not Granger Cause IIP		6.21834	0.0146
GDP does not Granger Cause ALSIR	89	0.72900	0.3956
ALSIR does not Granger Cause GDP		8.78875	0.0039
IIP does not Granger Cause ALSIR	89	0.71497	0.4001
ALSIR does not Granger Cause IIP		5.74081	0.0187
IIP does not Granger Cause GDP	89	10.5636	0.0016
GDP does not Granger Cause IIP		0.00215	0.9631

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:14
Sample: 1992Q1 2014Q2
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	88	6.68924	0.0020
ALSI does not Granger Cause ALSIR		9.98954	0.0001
GDP does not Granger Cause ALSI	88	1.81121	0.1699
ALSI does not Granger Cause GDP		5.88418	0.0041
IIP does not Granger Cause ALSI	88	2.20005	0.1172
ALSI does not Granger Cause IIP		4.18310	0.0186
GDP does not Granger Cause ALSIR	88	2.74118	0.0703
ALSIR does not Granger Cause GDP		4.27606	0.0171
IIP does not Granger Cause ALSIR	88	2.08968	0.1302
ALSIR does not Granger Cause IIP		3.53163	0.0337
IIP does not Granger Cause GDP	88	5.12519	0.0080
GDP does not Granger Cause IIP		0.14033	0.8693

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:16
Sample: 1992Q1 2014Q2
Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	87	3.89819	0.0118
ALSI does not Granger Cause ALSIR		5.97950	0.0010
GDP does not Granger Cause ALSI	87	1.82863	0.1486
ALSI does not Granger Cause GDP		6.53673	0.0005
IIP does not Granger Cause ALSI	87	1.88630	0.1385
ALSI does not Granger Cause IIP		4.33652	0.0070
GDP does not Granger Cause ALSIR	87	2.54091	0.0622
ALSIR does not Granger Cause GDP		5.25432	0.0023
IIP does not Granger Cause ALSIR	87	1.70524	0.1726
ALSIR does not Granger Cause IIP		3.69829	0.0151
IIP does not Granger Cause GDP	87	3.90579	0.0117
GDP does not Granger Cause IIP		0.06013	0.9805

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:20
Sample: 1992Q1 2014Q2
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	86	2.92733	0.0261
ALSI does not Granger Cause ALSIR		4.45007	0.0027
GDP does not Granger Cause ALSI	86	1.53856	0.1994
ALSI does not Granger Cause GDP		5.26535	0.0008
IIP does not Granger Cause ALSI	86	1.84201	0.1293
ALSI does not Granger Cause IIP		4.30313	0.0034
GDP does not Granger Cause ALSIR	86	2.02418	0.0993
ALSIR does not Granger Cause GDP		4.26680	0.0036
IIP does not Granger Cause ALSIR	86	1.52882	0.2022
ALSIR does not Granger Cause IIP		4.06103	0.0049
IIP does not Granger Cause GDP	86	3.08384	0.0207
GDP does not Granger Cause IIP		1.23702	0.3023

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:24
Sample: 1992Q1 2014Q2
Lags: 5

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	85	2.32713	0.0510
ALSI does not Granger Cause ALSIR		3.39940	0.0081
GDP does not Granger Cause ALSI	85	0.84951	0.5192
ALSI does not Granger Cause GDP		4.79780	0.0007
IIP does not Granger Cause ALSI	85	1.61620	0.1663
ALSI does not Granger Cause IIP		3.18224	0.0117
GDP does not Granger Cause ALSIR	85	1.19328	0.3208
ALSIR does not Granger Cause GDP		3.94416	0.0032
IIP does not Granger Cause ALSIR	85	1.60471	0.1694
ALSIR does not Granger Cause IIP		2.94272	0.0177
IIP does not Granger Cause GDP	85	2.58859	0.0326
GDP does not Granger Cause IIP		1.18612	0.3242

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:26
Sample: 1992Q1 2014Q2
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	84	2.17738	0.0552
ALSI does not Granger Cause ALSIR		2.90745	0.0136
GDP does not Granger Cause ALSI	84	0.95691	0.4607
ALSI does not Granger Cause GDP		4.25429	0.0010
IIP does not Granger Cause ALSI	84	1.88445	0.0954
ALSI does not Granger Cause IIP		2.97798	0.0119
GDP does not Granger Cause ALSIR	84	1.14601	0.3451
ALSIR does not Granger Cause GDP		3.55496	0.0039
IIP does not Granger Cause ALSIR	84	1.58914	0.1630
ALSIR does not Granger Cause IIP		2.70128	0.0203
IIP does not Granger Cause GDP	84	2.70535	0.0201
GDP does not Granger Cause IIP		1.07296	0.3869

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:28
Sample: 1992Q1 2014Q2
Lags: 7

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	83	1.60483	0.1490
ALSI does not Granger Cause ALSIR		2.29259	0.0370
GDP does not Granger Cause ALSI	83	0.64430	0.7177
ALSI does not Granger Cause GDP		3.96929	0.0011
IIP does not Granger Cause ALSI	83	1.59697	0.1512
ALSI does not Granger Cause IIP		2.38009	0.0308
GDP does not Granger Cause ALSIR	83	0.82098	0.5733
ALSIR does not Granger Cause GDP		3.86478	0.0013
IIP does not Granger Cause ALSIR	83	1.44758	0.2011
ALSIR does not Granger Cause IIP		2.35387	0.0326
IIP does not Granger Cause GDP	83	2.53087	0.0225
GDP does not Granger Cause IIP		1.46634	0.1941

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:31
Sample: 1992Q1 2014Q2
Lags: 8

