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The relationship between foreign portfolio equity flows and industry returns on the JSE

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ABSTRACT

This research study analyses the nature of the relationship between industry-specific foreign portfolio equity flows (FPEF) and the returns of these respective industry indices on the Johannesburg Stock Exchange (JSE).

The primary aim of this study is to determine the predictability of one variable on the other by testing for Granger-causality in vector error correction (VEC) models and whether this effect can be exploited by identifying a FPEF style-based strategy that can outperform the benchmark. The time series consisted of FPEF and return data of the JSE All Share Index (ALSI) industry indices constituted by the 163 ALSI stocks from January 2009 to August 2016.

The study demonstrates that the interaction between FPEF and industry returns on the JSE is dynamic and not only differs across industries, but also between the short-term and long-term effects thereof. Additionally, portfolio construction based on following FPEF patterns, reveal no persistency of superior returns relative to the buy-and-hold portfolio indicating that there is no apparent benefit of applying this investment style.

Keywords: Foreign portfolio equity flows, industry returns, Johannesburg Stock Exchange, investment style, Granger-causality

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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ABBREVIATIONS

ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ALSI	All Share Index
ECT	Error correction term
ETF	Exchange Traded Funds
FPEF	Foreign Portfolio Equity Flows
GR	Geometric Returns
ICB	Industry Classification Benchmark
IRF	Impulse Response Function
IT	Information Technology
JSE	Johannesburg Stock Exchange
KS	Kolmogorov–Smirnov
LR	Likelihood-Ratio
NV	Net Value of Foreign Flows
PDF	Probability Distribution Function
QFII	Qualified Foreign Institutional Investors
QQ	Quantile-Quantile
ROE	Return on Equity
SW	Shapiro-Wilk
UK	United Kingdom
USA	United States of America
VAR	Vector Autoregression
VEC	Vector Error Correction

1. INTRODUCTION

1.1 RESEARCH PROBLEM

The relationship between FPEF and equity returns, especially in emerging markets where foreigners look to diversify their portfolios and seek higher risk-adjusted returns, has been a topic under ongoing investigation. A need has arisen to build on and develop this stream of research for the South African market as there have been varying findings between different emerging markets. There has also been a noticeable gap in conducting this research at industry level. Loncan and Caldeira (2015) conducted such a study for the Brazilian market; however, the findings thereof cannot be inferred to the South African market due to stock exchange dissimilarities and other market and industry differences. Therefore, finding empirical evidence, specific to the South African market would be of relevance. Additionally, the findings from this may provide a useful tool for investors, especially portfolio managers, investing in the JSE to apply an industry-specific style-based investment strategy that can consistently beat the market.

FPEF into the South African market is a topical issue as an article in PR Newswire (2016) suggested that the flow of capital from advanced economies into emerging economies' equity and bond markets will increase dramatically due to the fact that there is currently value in emerging markets above that of developed economies whose markets appear expensive and are experiencing low economic growth.

There has been a persistent increase in foreign participation in the South African equity market. Approximately ten years ago, around ten percent of the free-float of the industrial index was owned by foreigners, but this has risen to over 50% (Lamprecht, 2015). The drivers of this have been, in the main, the surge in exposure to Retailers as well as growth stocks such as those in Healthcare and Media. During the aftermath of the global financial crisis, investors were in search of growth and yield. South Africa partook in the emerging markets' consumer growth story and with good quality companies that had high returns on equity (ROE) and good dividend yields, it progressively drew the attention of foreign investors (Lamprecht, 2015).

With a reliable financial infrastructure, a status of being an economic powerhouse and with a market capitalisation to GDP ratio of 235% at the end of 2015 (The Global Economy, n.d.), South Africa has the most developed equity market in Africa which is appealing for international investors in quest of diversification or capital appreciation

(French, 2011). However, according to Manners (2016), with South Africa facing “unprecedented political and economic challenges, much-needed investment could soon dry up” (para. 10). This emphasises the importance of foreign participation in the South African financial markets.

The literature discusses various theories as to why a relationship exists. An issue that is of recurrent interest within the field of research, discussed by Qin and Bai (2014), which could drive this study’s propositions and hypotheses, is whether foreign investors are better informed at making investment decisions than local investors. This research will provide a greater understanding of the interaction between FPEF and the returns of the Johannesburg Stock Exchange (JSE) as, if foreign investors are indeed better informed, it will aim to determine if the replication of foreign flow patterns will be useful in generating superior returns. Due to the divergent industry characteristics such as size, geographical exposure and foreign ownership, this research goes a level deeper as it is conducted at industry level to capture the industry effects.

1.2 RESEARCH PURPOSE

The purpose of this research is to determine, at industry level, whether FPEF predict returns and whether returns predict FPEF. This speaks to the theoretical purpose of the study. The study will also aim to determine whether the tracking of FPEF trading patterns can be used and exploited to outperform the benchmark. This addresses the practical purpose of the study.

An example of the most relevant research applicable to this study is French (2011) who conducted research on the dynamic interaction between FPEF and the equity returns of the JSE; however, the data was collected over a different period of time and therefore may be dated. The data in French’s (2011) study spanned from 2002 to 2006. It is therefore necessary to conduct further research on this topic over and above that of French (2011) as global economies as well as the South African market have since evolved.

Firstly, there was the 2007 / 2008 global financial crisis between the time period relating to French’s (2011) research and the time period of this study. A behavioural finance study conducted by Dhiman, Pal and Dhiman (2010) revealed that the recession lead to a diminished reliance on an investors’ own intuition and media information when making investment decisions; suggesting a subsequent shift to a more fundamental approach towards the market as opposed to relying on analyst recommendations or vague valuation methods which were applied before the recession. This shift may have affected FPEF as a change in valuation methods affects which markets, sectors and stocks are invested in. Change in investor behaviour affects equity prices, risk pricing and market stability in emerging markets due to FPEF being easily reversible (Nyang`oro, 2013).

Additionally, on the topic of policies, changes in economic conditions such as the advent of the global financial crisis resulted in quantitative easing policies being undertaken by the United States, the United Kingdom, and the Eurozone. As the interest paid by bonds will be low during a QE programme, investors typically purchase stocks in pursuit of a better yield thus affecting equity flows (Trendshare, 2015). In terms of the country (or political) risk associated with equity, South Africa had a change in regime after the period to which French's (2011) study relates, with Jacob Zuma succeeding Thabo Mbeki in 2009. Since then, South Africa's macroeconomic environment has changed. There has been unsatisfactory GDP growth (Trading Economics n.d.a), increasing debt to GDP (Trading Economics, n.d.b) and decreased policy certainty. Such events may affect returns through the impact on the country risk associated with equity risk premium thus affecting investors' decisions or mandates.

Findings for other emerging markets may not be applicable to the JSE as the different characteristics of each market may affect FPEF as well as industry returns and, even more broadly, market performance in general. The characteristics of a market's stock exchange differ in terms of market capitalisation / size, liquidity, volatility, regulations, non-resident restrictions and investability, amongst other factors (Cumming, Johan & Li, 2011).

There is especially a gap in conducting this research at industry level in the South African market. Research has indicated that industry portfolios may have significant explanatory power, although to varying degrees, in anticipating the movements of other industries, market returns and / or predictors of economic activity (Laopodis, 2016). Laopodis' (2016) study derived some useful insights regarding industry information leadership which included the fact that many industries provide some valuable information to the stock market one to two months ahead.

1.2.1 The business purpose of the study

The business need for this study is the investment implications of its findings. This could be useful to investors as an alternative style of investment that could yield superior investment returns by using the patterns of FPEF to predict industry returns. French (2011) also stated that an unexpected withdrawal of equity and the consequent destabilising effects on equity markets are of concern. Investors therefore need to consider this as it may affect the value of their investment in equity markets.

Practically, the research proposed is a topical issue particularly with regards to policies around the globalisation and liberalisation of financial markets as well as foreign ownership restrictions. As Sanvicente (2014) suggested, policy-makers may want to carefully consider policies relating to the trading of foreigners that evoke any volatility, liquidity or other market issues. This study may therefore be useful for policy-making practitioners and economists as the effects of policies regarding the globalisation and liberalisation of financial markets have been under ongoing investigation and yielding conflicting results.

Since French's (2011) study, there have also been changes in macro-economic and political factors which may have affected the expected returns of stocks and markets and may have also influenced FPEF as a result of change in investor sentiment. Another aspect to consider in terms of investor changes and market transformations that have occurred since French (2011) conducted his research is that the evolution of the globalisation and liberalisation of a market may have an effect on another. Over the years there has been some easing in foreign ownership restrictions in China (Shenzen Stock Exchange, n.d.). Similar changes have occurred in other countries such as India (Misra, 2012). Such changes may redirect the flow of foreign equity as more opportunities and options for investment in emerging markets present themselves. This may change the scope of foreign investors invested in the JSE or contemplating the exposure to the South African market.

Gupta and Modise (2013) also suggested that macroeconomic variables are not useful in predicting stock market returns; therefore, foreigners may be inconsequentially using these as a precursor for market performance when other investment criteria, such as that relating to industry performance, would in fact be more effective. This will contribute to the secondary purpose of the study: that foreign investors can use the findings for portfolio diversification when considering which South African assets to invest in.

1.2.2 The academic purpose of the study

There has been some extensive and relatively widespread research done on this topic which includes studies relating to emerging markets as a whole (Chang, 2010; Qin & Bai, 2014; Richards, 2005) and individual emerging market countries, such as Kenya, Brazil and India (Nyang`oro, 2013; Sanvicente, 2014; Srinivasan, Kalaivani & Bhat, 2010), but research which applies to South Africa is limited and this study aims to fill these gaps in research from a theoretical perspective which can be applied practically.

As mentioned, research on this topic has been conducted at industry level in markets such as Brazil (Loncan & Caldeira, 2015); however, in a South African context, this domain has not been adequately addressed through the provision of empirical evidence. The results from this study will therefore be useful in contributing to literature by filling this gap.

The studies that have been conducted on this topic have various conclusions. French (2011), Griffin, Nardari and Stulz' (2004), Qin and Bai (2014), Richards (2005) and Srinivasen (2010) argued that equity returns predict flows (referred to in literature as the positive feedback hypothesis, momentum trading, return chasing or trend chasing), whereas Nyang`oro (2013) and Sanvicente (2014) contended that flows predict equity returns (known as the information contribution hypothesis). Jinjarak et al. (2011) found evidence that a bilateral relationship could exist between FPEF and returns. Another argument presented by Chang (2010) claimed that flows have a temporary price effect and prices are expected to revert to initial equilibrium levels (known as the price-pressure hypothesis) implying that, ultimately, neither variable has a sustained effect on the other. This research will contribute towards this ongoing inconclusive debate regarding the nature of the relationship between FPEF and equity returns.

1.3. RESEARCH AIM

The first primary objective of this study is to uncover the dynamic interaction between FPEF into various industries and the returns of these respective industries within the context of the South African equity market. This interaction has been of recurrent significance to investors, economists and policy makers, and is of greater importance during periods of changes in capital flow distribution or financial turmoil. Therefore, this research aims to be of practical use to the aforementioned stakeholders in the market and the economy.

The sequence of FPEF and JSE ALSI industry returns (in other words, whether FPEF have an effect on industry returns, whether industry returns have an effect on FPEF or whether the effect is in both directions) will be determined by the application of a quantitative research methodology. Statistical models with forecast ability that will test the stated hypotheses will be applied using time series data from the JSE, Bloomberg FactSet.

Secondly, this study will also aim to determine if the said dynamic interaction can be exploited by means of a style engine in order to yield superior sustainable investment returns. As could best be determined, there is sparse documented academic and theoretical research examining the use of FPEF, especially at industry level, as an investment style that can be applied to the South African market.

The findings will also be useful to foreign investors themselves as they can use the conclusions drawn as a consideration when making investment decisions applicable to the South African market.

In order to achieve these research aims and objectives, this study will emphasise and argumentatively integrate some literature on the role of FPEF in the South African market; disparities between the JSE and other emerging market bourses; the effect of information asymmetry; equity returns predicting FPEF; FPEF predicting equity returns; the bilateral interaction between FPEF and returns; and the importance of conducting this research at an industry level.

2. LITERATURE REVIEW

2.1. INTRODUCTION

Compared to other emerging markets, foreign flows into the South African market are relatively easily extractable (Gidlow, 2009); therefore, it is important to assess the impact thereof. Literature has explored the economic advantages and disadvantages of FPEF which may or may not have a direct or indirect effect on returns. The emphasis of this literature review is on various studies and theories regarding how equity returns predict FPEF as well as how FPEF predict returns in a number of markets and regions. It is important to note that the interaction is not necessarily mutually exclusive. A bidirectional interaction may be found to be significant in the same market.

2.2. THE ROLE OF FPEF IN THE SOUTH AFRICAN MARKET

South Africa has had a wave of abolishment and re-instatement of exchange controls on foreign (non-resident) investors. “Foreign investors” refers to individuals or institutions who invest funds in assets outside of their home country (Study.com. n.d.), in this case, into South Africa (and equity assets specifically will be relevant to this study). Exchange controls on foreign investors were first introduced in 1961 and then abolished in 1983. These were again re-instated in 1985 and finally abolished in 1995 (Aron, Leape & Thomas, 2010). Since 1993, there has only been one considerably extended bear equity market period, between May 1992 and April 2003, which occurred concurrently with net foreign portfolio equity outflows (Gidlow, 2009), and which raises the question of what the interaction between FPEF and equity returns is and how foreign exchange controls affect this linkage.

Although South Africa does not comprise the largest share of the main emerging market index for shares, it is fourth after Korea, Brazil and Taiwan. The South African equity market is the most liquid and easiest to trade of all the emerging markets (Gidlow, 2009). Therefore, whenever there is any panic around emerging markets, South African stocks are the easiest to trade (Gidlow, 2009). The high correlation between liquidity and flows (Sanvicente, 2014) may be relevant to this study as equity returns could, in turn, be affected.

Some historical advantages of FPEF into the JSE specifically include: helping the South African Reserve Bank (SARB) to eliminate its net commitments to sell dollars on its forward exchange account; helping the SARB to boost foreign reserves; helping to finance large current account deficits; and helping to supplement fairly low domestic savings (Gidlow, 2009). Nyang`oro (2013) stated that the rationale for financial liberalisation is that FPEF may be encouraged with the key objective being the development of market activity and access to foreign capital.

Some disadvantages of FPEF include the destabilising characteristic of FPEF as large sell-offs negatively impact equity values (French, 2011). The sudden reversal of capital and the destabilizing effects this has on equity markets is concerning (French, 2011). This phenomenon was observed on December 09, 2015, after South African president, Jacob Zuma, announced a new finance Minister. Another disadvantage is contagion risk where a shock in a particular market affects other markets. To place this into the particular context of this study, this is risk associated with volatility originating in another emerging market which may result in investors decreasing emerging market exposure as a whole (Mohammed, 2006). This places markets with a high degree of FPEF at risk.

Mohammed (2006) argued that the inflows of portfolio capital into the South African market have historically contributed to consumption-driven economic growth as opposed to investment booms. This in turn led to a substantial rise in imported consumer goods resulting in a deterioration of the current account. This was evident during 2003 to 2006 in the resilience of the banking and retail sectors and, simultaneously, the weak prevailing environment in the tradable goods sectors, especially the mining sector, notwithstanding the boom in global commodity prices (Gidlow, 2009).

Gupta and Modise (2013) considered how South African macroeconomic variables including “different interest rates, employment, inflation, money supply, industrial production, global oil production and crude oil price” (p. 261) predict South African stock returns. The results suggested that macroeconomic and financial variables don’t provide much explanatory power in this regard (in a linear predictive regression framework). This therefore suggests that foreigners using economic indicators for investment decision-making for a particular market may be irrelevant.

2.3. DISPARITIES BETWEEN THE JSE AND OTHER EMERGING MARKET BOURSES

Thapa and Poshakwale (2012) explored whether country-specific market characteristics explain disparities in the allocation of FPEF. For this study, it is essential to understand the factors informing the allocation of funds to foreign equity markets as it is imperative to ascertain why the relationship between FPEF and returns (in the broader market context) should differ between South Africa and the other markets (emerging markets particularly) already discussed in the literature. Their findings revealed that notwithstanding the fact that each individual host country may demonstrate an asymmetric effect, it is country-specific equity market factors, namely market size, liquidity / efficiency and transaction costs, that are the primary factors informing the country allocation decisions of foreigners. As discussed earlier, the South African equity market is bigger, more developed and more liquid than its African counterparts (French, 2011); therefore, these characteristics may affect the distribution of foreign investor capital.

Foreigners' allocation of funds and the development of a capital market may also be considered to be a bilateral relationship and have elements of reverse causality (Thapa & Poshakwale, 2012). Thapa and Poshakwale's (2012) research states that the growth in FPEF may itself trigger reform measures towards greater development of local capital markets. Therefore, as more foreigners invest into the South African equity market, the market may become more developed, thus resulting in foreigners allocating more to the South African market as the primary factors informing the allocation decision become more pronounced. These mutual influences discussed may therefore influence the disparities in the relationship between FPEF and returns in general between the JSE and other equity markets.

Aron et al. (2010) conducted research in which it was stated that large amounts of portfolio investment inflows since the mid-1990s have been underpinned by the prevalence of large domestic capital markets in South Africa. This is predominantly applicable to portfolio equity investment, which has become a vital source of substantial long-term external financing for South Africa. Foreign portfolio equity investment has also been assisted by dual listings on key international bourses by a number of South African companies. Their research stated that the JSE is considerably bigger than the norm for middle-income economies and it is also liquid, particularly in terms of the value of shares traded.

2.4. THE EFFECT OF INFORMATION ASYMMETRY

Qin and Bai (2014) discuss how well-informed investors are. They claim that this affects the efficiency of the incorporation of new information into equity prices and illustrate how this affects returns. They based their study on how the participation of foreign investors in local stock markets impacts the pricing efficiency of the stocks on the information asymmetry that exists between local and foreign investors. Qin and Bai (2014) stated there is varying research regarding how well-informed foreign investors are. Some researchers, such as Bae, Ozogus, Tan and Wirjanto (2012), concluded that foreign investors are better informed than local investors due to the fact that they tend to be large, professional investors implying they have more resources and skills at their disposal as well as easier access to information. Research conducted by Chang (2010), applicable to emerging markets, also indicated that market participants, and the market in general, track qualified foreign institutional investors' (QFII) trading and replicate it. This disseminates information amongst investors more swiftly; therefore, information is priced into stocks more efficiently. Bae et al. (2012) therefore claimed that the greater the participation of foreigners in a market, the quicker the price-adjustment of equities.

Contrary to this, Qin and Bai (2014) also stated that foreign investors may possibly be less well-informed than local investors due to geographical, lingual and / or cultural obstacles; therefore, information is diffused more gradually, resulting in a sustained momentum in share prices and a slower price-adjustment of equities. Lastly, they discussed a stream of research that found that because foreign investors are less well informed, they employ straightforward investment strategies such as momentum-type style investing.

2.5. EQUITY RETURNS PREDICTING FPEF

There are various theories in literature which explain equity returns predicting FPEF which include:

2.5.1. Portfolio rebalancing

Investors sell the best performing stocks as they become overweight in the portfolio (French, 2011). Hau and Rey (2006) explain that the justification for this can be attributed to the ‘‘uncovered equity parity’’ condition. Whenever foreign portfolios outperform local portfolios, local investors have higher comparative exchange rate risk. They repatriate some of the foreign holdings to reduce the exchange rate risk.

2.5.2. Feedback trading

This theory refers to investors whose investment decisions are guided by past price movements (Misra, 2012).

1. Positive feedback trading - According to Qin and Bai (2014), foreigners trade in herds and, since foreign investor trading is highly correlated, this may lead to prices demonstrating momentum as prices continue to rise as foreigners buy and fall as investors sell. Misra (2012) explains that when the market is in a bull run, foreigners rush into the market and when the market exhibits bear trends, foreigners rush out of the market. There can be destabilising effects on prices if this rush is based on market sentiment rather than valuation fundamentals.
2. Negative feedback trading – This is also known as contrarian trading and it proposes that investors purchase equities when prices are decreasing and sell when prices are increasing. Ülkü (2015) collected data from eight developing European countries and compared these to results out of Asia in order to ascertain the extent to which one can generalise the conclusions and to discover new stylised facts. He found evidence of negative feedback trading which exhibited an asymmetry: foreigners sell following a rise in returns, but do not purchase following a decline in returns. However, the asymmetry emerged with a lag, which suggested that the initial response to information is symmetrical.

Researchers who found evidence of both types of feedback trading within their studies include Srinivasen et al. (2010) who found that, in the Indian market, negative feedback trading manifested before the 2007 / 2008 global financial crisis and positive feedback manifested during the crisis. Richards (2005) found evidence of negative feedback trading in individual foreign investors and positive feedback trading in foreign institutional investors in Asian emerging equity markets.

Evidence provided in Chang's (2010) study indicates that other market participants, and the market in its entirety, track foreign institutional investment trading activities and emulate these. This may result in the market overshooting and therefore generating hyper-volatility. Simply explained, returns respond significantly positively to foreign investor flows. Returns then subsequently typically revert to the mean, indicating that prices may overshoot fundamentals. This type of positive feedback trading may be consistent with price pressure hypothesis. Nyang`oro (2013) explains the price pressure hypothesis: foreign equity inflows affect equity returns by temporarily increasing the price due to temporary illiquidity which absorbs the foreign demand. The price then reverses. This is due to the fact that the price initially rises based on information asymmetry and then reverts to its initial level due to the learning process.

It has been found that for many emerging Asian markets, foreign investors chase past return realizations of the flows sequence (Griffin et al., 2004). Other research in emerging markets claims that highly investible stocks (referring to the level at which QFII can invest in a stock) exhibit considerably higher momentum in returns than non-investible stocks (Qin & Bai, 2014). In the setting of the African market, Nyang`oro (2013), found that in Kenya, stock market return is impacted by lagged unexpected flows, but not by its simultaneous value.

The undesirable aspect of positive feedback trading, as found by Dornbusch and Park (1995), is that foreign investors pursue positive feedback trading strategies that result in share prices overreacting to changes in fundamentals and such trading strategies may cause bubbles and crashes in local markets. The result of this includes the fact that in the case of an information technology (IT) bubble, investors may subsequently shift their capital to non-cyclical consumer goods, financials, resources, utilities, and smaller bubble sectors (Anderson, Brooks & Katsaris, (2010). The speculative bubble that grew during the 1990s and subsequently collapsed was ubiquitous in the USA, rather than being restricted to IT-related industries.

Existing evidence points towards a strong correlation between net flows of FPEF and market returns in which FPEF follow market returns in the South African market (French, 2011). French (2011) found that favourable equity returns on the JSE predicted greater net foreign equity flows in succeeding periods. This indicates that foreign investors are relying on past performance when making investment decisions (French, 2011). However, he found that net foreign equity flows do not appear to Granger-cause returns and this is consistent with expected and unexpected flows. He suggested that the lack of evidence of net foreign equity flows causing a movement in equity returns indicates that foreign investors are not yielding unwarranted influence on the returns of JSE stocks.

2.6. FPEF PREDICTING EQUITY RETURNS

Sanvicente’s (2014) study, conducted on the Brazilian market, found that the impact of flows on the index is a result of liquidity. Given that flows and liquidity typically have a high correlation, there is a lack of clarity as to whether returns are mostly affected by capital flows or returns.

Evidence in literature of equity returns predicting FPEF appears to be a lot more abundant than FPEF predicting equity flows. There are various theories in literature which explain the latter:

2.6.1. Supply-demand dynamics and information contribution hypothesis

Market dynamics bring about a shift in demand therefore resulting in a change in prices (French, 2011). Twerefou and Nimo (2005) stated that prices are driven by new information entering the market and are based on the demand and supply of securities. They also stated that the ability to demand and supply stocks are predominantly informed by the performance of key macroeconomic factors. Sanvicente (2014) explained the information arrival process as the adjustment of the stock towards a new equilibrium price. The arrival of new information into the market leads to a change in the demand for stock; "when new, positive (negative) types of information cause an increase (decrease) in demand for a particular security, there is a resultant price increase (decrease); with this, the attendant volume of trading which was required tends to create a new equilibrium for prices" (p. 89).

2.6.2. Base-broadening hypothesis

Nyang`oro (2013) found that this hypothesis holds in the Kenyan market. By including foreign investors as an investor category, this broadens the investor base. Therefore, diversification is augmented and the larger investment base spreads the risk thus reducing the equity risk premium (Nyang`oro, 2013). This theory therefore posits that portfolio flows impact share prices or market returns through the change in risk premium (Misra, 2012; Nyang`oro, 2013).

2.7. BILATERAL INTERACTION BETWEEN FPEF AND RETURNS

Jeon and Moffett (2010) examined whether the positive relationship between changes in foreign ownership and irregular herding returns are attributable to returns predicting the activity of foreign investors or the positive impact of foreign investors on returns. They found a strong, positive correlation between changes in foreign ownership and stock returns. Since the ownership data was observed once at the end of the year, the significant relationship between changes in foreign ownership and irregular returns may have come from either the positive influence of changes in "foreign ownership on stock returns or intra-year positive feedback trading by foreign investors" (p. 699). Their results supported both hypotheses. Additionally, their results suggested that there are information asymmetries between foreign and local institutional investors. This indicated that foreign institutional investors tend to trade shares that local institutional investors trade during the herding year.

Using EPRF Global data, an institution that provides fund flows and asset allocation data to financial institutions around the world (EPRF, n.d.), Jinjarak, Wongswan and Zheng (2011) conducted a study which involved gathering a sample of equity fund investments from 1995 to 2008, covering FPEF to sixty seven countries, of which twenty were developed markets and fourty seven were developing markets. The findings of Jinjarak et al. (2011) suggested that past equity returns contain useful information for current equity flows. The evidence of flow and return persistence as well as positive feedback trading was found to be significant therefore indicating a bilateral interaction. Whilst the study focused on measuring the interactions between foreign net inflows and local market returns, the results have wide reaching implications and applications. For example, the finding that a temporary increase in local equity returns leads to a transient increase in net foreign inflows (local market returns forecast net foreign inflows positively) can be a valuable contribution for international portfolio models which endeavour to rationalise the behaviour of local and foreign investors.

2.8. INDUSTRY EFFECTS

2.8.1. Industry Effects on FPEF

Another gap is that French's (2011) study pertains to the dynamic interaction between FPEF and the equity returns of the JSE in aggregate whereas this study aims to determine its interaction with the equity returns of the ALSI on a disaggregate industry-by-industry level and therefore requires more granular data and interpretation. To be more specific:

1. It is relevant to conduct this research at industry level as the percentage of foreign ownership may vastly differ across various industries. The larger the foreign holdings within a specific industry, the more influence foreigners may have on this industry in terms of strategic decision-making; therefore, the amount and type of information they have will affect this decision-making process. This makes it appropriate to conduct this research by industry as foreigners would be the most active traders in industries where they have high equity holdings.

2. Likewise, there are industries with different global revenue, profit and asset exposures. For example, the basic materials index has 82% international revenue exposure whereas the financials index has 18% international revenue exposure (FactSet, 2016). These will require differing degrees of expertise on the local market as well as the type of information necessary for investment decision-making purposes. Bae et al. (2012) argued that the participation of foreign investors in equity markets seems to be instrumental for the speed of stock price-adjustment especially for the dissemination of information that is global in nature. These two considerations add a different dynamic to Qin and Bai's (2014) argument of how well-informed investors are as it is relevant to consider this at an industry level. Therefore, the effect of FPEF into respective industries may differ accordingly.

Qin and Bai (2014) stated that emerging markets are relatively less developed and lack breadth in their industrial sectors; therefore, many stocks might come from the same industry. To illustrate this in the South African market, the industrial index has a four percent weighting in the ALSI whereas the consumer goods index has a 26% weighting (FactSet, 2016). It is therefore appropriate to consider an industry effect in this study as a study at an aggregate market level may skew the results.

Loncan and Caldeira (2015) conducted a Brazilian study of whether the exposure of returns to foreign capital affected various sectors of economic activity differently. They concluded that the impact of foreign portfolio capital flows on the returns of different sectors differed in direction and magnitude:

1. The effect of foreign capital on the returns of the Cyclical Consumption, Basic Materials, Industrial Goods, Public Utilities and Oil and Gas sectors were positive and statistically significant.
2. The effect of foreign capital on the returns of the Non-cyclical Consumption and Telecommunications sectors were negative and statistically significant.
3. For the remaining two sectors, Real Estate and Construction and Transport, there was no statistically significant relationship found.

Loncan and Caldeira (2015) then stated that their findings reveal two things. Firstly, foreign investors monitor the exposure of stocks to macroeconomic factors and the prevailing business cycle when considering their investment strategies, making the sector under which a stock falls pertinent in understanding the effect of foreign flows on returns. Secondly, foreign investors redistribute capital to other sectors, in which the returns of capital would be potentially higher due to the economic impetus.

2.8.2. Industry Effects on Returns

Chen, Chen and Lee (2013) stated that existing literature on the topic of the relationship between sentiment and industry returns is thin. Their research involved determining whether fledging, loss-making, or growth industries are more affected by investor sentiment and whether more speculative industries co-move more with sentiment changes. This study used the Industry Classification Benchmark (ICB) for industry classification. Notwithstanding the fact that their study focused on local and global sentiment whereas this study focuses on foreigners' trading (whether due to sentiment, or fundamental analysis), Chen et al.'s (2013) study and findings will be useful in investigating the linkage between FPEF and market returns at industry level, rather than at a broader market level. By means of a predictive regression model, the findings suggested that expected industry returns react dissimilarly to local and global sentiment. More specifically and more relevant for this study, they concluded that greater global market bullishness lowers industry returns (Chen et al., 2013).

In order to justify why this study is necessary on an industry level as opposed to just a market level, literature exploring whether industry returns have significant power in explaining the movements of market returns needed to be considered. Lee, Chen and Chang (2013) found that in developed markets, the industry and the market have a feedback relationship, but in economies that are highly controlled, the influence from the stock market prevails. The dominance of different industries in explaining overall stock market returns also needed to be explored. Tse (2015) found that industries can inform the stock market because industry portfolio returns that are informative about macroeconomic variables have been shown to lead the market. Different industries are important for different markets. Roll's (1992) study found that the Basic Goods sector is essential for producers such as South Africa. He suggested that industry effects are constrained by country resources and augmented by national advantages. Features of the study conducted by Lee et al. (2013) included analysing ten different industries as classified by the ICB across different Asian markets in order to explore if the industry-market return nexus is different within comparable cultures and economies. There are several factors that determine the dominance of certain industries including GDP growth rate, exports, oil price, the exchange rate and government support.

Laopodis' (2016) study entailed analysing the ability of an industry's returns to predict the stock market which is conditional upon that industry's power to explain predictors of economic activity. Therefore, if an industry's return is correlated to another industry's information, the latter industry is considered an information leader. A widely accepted presupposition is that investors in diverse sectors are informed about their own markets and logically exploit them (Laopodis, 2016). For the markets in which they do not participate, they have three possible options: 1) to obtain the relevant information and use this to make investment decisions; 2) investors cannot process the information either because it is difficult to access or due to information overload; or 3) they simply ignore any information from other markets as they think it is immaterial. His study derived some useful insights which included the fact that many industries provided valuable information to the stock market one to two months ahead.

Laopodis (2016) investigated the predictive ability of seventeen industries (which represented important sectors of the economy) on the industries themselves, the stock market in general and various economic variables for the USA from 1957 to 2013 in order to establish if there is significant interaction amongst them. His findings suggested that there is significant explanatory power of industry returns to various economic factors as well as the stock market. His study revealed that certain industries, namely Oil and Financials, offered consistent information leadership to other industries. The presence of these suggest that there are significant, reciprocated interactions amongst industries and the stock market, evident in the ability of industries to explain different predictors of economic activity.

The conclusions from this research, which apply to this study, are that, firstly, most industry portfolios provided significant explanatory power, although to varying degrees, for many of the predictors of economic activity. Secondly , many industries provided valuable information to the stock market as early as one or two months ahead (Laopodis, 2016). Thirdly, the investigation of the dynamic interactions among industries and the stock market, in the presence of all of the fundamental variables, unexpected events impacting the stock market in turn influenced many industry returns and the shock was absorbed within one or two months (Laopodis, 2016). Likewise, the industries appeared to affect the stock market's returns but this may have been absorbed within several months.

Wen, Lin, Li and Roca (2015) found that lagged market and industry returns of the USA prior to 1996, could significantly predict South African market and industry returns. They stated that their findings have a number of implications for foreign investors in terms of return predictability which includes diversification. Their study is applicable to this research as the returns of foreign investors in their local market may affect their trading activities and diversification decisions in other markets.

2.9. LITERATURE REVIEW CONCLUSION

It is evident from the literature review that the role of foreign investor capital in the South African market is one of importance and needs particular attention as it can encourage and enhance key economic and market developments (Thapa & Poshakwale, 2012). These developments can therefore result in a widening gap of disparities between different emerging markets regarding the characteristics of their respective exchanges which may then in turn influence the allocation of foreign capital of equity investors (Thapa & Poshakwale, 2012).

Section 1.1. revealed that the South African equity market has evolved since the global financial crisis with different industries having different global exposure. This, in turn, affected investor sentiment and behaviour thus affecting investment decisions especially for foreigners investing in emerging markets due to risk and stability concerns (Dhiman et al., 2010). This notion was supported by Bayar (2013) who stated that with the financial crisis, a new postulation emerged to the fields that traditional finance failed to explain by incorporating the cognitive psychology into the decision-making process.

Not only is literature regarding the relationship between FPEF and equity returns in the context of the South African market underdeveloped, but there is also a need to further the academic knowledge by determining the nature of this relationship using more recent time series data as well as conducting the research at an industry level.

From a more practical stance, there was a lack of sufficient literature and empirical evidence demonstrating the effectiveness of using FPEF for the forecasting of industry returns and applying the results to build a portfolio that can persistently beat the benchmark. Conducting a study to fill this gap will enable the research to transcend from its academic purpose and add value from a business-oriented perspective. An important consideration when analysing a style-based investment or trading strategy is that the sustainability of that particular style must be considered and the style's performance may diminish as it becomes more prominent and begins to be widely replicated (Barberis & Shleifer, 2003).

3. RESEARCH PROPOSITIONS AND HYPOTHESES

Research hypotheses have been structured under research propositions. The hypotheses were tested at a 5% level of significance.

The first two research hypotheses, 1a and 1b, are expressed in terms of the VEC models fitted to test them. These pth order VEC models (in other words, VEC models with p lags) have the following general specifications (Sims, 1980):

Equation 1: VEC model

$$\Delta y_t = \beta_{y0} + \beta_{y1}\Delta y_{t-1} + \ldots + \beta_{yp}\Delta y_{t-p} + \gamma_{y1}\Delta x_{t-1} + \ldots + \gamma_{yp}\Delta x_{t-p} \quad -\lambda_y\left(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}\right) + v_t^y$$

$$\Delta x_t = \beta_{x0} + \beta_{x1}\Delta y_{t-1} + \ldots + \beta_{xp}\Delta y_{t-p} + \gamma_{x1}\Delta x_{t-1} + \ldots + \gamma_{xp}\Delta x_t \quad -\lambda_x\left(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}\right) + v_t^x$$

where Δ refers to first-order differencing; y is the vector of the JSE ALSI industry returns; x is the vector of industry-specific net FPEF; β is the regression coefficient; v is the error term (the portion of the dependent variable that cannot be explained by the independent variable); t is the time period; $y_t=\alpha_0+\alpha_1 x_t$ is the long-run cointegrating relationship between returns and net FPEF; and λ_y and λ_x are the error-correction parameters that measure how returns and net FPEF react to deviations from long-run equilibrium.

There were various VEC models as a VEC model for each of the industry indices was estimated for analysis and subsequently, from this, separate VEC models for net industry-specific FPEF predicting JSE ALSI industry returns and JSE ALSI industry returns predicting net industry-specific FPEF were also estimated. The relationship between flows and returns is not well established; therefore, neither variable is conclusively known to be affected by the other (exogenous). The two variables are considered vectors as the study considers both direction and magnitude therefore giving the scalar magnitude a direction.

3.1. PROPOSITION 1a

FPEF predict returns at the industry level.

3.1.1. Hypothesis 1a

The null hypothesis states that net industry-specific FPEF do not predict JSE ALSI industry returns (the regression coefficients are not significantly different from zero). The alternative hypothesis states that net industry-specific FPEF

predict JSE ALSI industry returns (at least one regression coefficient is significantly different from zero).

H1$_0$: $\beta_{x1} = \beta_{x2} = ... = \beta_{xp} = 0$

H1$_A$: At least one $\beta_{xk} \neq 0$

3.2. PROPOSITION 1b

Industry-level returns predict FPEF in that industry.

3.2.1. Hypothesis 1b

The null hypothesis states that JSE ALSI industry returns do not predict net industry-specific FPEF (the regression coefficients are not significantly different from zero). The alternative hypothesis states that JSE ALSI industry returns predict net industry-specific FPEF (at least one regression coefficient is significantly different from zero).

H1$_0$: $\beta_{y1} = \beta_{y2} = ... = \beta_{yp} = 0$

H1$_A$: At least one $\beta_{yk} \neq 0$

3.3. PROPOSITION TWO

Industry-level FPEF form the basis of a sustainable investment style.

3.3.1. Hypothesis two

Three portfolios (A, B and C) were constructed based on the observation of net FPEF into different industries and were ranked from the highest normalised flow to the lowest normalised flow. The following hypothesis was tested on each portfolio against a benchmark portfolio.

The null hypothesis states that the monthly portfolio returns from an industry rotation investment style portfolio based on the net FPEF into different industries (IND) are not significantly greater than the monthly portfolio returns from a buy-and-hold strategy (BH). The alternative hypothesis states that the monthly portfolio returns from an industry rotation investment style based on the net FPEF into different industries (IND) are significantly greater than the monthly portfolio returns from a buy-and-hold strategy (BH).

$H2_0$: $\mu_{IND} \leq \mu_{BH}$

$H2_A$: $\mu_{IND} > \mu_{BH}$

where μ_{IND} is the population mean of the monthly portfolio returns of an industry rotation investment style portfolio and μ_{BH} is the population mean of the monthly portfolio returns of a buy-and-hold portfolio.

4. RESEARCH METHODOLOGY

4.1. RESEARCH METHODOLOGY AND DESIGN

The research is a quantitative, descriptive study as it sought to accurately describe the relationship between FPEF and JSE industry returns. It is deductive in nature as the research approach involved the testing of theoretical propositions; moving from general theory to specific observations (Saunders & Lewis, 2012). In the context of this research, the literature suggests that foreign investors have certain behaviours with regards to market signals as well as the fact that stock market prices react to certain trading activities. This study specifically observed the relationship between FPEF and JSE ALSI industry returns.

This study cannot be considered to be exploratory as this research is not a new phenomenon. As discussed in the literature review, there has already been an extensive amount of work done on the topic on a broader market level; however, definitive conclusions have not been drawn due to the different data analysis procedures used and the varying market-to-market dynamics.

The possibility of the research being causal in design was also considered - in terms of it primarily aiming to determine whether FPEF cause JSE ASLI industry total return realisations (including dividends) or that JSE ALSI industry total return realisations cause FPEF. However, not all of the following conditions of causality were met therefore ruling out the possibility of the research being causal in design (Statistics Solutions, n.d.):

i. Temporal precedence - The researcher was not able to illustrate that cause precedes effect.
ii. There must be correlation between the two variables.
iii. There must be no plausible alternative explanations - Firstly, both variables may be affected by the other. Secondly, this data analysis would not be able to be conducted in controlled experimental conditions as it would not be possible to control for nor eliminate confounding variables that may damage the validity of the experiment (there are other macro- and firm-specific factors that provide alternative explanations for movements in FPEF as well as industry returns).

The first and third conditions of causality are not met. The analysis used will instead involve testing for Granger-causality which is explained in section 4.5.1. Granger-causality differs from true causality as Granger-causality only relates to linear prediction, in other words, one event happens before another (Sorensen, 2005) whereas true causality has to meet the aforementioned conditions.

4.2. POPULATION AND SAMPLE

This research made use of census sampling as the sample is the entire population. The constituents of the ALSI (163 stocks) constituted the population. These stocks were found to be the most appropriate for this study as they are the biggest in market capitalisation which makes them more liquid and therefore more easily investible / tradable. The ALSI constitutes 99% of the size of the JSE by market capitalisation (JSE, n.d.a); therefore, inferences about the relationship between FPEF and returns on the ALSI could be extended without much loss of validity to the JSE in its entirety. These stocks were segmented into different industry indices, as shown in Table 3 of section 4.4., which included: Oil and Gas, Basic Materials, Industrials, Consumer Goods, Healthcare, Consumer Services, Telecommunication, Utilities, Financials and Technology (JSE, n.d.b). The industries are categorised by the ICB which is a definitive system classifying over 70 000 firms and 75 000 stocks worldwide; facilitating the comparison of firms across regional boundaries (ICB, 2010).

There are no underlying stocks in the Utilities industry; therefore, this industry was excluded from the analysis making the number of applicable industries nine. The Oil and Gas industry had no underlying stocks as from January 2016 due to Sasol being reclassified under the Basic Materials industry and Montauk Holdings being delisted, both in 2015; therefore, Oil and Gas was only included for analysis up until December 2015 reducing the number of applicable industries after this date to eight .

4.3. UNIT OF ANALYSIS

The unit of analysis was a single industry index as classified by the ICB and is composed through the aggregation of various underlying ALSI stocks. The underlying ALSI stocks that constituted the industry indices did not directly match up with the stocks that compose the FPEF data as given by the JSE. The first mismatch was the fact that FPEF as provided by the JSE included the total market, JSE main board and AltX (an alternative board for smaller companies to raise capital), whereas the industry indices used in this study are comprised of the shares that constitute the ALSI. Despite this mismatch, a high degree of overlap, which was preferable, was found. An overlap was found in terms of the way the industries were classified and, because the AltX is so small in size, the ALSI's market capitalisation is still approximately 99% of the combined market capitalisation of the JSE and AltX; therefore, this reduces misrepresentation thus adding to the validity of the data (Satrix, 2016; Sharedata, n.d.). The units of observation were: i) the monthly arithmetic returns to industry indices (Table 1) (includes capital and gross dividend returns) and ii) the industry-specific FPEF by industry as represented by the net purchases / sales value (Table 2).