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	82	1.64344	0.1298
ALSI does not Granger Cause ALSIR		2.40062	0.0246
GDP does not Granger Cause ALSI	82	1.32012	0.2495
ALSI does not Granger Cause GDP		3.68530	0.0013
IIP does not Granger Cause ALSI	82	1.27497	0.2720
ALSI does not Granger Cause IIP		1.99646	0.0607
GDP does not Granger Cause ALSIR	82	1.38244	0.2209
ALSIR does not Granger Cause GDP		3.57790	0.0017
IIP does not Granger Cause ALSIR	82	1.35981	0.2310
ALSIR does not Granger Cause IIP		2.00914	0.0590
IIP does not Granger Cause GDP	82	2.25855	0.0339
GDP does not Granger Cause IIP		1.30551	0.2566

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:36
Sample: 1992Q1 2014Q2
Lags: 9

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	81	1.41456	0.2015
ALSI does not Granger Cause ALSIR		2.08012	0.0449
GDP does not Granger Cause ALSI	81	1.14728	0.3444
ALSI does not Granger Cause GDP		3.31265	0.0023
IIP does not Granger Cause ALSI	81	1.08070	0.3897
ALSI does not Granger Cause IIP		1.83482	0.0796
GDP does not Granger Cause ALSIR	81	1.10266	0.3744
ALSIR does not Granger Cause GDP		3.32724	0.0022
IIP does not Granger Cause ALSIR	81	1.09248	0.3814
ALSIR does not Granger Cause IIP		1.77072	0.0921
IIP does not Granger Cause GDP	81	1.98580	0.0561
GDP does not Granger Cause IIP		1.16070	0.3358

Pairwise Granger Causality Tests
Date: 03/26/16 Time: 16:42
Sample: 1992Q1 2014Q2
Lags: 10

Null Hypothesis:	Obs	F-Statistic	Prob.
ALSIR does not Granger Cause ALSI	80	1.62605	0.1215
ALSI does not Granger Cause ALSIR		2.27623	0.0249
GDP does not Granger Cause ALSI	80	1.01748	0.4401
ALSI does not Granger Cause GDP		3.10628	0.0031
IIP does not Granger Cause ALSI	80	0.89387	0.5443
ALSI does not Granger Cause IIP		1.69179	0.1041
GDP does not Granger Cause ALSIR	80	1.06901	0.4002
ALSIR does not Granger Cause GDP		3.06503	0.0034
IIP does not Granger Cause ALSIR	80	0.92139	0.5202
ALSIR does not Granger Cause IIP		1.59142	0.1317
IIP does not Granger Cause GDP	80	1.68365	0.1061
GDP does not Granger Cause IIP		0.98863	0.4634

Appendix 6: Cointegration: The Johansen Procedure

Date: 03/26/16 Time: 17:39
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Trend assumption: Linear deterministic trend
Series: ALSI GDP IIP
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.313855	69.05079	29.79707	0.0000
At most 1 *	0.212608	36.65755	15.49471	0.0000
At most 2 *	0.170740	16.10104	3.841466	0.0001

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.313855	32.39324	21.13162	0.0009
At most 1 *	0.212608	20.55651	14.26460	0.0045
At most 2 *	0.170740	16.10104	3.841466	0.0001

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

ALSI	GDP	IIP
-62.09788	48.04943	79.60759
57.38020	46.64332	15.22825
-2.163752	-199.5779	94.83587

Unrestricted Adjustment Coefficients (alpha):

D(ALSI)	-0.001086	-0.015213	0.001355
D(GDP)	-0.003064	0.000295	0.003688
D(IIP)	-0.010604	-0.002077	-0.001467

1 Cointegrating Equation(s):		Log likelihood	680.4878

Normalized cointegrating coefficients (standard error in parentheses)

ALSI	GDP	IIP
1.000000	-0.773769	-1.281970
	(0.57877)	(0.31358)

Adjustment coefficients (standard error in parentheses)

D(ALSI)	0.067447
	(0.23802)
D(GDP)	0.190294
	(0.07192)
D(IIP)	0.658469
	(0.11971)

2 Cointegrating Equation(s):		Log likelihood	690.7661

Normalized cointegrating coefficients (standard error in parentheses)

ALSI	GDP	IIP
1.000000	0.000000	-0.527361
		(0.21571)
0.000000	1.000000	0.975238
		(0.27406)

Adjustment coefficients (standard error in parentheses)

D(ALSI)	-0.805478	-0.761774
	(0.28804)	(0.22813)
D(GDP)	0.207233	-0.133475
	(0.09788)	(0.07752)
D(IIP)	0.539266	-0.606401
	(0.16172)	(0.12809)

Date: 03/26/16 Time: 17:51
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Trend assumption: Linear deterministic trend
Series: ALSIR GDP IIP
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.312311	68.75473	29.79707	0.0000
At most 1 *	0.213945	36.55472	15.49471	0.0000
At most 2 *	0.168336	15.85211	3.841466	0.0001

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.312311	32.20001	21.13162	0.0009
At most 1 *	0.213945	20.70260	14.26460	0.0042
At most 2 *	0.168336	15.85211	3.841466	0.0001

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

ALSIR	GDP	IIP
-46.11181	7.478755	87.70764
42.56539	116.4839	-6.787280
11.38677	-180.9308	88.98155

Unrestricted Adjustment Coefficients (alpha):

D(ALSIR)	0.000273	-0.017070	-0.002052
D(GDP)	-0.002733	-0.000636	0.003811
D(IIP)	-0.010790	-0.001923	-0.001228

1 Cointegrating Equation(s): Log likelihood 668.2395

Normalized cointegrating coefficients (standard error in parentheses)

ALSIR	GDP	IIP
1.000000	-0.162187	-1.902064
	(0.78613)	(0.42280)

Adjustment coefficients (standard error in parentheses)

D(ALSIR)	-0.012583
	(0.19831)
D(GDP)	0.126010
	(0.05446)
D(IIP)	0.497546
	(0.08951)

2 Cointegrating Equation(s): Log likelihood 678.5908

Normalized cointegrating coefficients (standard error in parentheses)

ALSIR	GDP	IIP
1.000000	0.000000	-1.804565
		(0.32401)
0.000000	1.000000	0.601154
		(0.20294)

Adjustment coefficients (standard error in parentheses)