Table 1 Monthly arithmetic returns to industry indices

	Oils and Gas	Basic Materials	Industrials	Consumer Goods	Healthcare	Consumer Services	Telecommunications	Utilities	Financials	Technology
2009 Jan	(1.4%)	(3.1%)	(6.2%)	(4.0%)	13.4%	(2.1%)	(8.1%)	0.0%	(7.0%)	(7.7%)
2009 Feb	(8.7%)	(9.4%)	(10.6%)	(10.5%)	(1.8%)	(8.1%)	(12.4%)	0.0%	(10.8%)	(4.7%)
2009 Mar	9.1%	14.9%	4.3%	1.1%	0.9%	3.4%	21.2%	0.0%	12.0%	8.5%
2009 Apr	(5.3%)	(2.0%)	8.8%	2.5%	4.9%	5.5%	5.2%	0.0%	5.1%	13.2%
2009 May	16.7%	16.2%	3.2%	12.7%	5.0%	7.2%	3.1%	0.0%	2.6%	10.1%
2009 Jun	(10.3%)	(8.5%)	1.6%	(3.7%)	5.2%	3.7%	3.5%	0.0%	4.1%	3.5%
2009 Jul	3.0%	10.6%	7.1%	15.2%	9.5%	10.0%	7.8%	0.0%	10.2%	8.6%
2009 Aug	5.4%	2.0%	8.7%	3.5%	(0.5%)	4.3%	(0.0%)	0.0%	4.7%	(0.6%)
2009 Sep	(3.6%)	(0.1%)	4.5%	0.7%	2.8%	5.5%	(3.7%)	0.0%	(0.2%)	1.5%
2009 Oct	6.9%	7.1%	1.4%	11.4%	9.0%	6.5%	(3.3%)	0.0%	4.8%	17.9%
2009 Nov	(1.7%)	6.5%	(4.7%)	3.9%	1.3%	(3.4%)	0.9%	0.0%	(1.2%)	(1.6%)
2009 Dec	2.5%	2.6%	4.2%	2.7%	9.7%	6.8%	(0.8%)	0.0%	2.9%	(1.0%)
2010 Jan	(3.7%)	(6.1%)	(2.5%)	(0.7%)	(5.3%)	(4.1%)	(6.8%)	0.0%	1.2%	6.5%
2010 Feb	(1.8%)	(0.4%)	1.3%	(3.2%)	3.3%	6.6%	1.7%	0.0%	1.1%	9.9%
2010 Mar	7.4%	9.7%	7.8%	8.2%	7.4%	7.4%	0.4%	0.0%	7.4%	(1.5%)
2010 Apr	0.4%	(1.8%)	0.1%	3.3%	2.8%	0.1%	(0.1%)	0.0%	0.8%	2.9%
2010 May	(7.0%)	(6.4%)	(3.2%)	(7.4%)	(3.5%)	0.2%	(0.1%)	0.0%	(5.5%)	5.7%
2010 Jun	(1.9%)	(4.3%)	(4.1%)	2.0%	(1.7%)	(3.8%)	(5.7%)	0.0%	(3.1%)	(7.9%)
2010 Jul	5.2%	6.6%	5.9%	4.8%	5.7%	12.1%	13.5%	0.0%	10.5%	29.2%
2010 Aug	(2.8%)	(6.3%)	0.3%	(2.3%)	0.4%	(2.6%)	2.5%	0.0%	(3.4%)	(3.0%)
2010 Sep	11.4%	7.2%	9.0%	11.2%	7.8%	14.2%	6.8%	0.0%	7.9%	(0.8%)
2010 Oct	3.3%	8.7%	2.6%	1.2%	1.4%	4.0%	(0.3%)	0.0%	(2.2%)	(2.6%)
2010 Nov	(0.0%)	(0.7%)	0.0%	4.1%	0.8%	(0.7%)	(3.2%)	0.0%	(2.4%)	(1.9%)
2010 Dec	9.8%	7.2%	5.6%	3.9%	1.1%	4.8%	11.2%	0.0%	4.7%	4.3%
2011 Jan	0.2%	(0.1%)	(5.4%)	(1.2%)	(4.2%)	(7.0%)	(8.4%)	0.0%	(1.5%)	0.6%
2011 Feb	9.8%	4.7%	(1.7%)	1.7%	(0.3%)	4.6%	0.6%	0.0%	(0.4%)	1.2%
2011 Mar	2.8%	(2.2%)	(1.8%)	1.3%	(1.0%)	(0.8%)	12.4%	0.0%	2.7%	0.4%
2011 Apr	(2.4%)	0.6%	2.4%	4.1%	2.3%	5.3%	6.1%	0.0%	2.9%	(1.7%)
2011 May	(4.5%)	(2.4%)	0.6%	2.3%	3.9%	(0.9%)	(0.6%)	0.0%	0.4%	7.1%
2011 Jun	(1.8%)	(3.0%)	(0.3%)	(2.1%)	1.0%	(1.4%)	(0.1%)	0.0%	(2.0%)	(0.7%)
2011 Jul	(5.7%)	(4.0%)	(0.7%)	1.2%	(0.6%)	(1.2%)	0.8%	0.0%	(1.6%)	5.3%
2011 Aug	0.8%	(1.8%)	(1.8%)	(1.2%)	(1.0%)	3.7%	0.3%	0.0%	1.3%	1.0%
2011 Sep	(1.1%)	(5.2%)	(2.2%)	(1.9%)	4.1%	(3.6%)	(5.6%)	0.0%	(2.9%)	(0.1%)
2011 Oct	9.8%	10.9%	6.1%	15.6%	3.9%	8.9%	3.4%	0.0%	5.7%	4.7%
2011 Nov	8.7%	1.1%	1.8%	(0.8%)	0.4%	3.1%	4.5%	0.0%	0.8%	3.2%
2011 Dec	(0.9%)	(5.7%)	(0.1%)	(3.6%)	1.0%	(1.3%)	(1.3%)	0.0%	1.9%	4.4%
2012 Jan	3.5%	8.7%	8.2%	5.0%	3.6%	4.5%	(5.0%)	0.0%	6.1%	5.0%
2012 Feb	0.2%	(1.8%)	5.4%	3.4%	3.8%	4.5%	1.8%	0.0%	4.1%	3.0%
2012 Mar	(7.3%)	(8.0%)	3.7%	2.2%	6.7%	2.6%	3.2%	0.0%	2.1%	2.1%
2009 Apr	1.2%	2.7%	1.5%	3.8%	4.6%	4.9%	0.5%	0.0%	2.6%	3.0%
2012 May	(2.2%)	(7.5%)	(3.2%)	(2.0%)	(0.4%)	(2.4%)	(2.1%)	0.0%	(1.0%)	(2.3%)
2012 Jun	(5.2%)	2.2%	1.4%	0.3%	6.4%	3.2%	2.9%	0.0%	3.0%	5.0%
2012 Jul	0.6%	(2.4%)	5.5%	5.9%	8.7%	6.0%	5.0%	0.0%	3.8%	1.8%
2012 Aug	5.3%	(1.7%)	0.2%	7.5%	(0.0%)	4.9%	7.9%	0.0%	2.4%	5.4%
2012 Sep	2.6%	6.3%	0.8%	(3.0%)	0.4%	2.0%	0.9%	0.0%	0.2%	6.2%
2012 Oct	2.6%	6.6%	2.0%	5.5%	6.9%	5.6%	(1.1%)	0.0%	1.5%	(0.3%)
2012 Nov	1.3%	(2.1%)	0.1%	11.1%	(1.1%)	1.6%	5.2%	0.0%	2.7%	4.3%
2012 Dec	(3.2%)	4.1%	6.5%	(2.2%)	8.8%	3.5%	7.9%	0.0%	5.3%	(5.1%)
2013 Jan	6.7%	3.2%	1.7%	9.8%	(1.3%)	(4.4%)	(1.0%)	0.0%	3.1%	0.8%
2013 Feb	(0.9%)	(6.8%)	5.2%	(0.6%)	1.5%	(0.9%)	(0.6%)	0.0%	(0.4%)	9.7%
2013 Mar	6.1%	(3.5%)	3.3%	5.4%	8.6%	1.5%	(5.5%)	0.0%	3.1%	1.8%
2013 Apr	(3.4%)	(9.3%)	(2.4%)	(0.5%)	3.4%	1.5%	(0.6%)	0.0%	1.2%	(1.0%)
2013 May	16.8%	11.1%	5.4%	11.7%	6.7%	10.6%	12.3%	0.0%	(0.3%)	10.0%
2013 Jun	(4.7%)	(14.4%)	(2.9%)	(4.7%)	2.6%	(1.6%)	0.5%	0.0%	(2.4%)	(3.0%)
2013 Jul	5.3%	9.8%	(0.4%)	4.2%	(1.2%)	4.6%	2.0%	0.0%	1.4%	7.6%
2013 Aug	6.0%	7.6%	0.7%	1.4%	3.4%	0.4%	1.5%	0.0%	(0.9%)	2.1%
2013 Sep	(0.6%)	3.0%	4.3%	5.5%	5.4%	8.8%	6.3%	0.0%	6.3%	4.4%
2013 Oct	9.9%	1.5%	4.0%	1.9%	6.8%	4.0%	1.1%	0.0%	7.1%	4.3%
2013 Nov	(1.7%)	(2.5%)	(1.3%)	1.2%	(3.2%)	(0.3%)	0.3%	0.0%	(2.6%)	(1.7%)
2013 Dec	2.1%	2.1%	2.4%	1.4%	3.4%	6.0%	9.2%	0.0%	2.4%	(2.3%)
2014 Jan	3.7%	5.4%	(6.7%)	(3.3%)	(9.3%)	(2.5%)	(8.8%)	0.0%	(6.9%)	(5.4%)
2014 Feb	2.4%	5.2%	0.3%	4.0%	3.6%	8.6%	0.0%	0.0%	7.2%	4.9%
2014 Mar	8.0%	(1.9%)	5.5%	(0.4%)	4.4%	(2.5%)	12.2%	0.0%	6.2%	(5.3%)
2014 Apr	1.5%	3.8%	4.6%	6.6%	2.8%	(6.8%)	(1.9%)	0.0%	4.1%	3.2%
2014 May	0.8%	(4.5%)	1.5%	3.5%	2.8%	9.6%	5.4%	0.0%	1.2%	(0.5%)
2014 Jun	6.2%	2.7%	(0.1%)	2.8%	3.8%	4.0%	1.3%	0.0%	2.4%	5.2%
2014 Jul	(2.0%)	5.8%	1.4%	(5.5%)	2.5%	5.5%	(0.8%)	0.0%	1.2%	5.3%
2014 Aug	(0.2%)	(6.1%)	1.1%	0.4%	4.6%	0.2%	9.8%	0.0%	0.4%	(1.6%)
2014 Sep	(0.8%)	(6.7%)	(4.2%)	0.9%	3.2%	(5.7%)	(1.0%)	0.0%	(1.1%)	(0.8%)
2014 Oct	(8.3%)	(9.1%)	5.7%	0.2%	8.6%	9.7%	2.6%	0.0%	6.7%	7.8%
2014 Nov	(15.9%)	(3.2%)	(1.2%)	5.1%	1.9%	5.2%	(8.4%)	0.0%	3.0%	1.5%
2014 Dec	(6.7%)	(3.7%)	0.2%	(0.1%)	3.2%	2.9%	1.0%	0.0%	0.8%	0.0%
2015 Jan	(2.3%)	2.5%	3.1%	0.1%	6.6%	11.7%	(7.1%)	0.0%	4.5%	7.5%
2015 Feb	0.6%	10.0%	(0.6%)	5.1%	0.8%	0.3%	2.9%	0.0%	3.4%	7.3%
2015 Mar	(7.6%)	(8.9%)	(1.7%)	(3.1%)	(4.0%)	5.1%	2.1%	0.0%	2.9%	9.2%
2015 Apr	5.7%	9.0%	0.5%	3.4%	(2.2%)	1.0%	15.2%	0.0%	4.2%	2.0%
2015 May	13.8%	(4.6%)	(4.5%)	0.3%	(5.8%)	(3.4%)	(10.2%)	0.0%	(5.8%)	1.9%
2015 Jun	99.3%	(4.7%)	0.1%	(3.0%)	(0.7%)	4.7%	5.6%	0.0%	(0.5%)	(1.8%)
2015 Jul	54.9%	(5.2%)	(0.3%)	6.7%	4.0%	(4.2%)	(6.0%)	0.0%	3.9%	8.8%
2015 Aug	(23.1%)	(0.9%)	(0.7%)	(5.1%)	(4.0%)	(2.4%)	(11.8%)	0.0%	(3.0%)	(0.4%)
2015 Sep	5.0%	(8.6%)	(2.1%)	15.1%	(7.8%)	(1.1%)	0.4%	0.0%	(1.7%)	(11.3%)
2015 Oct	9.5%	8.9%	6.8%	7.9%	8.1%	12.3%	(7.6%)	0.0%	6.9%	0.5%
2015 Nov	(11.7%)	(14.5%)	(5.0%)	(1.2%)	(4.1%)	3.3%	(7.1%)	0.0%	(3.4%)	(5.1%)
2015 Dec	(16.3%)	(2.0%)	(5.6%)	3.4%	(0.2%)	(1.4%)	(5.6%)	0.0%	(6.3%)	(6.3%)
2016 Jan	0.0%	(2.7%)	1.8%	(2.6%)	(5.4%)	(5.5%)	3.0%	0.0%	(3.3%)	(7.7%)
2016 Feb	0.0%	15.6%	(2.0%)	(1.0%)	(0.4%)	(4.8%)	(3.5%)	0.0%	(1.5%)	5.1%
2016 Mar	0.0%	5.1%	7.8%	0.8%	8.8%	10.1%	7.2%	0.0%	11.5%	4.4%
2016 Apr	0.0%	13.4%	2.0%	(2.2%)	2.3%	(2.4%)	8.3%	0.0%	(0.3%)	(4.7%)
2016 May	0.0%	(3.8%)	0.0%	6.8%	(1.4%)	10.6%	(13.7%)	0.0%	(2.0%)	(0.6%)
2016 Jun	0.0%	(2.5%)	3.0%	(9.3%)	5.6%	(1.9%)	14.6%	0.0%	(2.1%)	(0.0%)
2016 Jul	0.0%	4.3%	5.7%	(2.0%)	0.8%	0.6%	(2.2%)	0.0%	2.8%	8.6%
2016 Aug	0.0%	(0.8%)	(2.1%)	3.5%	(1.7%)	4.2%	(10.6%)	0.0%	(3.3%)	0.7%

Table 2 Industry-specific FPEF data - net purchases / sales value (Rm)

	Oils and Gas	Basic Materials	Industrials	Consumer Goods	Healthcare	Consumer Services	Telecommunications	Utilities	Financials	Technology
2009 Jan	(1,009)	1,371	3	133	39	215	57	0	(2,622)	(49)
2009 Feb	170	3,714	187	686	154	303	486	0	(1,283)	28
2009 Mar	26	15,085	709	(443)	212	(498)	2,010	0	(2,115)	193
2009 Apr	(1,261)	(977)	518	(2,303)	(24)	431	857	0	2,906	(21)
2009 May	615	4,251	1,276	(383)	359	(1,371)	1,850	0	2,492	273
2009 Jun	(1,502)	6,248	1,521	1,423	303	1,402	(120)	1	1,274	200
2009 Jul	(414)	1,676	366	(129)	336	3,480	1,010	0	2,608	(95)
2009 Aug	(384)	1,989	772	3,257	237	2,627	425	1	3,429	9
2009 Sep	(855)	490	2,372	185	(64)	2,332	(634)	1	(825)	(81)
2009 Oct	(562)	2,182	655	1,210	23	2,995	964	0	231	194
2009 Nov	(2,047)	4,352	243	(336)	182	666	129	0	(167)	137
2009 Dec	(648)	783	367	1,606	178	1,169	(589)	0	(1,211)	3
2010 Jan	(84)	1,573	126	2,977	(7)	1,032	(167)	0	(1,228)	(10)
2010 Feb	(1,387)	(1,037)	(111)	2,214	163	2,980	1,512	1	(1,404)	(48)
2010 Mar	(1,178)	(2,335)	302	320	652	4,917	(693)	0	1,885	(22)
2010 Apr	(613)	(859)	598	245	393	392	(89)	1	1,966	24
2010 May	(1,937)	(1,238)	1,078	926	469	2,096	2,406	0	572	(283)
2010 Jun	777	(2,539)	(942)	1,580	2	668	1,933	(0)	1,020	(108)
2010 Jul	(301)	(6,270)	(148)	2,129	98	3,417	144	0	3,498	1,247
2010 Aug	(679)	(4,419)	732	1,798	337	1,947	2,796	(0)	119	229
2010 Sep	(245)	(8,443)	810	(412)	259	1,445	780	(0)	(440)	(54)
2010 Oct	20	(1,716)	690	51	(220)	2,275	723	6	380	18
2010 Nov	(84)	2,009	1,113	2,332	254	2,831	1,406	0	(529)	20
2010 Dec	(77)	2,308	466	105	51	1,507	1,237	(0)	(172)	31
2011 Jan	396	1,216	744	(464)	(123)	(2,433)	(435)	(0)	1,360	(13)
2011 Feb	211	2,537	(588)	1,191	(843)	705	(964)	(0)	(2,275)	(28)
2011 Mar	2,150	(2,420)	401	(1,610)	(1,010)	(344)	1,781	(0)	(32)	2
2011 Apr	1,562	(188)	1,100	734	(734)	1,051	1,537	(0)	347	18
2011 May	(1,196)	(3,256)	(222)	782	903	306	2,916	(0)	442	(17)
2011 Jun	(47)	(4,075)	166	88	910	852	1,911	0	(114)	(5)
2011 Jul	(992)	(4,186)	(156)	1,187	346	(335)	3,166	0	(980)	14
2011 Aug	(2,051)	(8,909)	(213)	3,049	508	794	1,099	0	(1,138)	3
2011 Sep	(382)	(7,977)	(176)	2,013	378	(1,301)	(479)	0	727	6
2011 Oct	61	(2,638)	338	1,121	383	980	(947)	0	1,140	25
2011 Nov	1,474	(3,164)	693	712	199	187	604	0	179	25
2011 Dec	1,561	(1,155)	1,067	(756)	435	(3,102)	1,256	(0)	270	2
2012 Jan	811	(4,627)	1,977	(1,992)	435	(505)	(2,945)	(0)	(50)	27
2012 Feb	1,779	(5,365)	1,687	(928)	275	765	(312)	0	943	6
2012 Mar	(1,508)	(4,637)	2,825	711	727	2,249	2,372	(0)	1,897	(3)
2009 Apr	(326)	(8,136)	1,328	1,970	845	3,033	488	(0)	901	29
2012 May	546	(7,430)	1,867	1,378	792	3,866	1,223	(0)	2,921	19
2012 Jun	126	(3,852)	680	(2,300)	1,019	1,497	2,176	(0)	447	75
2012 Jul	18	(2,860)	1,479	(2,353)	891	(727)	2,836	0	464	34
2012 Aug	(590)	(1,920)	182	(316)	(131)	(1,104)	2,425	(0)	433	66
2012 Sep	(185)	(1,601)	156	(1,172)	(82)	838	979	(0)	508	46
2012 Oct	(632)	(5,236)	117	(767)	511	(294)	41	0	(1,351)	48
2012 Nov	121	(543)	816	(1,647)	682	(473)	3,046	1	322	27
2012 Dec	182	(1,175)	1,137	(3,998)	616	3,664	856	0	3,514	11
2013 Jan	(384)	3	2,432	(3,665)	256	230	(142)	0	1,836	66
2013 Feb	509	(1,769)	3,958	(161)	212	1,630	976	(0)	2,608	111
2013 Mar	284	(3,820)	1,791	(2,493)	743	(1,934)	(1,986)	(0)	1,439	78
2013 Apr	474	(7,469)	2,799	(1,597)	777	3,386	2,990	0	6,551	24
2013 May	418	(4,589)	2,959	(1,073)	(130)	1,899	1,914	(0)	2,749	201
2013 Jun	528	(1,325)	1,397	(968)	801	408	3,600	0	3,503	58
2013 Jul	611	(3,805)	1,062	(3,661)	1,060	2,910	294	0	999	53
2013 Aug	31	831	1,159	(2,483)	2,557	3,803	1,629	(0)	(2,672)	32
2013 Sep	33	115	1,533	(2,384)	18	(360)	(611)	0	787	40
2013 Oct	735	(2,309)	2,121	(5,579)	280	(3,119)	(912)	(0)	859	33
2013 Nov	732	(4,891)	356	(2,477)	(4,453)	(2,857)	(40)	(0)	(3,282)	164
2013 Dec	616	(1,908)	402	(1,629)	629	(84)	1,221	0	(978)	124
2014 Jan	723	(862)	794	(2,290)	(843)	113	(674)	0	(2,326)	138
2014 Feb	1,335	(1,090)	(655)	(2,663)	1,010	8,634	(175)	0	(301)	28
2014 Mar	944	(3,704)	2,305	(1,223)	336	2,271	2,861	0	4,025	134
2014 Apr	1,960	(4,353)	2,268	135	815	804	1,450	(0)	6,313	95
2014 May	859	(6,431)	1,144	(2,585)	(322)	1,863	3,258	(0)	4,307	80
2014 Jun	500	(3,520)	(792)	(1,379)	1,277	606	81	0	1,118	53
2014 Jul	1,253	(1,127)	1,115	(7,219)	1,753	(651)	1,819	0	2,857	39
2014 Aug	1,592	(25)	1,514	(3,913)	1,835	108	4,322	(0)	3,667	71
2014 Sep	1,070	(1,572)	763	(9,179)	2,070	2,830	2,422	0	2,242	16
2014 Oct	(481)	(2,060)	702	(2,812)	2,445	5,146	2,089	0	616	(18)
2014 Nov	(2,738)	(4,194)	(643)	(4,561)	523	3,074	(893)	0	(2,170)	(1)
2014 Dec	(1,471)	(3,043)	(183)	(3,033)	363	(509)	1,245	0	(1,701)	19
2015 Jan	210	(4,018)	1,055	(1,942)	924	1,043	(2,662)	(0)	1,112	63
2015 Feb	1,661	(2,124)	604	2,238	113	(10,094)	2,957	0	3,646	318
2015 Mar	996	1,455	943	5,238	(5,986)	4,102	2,678	(0)	8,716	489
2015 Apr	11	2,244	(729)	(497)	904	94	1,572	0	(1,010)	99
2015 May	(5)	3,566	(345)	(579)	806	(342)	993	0	1,345	159
2015 Jun	3	(499)	1,453	(962)	1,020	5,561	4,523	0	2,736	44
2015 Jul	1	816	232	(2,440)	149	4,046	(3,719)	(0)	4,809	31
2015 Aug	2	(13)	(230)	1,006	1,095	(2,119)	1,175	(0)	2,200	200
2015 Sep	2	(3,960)	1,022	(2,798)	80	(1,603)	3,784	(0)	339	393
2015 Oct	(1)	(3,638)	1,548	(16,984)	314	5,057	(5,286)	0	(4,408)	150
2015 Nov	(1)	(2,125)	(899)	(5,668)	(1,361)	(400)	(3,350)	0	2,567	(75)
2015 Dec	1	(554)	(750)	1,784	(1,225)	(4,752)	854	0	(2,639)	38
2016 Jan	(0)	3,243	68	(2,867)	340	(6,775)	958	0	195	(95)
2016 Feb	1	1,437	615	(4,582)	(4,152)	(929)	1,714	0	(3,362)	(41)
2016 Mar	79	1,295	1,276	(8,440)	(159)	(996)	405	0	4,502	205
2016 Apr	19	(3,490)	1,798	(19,756)	(173)	1,294	(168)	0	(136)	(57)
2016 May	1	(1,681)	(3,666)	(6,607)	(342)	7,138	(919)	0	(10,192)	(37)
2016 Jun	(1)	(7,477)	1,391	(11,878)	69	(25)	2,080	0	(4,235)	28
2016 Jul	0	(907)	1,136	(7,459)	419	1,063	2,213	0	17	29
2016 Aug	(3)	(1,301)	617	(4,132)	704	968	1,415	0	(776)	122

4.4. DATA GATHERING PROCESS

Time-series data from January 2009 to August 2016 was collected. This was secondary data obtained from the JSE, Bloomberg and FactSet. All three sources aggregate the industries according to the ICB codes as shown in Table 3.

A comprehensive set of FPEF data was obtained from the JSE. The data included foreign equity trading figures in the form of purchase value, sales value, net (purchases / sales) value, purchase volume, sales volume, net (purchases / sales) volume, purchase trades and sales trades. Most of the data was provided at industry level but for some months the data was provided at sector level in which case data had to be aggregated to industry level. The data was checked for errors and when these were found, the correct data was requested from the JSE. The total returns (capital and dividend returns included) and weightings of the industry indices were collected from Bloomberg and FactSet databases.

The following data discussion relates to the testing for hypothesis one. For both the return and foreign flow data, from January 2009 to December 2015, the data contained nine industry indices for 84 months – therefore a total of 756 observations during this period. These industries included Oil and Gas, Basic Materials, Industrials, Consumer Goods, Healthcare, Consumer Services, Telecommunication Financials and Technology. Utilities had no underlying stocks. For both the return and foreign flow data, from January 2016 to August 2016, the data contained eight industry indices for eight months – therefore a total of 64 observations for this period. These industries included Basic Materials, Industrials, Consumer Goods, Healthcare, Consumer Services, Telecommunication Financials and Technology as Utilities as well as Oils and Gas having no underlying stocks.

The following data discussion relates to the testing for hypothesis two. A three-month moving average approach was used. The period from January 2009 to August 2009 was applicable for the foreign flow data. However, the period from March 2009 to August 2009 was applicable for the return data as returns only became relevant from the first foreign flow three-month moving average data point. For the foreign flow data, from January 2009 to December 2015, the data contained nine industry indices for 84 months – therefore a total of 756 observations during this period. For the return data, from March 2009 to December 2015, the data contained nine industry indices for 82 months – therefore a total of 738 observations. For both the return and foreign flow data, from January 2016 to August 2016, the data contained eight industry indices for eight months – therefore a total of 64 observations.

Table 3 ICB Classifications

Industry	ICB Code	Super-sector name	ICB Code	Sector name	ICB Code
Oil and Gas	0001	Oil & Gas	0500	Oil & Gas Producers	0530
Basic Materials	1000	Chemicals	1300	Chemicals	1350
		Basic Resources	1700	Forestry & Paper	1730
				Industrial Metals & Mining	1750
				Mining	1770
Industrials	2000	Construction & Materials	2300	Construction & Materials	2350
		Industrial Goods & Services	2700	Electronic & Electrical Equipment	2730
				Industrial Engineering'	2750
				Industrial Transportation	2770
				Support Services	2790
				General Industrials	2720
Consumer Goods	3000	Automobiles & Parts	3300	Automobiles & Parts	3350
		Food & Beverage	3500	Beverages	3530
				Food Producers	3570
		Personal & Household Goods	3700	Household Goods & Home Construction	3720
				Leisure Goods	3740
				Personal goods	3760
				Tobacco	3780
Healthcare	4000	Healthcare	4500	Healthcare Equipment & Services	4530
				Pharmaceuticals & Biotechnology	4570
Consumer Services	5000	Retail	5300	Food & Drug Retailers	5330
				General Retailers	5370
		Media	5500	Media	5550
		Travel & Leisure	5700	Travel & Leisure	5750
Telecommunications	6000	Telecommunications	3500	Fixed Line TeleCommunications	6530
				Mobile Telecommunications	6570
Utilities	7000	Utilities	7500	Electricity	7530
				Gas, Water & Multi-utilities	7570
Financials	8000	Banks	8300	Banks	8350
		Insurance	8500	Non-life Insurance	7530
				Life Insurance	8570
		Real Estate	8600	Real Estate Investment & Services	8630
				Real Estate Investment Trusts	8670
		Financial Services	8700	Financial Services	8770
				Equity Investment Instruments	8980
				Non-equity Investment Instruments	8990
Technology	9000	Technology	9500	Software & Computer Services	9530
				Technology Hardware & Equipment	9570

Table 4 illustrates the weight of each industry index in the ALSI and the number of stocks underpinning each industry index for the first and last months of the sample period. This gives an indication of the significance of the index to the ALSI and how tradable the industry index could be through an investment vehicle / fund replicating the composition of industry indices.

Table 4 Industry weight and number of underlying stocks

Industry	January 2009 weight (%)	August 2016 weight (%)	January 2009 number of underlying stocks	August 2016 number of underlying stocks
Oil and Gas	6.61	0	1	0
Basic Materials	38.73	18.49	33	23
Industrials	6.39	4.35	33	24
Consumer Goods	11.73	26.33	12	16
Healthcare	1.56	3.90	5	7
Consumer Services	7.68	21.43	25	24
Telecommunications	7.76	3.92	4	4
Utilities	0	0	0	0
Financials	19.08	21.23	48	63
Technology	0.47	0.36	5	2
Total	**100**	**100**	**166**	**163**

4.5. ANALYSIS APPROACH

4.5.1. Analysis for hypothesis 1a and hypothesis 1b

This analysis was conducted using Stata. All tests were conducted at a 5% level of significance.

There was data for ten different industries (as mentioned before, initially only nine apply and then eight) for which the researcher created bivariate models which included net foreign flow values and geometric returns. The variables were named such that for each respective industry, NV indicated the net foreign flow value and GR indicated the geometric return. For example, for the Financials industry, the two variables were denoted by NV_Financials and GR_Financials respectively.

For each industry, the first step in the analysis for hypothesis 1a and 1b involved investigating the relationship between the two variables by ensuring that the variables were stationary (also referred to as a white noise series or a series that does not contain a unit root) as the models would be misspecified and result in spurious regression whose ordinary least square estimates were invalid if there were non-stationary variables (French, 2011). A stationary time series is one whose properties do not depend on the time at which the series is observed (Nason, 2006). In other words, stationarity means that parameters such as mean and variance should be constant over time and should not drift nor follow any trends otherwise estimating the regressions will lead to erroneous results (Nason, 2006). In general, a stationary time series will have no predictable patterns in the long-term.

The first step in determining the stationarity of the series was to plot time series. This involved plotting the variables against time. The purpose of this was to graphically reveal important features of the data (for example, stationarity, trends and structural breaks). If no obvious trends were present, this suggested that the variables were stationary. However, more formal tests needed to be explored to accurately determine the possible stationarity of the series. Autocorrelation functions (ACFs) were then generated. For a stationary time series, it is expected that only a few autocorrelations are significantly different from zero, in other words, the ACF drops to zero relatively quickly. If the autocorrelation coefficients are persistently large, meaning they are very slowly dropping towards zero, this indicates that the time series is most likely non-stationary. It is then necessary to defer to statistical testing for stationarity and the Augmented Dickey Fuller (ADF) test was most appropriate for this (Srinivasan et al., 2010).

It was important to establish a suitable lag length so that residuals (unexpected flows) are uncorrelated and homoskedastic (Hyndman & Athanasopoulos, 2013). Each variable is a linear function of the lag p values for all variables in the set. The present (time t) observation of each variable depends on its own lagged values as well as on the lagged values of each other variable. For purposes of the specification of the time series models, an appropriate lag length was found on the basis of Akaike Information Criterion (AIC) to ensure that the data was adequately modelled. Lutkepohl (1993) stated that over-specifying the lag length (deciding on a higher order lag length than the true lag length) results in an increase in forecast errors of the model and that under-specifying the lag length often generates serially correlated residuals.

The ADF test could then be conducted to test the following hypothesis:

H_0: Series has unit root / not stationary

H_1: Series is stationary

If the time series were found to contain a unit root, differences between consecutive observations were computed. This is known as first-order differencing (DeFusco, McLeavey, Pinto & Runkle, 2014b) which has the following equation:

Equation 2: First-order differencing

$$y'_t = y_t - y_{t-1}$$

Should the differenced data still not appear stationary, it may be necessary to difference the data a second time (second-order differencing) to achieve stationarity. This would be written as:

Equation 3: Second-order differencing

$$y''_t = y'_t - y'_{t-1}$$

The next step of the data analysis was to conduct the Johansen test for long-run cointegration. This was to test if there was an underlying relationship between the two variables. Testing for cointegration is an essential step to ensure that empirically meaningful relationships are being modelled. If variables have different trends, they cannot remain in a sustained long-run relation with one another over time.

The Johansen approach is sensitive to the lag length (Ahking, 2002). Therefore, the lag length needed to be determined in a systematic manner. The AIC was again used to determine the appropriate lag length. When estimating regressions on time series data, it is sometimes necessary to include lagged values of the dependent variable as independent variables making the regression a vector autoregression (VAR). If there was a long-run cointegration relationship found between the variables, the VCE model was the most appropriate model in comparison to the VAR model which is suitable when there is no cointegration. As aforementioned, in order to determine if the time series were co-integrated, the Johansen procedure was used to test this. The time series for all industries were found to be co-integrated, therefore VEC analysis, which can be regarded as restricted VAR models (the error correction term has to be included in the VAR (Kestel, n.d.), is practical in the context of this study as it is useful for suggesting adaptations of narrowly defined theoretical models (Juselius, 2010). Aron et al. (2010) and Loncan and Caldeira (2015), literature relevant to this study, employed VEC analysis in their methodology. The VEC model should be run in first-order differences (Sjö, 2008).

As stated in section 3., the VEC models have the general specifications:

$$\Delta y_t = \beta_{y0} + \beta_{y1}\Delta y_{t-1} + \ldots + \beta_{yp}\Delta y_{t-p} + \gamma_{y1}\Delta x_{t-1} + \ldots + \gamma_{yp}\Delta x_{t-p} \quad -\lambda_y\left(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}\right) + v_t^y$$

$$\Delta x_t = \beta_{x0} + \beta_{x1}\Delta y_{t-1} + \ldots + \beta_{xp}\Delta y_{t-p} + \gamma_{x1}\Delta x_{t-1} + \ldots + \gamma_{xp}\Delta x_t \quad -\lambda_x\left(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}\right) + v_t^x$$

where Δ refers to first-order differencing; y is the vector of the JSE ALSI industry returns; x is the vector of industry-specific net FPEF; β is the regression coefficient; v is the error term (the portion of the dependent variable that cannot be explained by the independent variable); t is the time period; $y_t=\alpha_0+\alpha_1 x_t$ is the long-run cointegrating relationship between returns and net FPEF; and λ_y and λ_x are the error-correction parameters that measure how returns and net FPEF react to deviations from long-run equilibrium (Sims, 1980).

The current (time t) observation of each differenced variable depends on its own lags as well as on the lags of the other differenced variable in the VEC models.

The researcher then tested for Granger-causality by VEC analysis. Granger-causality statistics test if the lagged values of one variable are useful in predicting another variable. If the lagged value of a variable (y) is useful in predicting another variable (x), then y is said to 'Granger-cause' x (Stock & Watson, 2001; Zivot & Wang, 2006). Running Granger-causality tests for both variables can result in four possible outcomes, as presented in Table 5: no Granger-causality, unilateral Granger-causality in either direction, or "feedback," with Granger-causality being bidirectional (Sims, 1980).

Table 5 Granger-causality possible outcomes

	Fail to reject: $\beta_{y1} = \beta_{y2} =\ldots= \beta_{yp} = 0$	Reject: $\beta_{y1} = \beta_{y2} =\ldots= \beta_{yp} = 0$
Fail to reject: $\beta_{x1} = \beta_{x2} =\ldots= \beta_{xp} = 0$	x does not predict y y does not predict x No Granger-causality	x does not predict y y predicts x y Granger-causes x
Reject: $\beta_{x1} = \beta_{x2} =\ldots= \beta_{xp} = 0$	x predicts y y does not predict x x Granger-causes y	x predicts y y predicts x Bidirectional Granger-causality

Post-estimation specification testing was then conducted in order to test whether correct assumptions were used, the models are not misspecified and that the tests yield valid results. This was done by checking for stability (through the number of co-integrating equations), normality of errors and estimating the impulse response function (IRF) to measure the effects of a shock to the variables.

One of the primary uses of a VEC model is for forecasting. The model's ability to forecast was also determined as co-integrating VEC models can also be used to produce forecasts by determining if the forecast errors remain finite or diverge to infinity. The forecast ability of the model may be a useful business value-add for purposes of style investing. However, this may not always be applicable as, after testing, the forecast ability may not be reliable. The following section discusses the procedure followed to build a style engine which would then be relevant in terms of the study adding value practically.

4.5.2. Analysis for hypothesis two

This analysis was conducted using Excel and SPSS. All tests were conducted at a 5% level of significance.

This part of the analysis was conducted by comparing the monthly portfolio returns from a buy-and-hold strategy with the monthly portfolio returns from the portfolio constructed by the emulation of net FPEF patterns. A consistent and sustainable outperformance in the latter portfolio will indicate that the investment decisions of foreigners in the JSE can be exploited and a style engine based on such an investment strategy can be used to predict returns that will outperform a buy-and-hold strategy.

The next step of the analysis involved building an actual style engine and determining the process for portfolio construction.

4.5.2.1. Style engine

The procedure entailed constructing three portfolios: A, B and C, initially all identical. These portfolios were replicas of the ALSI as at the end of January 2009, the start of the holding period, categorised into the nine applicable industries on the JSE as classified by the ICB. The fixed holding period for this study was one month, in other words, industry rotations were conducted at the end of every month due to the fact that there were only 92 monthly observations for each industry.

A myriad of FPEF data was provided by the JSE including purchase value, sales value, net (purchases / sales) value , purchase volume, sales volume, net (purchases / sales) volume, purchase trades, sales trades. This data had to be transformed in such a way that it could be used for ranking purposes, specifically as an indicator for allocating funds into the industries. The first consideration was to normalise the data to make it more analogous across industries by transforming the data from absolute numbers to relative numbers. This was done by dividing the net foreign (purchases / sales) value by the total trade value (includes resident and non-resident). Hereafter, this will be referred to as the NV metric. The alternative consideration to finding an allocation indicator involved running an autoregressive model and using the unexpected flows from the results (residuals) as an indicator for industry allocation. However, for the simplicity of the model, to ensure its pragmatic use, the NV metric was chosen as the residual process may be cumbersome as a procedure to normalise the data would also have to be determined. This was identified at this stage as a possibility for future research. The allocation indicator was ranked 1 to 9. At the start of each holding period, portfolios A, B and C were each composed of three industries according to various ranking methods. Different ranking methods for building the style engine, and more specifically constructing the portfolios in terms of utilising the NV metric as an allocation indicator for allocating to the nine industries, were considered and the following two were tested on the style engine:

1. Weighting allocation to the top three industries with the highest three-month moving average allocation indicator equally (in other words, 33.33% equally).
2. Weighting allocation to the industries with only a positive allocation indicator; with the industries having the higher allocation indicator being allocated commensurately more.

It was decided that a three-month average NV metric was most appropriate as opposed to just simply using only the previous month as an allocation indicator as the former a) smooths out any erratic movements and b)would incorporate any effects that take more than one month to take effect . Portfolio A composed of the industries ranked 1,2 and 3; portfolio B composed of the industries ranked 2,3 and 4; and portfolio C composed of the industries ranked 7,8 and 9. Due to the fact that as from January 2016, there were only eight industries (as discussed earlier), the Oil and Gas index had no underlying stocks as from that month resulting in portfolio C being composed of only the bottom two industries, 7 and 8. This process was repeated for the data from January 2009 to the most recent period available, August 2016.

Industries with the highest rank were predicted to yield the highest returns. We assumed that allocation started with a notional value of R100 at the end of January 2009. For each month under observation, the relevant sample period would be the prior three months thereof, leading up to the start of each holding period. After holding the portfolio for a month, industry rotations (as determined by the allocation indicator) occurred monthly by re-investing in the ALSI industry indices up until the last period, August 2016. Transaction costs of 20, 60 and 100 basis points of the trade value were considered. Some nuances were involved in the calculation of the transaction costs as the researcher needed the desired allocation as calculated by the allocation indicator to be reflected post transaction costs. This was calculated through an iterative process. The allocated values were then grown by the following month's arithmetic return as provided by the aforementioned databases in order to determine a cumulative portfolio value as calculated by the monthly holding period returns for the said month. This approach was followed for every month in the dataset and the value of the ending portfolio value (end of August 2016) was compared to that of the benchmark portfolio.

Depending on whether there is a clear pattern and consistency in terms of the portfolio values at the end of the sample period, in other words, portfolio A outperforms B which outperforms C or portfolio C outperforms B which outperforms A, optimising the returns of the best ranked portfolio (A) in terms of the weighting for allocation was considered but not applied as no clear pattern was determined.

The distribution curves of the monthly portfolio returns had to be tested for normality. However, in order to perform a parametric test (such as at-test), the following paired sample t-test assumptions need to be met (Laerd Statistics, 2016):

1. The dependent variable should be measured on a continuous scale (in other words, it should be measured at the interval or ratio level).
2. The independent variable should be comprised of two categorical, related groups or matched pairs. Related groups indicate that the same subjects are present in both groups.
3. There should be no significant outliers in the differences between the two related groups.
4. The distribution of the differences in the dependent variable between the two related groups should be approximately normally distributed. Signs of non-normality are skewness (lack of symmetry) or kurtosis (light or heavy tails).

The normality of the distribution curves had to then be tested for. A probability density function (PDF) and a Quantile-Quantile plot (QQ), also known as a normal probability plot, were generated for each of the portfolio return differences. The Kolmogorov-Smirnov test was then used to statistically test for the normality of the portfolio return differences.

The geometric returns are related to logarithmic transformation of the data, ln(1+r). Compared to the arithmetic returns, the geometric returns are generally not excessively influenced by outliers in a skewed distribution.

T-tests were used for portfolio return differences that were normally distributed. The Wilcoxon rank-sum test was appropriate for portfolio return differences that were not normally distributed as, in such instances, parametric tests, such as t-tests, would present inaccurate p-values due to the violation of some of the said assumptions (DeFusco, McLeavey, Pinto & Runkle, 2014a).

The Sharpe ratio, which uses standard deviation, was then calculated to measure the portfolios' risk-adjusted returns. The Sharpe ratio is the amount of excess return (more specifically, return in excess of the risk-free rate) earned per unit of risk (investopedia, n.d.a). It is useful to compare the Sharpe ratios of the portfolios to the Sharpe ratios of the benchmark (in this case the ALSI) and the other peer group portfolios for a more comprehensive comparative analysis rather than a less informative, pure return basis (Wealth Management Systems Inc., n.d.). The following were also considered and specified for the possible comparison of returns (i) and testing of the hypothesis (ii, iii and iv):

1. Besides the Sharpe ratio, other risk-adjusted return measures were considered:
   i) Treynor ratio: $(r_{IND} – r_{BH}) / \beta_{IND}$ (Investopedia, n.d.c)
   ii) Sortino ratio: $(r_{IND} – r_{BH}) / \sigma_d$ (Investopedia, n.d.b)

where r_{IND} is the returns from the industry rotation investment style portfolio; r_{BH} is the returns from the buy-and-hold strategy portfolio; β_{IND} is the beta of the industry rotation investment style portfolio; and σ_d is the standard deviation of negative asset returns.

2. Determining a certain asset class (such as bonds or cash) in which to invest should there be net outflows
3. Whether the investment style will be applied to all JSE ALSI industries or just one or a couple

4. Determining at what level of change in net FPEF a sector rotation should be conducted. This means that the researcher needs to consider at what incremental increase (decrease) in net FPEF a sector should be invested into (divested out of).

4.6. LIMITATIONS

The credibility of the data collected, research findings and conclusions need to be considered. Any factors that render the findings invalid may cause the following limitations in terms of both validity and the reliability:

1. Saunders and Lewis (2012) describe validity as the extent to which the data collected precisely measures what it intended to measure. The most relevant types of validity and factors threatening internal validity to consider for this study are:
   i) Predictive validity – lack of availability of a comprehensive dataset in terms of the number of data points (or observations) and the frequency of the data may result in limitations with regards to the model's accuracy.
   ii) External validity
      - The findings will not be generalisable / transferable to other global markets or even emerging markets due to each exchange having different regulations, investability restrictions, characteristics, sizes and liquidity, amongst other factors.
      - There is a question of investability regarding exploiting the FPEF-based style emerging from this study. Doing so directly would involve investing in the relevant industries and the instruments for such implementation do not necessarily exist. As will be discussed in section 6.3.2., investing in the underlying stocks would most likely not be feasible due to impact of transaction costs.
   iii) History – Specific events that coincide with the time series which may have had an effect on findings may threaten validity.
2. Saunders and Lewis (2012) describe reliability as the extent to which the methods employed for the collection and analysis of data will produce consistent findings. Below are the principal factors that may threaten the reliability of the study's findings:

i) Triangulation – in order to improve the reliability of the findings, the researcher attempted to cross-check the aggregate of the FPEF by industry sourced from the JSE against the total (high-level) FPEF from other databases such as Bloomberg; however, this could not be accessed and other sources found on the internet state the JSE as their primary source. The JSE has been known to provide some erroneous data. An example of this is a programming error (affecting the manner in which statistical data is generated from their core transactional systems) that was detected which incorrectly calculated the non-resident equity statistics for the period 31 May to 20 July 2016 (van Niekerk, 2016). Subsequent to this, the researcher requested the correct data from the JSE.

3. Although it was considered whether foreign equity flow that was specifically for the purposes of foreign direct investment (FDI) should be stripped out of the data, as it is only equity investments that are easily investible / divestible that are of interest to this study, this would be difficult to ascertain as some investors may accumulate stock incrementally to a level where their investment is defined as FDI and this would be difficult to track.

Flexibility in terms of the rebalancing of portfolios was limited due to the following two limitations:

1. The length of the historical time series - There were only 92 data points provided by the JSE for FPEF. Having more data points would have allowed the researcher to test the style engine using quarterly rebalancing.
2. The frequency of the historical time series – The JSE only made monthly data available. Using daily or weekly instead of monthly data could have also allowed the researcher to be more flexible in terms of the frequency of rebalancing.

However, quarterly rebalancing may be slow to incorporate new information and high frequency in portfolio rebalancing leads to high transaction costs. For these reasons, monthly rebalancing is considered to have been most appropriate for this study.

5. RESULTS

The results are presented in the order of the propositions, hypotheses and methodology stipulated in Chapter 3 and Chapter 4 respectively.

5.1. RESULTS FOR HYPOTHESIS 1a AND 1b

5.1.1. Tests of assumptions: stationarity

The results for all of the tests ran for hypothesis 1a and 1b for Financials are presented. Hereafter, a summary of the results for the remaining industries will be discussed; however, a full presentation of the results and output can be found in the Appendices (Appendix A to Appendix J).

5.1.1.1. Time series analysis

Figure 1 NV_Financials time series

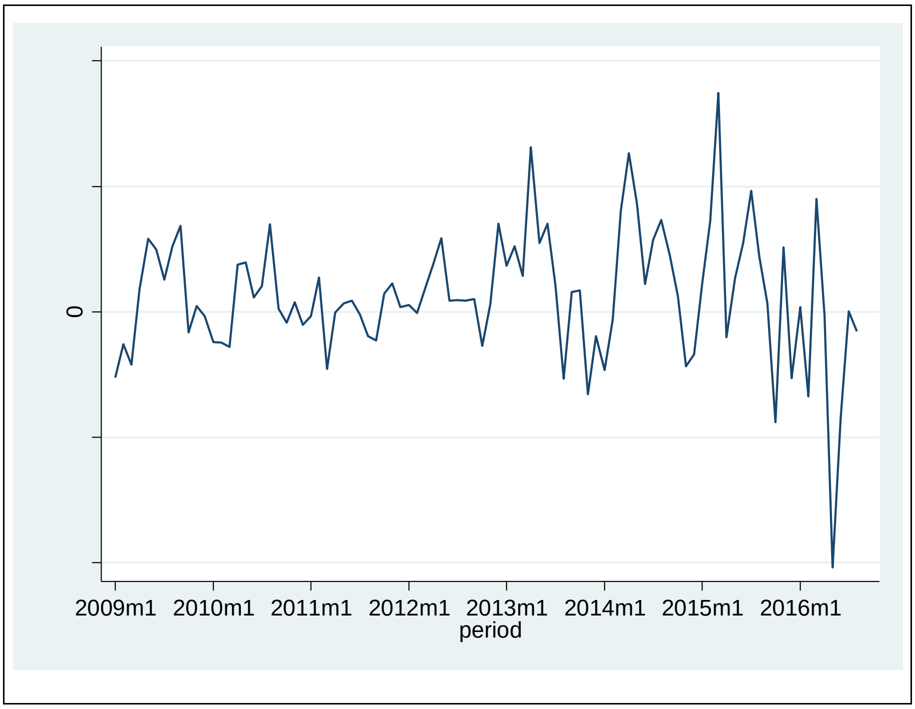
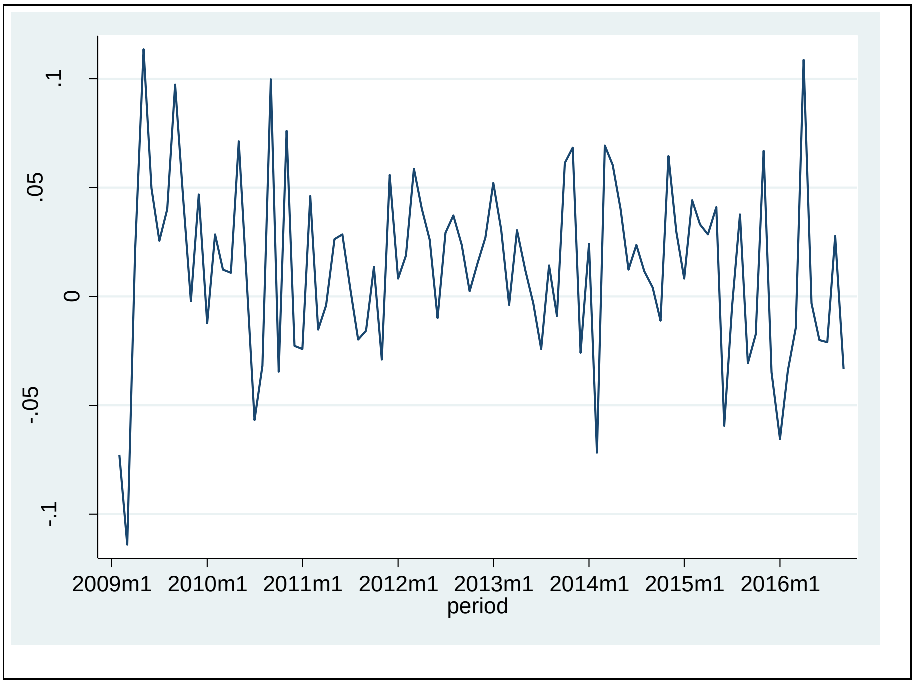


Figure 2 GR_Financials time series



The time series illustrated in Figure 1 and Figure 2 exhibit no obvious trends or patterns therefore indicating that there may be stationarity in the time series. The time series for the rest of the industries can be found in Appendix A.

5.1.1.2. Aurocorrelation Function Plots

Figure 3 ACF plot for NV_Financials

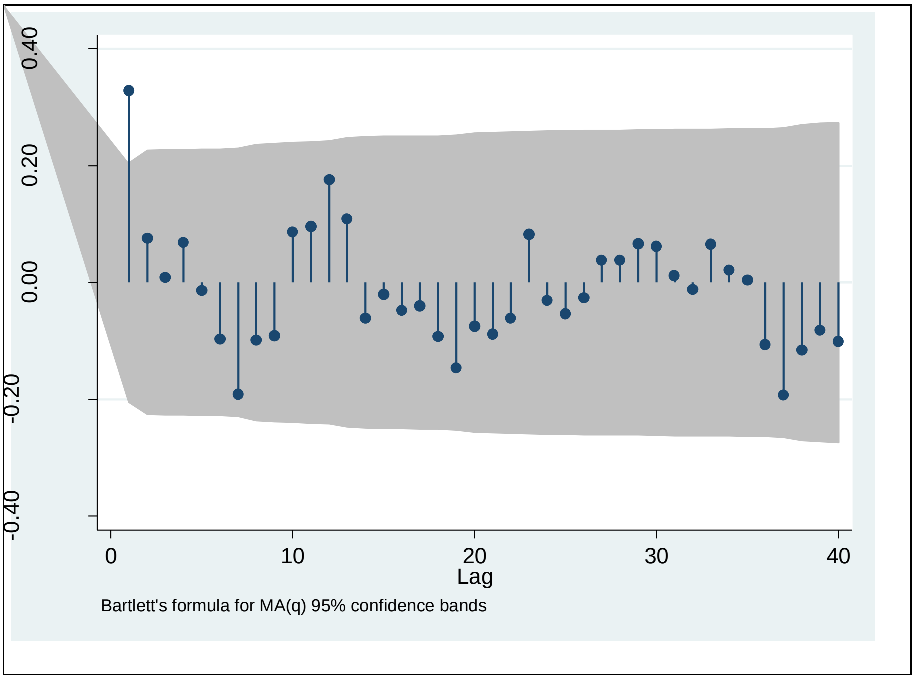
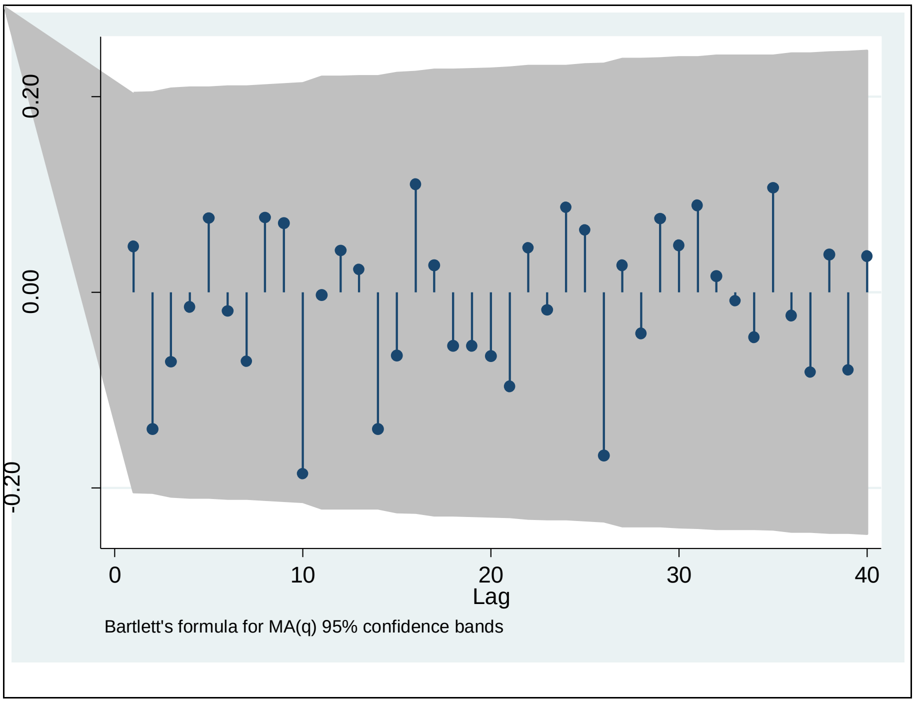


Figure 4 ACF plot for GR_Financials



As shown in Figure 3 and Figure 4 for both variables, the measured correlations rapidly become insignificant with increasing lag length; therefore, this suggests that the time series are stationary. The ACF plots for the rest of the industries can be found in Appendix B.