D(ALSIR)	-0.739178	-1.986351
	(0.23987)	(0.44616)
D(GDP)	0.098955	-0.094478
	(0.07398)	(0.13760)
D(IIP)	0.415679	-0.304732
	(0.12102)	(0.22509)

Appendix 7: VECM and Long-run homogeneity

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:03
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
GDP(-1)	1.000000
ALSI(-1)	-1.672472
	(0.40656)
	[-4.11375]
IIP(-1)	2.274457
	(0.50006)
	[4.54837]
C	-0.012524

Error Correction:	D(GDP)	D(ALSI)	D(IIP)
CointEq1	-0.092345	-0.010201	-0.387564
	(0.04272)	(0.14466)	(0.07316)
	[-2.16156]	[-0.07052]	[-5.29780]
D(GDP(-1))	-0.640674	0.213921	0.481520
	(0.12438)	(0.42115)	(0.21298)
	[-5.15113]	[0.50794]	[2.26087]
D(GDP(-2))	-0.469593	-0.036505	0.313778
	(0.13590)	(0.46018)	(0.23272)
	[-3.45535]	[-0.07933]	[1.34831]
D(GDP(-3))	0.062742	-0.070338	0.368020
	(0.11582)	(0.39218)	(0.19833)
	[0.54172]	[-0.17935]	[1.85558]
D(ALSI(-1))	-0.021177	-0.819250	-0.403487
	(0.07407)	(0.25082)	(0.12684)
	[-0.28590]	[-3.26634]	[-3.18107]
D(ALSI(-2))	-0.043665	-0.524146	-0.248881
	(0.06175)	(0.20908)	(0.10573)
	[-0.70716]	[-2.50688]	[-2.35381]
D(ALSI(-3))	0.010616	-0.163426	-0.052172
	(0.04393)	(0.14876)	(0.07523)
	[0.24166]	[-1.09862]	[-0.69353]
D(IIP(-1))	0.299227	0.010496	0.083745
	(0.08260)	(0.27971)	(0.14145)
	[3.62244]	[0.03753]	[0.59205]
D(IIP(-2))	0.178486	-0.321610	-0.093952
	(0.07351)	(0.24891)	(0.12588)
	[2.42805]	[-1.29205]	[-0.74637]
D(IIP(-3))	0.075635	-0.431569	-0.189564
	(0.06213)	(0.21038)	(0.10639)
	[1.21734]	[-2.05135]	[-1.78174]
C	-0.001789	-0.001113	-0.001325
	(0.00240)	(0.00812)	(0.00411)
	[-0.74632]	[-0.13709]	[-0.32274]
S2	-0.000449	0.001123	0.001808
	(0.00345)	(0.01169)	(0.00591)
	[-0.13001]	[0.09608]	[0.30577]

S3	-0.001131	-0.005044	-0.001386
	(0.00348)	(0.01179)	(0.00596)
	[-0.32487]	[-0.42796]	[-0.23246]
S4	0.006713	0.011950	0.004323
	(0.00349)	(0.01180)	(0.00597)
	[1.92585]	[1.01244]	[0.72427]
R-squared	0.566886	0.491529	0.498915
Adj. R-squared	0.488685	0.399721	0.408441
Sum sq. resids	0.008024	0.092007	0.023530
S.E. equation	0.010557	0.035747	0.018078
F-statistic	7.249091	5.353912	5.514477
Log likelihood	276.9944	172.1015	230.7357
Akaike AIC	-6.116149	-3.676780	-5.040366
Schwarz SC	-5.716604	-3.277235	-4.640821
Mean dependent	-0.000444	0.000202	-0.000428
S.D. dependent	0.014764	0.046139	0.023504

Determinant resid covariance (dof adj.)	4.08E-11
Determinant resid covariance	2.39E-11
Log likelihood	685.4869
Akaike information criterion	-14.89504
Schwarz criterion	-13.61079

Vector Error Correction Estimates

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:01
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
GDP(-1)	1.000000		
ALSIR(-1)	2.410524		
	(0.53683)		
	[4.49032]		
IIP(-1)	-4.522892		
	(0.85372)		
	[-5.29789]		
C	-0.002585		
Error Correction:	**D(GDP)**	**D(ALSIR)**	**D(IIP)**
CointEq1	0.039415	-0.075959	0.212823
	(0.02443)	(0.08926)	(0.04174)
	[1.61355]	[-0.85094]	[5.09871]
D(GDP(-1))	-0.739079	0.200774	-2.80E-05
	(0.12790)	(0.46738)	(0.21855)
	[-5.77842]	[0.42957]	[-0.00013]
D(GDP(-2))	-0.537062	-0.166100	-0.016849
	(0.13906)	(0.50815)	(0.23762)
	[-3.86206]	[-0.32687]	[-0.07091]
D(GDP(-3))	0.050222	-0.119424	0.240169
	(0.12048)	(0.44024)	(0.20586)
	[0.41686]	[-0.27127]	[1.16665]
D(ALSIR(-1))	0.020129	-0.499037	-0.308476
	(0.06146)	(0.22459)	(0.10502)
	[0.32750]	[-2.22195]	[-2.93724]
D(ALSIR(-2))	-0.016245	-0.283861	-0.213365
	(0.05204)	(0.19017)	(0.08892)
	[-0.31216]	[-1.49269]	[-2.39940]
D(ALSIR(-3))	0.034623	-0.025612	-0.030336
	(0.04006)	(0.14639)	(0.06845)
	[0.86426]	[-0.17496]	[-0.44316]
D(IIP(-1))	0.287991	-0.337704	0.179625
	(0.09135)	(0.33382)	(0.15610)
	[3.15255]	[-1.01164]	[1.15073]
D(IIP(-2))	0.180796	-0.541579	0.000379
	(0.07950)	(0.29052)	(0.13585)
	[2.27406]	[-1.86416]	[0.00279]
D(IIP(-3))	0.070622	-0.473752	-0.142570
	(0.06574)	(0.24021)	(0.11232)
	[1.07434]	[-1.97224]	[-1.26927]
C	-0.002296	-0.004747	-0.001621
	(0.00250)	(0.00913)	(0.00427)
	[-0.91847]	[-0.51971]	[-0.37948]
S2	0.000416	0.002830	0.002603
	(0.00363)	(0.01327)	(0.00620)
	[0.11465]	[0.21331]	[0.41952]