5.1.1.3. Akaike information criterion tests

Figure 5 AIC test for NV_Financials

varsoc NV_Financials

Selection-order criteria
Sample: **2009m5 - 2016m8** Number of obs = **88**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2031.65				6.8e+18	46.1967	46.208	46.2248
1	-2026.84	9.6337*	1	0.002	6.2e+18*	46.1099*	46.1326*	46.1662*
2	-2026.75	.17422	1	0.676	6.3e+18	46.1307	46.1647	46.2151
3	-2026.75	.00394	1	0.950	6.5e+18	46.1533	46.1987	46.266
4	-2026.35	.80142	1	0.371	6.6e+18	46.167	46.2237	46.3077

Endogenous: NV_Financials
Exogenous: _cons

Figure 6 AIC test for GR_Financials

varsoc GR_Financials

Selection-order criteria
Sample: **2009m6 - 2016m9** Number of obs = **88**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	165.156				.001404*	-3.73081*	-3.71947*	-3.70266*
1	165.198	.08429	1	0.772	.001435	-3.70905	-3.68636	-3.65274
2	165.409	.42237	1	0.516	.001461	-3.69112	-3.65709	-3.60666
3	165.441	.06384	1	0.801	.001493	-3.66912	-3.62375	-3.55651
4	165.486	.0908	1	0.763	.001526	-3.64742	-3.59071	-3.50666

Endogenous: GR_Financials
Exogenous: _cons

The results in Figure 5 and Figure 6 suggest that the appropriate lag length is one for NV_Financials and zero for GR_Financials (as indicated by the asterisk*). It is important to note that the lowest AIC value is most appropriate (Gordon, Negrete-Yankelevich & Sosa, 2015).

A summary of the results of remaining industries is presented in Table 6 and the comprehensive output can be found in Appendix C.

Table 6 AIC tests for remaining industries

Variable	NV lag	GR lag
Oil and Gas	1	1
Basic Materials	1	2
Industrials	1	0
Consumer Goods	1	1
Healthcare	0	0
Consumer Services	0	4
Telecommunications	0	0
Technology	2	0

5.1.1.4. Augmented Dickey Fuller tests

Figure 7 ADF test for NV_Financials

```
. dfuller  NV_Financials, lags(1)

Augmented Dickey-Fuller test for unit root          Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.657            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Figure 8 ADF test for GR_Financials

```
. dfuller  GR_Financials, lags(0)

Dickey-Fuller test for unit root                    Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -9.156            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

ADF tests were conducted in order to ascertain if the series are nonstationary through statistical testing as opposed to just graphical observation. The test used the following hypothesis:

H_0: Series has unit root/ not stationary

H_1: Series is stationary

When the absolute value of the test statistic is greater than the absolute critical value, the null hypothesis is rejected. Figure 7and Figure 8 reveal that the absolute value of both test statistics are greater than the 5% absolute critical values, therefore, the series are stationary.

ADF tests for the remaining industries reveal that both the NV and GR are stationary for all industries, in other words, the variables are said to be stationary at levels or integrated of order zero, I(0). The comprehensive output can be found in Appendix D.

5.1.1.5. Test of assumptions: cointegration

Figure 9 Lags for Johansen test for cointegration of Financials

. varsoc NV_Financials GR_Financials

Selection-order criteria
Sample: 2009m6 - 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1842.84				9.0e+15	42.4102	42.433	42.4669*
1	-1834.15	17.376*	4	0.002	8.1e+15*	42.3024*	42.3709*	42.4725
2	-1833.47	1.3722	4	0.849	8.7e+15	42.3786	42.4927	42.662
3	-1832.37	2.1979	4	0.699	9.3e+15	42.4453	42.6051	42.8421
4	-1829.48	5.7752	4	0.217	9.6e+15	42.4709	42.6763	42.981

Endogenous: NV_Financials GR_Financials
Exogenous: _cons

The output of the lags to be used for the Johansen test (Figure 9 suggests that one lag is most appropriate for this bivariate model as indicated by the AIC, represented by the asterisk* in the output. In section 5.1.1.3., the lags between single times series were being established in order to determine appropriate lags so that residuals (unexpected flows) are uncorrelated and homoskedastic (Hyndman & Athanasopoulos, 2013). However in this part of the analysis, an appropriate lag length between the two different time series is being established because this is a critical element in the specification of VAR models (Ozcicek, 1999). For each variable, an equation explaining its evolution based on its own lags and also the lags of the other variables in the model needs to be determined.

A summary of the results of remaining industries is presented in Table 7 and the comprehensive output can be found in Appendix E.

Table 7 Lags for Johansen test for cointegration for remaining industries

Variable	Lag
Oil and Gas	1
Basic Materials	1
Industrials	1
Consumer Goods	1
Healthcare	3
Consumer Services	1
Telecommunications	1
Technology	2

Figure 10 Johansen test for cointegration

```
. vecrank NV_Financials GR_Financials, trend(constant) lags(1)

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =      90
Sample:  2009m3 - 2016m8                                         Lags =       1
-------------------------------------------------------------------------------
                                                         5%
maximum                                      trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0       2     -1957.3066        .       38.9545     15.41
    1       5     -1937.8294     0.35133     0.0000*     3.76
    2       6     -1937.8294     0.00000
-------------------------------------------------------------------------------
```

The Johansen test for cointegration uses the following hypothesis:

H_0: There is no cointegration among the variables NV_Financials and GR_Financials

H_1: There is cointegration among the variables NV_Financials and GR_Financials

The output in Figure 10 reveals that the log likelihood of the unconstrained model which comprises the cointegrating equations is significantly different from the log likelihood of the constrained model which does not comprise the cointegrating equations; therefore, the null hypothesis of no cointegration is rejected in favour of the alternative hypothesis. In this case, (as indicated the asterisk*) there is one cointegrating equation in the bivariate model. Since the variables are cointegrated, the VCEM is the most appropriate model in comparison to the VAR.

The Johansen tests for cointegration for the remaining industries reveal that the series for all industries are cointegrated. The comprehensive output can be found in Appendix E. As mentioned in section 4.5.1., VEC models (as opposed to VAR or any other models) are most appropriate for this study because the time series for all industries are co-integrated. The VEC model should be run in first-order differences (Sjö, 2008). Stata automatically runs these models in first-order differences accordingly.

5.1.1.6. Vector error correction model

Figure 11 VCEM – Fit of model

```
. vec  NV_Financials GR_Financials

Vector error-correction model

Sample:  2009m4 - 2016m8                        No. of obs     =         89
                                                AIC            =   42.96529
Log likelihood = -1902.955                      HQIC           =   43.06672
Det(Sigma_ml)  =  1.28e+16                      SBIC           =   43.21695

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_NV_Financials      4     2.5e+09   0.3551   46.80098   0.0000
D_GR_Financials      4     .049128   0.2664   23.38651   0.0001
----------------------------------------------------------------
```

The header for the VEC model in Figure 11 includes information regarding the sample size, the time span, the fit of each equation and overall model fit statistics. The p-values for both equations NV_Financials and GR_Financials are less than the 5% level of significance which point towards a good fit of the VEC model. The comprehensive output for the remaining industries can be found in Appendix F.

Figure 12 VEC model – Granger-causality

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_NV_Finan~s						
_ce1 L1.	-.6928744	.125791	-5.51	0.000	-.9394202	-.4463286
NV_Financi~s LD.	.0565538	.1072597	0.53	0.598	-.1536714	.266779
GR_Financi~s LD.	-5.47e+09	4.81e+09	-1.14	0.255	-1.49e+10	3.95e+09
_cons	-1.31e-07	2.61e+08	-0.00	1.000	-5.11e+08	5.11e+08
D_GR_Finan~s						
_ce1 L1.	-2.38e-12	2.51e-12	-0.95	0.343	-7.31e-12	2.54e-12
NV_Financi~s LD.	6.70e-12	2.14e-12	3.12	0.002	2.50e-12	1.09e-11
GR_Financi~s LD.	-.463592	.0960127	-4.83	0.000	-.6517735	-.2754106
_cons	.0017053	.0052086	0.33	0.743	-.0085033	.011914

The error correlation terms (ECTs) in both cases (ce1), -0.69 and -2.38e-12, are negative and significant which implies that any fluctuations between the NV and GR explanatory and dependent variables will give rise to long-run causality between the variables (Asari, Baharuddin, Jusoh, Mohamad, Shamsudin & Jusoff, 2011). In other words, the short-run part of the VEC model reflects adjustments of NV and GR that are required to maintain their long-run equilibrium relationship. More specifically, as an example, the number -0.69 implies a +6.9% NV_financials adjustment occurs in the previous period to the equilibrium monthly in order to reach long-run equilibrium steady state position (Dhungel, 2014). A positive ECT implies there are some instabilities in the long-run.

With a p-value of 0.255, the lagged differenced GR_Financials variable does not Granger-cause the differenced NV_Financials variable in the short-term and with a significant p-value of 0.002, the lagged differenced NV_Financials variable Granger-causes the differenced GR_Financials variable in the short-term. It is likely to increase it by 6.70e-12% as indicated by the coefficient (positive direction). Therefore, this model has succeeded in serving its purpose of determining both the direction and magnitude of the vectors.

A summary of the results for all industries can be found in Table 8. The comprehensive output for the remaining industries can be found in Appendix F. In all instances where there is Granger-causality, the direction is positive. The output for Consumer Goods yielded an error indicating it that the model was misspecified (discussed further in section 5.1.2.1.). Even though various combinations of lags were tested, in each case, the data was insufficient to allow the model to converge on a unique specification. The solution for this may be simply to collect more data or more finely-grained time series.

Table 8 Short- and long-run Granger-causality

Variable	Short-run		Long-run	
	GR Granger-causes NV	**NV Granger-causes GR**	**GR Granger-causes NV**	**NV Granger-causes GR**
Oil and Gas	No	No	Yes	Yes
Basic Materials	No	No	Yes	Yes
Industrials	No	Yes	Yes	Yes
Consumer Goods	N/A	N/A	N/A	N/A
Healthcare	No	No	Yes	No
Consumer Services	No	No	Yes	No
Telecommunications	No	No	Yes	No
Financials	No	Yes	Yes	Yes
Technology	No	Yes	Yes	No

5.1.2. Postestimation specification testing

5.1.2.1 Testing for the number of cointegrating equations

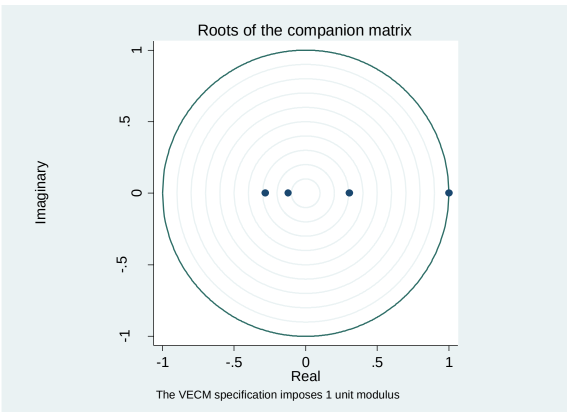
Figure 13 Vecstable command - stability check

```
. vecstable,graph

  Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
.3039694	.303969
-.2822372	.282237
-.1216448	.121645