S3	-0.001110	-0.003683	-0.001974
	(0.00363)	(0.01326)	(0.00620)
	[-0.30577]	[-0.27771]	[-0.31836]
S4	0.007717	0.023445	0.005151
	(0.00365)	(0.01334)	(0.00624)
	[2.11424]	[1.75767]	[0.82590]
R-squared	0.550440	0.440944	0.482110
Adj. R-squared	0.469270	0.340004	0.388602
Sum sq. resids	0.008329	0.111220	0.024319
S.E. equation	0.010756	0.039303	0.018378
F-statistic	6.781283	4.368355	5.155820
Log likelihood	275.3918	163.9468	229.3173
Akaike AIC	-6.078880	-3.487135	-5.007379
Schwarz SC	-5.679335	-3.087590	-4.607834
Mean dependent	-0.000444	0.000136	-0.000428
S.D. dependent	0.014764	0.048379	0.023504
Determinant resid covariance (dof adj.)		5.15E-11	
Determinant resid covariance		3.02E-11	
Log likelihood		675.4875	
Akaike information criterion		-14.66250	
Schwarz criterion		-13.37825	

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:05
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
IIP(-1)	1.000000		
ALSI(-1)	-0.735328		
	(0.16326)		
	[-4.50397]		
GDP(-1)	0.439665		
	(0.37170)		
	[1.18284]		
C	-0.005506		
Error Correction:	**D(IIP)**	**D(ALSI)**	**D(GDP)**
CointEq1	-0.881498	-0.023202	-0.210034
	(0.16639)	(0.32902)	(0.09717)
	[-5.29780]	[-0.07052]	[-2.16156]
D(IIP(-1))	0.083745	0.010496	0.299227
	(0.14145)	(0.27971)	(0.08260)
	[0.59205]	[0.03753]	[3.62244]
D(IIP(-2))	-0.093952	-0.321610	0.178486
	(0.12588)	(0.24891)	(0.07351)
	[-0.74637]	[-1.29205]	[2.42805]
D(IIP(-3))	-0.189564	-0.431569	0.075635
	(0.10639)	(0.21038)	(0.06213)
	[-1.78174]	[-2.05135]	[1.21734]
D(ALSI(-1))	-0.403487	-0.819250	-0.021177
	(0.12684)	(0.25082)	(0.07407)
	[-3.18107]	[-3.26634]	[-0.28590]
D(ALSI(-2))	-0.248881	-0.524146	-0.043665
	(0.10573)	(0.20908)	(0.06175)
	[-2.35381]	[-2.50688]	[-0.70716]
D(ALSI(-3))	-0.052172	-0.163426	0.010616
	(0.07523)	(0.14876)	(0.04393)
	[-0.69353]	[-1.09862]	[0.24166]
D(GDP(-1))	0.481520	0.213921	-0.640674
	(0.21298)	(0.42115)	(0.12438)
	[2.26087]	[0.50794]	[-5.15113]
D(GDP(-2))	0.313778	-0.036505	-0.469593
	(0.23272)	(0.46018)	(0.13590)
	[1.34831]	[-0.07933]	[-3.45535]
D(GDP(-3))	0.368020	-0.070338	0.062742
	(0.19833)	(0.39218)	(0.11582)
	[1.85558]	[-0.17935]	[0.54172]
C	-0.001325	-0.001113	-0.001789
	(0.00411)	(0.00812)	(0.00240)
	[-0.32274]	[-0.13709]	[-0.74632]
S2	0.001808	0.001123	-0.000449
	(0.00591)	(0.01169)	(0.00345)
	[0.30577]	[0.09608]	[-0.13001]

S3	-0.001386	-0.005044	-0.001131
	(0.00596)	(0.01179)	(0.00348)
	[-0.23246]	[-0.42796]	[-0.32487]
S4	0.004323	0.011950	0.006713
	(0.00597)	(0.01180)	(0.00349)
	[0.72427]	[1.01244]	[1.92585]
R-squared	0.498915	0.491529	0.566886
Adj. R-squared	0.408441	0.399721	0.488685
Sum sq. resids	0.023530	0.092007	0.008024
S.E. equation	0.018078	0.035747	0.010557
F-statistic	5.514477	5.353912	7.249091
Log likelihood	230.7357	172.1015	276.9944
Akaike AIC	-5.040366	-3.676780	-6.116149
Schwarz SC	-4.640821	-3.277235	-5.716604
Mean dependent	-0.000428	0.000202	-0.000444
S.D. dependent	0.023504	0.046139	0.014764

Determinant resid covariance (dof adj.)	4.08E-11
Determinant resid covariance	2.39E-11
Log likelihood	685.4869
Akaike information criterion	-14.89504
Schwarz criterion	-13.61079