```
  The VECM specification imposes a unit modulus.
```



The *vecstable* command was used to check whether the number of cointegrating equations has been correctly specified, in other words, to check the stability condition of the VEC model estimates. The graph of the eigenvalues of the companion matrix shows that none of the remaining eigenvalues appears close to the unit circle. Therefore, this means that the stability check does not suggest that the model is misspecified.

The graph of the eigenvalues of the companion matrix of the remaining industries can be found in Appendix G. The stability checks do not suggest that all the remaining industry models, expect Consumer Goods, are misspecified. The graph of the eigenvalues for Consumer Goods shows that one of the eigenvalues appears to be close to the unit circle. The stability check therefore suggests that the model is not stable.

5.1.2.2. Testing for the normality of errors

Figure 14 Normality of errors

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_Financials	30.500	2	0.00000
D_GR_Financials	4.768	2	0.09220
ALL	35.267	4	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_Financials	-.38128	2.156	1	0.14198
D_GR_Financials	.50067	3.718	1	0.05382
ALL		5.875	2	0.05301

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_Financials	5.7646	28.343	1	0.00000
D_GR_Financials	3.532	1.049	1	0.30565
ALL		29.393	2	0.00000

The Jarque-Bera statistic is an indication of the distribution's skewness and kurtosis of which the values would be zero for a truly normal distribution. In Figure 14, the p-values of zero for "ALL" indicate that the null hypothesis of normal distribution is rejected.

The normality of errors was tested; however, normality is not a necessary condition for the validity of many of the statistical procedures related to VAR and VEC models (Belsley & Kontoghiorghes, 2009). If the errors do not come from a normal distribution, but they are independently and identically distributed with zero mean and finite variance, the parameter estimates are still consistent (the sample parameter converges to the population parameter, but they are not efficient (the most efficient parameter estimator would have a sample distribution with the smallest variance) (Müller, 2012). The output of the normality tests for the rest of the industries are in Appendix H.

5.1.2.3. Effects of shocks

The study uses IRF as an additional check of the cointegration test's findings. IRFs are generated to determine whether the effect of shocks in the VECM representation is transitory or permanent, in other words, the effect of shocks will either die out over time or not.

Figure 15 IRF - Shock to NV and effect on GR

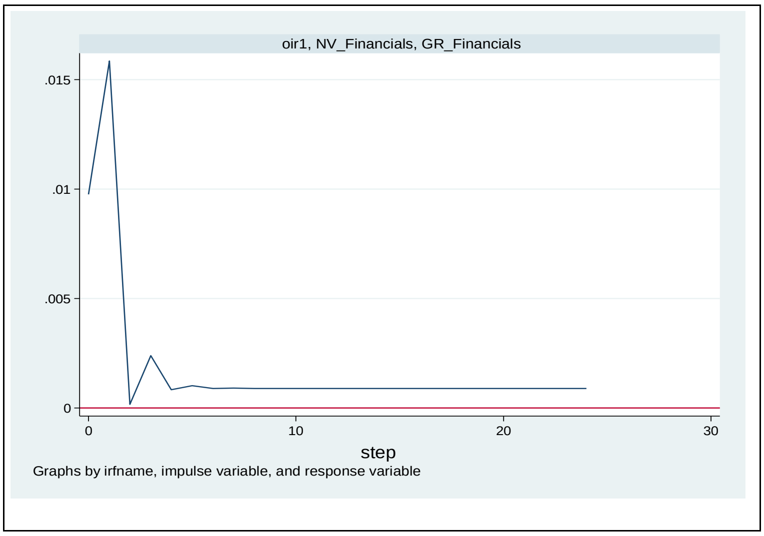
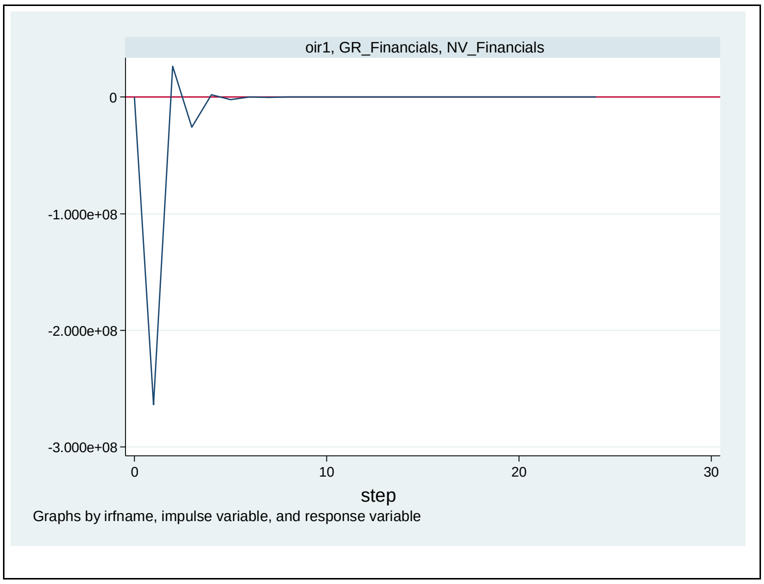


Figure 16 IRF – Shock to GR and effect on NV



The graphs in Figure 15 and Figure 16 indicate that an unexpected shock to NV_Financials has a permanent effect on GR_Financials, but an unexpected shock to GR_Financials has a transitory effect on NV_Financials. The way in which to read these results is that NV drops on impact, then rises after a month or two to above its equilibrium level, oscillating at this level, then returns to its steady-state value after a total of approximately seven months.

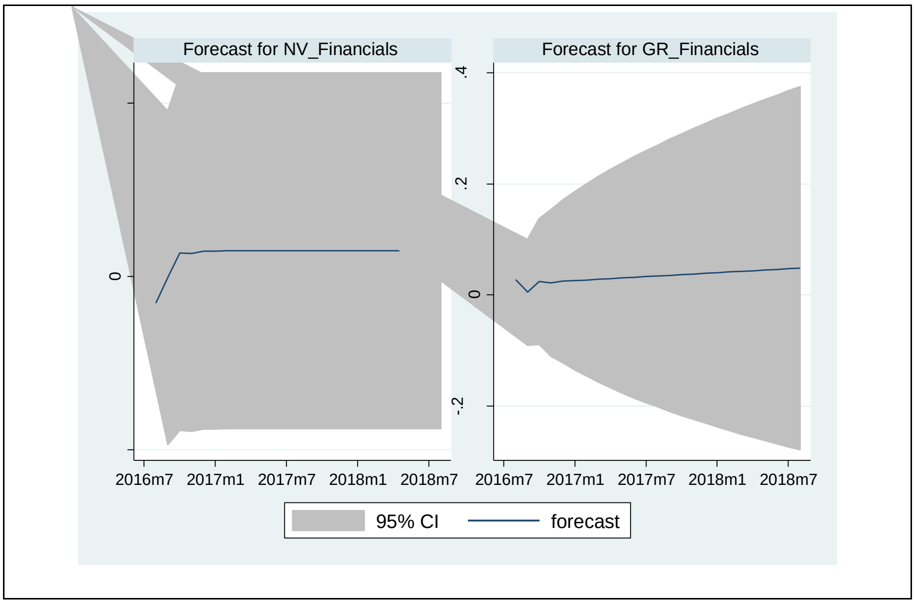
A summary of the effect of shocks for each of the remaining industries is presented in Table 9. A comprehensive output for the remaining industries can be found in Appendix I.

Table 9 Effect of shocks for remaining industries

Variable	Effect of NV on GR	Effect of GR on NV
Oil and Gas	Permanent	Permanent
Basic Materials	Permanent	Transitory
Industrials	Permanent	Transitory
Consumer Goods	Permanent	Permanent
Healthcare	Permanent	Transitory
Consumer Services	Permanent	Transitory
Telecommunications	Permanent	Transitory
Technology	Permanent	Transitory

5.1.2.4. Forecasting

Figure 17 Lagrange-multiplier test



Cointegrating VEC models are also used to produce forecasts or assess the forecasting ability of the model. The variances of the forecast errors for the levels of a cointegrating VECM should diverge with the forecast horizon. Because all the variables in the model are stationary, the forecast errors for the dynamic forecasts of NV_Financials remain finite. In contrast, the forecast errors for the dynamic forecasts of GR_Financials diverge to infinity; therefore, the forecast ability of the model is not reliable. The remaining industries produce the same results as shown in Appendix J. (Consumer Goods results not included due to the model misspecification).

5.2. RESULTS FOR HYPOTHESIS TWO

The study now turns from the theoretical aspects of demonstrating a statistical, Granger-causal connection between the time series to the more practical aspects of whether this effect can be exploited in an investment style. This section presents the results of the portfolios constructed from the style engine. Firstly, the results are presented graphically in the form of cumulative values using the monthly holding period arithmetic returns (HPR) for portfolios A, B and C:

Equation 4: HPR

$$HPR = [(1+r_1) \times (1+r_2) \times \ldots (1+r_3)] - 1$$

where r = % return per period and n = number of periods.

Portfolios were composed according to the industry rankings as indicated by the NV metric. Portfolio A composed of the industries ranked 1, 2 and 3; portfolio B composed of the industries ranked 2, 3 and 4; and portfolio C composed of the industries ranked 7, 8 and 9. They were constructed this way in order to determine if the industries in which foreigners are investing in the most are generating the most returns. These were then plotted in a graphical format as depicted in Figure 18.

Figure 18 Portfolio A, B and C cumulative values

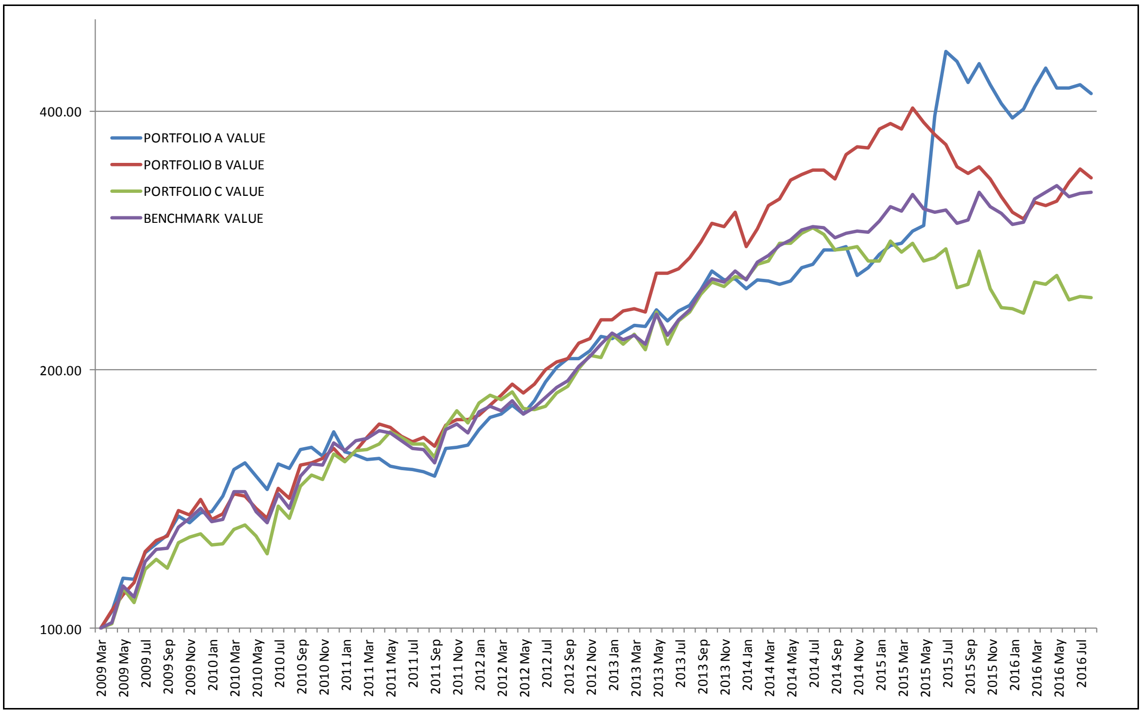
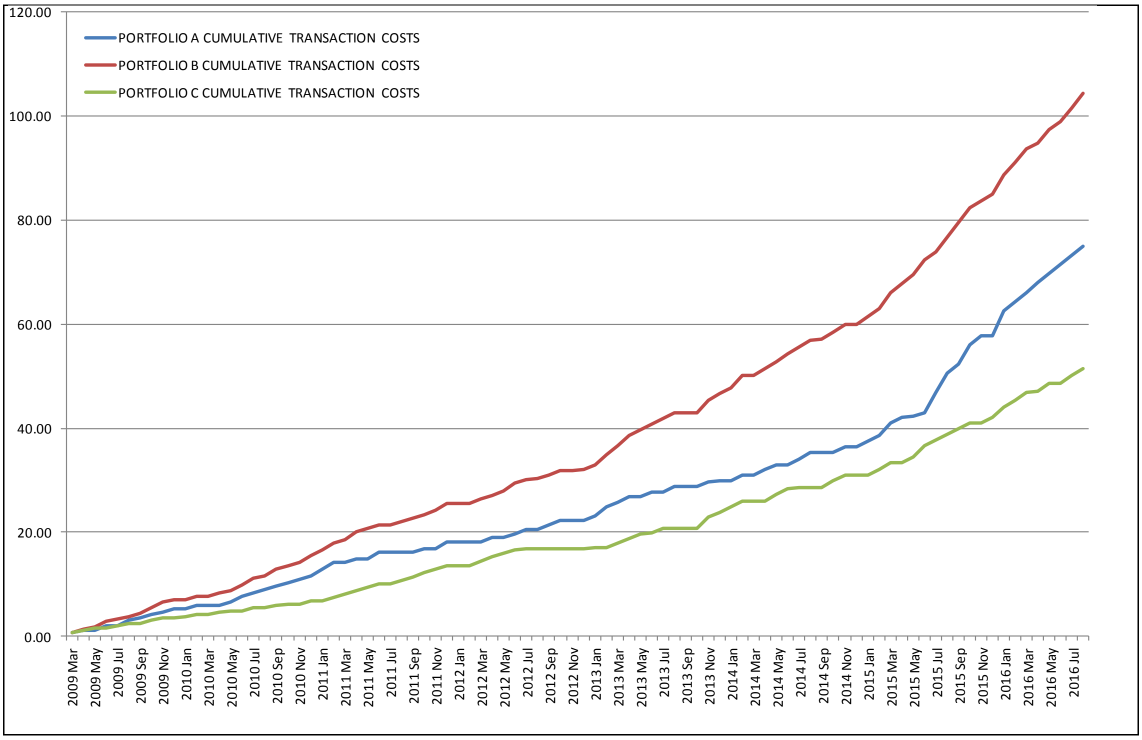


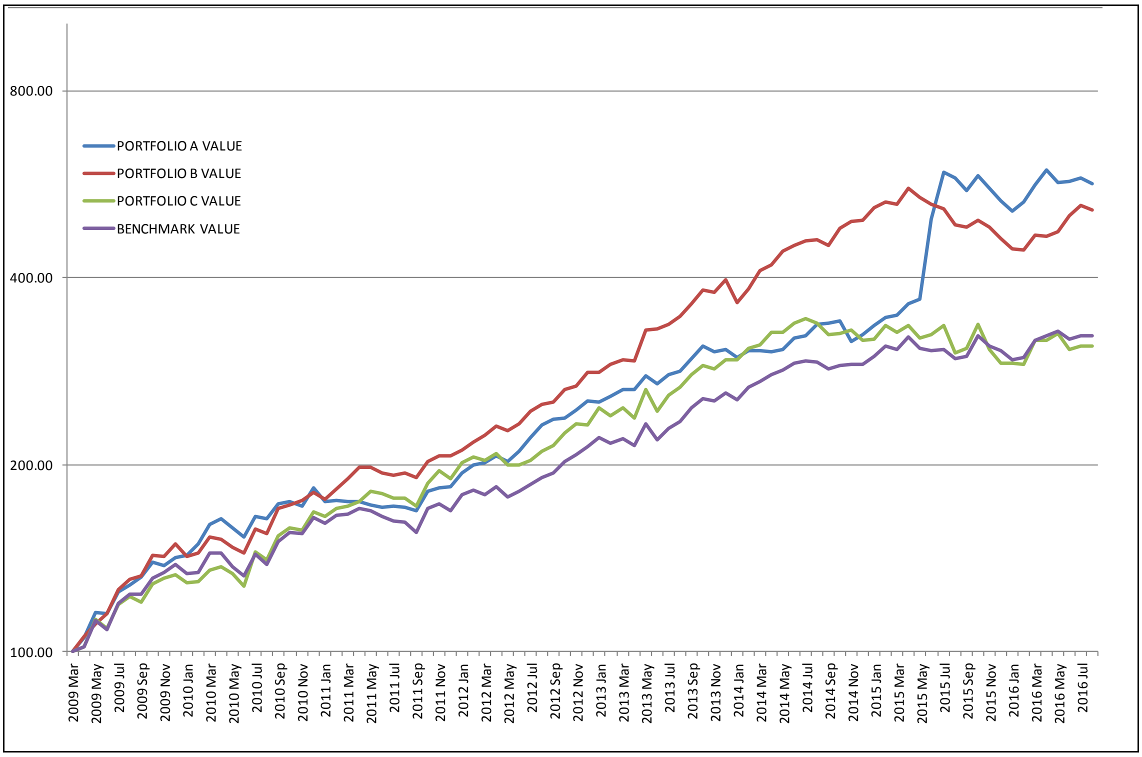
Figure 19 illustrates the fact that the portfolios do not reliably rank-order nor consistently beat the benchmark. Transaction costs are also impacting portfolio performance substantially negatively and preventing the portfolios from outperforming the benchmark. From the graph, it can be observed that the portfolios may have outperformed the benchmark were transaction costs to be excluded. In order to be conservative regarding portfolio performance, the researcher settled on transaction costs of 60 basis points of the trade value.

Figure 19 Cumulative transaction costs



To illustrate the impact of transaction costs, Figure 20 is a depiction of what the portfolio performance would be excluding transaction costs.

Figure 20 Portfolio A, B and C values ex. transaction costs



The descriptive statistics for each of the portfolios are shown in Table 10 Descriptive statistics. The geometric means of the portfolios are greater than zero meaning that the portfolio returns are sustainable. Portfolios A and B have the highest geometric means; however, portfolio A also has the highest risk. This indicates that calculating a risk adjusted return, such as the Sharpe ratio discussed in section 4.5.2.1. would be appropriate. By doing this, it can be concluded that despite portfolio A's outlier (maximum geometric return of 12.8%), portfolio B has the highest risk-adjusted return.

These results indicate that there is no clear pattern in terms of using net FPEF as an investment style; however, we test this statistically to determine if there is any difference in returns between any of the portfolios and the benchmark portfolio (ALSI).

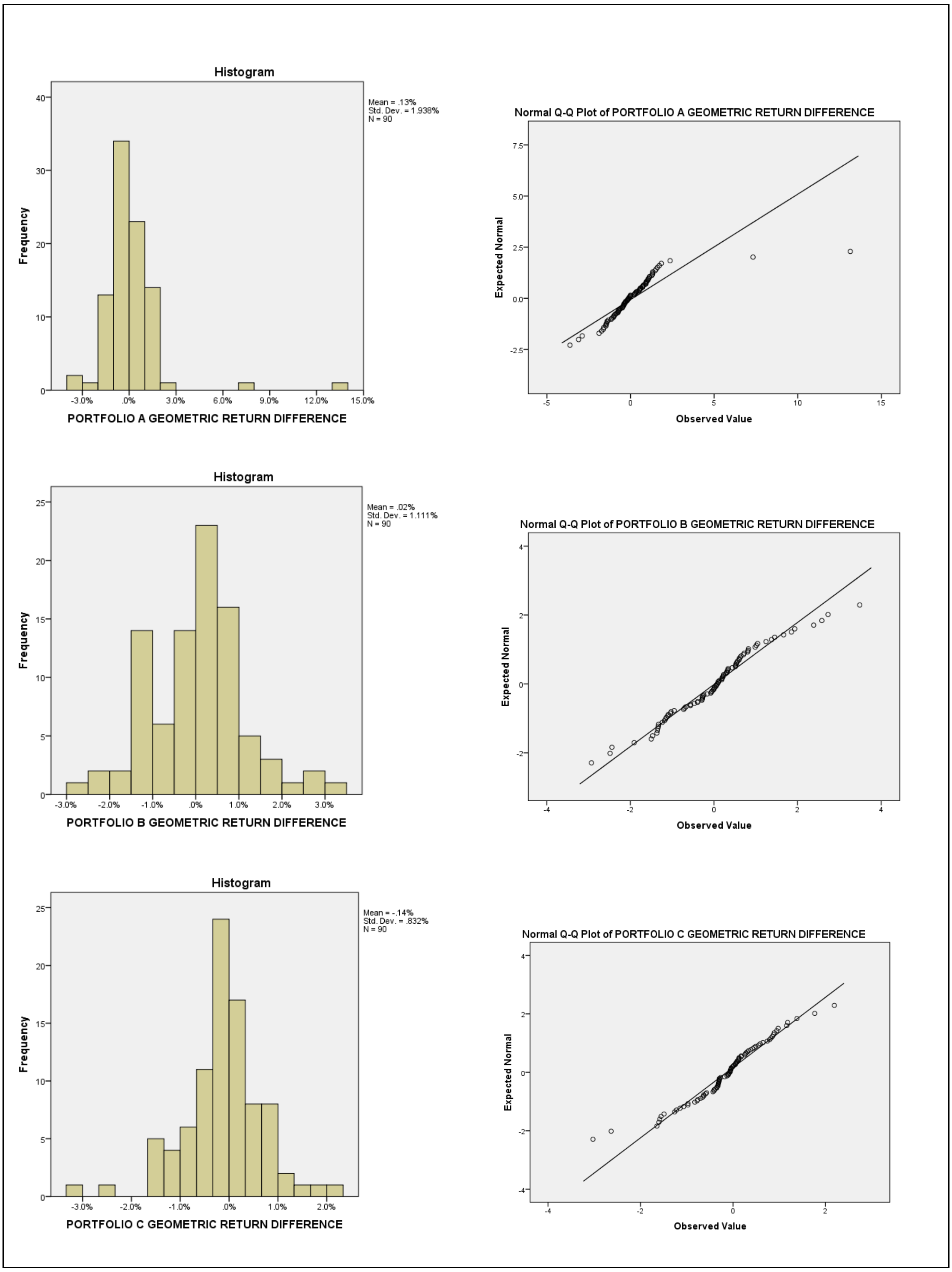
Table 10 Descriptive statistics

	Portfolio A	**Portfolio B**	**Portfolio C**	**Benchmark Portfolio**
Geometric mean	0.8%	0.8%	0.5%	0.6%
Std. deviation	2.1%	1.6%	1.9%	1.5%
Max	12.8%	4.9%	5.6%	4.3%
Min	-3.4%	-3.8%	-4.4%	-2.5%
N	90	90	90	90
Sharpe Ratio*	9.3%	9.4%	-5.1%	-5.1%

**Risk-free-rate of 8.3%*

The normality of the distribution curves for each of the portfolio return differences then had to be tested using the method suggested by (Shier, 2004). "Portfolio return differences" refers to the relevant portfolio's geometric returns less the benchmark geometric returns. The PDF and QQ plots for each of these were generated. These are presented in Figure 21.

Figure 21 PDF and QQ plots for Portfolio return differences



From the plots, the normality of the distributions cannot be easily determined visually; therefore, in order to be accurate in determining whether the distributions were normally distributed or not, normality tests, namely the Kolmogorov–Smirnov (KS) and the Shapiro-Wilk (SW) tests, were performed to statistically determine if the QQ plots of the observed values differ significantly from the QQ plots of the expected returns through hypothesis testing. The Kolmogorov–Smirnov test serves as a goodness of fit test and is preferred to the Shapiro Wilk test as the former test is not sensitive to problems in the tails (Stephens, 2005). In the case of the normality of a distribution, samples are standardized and compared with a standard normal distribution. The hypothesis was as follows:

H_0: The portfolio return differences follow a normal distribution

H_1: The portfolio return differences do not follow a normal distribution

The results are presented in Table 11.

Table 11 Kolmogorov-Smirnov and Shapiro Wilk tests

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PORTFOLIO A GEOMETRIC RETURN DIFFERENCE	.179	90	.000	.678	90	.000
PORTFOLIO B GEOMETRIC RETURN DIFFERENCE	.090	90	.070	.974	90	.068
PORTFOLIO C GEOMETRIC RETURN DIFFERENCE	.116	90	.004	.963	90	.012

Portfolio A and C's p-values are lower than the 5% level of significance; therefore, the portfolio return differences do not follow a normal distribution. Portfolio B's p-value is higher than the 5% level of significance; therefore, the portfolio return differences follow a normal distribution. This means that a non-parametric test, namely the Wilcoxon signed rank test, had to be performed in order to determine whether the means of the returns of portfolios A and C were significantly different from those of the benchmark. Parametric tests, namely t-tests, had to be used in order to determine whether the mean of the returns of portfolios A was significantly different from that of the benchmark. Our hypothesis implies that an industry rotation investment style based on the net FPEF into different industries is superior to a buy-and-hold strategy; therefore, the results of a paired sample one-tailed test apply. The hypothesis was as stated in section 3.3. and the results are as follows:

Table 12 Wilcoxon tests for portfolios A and C return difference

	BENCHMARK GEOMETRIC RETURN - PORTFOLIO A GEOMETRIC RETURN	BENCHMARK GEOMETRIC RETURN - PORTFOLIO C GEOMETRIC RETURN
Z	-.153[b]	-1.516[b]
Asymp. Sig. (2-tailed)	.878	.130

Table 13 Paired sample t-test for portfolio B return differences

		Paired Differences			
		95% Confidence Interval of the Difference			
		Upper	t	df	Sig. (2-tailed)
Pair 1	PORTFOLIO B GEOMETRIC RETURN - BENCHMARK GEOMETRIC RETURN	0.2505%	.152	89	.880

Due to the fact that one-tailed tests apply, the p-values were multiplied by two. The p-values for all the portfolios are above the 5% level of significance; therefore, the null hypothesis is not rejected meaning the monthly portfolio returns from an industry rotation investment style based on the net FPEF into different industries are not significantly greater than the monthly portfolio returns from a buy-and-hold strategy.

It is important to note that there were two visible outliers in the data. The arithmetic returns for Oil and Gas for June 2015 and July 2015 were 99% and 56% respectively.

These are not erroneous and are genuine data points as they correspond with Montauk Holdings' share price movements during this period (Fin24, n.d.); therefore, these data points cannot simply be expunged. However, they do distort the results as portfolio A outperforms the other portfolios as from June 2015. The tests for the significance in means were run again, but this time up until May 2015 so as not to include the outliers. The null hypothesis was still rejected using this approach and the results thereof are presented in Appendix K to Appendix N.

6. RESULTS DISCUSSION

6.1. INTRODUCTION

The results are discussed in the order of research propositions and hypotheses. For the first proposition and hypothesis, a noticeable finding was that for all of the industries, industry returns do not predict net FPEF in the short-term whereas all of them do over the long-term. It is the effect of net FPEF on returns where the results not only vary between industries but also between the short- and long-term Granger-causality effects. For the second hypothesis, the results show that there is no considerable value in implementing the style engine built for this study in its current form as none of the portfolios' returns are significantly greater than those of the benchmark. This indicates some improvements and adjustments to the style engine may need to be considered. The results for each industry as well as the style engine are discussed in relation to whether they support or contradict the relevant literature.

From the results shown in Chapter 5, It is important to note that it is possible to have evidence of long-run Granger-causality, but not short-run Granger-causality and vice versa. This suggests that the impact of variations in NV on GR and GR on NV may be over a short horizon or long horizon.

6.2. DISCUSSION FOR HYPOTHESIS 1a and 1b

6.2.1. Oil and Gas

The results indicate that there is no short-run predictability between Oil and Gas net FPEF and returns; however, there is bidirectional predictability in the long-term. The long-run result is consistent with the findings of Loncan and Caldeira (2015) who found that the marginal effect of foreign flow on Oil and Gas returns was positive and statistically significant. Loncan and Caldeira (2015) mentioned that this may be the case as foreign investors may consider global macroeconomic conditions and the economy's business cycle characteristics when determining their investment strategies. This reinforces the relevance of the industry of foreign flow activity and its impact on industry returns. Although sentiment does not necessarily indicate flow, when investors are positive about the prospects of a certain stock, the stock will sell at a premium, and vice versa. The short-run result is consistent with the study conducted by Chen et al. (2013) which concluded that global sentiment revealed no significant positive effect for Oil and Gas, which was consistent with their suggestion that conventional industries exhibiting bond-like and safer characteristics are less impacted by sentiment.

6.2.2. Basic Materials

The results indicate the same as discussed for Oil and Gas: that there no is evidence of any short-run predictability, but there is bidirectional predictability in the long-term. Loncan and Caldeira (2015) found that foreign flows increased the returns for those sectors, such as Basic Materials, that are more exposed to the prevailing economic conditions. For Basic Materials, thriving conditions may be a business cycle characterised by consumption growth and elevating commodity prices (Loncan & Caldeira, 2015). South Africa is a global leader in mining as it has a wealth of mineral resources (Kearney, 2012). The Basic Materials index comprises mining / resources stocks. This supports the fact that commodity prices would be an important factor for foreigners to consider when making investment decisions. Resources stocks are highly correlated with the relevant commodity price. These two intimations therefore support the fact that there is long-term return chasing, as indicated by the bidirectional predictability, between the two constructs.

6.2.3. Industrials

The results indicate that Industrials net FPEF positively predict returns in the short-term and that there is bidirectional predictability in the long-term. Loncan and Caldeira (2015) state that Industrials showed the highest sensitivity to foreign capital. In general, the sectors, which includes Industrials, more directly impacted by the consumption and commodities business cycle experienced by the Brazilian economy between 2001 and 2003 were also the portfolios whose returns were more sensitive to foreign flows.

6.2.4. Consumer Goods

There is no results discussion for Consumer Goods as the model is misspecified and therefore not valid.

6.2.5. Healthcare

The results indicate that there is no short-run predictability between Healthcare net FPEF and returns; however, in the long-run, Healthcare returns predict net FPEF. Lee at al. (2013) suggest that the returns of Healthcare could be used to predict the overall market returns (industry leading hypothesis) for the markets applicable to their study. Extraordinary equity situations have also encouraged foreign inflows. For example, the presence of a flourishing South African private healthcare sector has attracted some foreign investors to buy into listed companies such as the Netcare group, since such investment opportunities are not are non-existent in many other countries (Gidlow, 2009).

6.2.6. Consumer Services

The results indicate that there is no short-run predictability between Consumer Services net FPEF and returns; however, in the short-run, Consumer Services returns predict net FPEF. There is a lack of literature available to support the discussion of these results. This may imply that, like Healthcare, there may be limited investment opportunities; therefore, the industry-leading hypothesis may similarly apply for Consumer Services.

6.2.7. Telecommunications

The results indicate that there is no short-run predictability between Telecommunications net FPEF and returns; however, in the long-run, Telecommunications returns predict net FPEF. Locan and Caldeira (2015) found that in Brazil, for Telecommunications, the effect of foreign capitals on returns was statistically significant and negative. The results they obtained suggested that some sector portfolios, such as Telecommunications, underwent a devaluation effect as opposed to a revaluation effect, as the marginal effect of FPEF on returns was negative. Although it was difficult to determine the reason for this devaluation, one possible explanation was that “foreign investors reallocated capital to other sectors, in which the marginal product of capital was higher (or expected to be higher) due to the economic momentum” (p.889).

6.2.8. Financials

The results indicate that Financials net FPEF positively predict returns in the short-term and that there is bidirectional predictability in the long-term. Laopodis (2016) discovered that Financials, amongst other industries, emerged as a persistent information leader for other industries. Tessitore and Usman (2005) also found that Financials is leading in its contribution to total industry effects and also found that it is a dominant industry in explaining stock market returns. This means that the ability of financials to absorb, process and disseminate information from economic fundamentals and subsequently inform the stock market and other industries may justify the FPEF-returns bidirectional predictability in the long-run as its prices may be the first to react before the rest of the market and foreign investors may recognise this.

6.2.9. Technology

The results indicate that Technology net FPEF positively predict returns in the short-term and that there is bidirectional predictability in the long-term. There was no short-term bidirectional effect detected over the period of the study which can usually result in a bubble and reallocation of capital to non-cyclical consumer stocks or have a ubiquitous effect on other industries (Dornbusch & Park, 1995). For the Asian emerging equity markets, it was found that in instances where foreign returns exhibit high explanatory power for flows, the most significant foreign returns—by an extremely high margin in the two biggest markets—are often IT-based indices as opposed to the broad indices which may be most applicable to the wealth of foreign investors (Richards, 2005). Chen et al. (2013) found that for Asian countries, Technology returns present an insignificant negative relationship with global sentiment.

6.2.10. Short and long-run Granger-causality implications

As discussed in Chapter one, the purpose and implications of this study may be useful for various economic participants. Both the long- and short-term results are relevant and applicable to policy makers and economists, to local investors for the implementation of active trading strategies (as will be discussed in section 6.3.) and to foreign investors looking to diversify outside of their local market.