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:07
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
IIP(-1)	1.000000		
ALSIR(-1)	-0.532961		
	(0.10944)		
	[-4.86981]		
GDP(-1)	-0.221097		
	(0.32506)		
	[-0.68018]		
C	0.000571		
Error Correction:	**D(IIP)**	**D(ALSIR)**	**D(GDP)**
CointEq1	-0.962577	0.343553	-0.178272
	(0.18879)	(0.40373)	(0.11048)
	[-5.09871]	[0.85094]	[-1.61355]
D(IIP(-1))	0.179625	-0.337704	0.287991
	(0.15610)	(0.33382)	(0.09135)
	[1.15073]	[-1.01164]	[3.15255]
D(IIP(-2))	0.000379	-0.541579	0.180796
	(0.13585)	(0.29052)	(0.07950)
	[0.00279]	[-1.86416]	[2.27406]
D(IIP(-3))	-0.142570	-0.473752	0.070622
	(0.11232)	(0.24021)	(0.06574)
	[-1.26927]	[-1.97224]	[1.07434]
D(ALSIR(-1))	-0.308476	-0.499037	0.020129
	(0.10502)	(0.22459)	(0.06146)
	[-2.93724]	[-2.22195]	[0.32750]
D(ALSIR(-2))	-0.213365	-0.283861	-0.016245
	(0.08892)	(0.19017)	(0.05204)
	[-2.39940]	[-1.49269]	[-0.31216]
D(ALSIR(-3))	-0.030336	-0.025612	0.034623
	(0.06845)	(0.14639)	(0.04006)
	[-0.44316]	[-0.17496]	[0.86426]
D(GDP(-1))	-2.80E-05	0.200774	-0.739079
	(0.21855)	(0.46738)	(0.12790)
	[-0.00013]	[0.42957]	[-5.77842]
D(GDP(-2))	-0.016849	-0.166100	-0.537062
	(0.23762)	(0.50815)	(0.13906)
	[-0.07091]	[-0.32687]	[-3.86206]
D(GDP(-3))	0.240169	-0.119424	0.050222
	(0.20586)	(0.44024)	(0.12048)
	[1.16665]	[-0.27127]	[0.41686]
C	-0.001621	-0.004747	-0.002296
	(0.00427)	(0.00913)	(0.00250)
	[-0.37948]	[-0.51971]	[-0.91847]
S2	0.002603	0.002830	0.000416
	(0.00620)	(0.01327)	(0.00363)
	[0.41952]	[0.21331]	[0.11465]

S3	-0.001974	-0.003683	-0.001110
	(0.00620)	(0.01326)	(0.00363)
	[-0.31836]	[-0.27771]	[-0.30577]
S4	0.005151	0.023445	0.007717
	(0.00624)	(0.01334)	(0.00365)
	[0.82590]	[1.75767]	[2.11424]
R-squared	0.482110	0.440944	0.550440
Adj. R-squared	0.388602	0.340004	0.469270
Sum sq. resids	0.024319	0.111220	0.008329
S.E. equation	0.018378	0.039303	0.010756
F-statistic	5.155820	4.368355	6.781283
Log likelihood	229.3173	163.9468	275.3918
Akaike AIC	-5.007379	-3.487135	-6.078880
Schwarz SC	-4.607834	-3.087590	-5.679335
Mean dependent	-0.000428	0.000136	-0.000444
S.D. dependent	0.023504	0.048379	0.014764

Determinant resid covariance (dof adj.)	5.15E-11
Determinant resid covariance	3.02E-11
Log likelihood	675.4875
Akaike information criterion	-14.66250
Schwarz criterion	-13.37825

Imposing linear homogeneity restriction

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:21
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,2)+B(1,3)=1, B(1,1)=1
Convergence achieved after 47 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	0.041646
Probability	0.838296

Cointegrating Eq:	CointEq1
GDP(-1)	1.000000
ALSI(-1)	-2.269295 (0.52048) [-4.36004]
IIP(-1)	3.269295 (0.52048) [6.28135]
C	-0.008474

Error Correction:	D(GDP)	D(ALSI)	D(IIP)
CointEq1	-0.062432 (0.03143) [-1.98637]	-0.007778 (0.10592) [-0.07343]	-0.285060 (0.05347) [-5.33113]
D(GDP(-1))	-0.661480 (0.12354) [-5.35451]	0.212102 (0.41632) [0.50946]	0.406732 (0.21017) [1.93528]
D(GDP(-2))	-0.482587 (0.13598) [-3.54901]	-0.037577 (0.45825) [-0.08200]	0.268745 (0.23133) [1.16173]
D(GDP(-3))	0.060023 (0.11645) [0.51544]	-0.070809 (0.39244) [-0.18043]	0.352167 (0.19811) [1.77761]
D(ALSI(-1))	-0.009416 (0.07404) [-0.12718]	-0.819790 (0.24951) [-3.28557]	-0.402227 (0.12596) [-3.19333]
D(ALSI(-2))	-0.035466 (0.06190) [-0.57300]	-0.524564 (0.20859) [-2.51478]	-0.249088 (0.10530) [-2.36548]
D(ALSI(-3))	0.015143 (0.04407) [0.34359]	-0.163653 (0.14853) [-1.10184]	-0.052191 (0.07498) [-0.69608]
D(IIP(-1))	0.297260 (0.08601) [3.45600]	0.012097 (0.28987) [0.04173]	0.123012 (0.14633) [0.84065]
D(IIP(-2))	0.177692 (0.07539) [2.35693]	-0.320527 (0.25407) [-1.26157]	-0.066690 (0.12826) [-0.51996]
D(IIP(-3))	0.075389 (0.06294) [1.19786]	-0.430993 (0.21210) [-2.03205]	-0.174815 (0.10707) [-1.63270]

C	-0.001824	-0.001112	-0.001350
	(0.00241)	(0.00812)	(0.00410)
	[-0.75735]	[-0.13701]	[-0.32948]
S2	-0.000432	0.001122	0.001798
	(0.00347)	(0.01169)	(0.00590)
	[-0.12439]	[0.09598]	[0.30473]
S3	-0.001130	-0.005045	-0.001409
	(0.00350)	(0.01179)	(0.00595)
	[-0.32301]	[-0.42804]	[-0.23673]
S4	0.006801	0.011948	0.004387
	(0.00350)	(0.01180)	(0.00596)
	[1.94237]	[1.01259]	[0.73651]
R-squared	0.562742	0.491531	0.500683
Adj. R-squared	0.483793	0.399725	0.410528
Sum sq. resids	0.008101	0.092006	0.023447
S.E. equation	0.010607	0.035747	0.018046
F-statistic	7.127893	5.353976	5.553605
Log likelihood	276.5849	172.1018	230.8877
Akaike AIC	-6.106626	-3.676785	-5.043900
Schwarz SC	-5.707081	-3.277241	-4.644355
Mean dependent	-0.000444	0.000202	-0.000428
S.D. dependent	0.014764	0.046139	0.023504
Determinant resid covariance (dof adj.)		4.08E-11	
Determinant resid covariance		2.40E-11	
Log likelihood		685.4661	
Akaike information criterion		-14.89456	
Schwarz criterion		-13.61031	

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:18
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,2)+B(1,3)=1, B(1,1)=1
Convergence achieved after 91 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):
Chi-square(1) 0.785584
Probability 0.375439

Cointegrating Eq:	CointEq1
GDP(-1)	1.000000
ALSIR(-1)	-1.686712
	(0.38793)
	[-4.34799]
IIP(-1)	2.686712
	(0.38793)
	[6.92577]
C	-0.040699

Error Correction:	D(GDP)	D(ALSIR)	D(IIP)
CointEq1	-0.076564	0.063234	-0.289352
	(0.03266)	(0.12202)	(0.05693)
	[-2.34422]	[0.51821]	[-5.08288]
D(GDP(-1))	-0.658823	0.078604	0.385506
	(0.12229)	(0.45688)	(0.21315)
	[-5.38736]	[0.17204]	[1.80863]
D(GDP(-2))	-0.486425	-0.245446	0.229729
	(0.13504)	(0.50453)	(0.23538)
	[-3.60197]	[-0.48648]	[0.97600]
D(GDP(-3))	0.061497	-0.167492	0.339802
	(0.11670)	(0.43600)	(0.20341)
	[0.52696]	[-0.38415]	[1.67056]
D(ALSIR(-1))	-0.013458	-0.564451	-0.298348
	(0.05943)	(0.22204)	(0.10359)
	[-0.22645]	[-2.54209]	[-2.88013]
D(ALSIR(-2))	-0.041337	-0.331244	-0.207986
	(0.05068)	(0.18934)	(0.08833)
	[-0.81568]	[-1.74949]	[-2.35462]
D(ALSIR(-3))	0.018595	-0.053675	-0.030142
	(0.03932)	(0.14692)	(0.06854)
	[0.47287]	[-0.36534]	[-0.43977]
D(IIP(-1))	0.299167	-0.219858	0.034890
	(0.07762)	(0.29000)	(0.13529)
	[3.85412]	[-0.75812]	[0.25788]
D(IIP(-2))	0.188145	-0.461684	-0.098332
	(0.07183)	(0.26835)	(0.12519)
	[2.61938]	[-1.72044]	[-0.78544]
D(IIP(-3))	0.075418	-0.430160	-0.194413
	(0.06236)	(0.23300)	(0.10870)
	[1.20931]	[-1.84621]	[-1.78855]

C	-0.002108	-0.004507	-0.001492
	(0.00245)	(0.00917)	(0.00428)
	[-0.85892]	[-0.49155]	[-0.34894]
S2	0.000307	0.002638	0.002606
	(0.00356)	(0.01331)	(0.00621)
	[0.08629]	[0.19819]	[0.41977]
S3	-0.001166	-0.003827	-0.001907
	(0.00356)	(0.01330)	(0.00621)
	[-0.32740]	[-0.28766]	[-0.30722]
S4	0.007257	0.022908	0.004760
	(0.00359)	(0.01341)	(0.00625)
	[2.02240]	[1.70884]	[0.76107]
R-squared	0.567216	0.437420	0.481257
Adj. R-squared	0.489075	0.335843	0.387595
Sum sq. resids	0.008018	0.111921	0.024359
S.E. equation	0.010553	0.039427	0.018394
F-statistic	7.258832	4.306296	5.138225
Log likelihood	277.0272	163.6766	229.2465
Akaike AIC	-6.116911	-3.480851	-5.005732
Schwarz SC	-5.717366	-3.081307	-4.606187
Mean dependent	-0.000444	0.000136	-0.000428
S.D. dependent	0.014764	0.048379	0.023504

Determinant resid covariance (dof adj.)	5.20E-11
Determinant resid covariance	3.05E-11
Log likelihood	675.0947
Akaike information criterion	-14.65336
Schwarz criterion	-13.36911

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:23
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,2)+B(1,3)=1, B(1,1)=1
Convergence achieved after 4 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	1.684445
Probability	0.194335

Cointegrating Eq:	CointEq1
IIP(-1)	1.000000
ALSI(-1)	-0.869018
	(0.25508)
	[-3.40680]
GDP(-1)	1.869018
	(0.25508)
	[7.32709]
C	-0.041222

Error Correction:	D(IIP)	D(ALSI)	D(GDP)
CointEq1	-0.544975	-0.192030	-0.187638
	(0.11100)	(0.21392)	(0.06171)
	[-4.90957]	[-0.89766]	[-3.04049]
D(IIP(-1))	-0.160715	0.103287	0.273250
	(0.11620)	(0.22394)	(0.06460)
	[-1.38308]	[0.46123]	[4.22969]
D(IIP(-2))	-0.252770	-0.263009	0.161063
	(0.11600)	(0.22356)	(0.06449)
	[-2.17900]	[-1.17646]	[2.49736]
D(IIP(-3))	-0.268508	-0.400522	0.067598
	(0.10491)	(0.20217)	(0.05832)
	[-2.55953]	[-1.98110]	[1.15902]
D(ALSI(-1))	-0.269517	-0.966514	-0.038297
	(0.11148)	(0.21484)	(0.06198)
	[-2.41766]	[-4.49878]	[-0.61791]
D(ALSI(-2))	-0.161718	-0.633025	-0.059053
	(0.09831)	(0.18945)	(0.05465)
	[-1.64504]	[-3.34132]	[-1.08048]
D(ALSI(-3))	-0.010667	-0.225517	-4.32E-05
	(0.07346)	(0.14157)	(0.04084)
	[-0.14521]	[-1.59293]	[-0.00106]
D(GDP(-1))	0.993180	0.469162	-0.440131
	(0.26093)	(0.50286)	(0.14507)
	[3.80634]	[0.93300]	[-3.03401]
D(GDP(-2))	0.651319	0.135461	-0.336129
	(0.25650)	(0.49431)	(0.14260)
	[2.53930]	[0.27404]	[-2.35712]
D(GDP(-3))	0.534422	-0.024456	0.115888
	(0.20389)	(0.39294)	(0.11336)
	[2.62108]	[-0.06224]	[1.02233]