Regarding the long-term results specifically, the effects surrounding this topic may be an unavoidable phenomenon in developing markets; therefore, the efforts of policy makers should be focussed towards ensuring that local markets and institutions are resilient enough to be robust to volatile inflows and outflows and the price changes that accompany them (Richards, 2005) and the same should be considered vice versa. The effect of shocks, as revealed by the IRFs in section 5.1.2.3., may be a useful tool in this regard. It will also be useful for them to understand the influence that returns have at attracting equity investment into Africa’s leading financial market (French, 2005). In the short-run, non-resident as well as resident investors may want to pay particular attention to the findings of this study as they may affect trading strategies and portfolio management decisions in terms of active investment criteria.

In terms of the academic / theoretical value, the results are meaningful for of filling the gap regarding the time that has lapsed since French’s (2011) study and they are also useful in providing more comprehensive insight into industry return and foreign flow dynamics in the context of the relevant country’s stock exchange; a topic which has been broadly inconclusive.

6.3. DISCUSSION FOR HYPOTHESIS TWO

Section 5.1.2.4. Forecasting demonstrated that the forecasting ability of the models is not accurate. This introduces the next part of the discussion, the style engine, and explains its relevance. The study now evolves from a theoretical approach of establishing the connection between FPEF and industry returns to an approach that would more useful from a business perspective by ascertaining whether the effects determined can be used to develop a FPEF investment style-based strategy.

6.3.1. Discussion of style engine

Hypothesis two intimated that the monthly portfolio returns from an industry rotation investment style based on the net FPEF into different industries are significantly greater than the monthly portfolio returns from a buy-and-hold strategy. The statistical testing did not support this; therefore, the null hypothesis was not rejected. From the results, it is apparent that there is no clear indication of an obvious pattern and consistency in terms of the portfolio values at the end of the sample period. An example of such a pattern would be: portfolio A outperformed B which outperformed C or portfolio C outperformed B which outperformed A, with the top performing portfolio also outperforming the benchmark. In fact, the results indicated that, according to the Sharpe ratio, portfolio B outperformed A which outperformed C, with the benchmark having the same Sharpe ratio as portfolio C.

From the results, there is no clear value-add that can be attained from replicating the movements of foreign investors and exploiting this as an investment style-based strategy which could result in portfolio outperformance relative to the benchmark.

Understanding why the method failed may be due to the following reasons:

1. For hypothesis one, it was found that net FPEF predict returns in the short-term for only three of the nine industries
2. More rigorous testing in the form of :
    i. A different allocation indicator may need to be considered
    ii. The use of different time lags may have been more effective
    iii. A different number of industries in which to invest per portfolio may also need to be considered

The results obtained from this part of the study do not provide empirical evidence of a net FPEF style-based effect on industry returns for the period 2009 to 2016. This contradicts literature such as that of Bae, Ozogus, Tan and Wirjanto (2012), Chang

(2010) and French (2011) which suggests that foreign investors are better informed and better equipped than local investors at making investment decisions.

6.3.2. The impact of industry rotation transaction costs

Some investment strategy studies such as those discussed by Muller and Ward (2013) ignore transaction costs in their analysis; however, this is of concern for this study. Thapa and Poshakwale (2012) stated that in a comparatively more developed market, transaction costs would be lower. This should be a key consideration as higher transaction costs may reduce the investment performance and may materially lower the value of a trading investment strategy that may have otherwise, at face value, seemed lucrative.

On the topic of the impact of transaction costs as well as the advantages and disadvantages of active style investing versus a buy-and-hold strategy, Shynkevich's (2012) study investigated the degree of success of a vast set of active trading rules on the short-term predictability of returns and profitability in equity and foreign exchange markets by extending the scope of research in three dimensions, one of which includes transaction costs that reduce any profits from active trading. The analysis was performed on sub- sector portfolios which is a distinctive approach as it was found that the risk-adjusted returns which short-term active trading rules may yield are broadly not statistically significant and the hypothesis of no outperformance of active trading rules over either buy-and-hold or risk-free benchmark return cannot be rejected in most industries (Shynkevich, 2012).

Given these findings, careful analysis of transaction costs and the percentage of the value traded thereof has to be taken when constructing a portfolio as these can erode portfolio performance.

6.4. DISCUSSION OF GENERAL OBSERVATIONS

6.4.1. Granger-Causality and rankings

Table 14 compares industry rankings with the long- and short- term effects of net FPEF and returns for each industry. The symbols represent the direction of the effect (as explained below Table 14) as concluded from hypothesis 1a and 1b and, to the right of that, drawn from the analysis for hypothesis two, the researcher illustrates the number of months that the relevant ranking used for the style engine between the sample period (January 2009-August 2016) was attained.

Table 14 Granger-causality and rankings

		Ranking (1 = best; 9=worst)								
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	Granger-causality	**Number of months ranking attained**								
Oil and Gas	⇔	9	10	6	3	3	3	11	17	20
Basic Materials	⇔	1	6	1	4	5	10	12	23	28
Industrials	← ⇔	10	16	15	23	7	12	5	2	0
Consumer Goods	N/A	4	4	10	4	6	6	7	24	25
Healthcare	⇒	18	11	15	13	14	3	7	4	5
Consumer Services	⇒	5	15	9	9	14	17	16	4	1
Telecommunications	⇒	10	13	19	14	11	11	9	3	0
Financials	← ⇔	1	0	6	11	25	22	18	6	1
Technology	← ⇒	32	15	9	9	5	6	5	7	2

Where:
GR Granger-causes NV in the short-run →
NV Granger-causes GR in the short-run ←
Bidirectional Granger-causality in the short-run ↔
GR Granger-causes NV in the long-run ⇒
NV Granger-causes GR in the long-run ⇐
Bidirectional Granger-causality in the long-run ⇔

Table 14 illustrates the usefulness of juxtapositioning elements of proposition one and two and makes it easy to observe which industries attract the most foreign interest and which ones are of least interest to foreign investors. What is most interesting about the table is that Technology, with NV Granger-causing GR in the short-run, far exceeded the other industries with regards to the number of times it produced the top ranking. This was also the portfolio with the highest cumulative return value at the end of the period. Basic Materials, with only long-term bidirectional Granger-causality and no short-run effects, was the portfolio that most frequently received the lowest ranking. This was also the industry with the lowest cumulative return value at the end of the period. This indicates that, through simulations and more rigorous testing, there could be a trading strategy that could exploit net FPEF patterns for superior investment returns.

6.5. RECONCILIATION OF HYPOTHESIS 1a AND 1b AND HYPOTHESIS TWO

The style engine work was established on the premise of a general theme of FPEF predicting returns across all industries being evident. In the event, this turned out to be only defensible for Financials, Industrials and Technology. Further work might focus on this subset of industries. The style engine was predicated on the FPEF effect manifesting over the short-run. In principle, one might benefit from a long-run association by rebalancing the portfolio much less frequently (for example, annually). However, testing this isn't feasible with the available data, which spans a relatively limited number of years.

7. CONCLUSION

7.1. PRINCIPAL FINDINGS

7.1.1. Proposition and hypothesis 1a and 1b

The principal findings from hypothesis 1a and 1b are that over the short-term, returns do not Granger-cause net FPEF for any of the industries; over the short-term, net FPEF Granger-cause returns for Industrials, Financials and Technology; over the long-term, returns Granger-cause net FPEF for all of the industries; and over the long-term, net FPEF Granger-cause returns for Oil & Gas, Basic Materials and Industrials, meaning long-term bidirectional predictably was found for Oil & Gas, Basic Materials, Industrials and Financials. The direction of the Granger causality in all cases is positive.

As discussed in section 6.2., literature suggested that Industrials is sensitive to foreign flows, Financials is an information leader for other industries and Technology exhibits the most significant returns where foreign returns predict flows. The results found in this study pertaining to these industries make an interesting contribution to literature as these are the three industries which can be highlighted as having a more prominent FPEF-predicts-returns effect as there was evidence of this effect in the short-run as opposed to only the long-run.

7.1.2. Proposition and hypothesis two

Hypothesis two tested whether the monthly portfolio returns from an industry rotation investment style based on the net FPEF into different industries are significantly greater than the monthly portfolio returns from a buy-and-hold strategy. The results indicate that there is no evidence of significant outperformance of the portfolios relative to the benchmark. The finding was that the order of outperformance, on a risk-adjusted return basis, was: the middle-ranked portfolio followed by the top-ranked portfolio followed by the lowest-ranked portfolio. The latter portfolio performed on par with the benchmark.

From the results, with the style engine as is, there is no clear benefit that can be achieved from following net FPEF patterns, exploiting this as an investment style-based strategy and using this to outperform a buy-and-hold strategy. The ranking method applied therefore performs poorly as an investment style.

7.2. IMPLICATIONS FOR INVESTMENT MANAGERS AND OTHER FINANCIAL MARKET STAKEHOLDERS

The main aim of this study was to uncover the dynamic interaction between FPEF into various industries and the returns of these respective industries within the context of the South African equity market. This interaction has been of persistent importance to various economic participants which include investors, economists and policy makers, and is of greater importance during periods of changes in capital flow distribution or financial turmoil. Therefore, the objective of this study was to find a pragmatic use for its findings for the aforementioned relevant stakeholders in the market and the economy.

The implications of the findings from the first hypothesis to policy makers and economists are that they may find them useful in examining financial capital mobility. They may want to observe the volatility of the NV metric to assess its effect on the stability of the market and other economic variables or assess the long-term industry effects of foreign flows into and out of South Africa in order to assist in the decision to either tighten or loosen financial market liberalisation. According to Dornbusch and Park (1995) who argue that foreign investors pursue positive feedback trading strategies that make stock prices overreact to changes in fundamentals and such trading strategies may cause bubbles and crashes in local markets, the detection of these in the short-run may have assisted economists in detecting industry bubbles.

The short-term implications may be useful to investors looking to construct an investment style-based strategy that outperforms a buy-and-hold strategy. Different industries showed different results as some were more exposed and sensitive to foreign flows than others. Technology appears to be a sector that has attracted high foreign investor interest whereas Basic Materials appears to draw less foreign attention. The latter may be expected due to commodities being plagued by negative investor sentiment. Such observations may assist in return predictability, building portfolios and investment decision-making processes. As mentioned, the results revealed no short-term bidirectional Granger-causality for any of the industries; therefore, a momentum strategy based on net FPEF may not be effective.

The above implications address the primary uses for this study. A secondary use for this study is that foreign investors can also use these findings for diversification purposes when considering which South African industries to invest in.

7.3. LIMITATIONS OF THE RESEARCH

The research had the following limitations:

1. Validity:
   i. The sample size (number of data points) was a limitation for the research. The length and frequency of the time series were not comprehensive enough to provide the desirable flexibility and allow for more robust testing.
   ii. The conclusions from this study cannot be inferred to other markets due to the differences between markets which include the rules and regulations, foreign investor limitations, market values and tradability of stocks, to name a few.
   iii. There are questions around investability. The ability to invest in an investment vehicle, such as an ETF, that is appropriate for the style engine discussed in this study may be an issue.
   iv. Certain events that correspond with the time series may have had an effect on findings.
2. Reliability:
   i. In terms of triangulation, the researcher attempted to cross-check the aggregate of the FPEF by industry sourced from the JSE against the total (high-level) FPEF from other databases; however, these could not be accessed and other sources found on the internet source their data and information from the JSE.
3. Foreign flows which were for the purpose of FDI as opposed to portfolio investment are less relevant for this study as they are not as easily investible nor divestible; however, as stated in section 4.6., these may be difficult to separate.

7.4. SUGGESTIONS FOR FUTURE RESEARCH

7.4.1. Improvements to data

Some suggestions for data improvement include:

1. Longer or more granular time series which would enable the researcher to lengthen time lags applied to the style engine and have more portfolio rebalancing flexibility.
2. A better metric for FPEF triangulated against external data and limited to the universe of stocks considered. Therefore, the current version of the style engine serves as a basis for developing one that will better capture the influence of foreign equity flows on industry performance

7.4.2. Refinements to statistical analysis

7.4.2.1. Expected and unexpected flows

Conducting a study of around this topic that is robust to all specifications of net flows (expected and unexpected) could produce useful findings. Warther (1995) suggested that monthly returns are strongly related to unexpected flows. This could be explored by estimating another VEC model between industry returns and unexpected foreign equity flows.

7.4.3. Investment style refinements

7.4.3.1. Selections of industries

Further work could be conducted on styles predicated on the industries shown in this study to possibly have some sort of FPEF effect, namely Industrials, Financials and Technology. Table 14 Granger-causality could be used as a basis for future research as more empirical work could be conducted for the industries that produced the most meaningful and interesting results such as Technology which drew the most foreign investor interest over the period and yielded the highest cumulative value or Basic Materials which drew the least foreign investor interest over the period and yielded the lowest cumulative value. Consumer Goods could also be further investigated as this test was misspecified.

7.4.3.2. Long-short portfolio

If an effective long-only portfolio can be constructed by the style engine, in order to further exploit net FPEF patterns (especially outflows), a long-short portfolio style engine could be considered so as to more efficiently capture and incorporate the effects of foreign outflows.

7.4.4. Extension of the study

7.4.4.1. Multivariate analysis

A similar study that includes the impact of macroeconomic and political variables as another element could be useful. Although these may not provide predictive information for returns as discussed in the literature review, this may not necessarily be the case for the investment decisions of foreign investors. Such a study could also include tracing country origination of flow as Baker, Wurgler and Yuan (2012) poposed that informational disparities within the different groups of foreign and domestic investors are greater than between the said groups. This study could be conducted in a South African context.

7.5. CONCLUSION

The study found that the interaction between FPEF and industry returns on the JSE is one that is dynamic and not only differs across industries, but also differs between the short-term and long-term effects. Portfolio construction, based on the direction and magnitude of foreign flows, revealed no significance in the outperformance of returns relative to the benchmark indicating that there is no clear benefit that can be derived from based on this investment style. This study can contribute to further avenues of academic study in this field of research.

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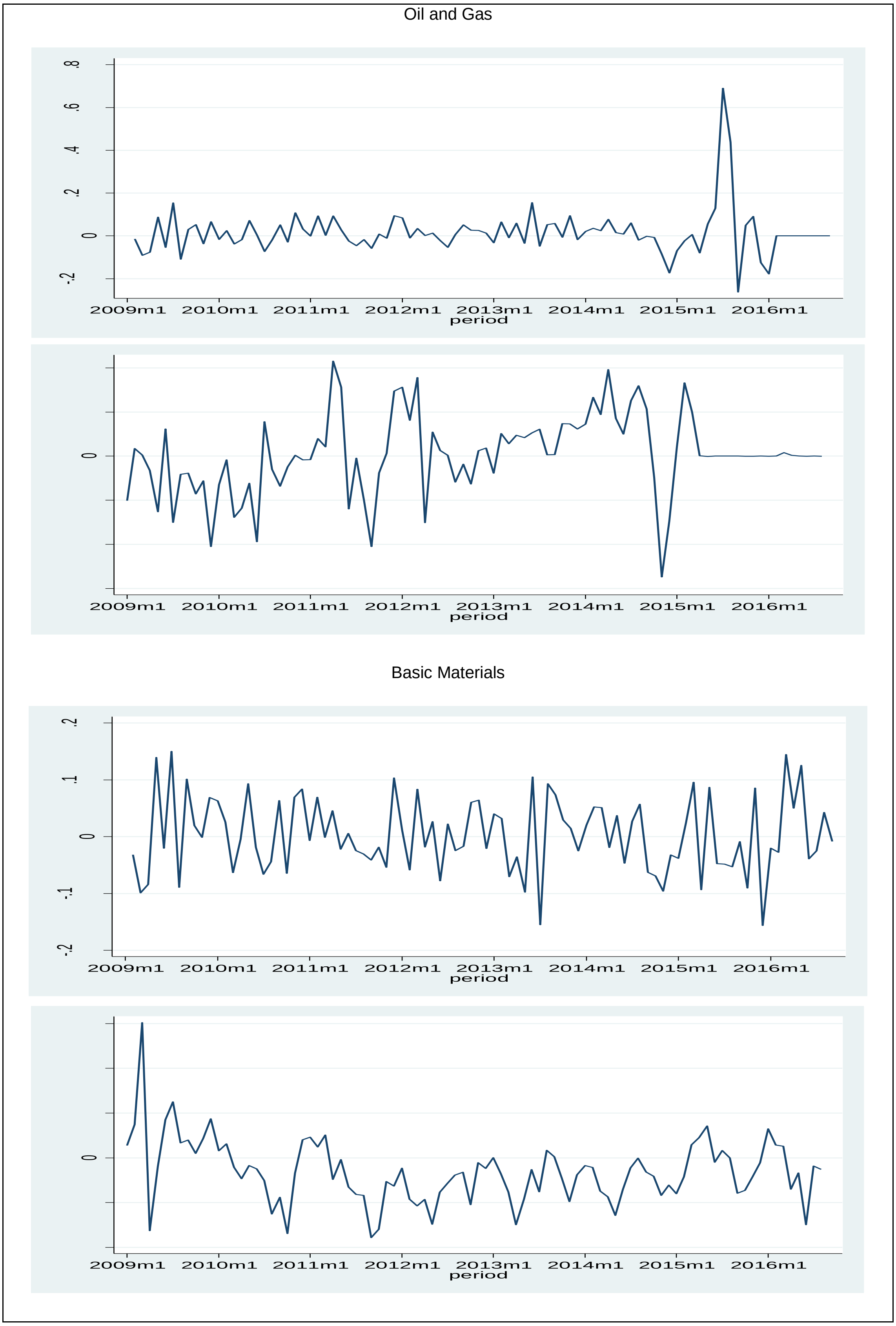
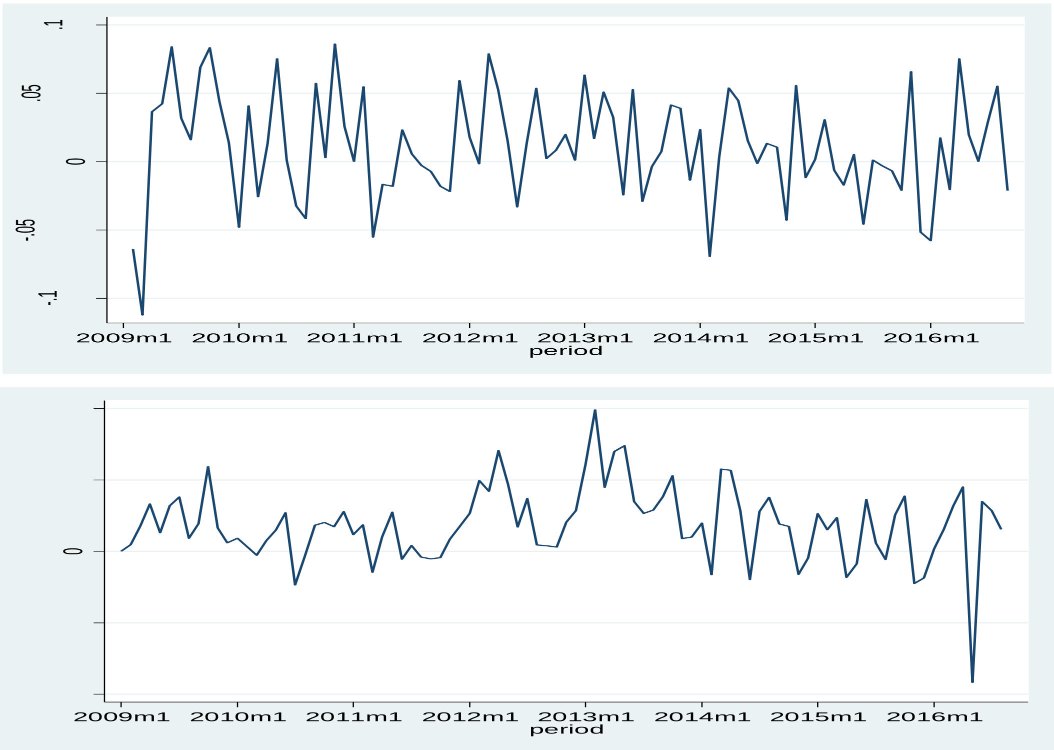
APPENDIX A: Time series

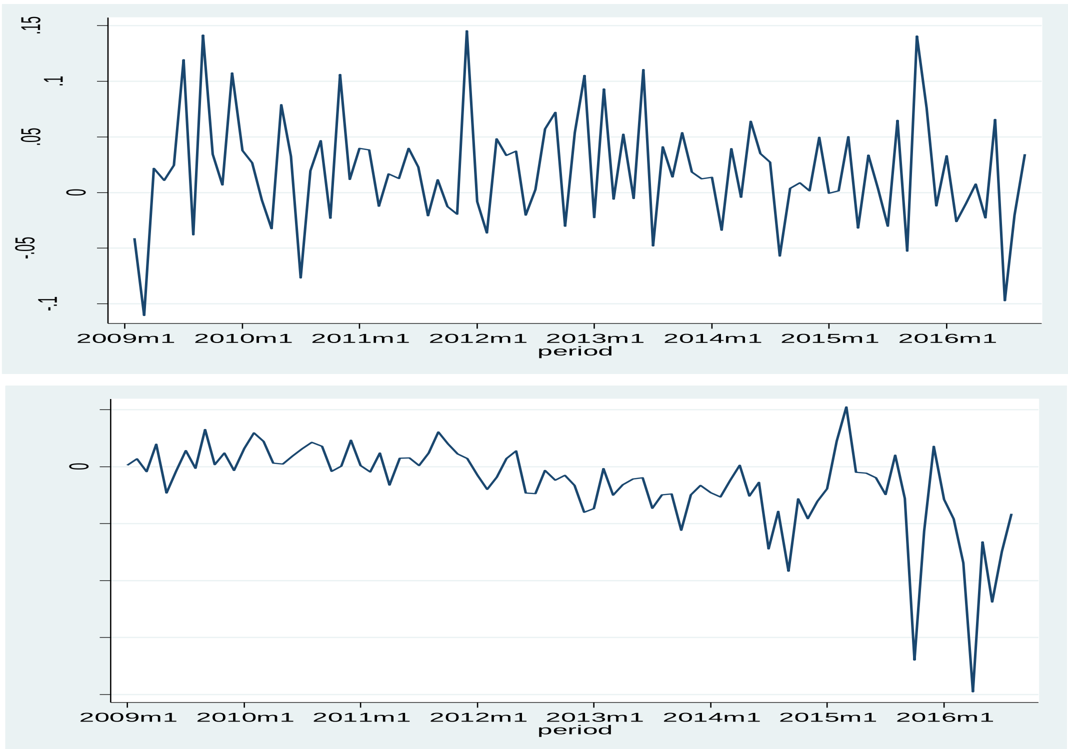
Figure 22 Time series



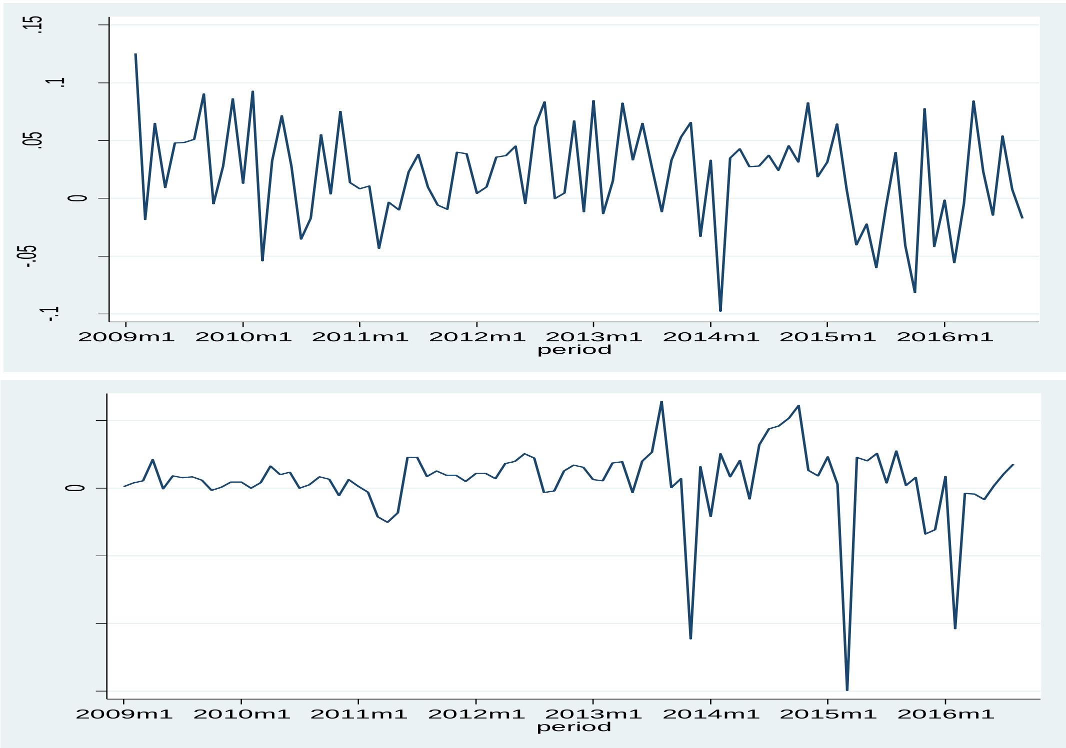
Industrials



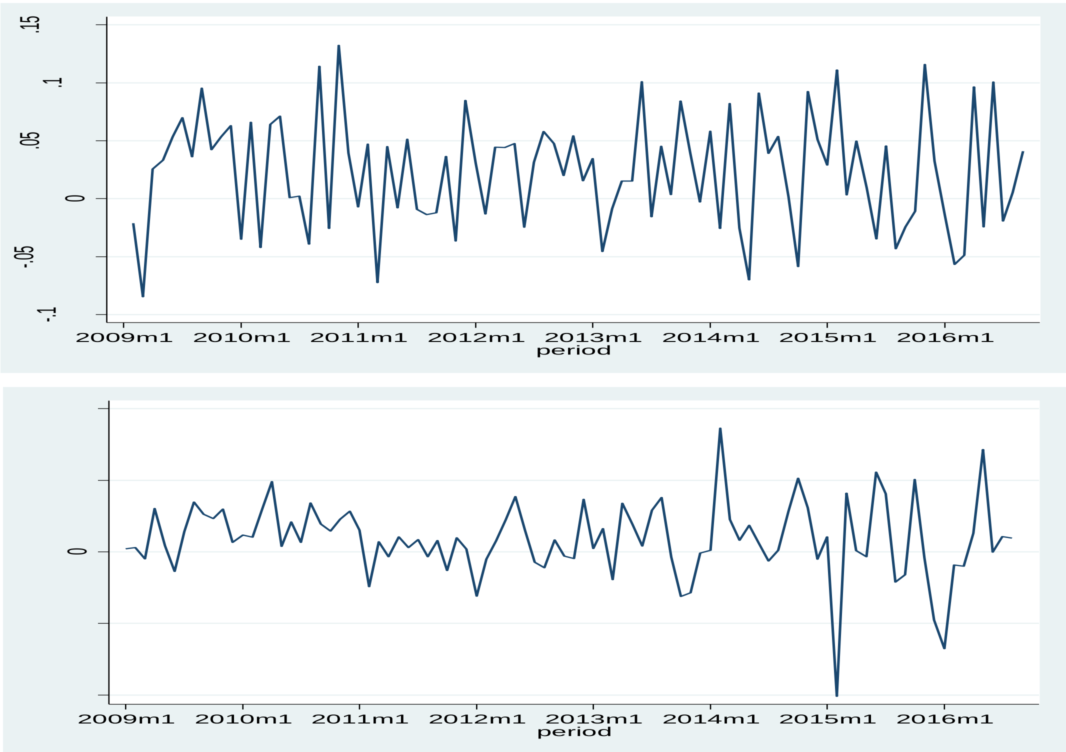
Consumer Goods



Healthcare

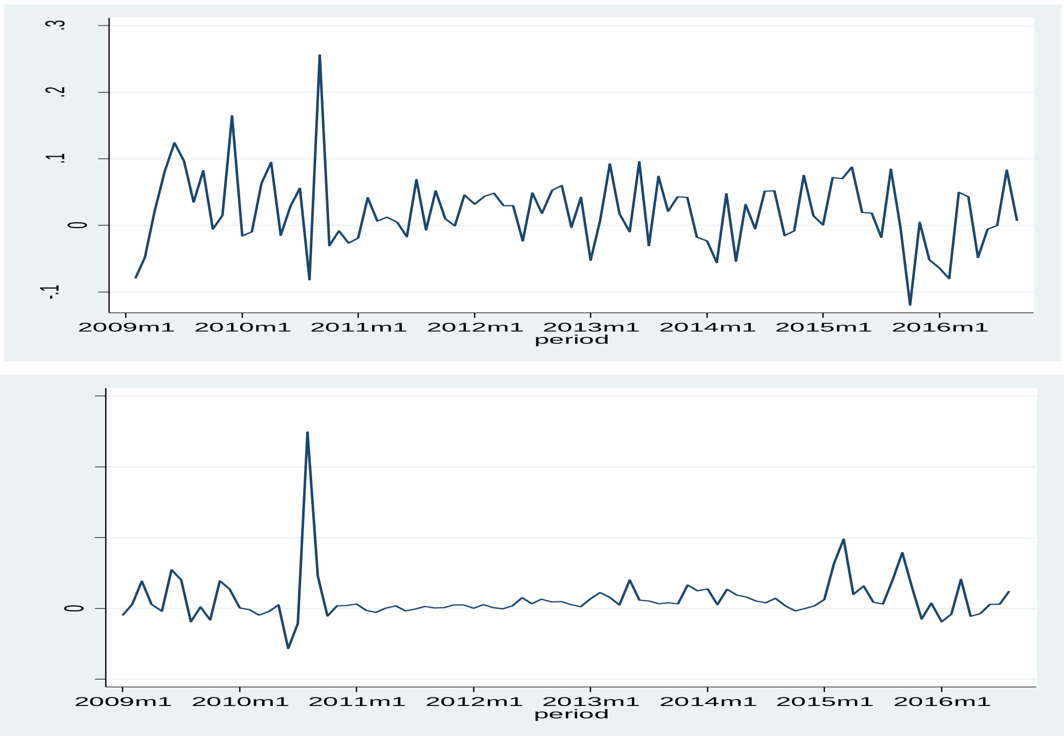


Consumer Services



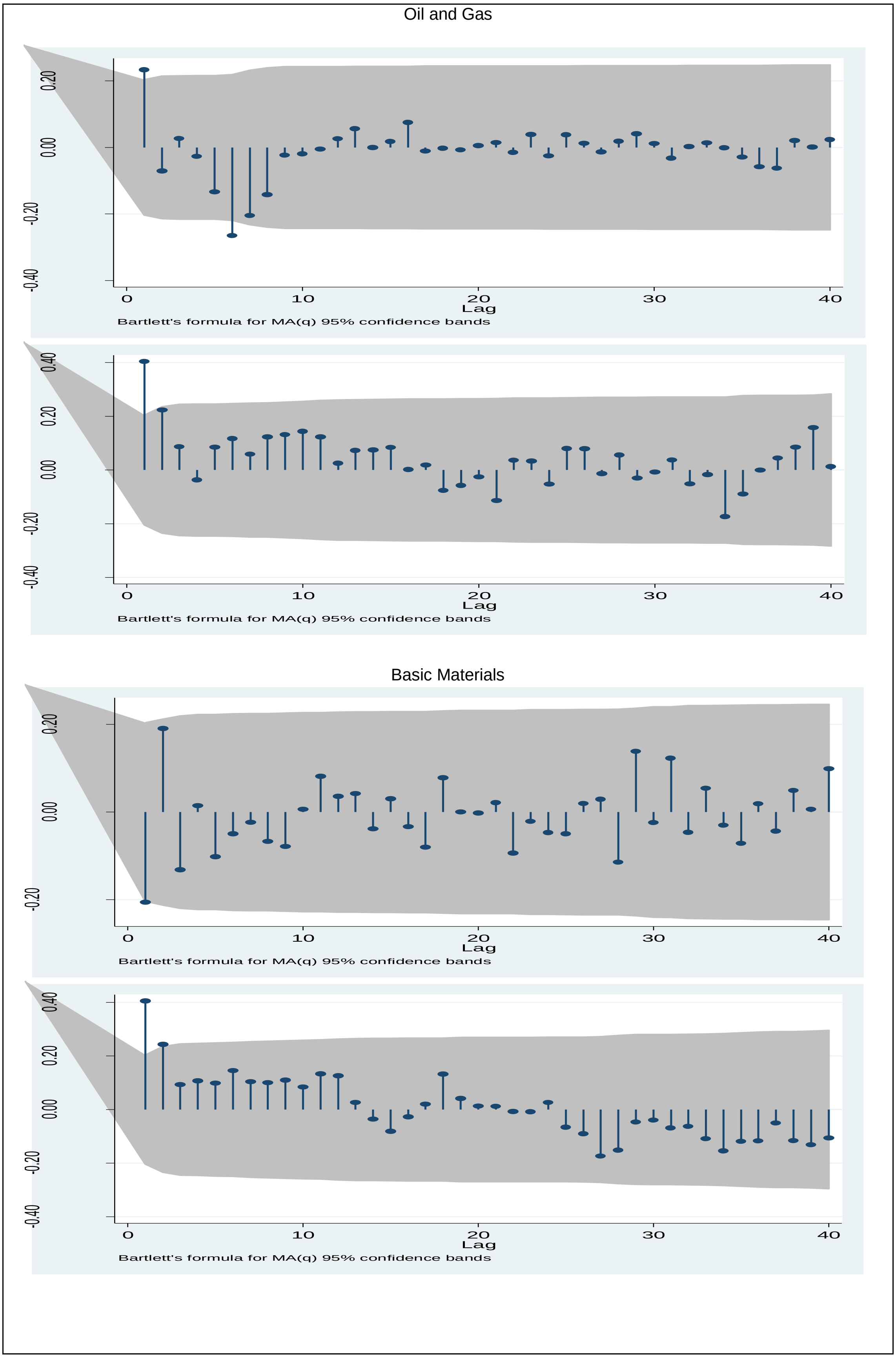
Telecommunications

Technology

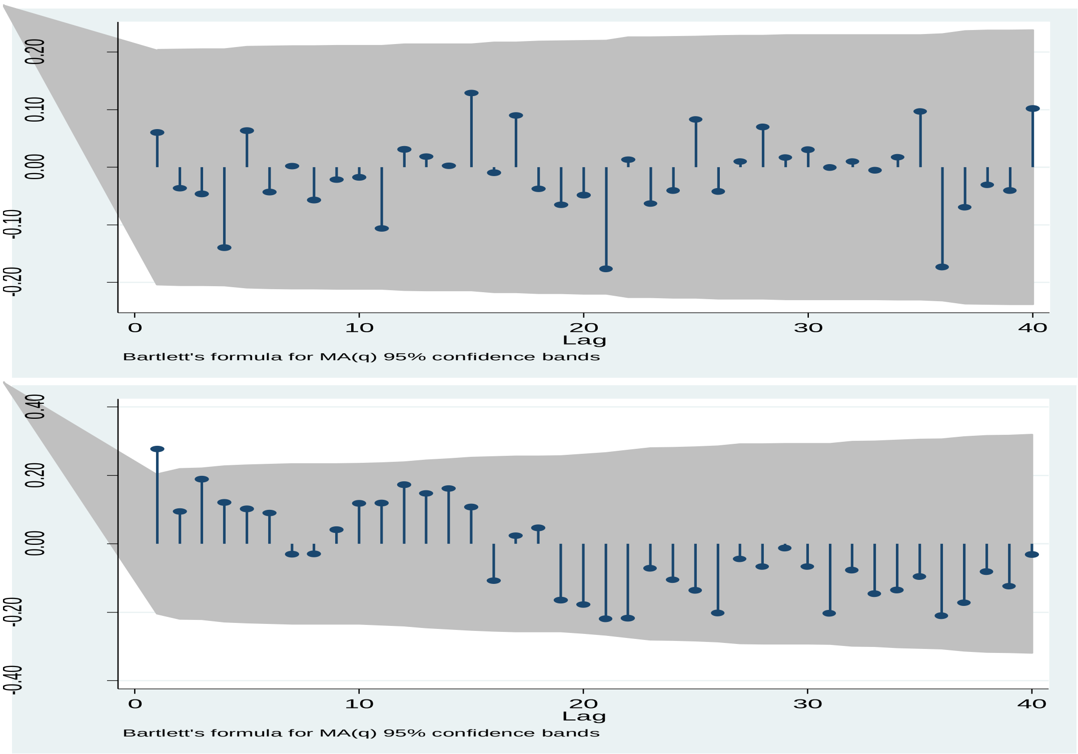


APPENDIX B: ACF plots

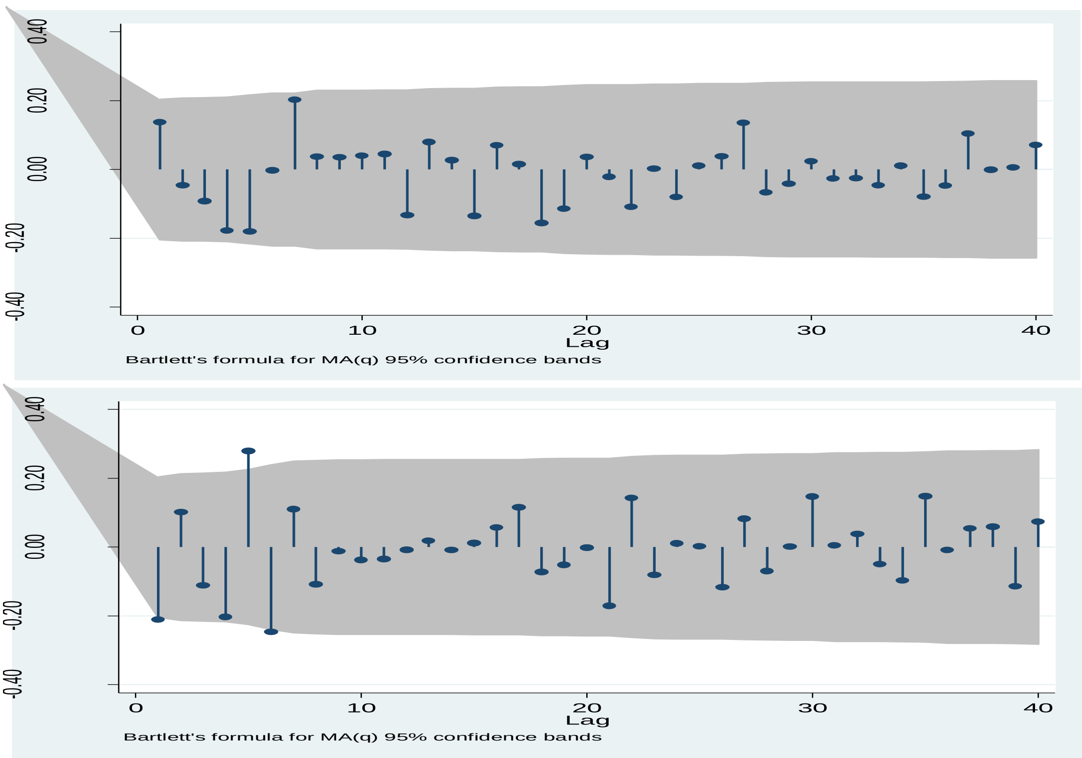
Figure 23 ACF plots



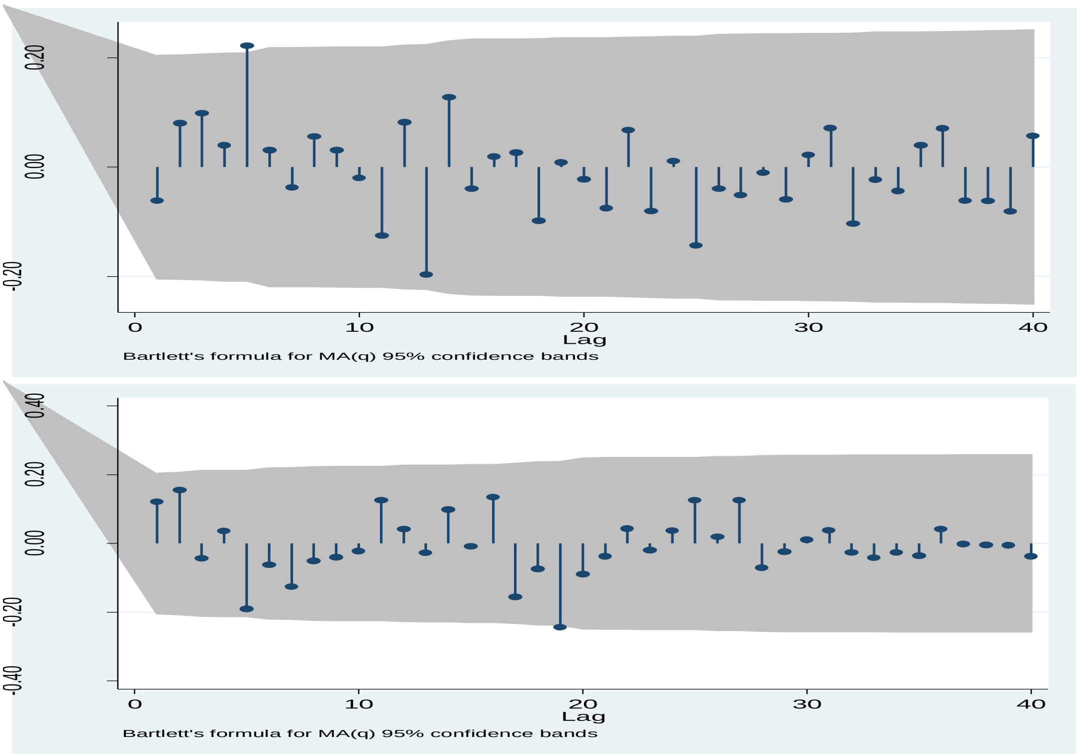
Industrials



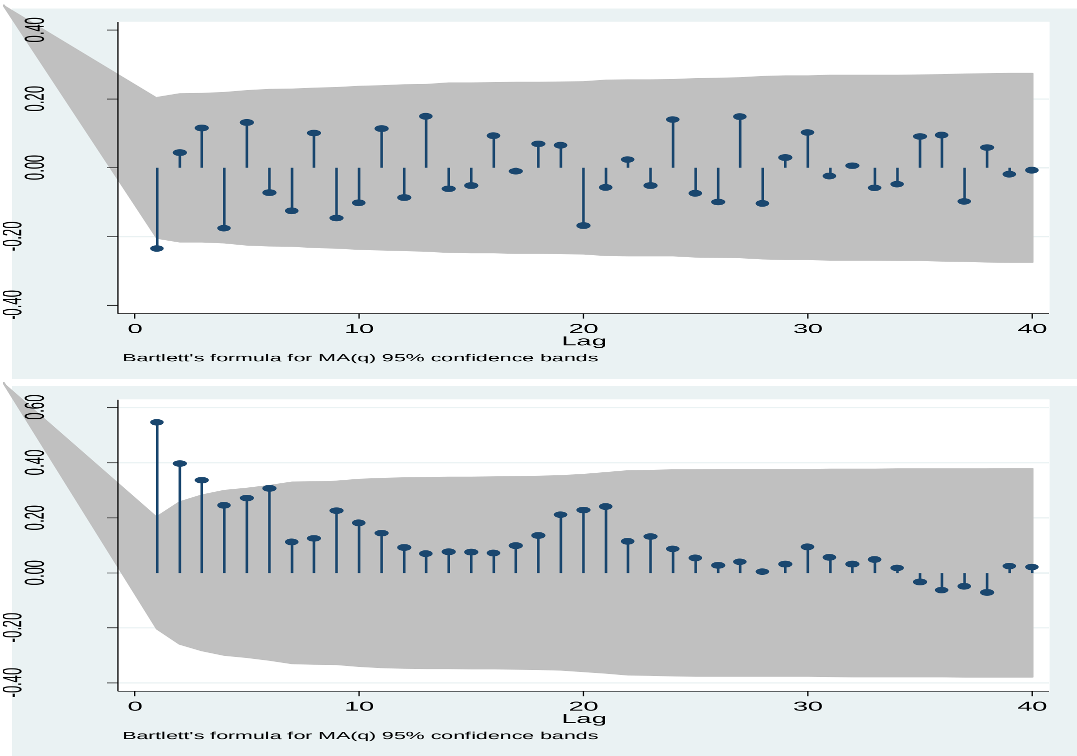
Consumer Goods



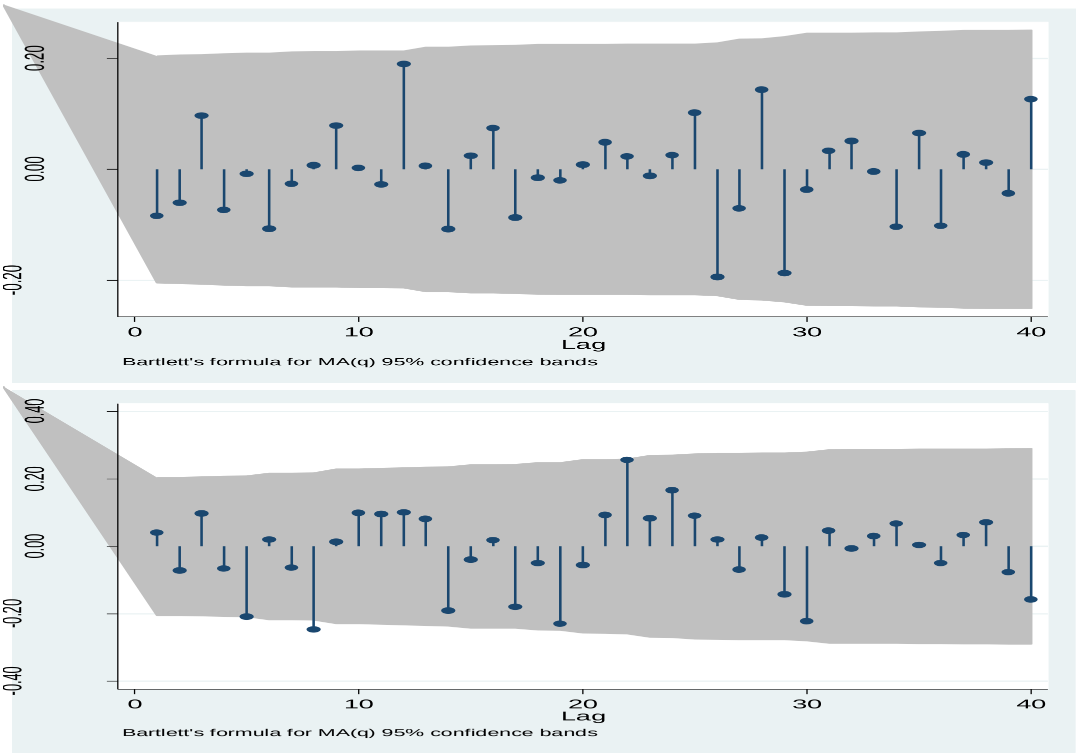
Healthcare



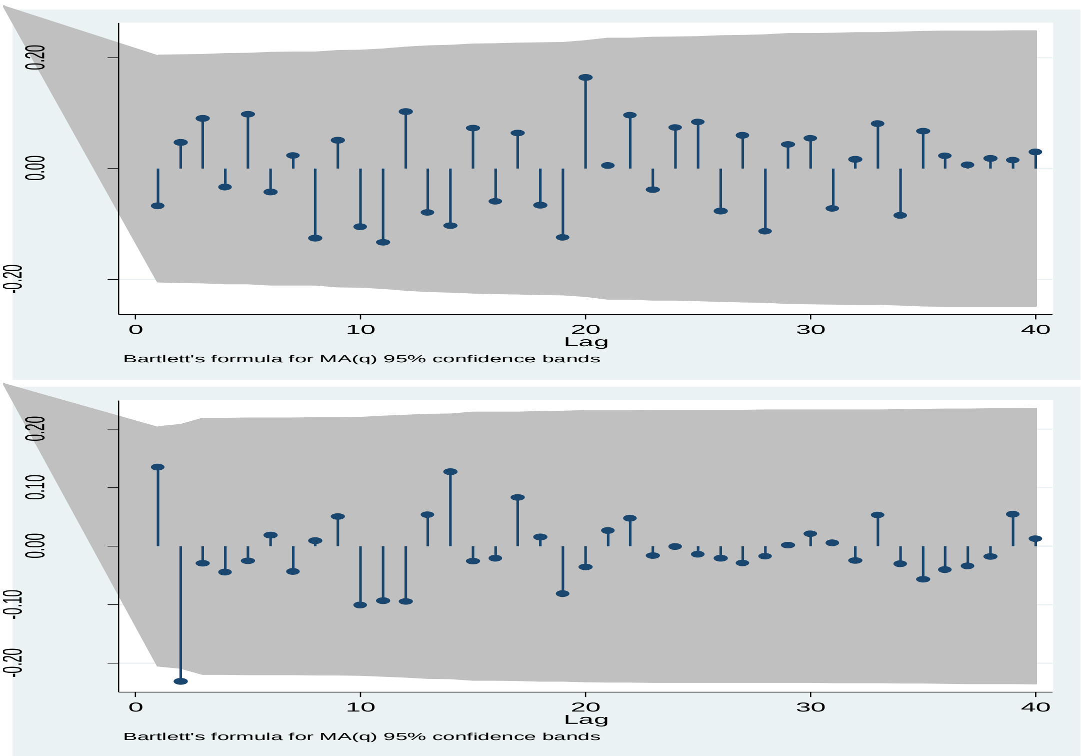
Consumer services



Telecommunications



Technology



Source:

APPENDIX C: AIC

Figure 24 AIC

Oil and Gas

. varsoc NV_OilsGas

Selection-order criteria
Sample: 2009m5 - 2016m8 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1941.23				8.7e+17	44.1416	44.1529	44.1697
1	-1932.91	16.648*	1	0.000	7.3e+17*	43.9751*	43.9978*	44.0314*
2	-1932.71	.38609	1	0.534	7.5e+17	43.9935	44.0275	44.0779
3	-1932.64	.13987	1	0.708	7.6e+17	44.0146	44.06	44.1272
4	-1932.3	.68993	1	0.406	7.8e+17	44.0295	44.0862	44.1703

Endogenous: NV_OilsGas
Exogenous: _cons

. varsoc GR_OilsGas

Selection-order criteria
Sample: 2009m6 - 2016m9 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	70.9576				.01194	-1.58995	-1.5786	-1.56179
1	73.3903	4.8652*	1	0.027	.011558*	-1.62251*	-1.59982*	-1.5662*
2	74.0964	1.4122	1	0.235	.011636	-1.61583	-1.5818	-1.53137
3	74.4033	.61383	1	0.433	.011821	-1.60007	-1.55471	-1.48747
4	74.6222	.43791	1	0.508	.012033	-1.58232	-1.52562	-1.44157

Endogenous: GR_OilsGas
Exogenous: _cons

Basic Materials

. varsoc NV_BasicMaterials

Selection-order criteria
Sample: 2009m5 - 2016m8 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2046.08				9.4e+18	46.5246	46.536	46.5528
1	-2028.62	34.931*	1	0.000	6.5e+18*	46.1504*	46.1731*	46.2067*
2	-2028.29	.66177	1	0.416	6.6e+18	46.1656	46.1997	46.2501
3	-2028.22	.13441	1	0.714	6.7e+18	46.1868	46.2322	46.2994
4	-2027.9	.63783	1	0.424	6.8e+18	46.2023	46.259	46.3431

Endogenous: NV_BasicMaterials
Exogenous: _cons

. varsoc GR_BasicMaterials

Selection-order criteria
Sample: 2009m6 - 2016m9 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	116.901				.004203	-2.63412	-2.62277	-2.60596
1	119.172	4.5425*	1	0.033	.004083	-2.66301	-2.64032	-2.6067*
2	120.748	3.1515	1	0.076	.00403*	-2.67609*	-2.64207*	-2.59164
3	120.89	.28337	1	0.594	.00411	-2.65659	-2.61122	-2.54398
4	121.046	.31235	1	0.576	.00419	-2.63741	-2.5807	-2.49665

Endogenous: GR_BasicMaterials
Exogenous: _cons

Industrials