C	-0.001534	-0.000688	-0.001699
	(0.00419)	(0.00807)	(0.00233)
	[-0.36625]	[-0.08529]	[-0.72984]
S2	0.002084	0.000893	-0.000461
	(0.00603)	(0.01162)	(0.00335)
	[0.34543]	[0.07678]	[-0.13735]
S3	-0.001124	-0.005056	-0.001074
	(0.00608)	(0.01172)	(0.00338)
	[-0.18481]	[-0.43135]	[-0.31777]
S4	0.004598	0.010798	0.006401
	(0.00609)	(0.01174)	(0.00339)
	[0.75512]	[0.92011]	[1.89091]
R-squared	0.478253	0.497121	0.591261
Adj. R-squared	0.384048	0.406324	0.517461
Sum sq. resids	0.024500	0.090995	0.007573
S.E. equation	0.018447	0.035550	0.010256
F-statistic	5.076758	5.475054	8.011656
Log likelihood	228.9982	172.5771	279.4851
Akaike AIC	-4.999958	-3.687840	-6.174072
Schwarz SC	-4.600414	-3.288295	-5.774527
Mean dependent	-0.000428	0.000202	-0.000444
S.D. dependent	0.023504	0.046139	0.014764

Determinant resid covariance (dof adj.)	4.16E-11
Determinant resid covariance	2.44E-11
Log likelihood	684.6447
Akaike information criterion	-14.87546
Schwarz criterion	-13.59121

Vector Error Correction Estimates
Date: 03/29/16 Time: 15:29
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,2)+B(1,3)=1, B(1,1)=1
Convergence achieved after 11 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):
Chi-square(1) 3.254614
Probability 0.071223

Cointegrating Eq:	CointEq1
IIP(-1)	1.000000
ALSIR(-1)	-0.539805 (0.18745) [-2.87978]
GDP(-1)	1.539805 (0.18745) [8.21463]
C	-0.045895

Error Correction:	D(IIP)	D(ALSIR)	D(GDP)
CointEq1	-0.564420 (0.11588) [-4.87055]	-0.204971 (0.24497) [-0.83672]	-0.179415 (0.06487) [-2.76580]
D(IIP(-1))	-0.115474 (0.11913) [-0.96933]	0.003780 (0.25182) [0.01501]	0.276851 (0.06668) [4.15165]
D(IIP(-2))	-0.195174 (0.11853) [-1.64660]	-0.309093 (0.25057) [-1.23358]	0.174555 (0.06635) [2.63078]
D(IIP(-3))	-0.241789 (0.10739) [-2.25157]	-0.341896 (0.22701) [-1.50610]	0.070016 (0.06011) [1.16475]
D(ALSIR(-1))	-0.169889 (0.08569) [-1.98250]	-0.777592 (0.18115) [-4.29250]	0.003585 (0.04797) [0.07473]
D(ALSIR(-2))	-0.130459 (0.07975) [-1.63580]	-0.494205 (0.16859) [-2.93139]	-0.034195 (0.04464) [-0.76596]
D(ALSIR(-3))	0.007561 (0.06576) [0.11497]	-0.157662 (0.13901) [-1.13415]	0.019803 (0.03681) [0.53796]
D(GDP(-1))	0.895475 (0.24945) [3.58980]	0.328668 (0.52732) [0.62328]	-0.490776 (0.13964) [-3.51468]
D(GDP(-2))	0.590652 (0.25304) [2.33418]	-0.077967 (0.53492) [-0.14576]	-0.368362 (0.14165) [-2.60054]
D(GDP(-3))	0.534302 (0.20596) [2.59415]	-0.149436 (0.43539) [-0.34322]	0.118509 (0.11529) [1.02789]

Appendix 8: VECM - Weak exogeneity

Vector Error Correction Estimates
Date: 03/31/16 Time: 16:29
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,1) = 1, A(2,1)=0
Convergence achieved after 87 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):
Chi-square(1) 0.002029
Probability 0.964076

Cointegrating Eq:	CointEq1
GDP(-1)	1.000000
ALSI(-1)	-1.714585
	(0.41248)
	[-4.15674]
IIP(-1)	2.302773
	(0.50735)
	[4.53883]
C	-0.012033

Error Correction:	D(GDP)	D(ALSI)	D(IIP)
CointEq1	-0.091095	0.000000	-0.380562
	(0.04211)	(0.00000)	(0.06919)
	[-2.16344]	[NA]	[-5.50049]
D(GDP(-1))	-0.642226	0.209922	0.474269
	(0.12422)	(0.42066)	(0.21293)
	[-5.17006]	[0.49903]	[2.22736]
D(GDP(-2))	-0.470959	-0.039345	0.307528
	(0.13581)	(0.45991)	(0.23280)
	[-3.46773]	[-0.08555]	[1.32100]
D(GDP(-3))	0.061720	-0.069707	0.363872
	(0.11583)	(0.39226)	(0.19855)
	[0.53283]	[-0.17771]	[1.83262]
D(ALSI(-1))	-0.022426	-0.809076	-0.406746
	(0.07453)	(0.25240)	(0.12776)
	[-0.30089]	[-3.20559]	[-3.18375]
D(ALSI(-2))	-0.044353	-0.516835	-0.250348
	(0.06196)	(0.20981)	(0.10620)
	[-0.71587]	[-2.46334]	[-2.35729]
D(ALSI(-3))	0.010319	-0.159405	-0.052642
	(0.04400)	(0.14899)	(0.07542)
	[0.23453]	[-1.06989]	[-0.69802]
D(IIP(-1))	0.298944	0.001081	0.080752
	(0.08247)	(0.27927)	(0.14136)
	[3.62503]	[0.00387]	[0.57126]
D(IIP(-2))	0.178174	-0.327643	-0.096415
	(0.07341)	(0.24861)	(0.12584)
	[2.42700]	[-1.31791]	[-0.76617]
D(IIP(-3))	0.075381	-0.434673	-0.191220
	(0.06208)	(0.21024)	(0.10642)
	[1.21416]	[-2.06746]	[-1.79682]

C	-0.001786	-0.001139	-0.001317
	(0.00240)	(0.00812)	(0.00411)
	[-0.74507]	[-0.14029]	[-0.32056]
S2	-0.000451	0.001140	0.001803
	(0.00345)	(0.01169)	(0.00592)
	[-0.13057]	[0.09755]	[0.30468]
S3	-0.001132	-0.005039	-0.001391
	(0.00348)	(0.01179)	(0.00597)
	[-0.32530]	[-0.42749]	[-0.23308]
S4	0.006709	0.012016	0.004318
	(0.00349)	(0.01180)	(0.00598)
	[1.92462]	[1.01790]	[0.72265]
R-squared	0.566933	0.491498	0.497954
Adj. R-squared	0.488741	0.399685	0.407307
Sum sq. resids	0.008024	0.092013	0.023575
S.E. equation	0.010556	0.035748	0.018095
F-statistic	7.250475	5.353252	5.493324
Log likelihood	276.9991	172.0989	230.6534
Akaike AIC	-6.116257	-3.676719	-5.038450
Schwarz SC	-5.716712	-3.277174	-4.638905
Mean dependent	-0.000444	0.000202	-0.000428
S.D. dependent	0.014764	0.046139	0.023504

Determinant resid covariance (dof adj.)	4.08E-11
Determinant resid covariance	2.39E-11
Log likelihood	685.4859
Akaike information criterion	-14.89502
Schwarz criterion	-13.61077

Vector Error Correction Estimates
Date: 03/31/16 Time: 16:31
Sample (adjusted): 1993Q1 2014Q2
Included observations: 86 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,1) = 1, A(2,1)=0
Maximum iterations (500) reached.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	0.282666
Probability	0.594959

Cointegrating Eq:	CointEq1
GDP(-1)	1.000000
ALSIR(-1)	3.954831
	(0.99946)
	[3.95695]
IIP(-1)	-8.595105
	(1.58945)
	[-5.40760]
C	0.018412

Error Correction:	D(GDP)	D(ALSIR)	D(IIP)
CointEq1	0.020731	0.000000	0.120448
	(0.01315)	(0.00000)	(0.02162)
	[1.57611]	[NA]	[5.57049]
D(GDP(-1))	-0.719322	0.124004	0.098661
	(0.12554)	(0.46059)	(0.21163)
	[-5.72964]	[0.26923]	[0.46620]
D(GDP(-2))	-0.520886	-0.219621	0.065877
	(0.13796)	(0.50616)	(0.23257)
	[-3.77550]	[-0.43390]	[0.28326]
D(GDP(-3))	0.060648	-0.170439	0.290078
	(0.11955)	(0.43860)	(0.20153)
	[0.50730]	[-0.38860]	[1.43941]
D(ALSIR(-1))	0.028032	-0.610015	-0.285575
	(0.05784)	(0.21220)	(0.09750)
	[0.48465]	[-2.87473]	[-2.92898]
D(ALSIR(-2))	-0.012017	-0.363947	-0.205392
	(0.05047)	(0.18516)	(0.08508)
	[-0.23811]	[-1.96555]	[-2.41418]
D(ALSIR(-3))	0.036459	-0.073683	-0.029620
	(0.03958)	(0.14520)	(0.06672)
	[0.92118]	[-0.50745]	[-0.44397]
D(IIP(-1))	0.290221	-0.195141	0.221995
	(0.09317)	(0.34181)	(0.15705)
	[3.11498]	[-0.57090]	[1.41349]
D(IIP(-2))	0.182878	-0.445528	0.032281
	(0.08070)	(0.29607)	(0.13603)
	[2.26614]	[-1.50482]	[0.23730]
D(IIP(-3))	0.072200	-0.420909	-0.122506
	(0.06631)	(0.24327)	(0.11178)
	[1.08886]	[-1.73023]	[-1.09600]

C	-0.002314	-0.004286	-0.001631
	(0.00250)	(0.00917)	(0.00421)
	[-0.92564]	[-0.46730]	[-0.38705]
S2	0.000428	0.002502	0.002602
	(0.00363)	(0.01333)	(0.00612)
	[0.11778]	[0.18779]	[0.42492]
S3	-0.001104	-0.003902	-0.001985
	(0.00363)	(0.01332)	(0.00612)
	[-0.30399]	[-0.29298]	[-0.32429]
S4	0.007735	0.022393	0.005037
	(0.00365)	(0.01339)	(0.00615)
	[2.11861]	[1.67174]	[0.81842]
R-squared	0.550057	0.436003	0.495553
Adj. R-squared	0.468817	0.334170	0.404472
Sum sq. resids	0.008336	0.112203	0.023688
S.E. equation	0.010760	0.039476	0.018138
F-statistic	6.770782	4.281550	5.440814
Log likelihood	275.3552	163.5684	230.4482
Akaike AIC	-6.078027	-3.478335	-5.033679
Schwarz SC	-5.678482	-3.078790	-4.634134
Mean dependent	-0.000444	0.000136	-0.000428
S.D. dependent	0.014764	0.048379	0.023504

Determinant resid covariance (dof adj.)	5.16E-11
Determinant resid covariance	3.03E-11
Log likelihood	675.3461
Akaike information criterion	-14.65921
Schwarz criterion	-13.37496