```
. varsoc NV_Industrials

Selection-order criteria
Sample:  2009m5 - 2016m8                         Number of obs      =        88
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1953.13				1.1e+18	44.4121	44.4234	44.4403
1	-1949.66	6.9535*	1	0.008	1.1e+18*	44.3558*	44.3785*	44.4121*
2	-1949.63	.05043	1	0.822	1.1e+18	44.378	44.412	44.4624
3	-1948.24	2.7906	1	0.095	1.1e+18	44.369	44.4144	44.4816
4	-1948.2	.06989	1	0.791	1.1e+18	44.3909	44.4476	44.5317

```
Endogenous:  NV_Industrials
 Exogenous:  _cons

. varsoc  GR_Industrials

Selection-order criteria
Sample:  2009m6 - 2016m9                         Number of obs      =        88
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	167.118				.001342*	-3.7754*	-3.76406*	-3.74725*
1	167.122	.00866	1	0.926	.001373	-3.75277	-3.73009	-3.69647
2	167.123	.00118	1	0.973	.001405	-3.73006	-3.69604	-3.64561
3	167.172	.09802	1	0.754	.001435	-3.70845	-3.66308	-3.59584
4	168.202	2.0611	1	0.151	.001435	-3.70914	-3.65243	-3.56838

```
Endogenous:  GR_Industrials
 Exogenous:  _cons
```

Consumer Goods

```
. varsoc  NV_ConsumerGoods

Selection-order criteria
Sample:  2009m5 - 2016m8                         Number of obs      =        88
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2067.29				1.5e+19	47.0066	47.0179	47.0347
1	-2051.62	31.344*	1	0.000	1.1e+19*	46.6731*	46.6958*	46.7294*
2	-2050.66	1.9178	1	0.166	1.1e+19	46.674	46.7081	46.7585
3	-2049.87	1.5808	1	0.209	1.1e+19	46.6788	46.7242	46.7914
4	-2049.86	.01397	1	0.906	1.1e+19	46.7014	46.7581	46.8421

```
Endogenous:  NV_ConsumerGoods
 Exogenous:  _cons

. varsoc  GR_ConsumerGoods

Selection-order criteria
Sample:  2009m6 - 2016m9                         Number of obs      =        88
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	142.66				.00234	-3.21954	-3.2082	-3.19139
1	146.76	8.2006*	1	0.004	.002181*	-3.29001*	-3.26732*	-3.2337*
2	146.874	.22659	1	0.634	.002226	-3.26985	-3.23583	-3.1854
3	147.709	1.6706	1	0.196	.002234	-3.26611	-3.22074	-3.1535
4	148.512	1.6059	1	0.205	.002244	-3.26163	-3.20492	-3.12087

```
Endogenous:  GR_ConsumerGoods
 Exogenous:  _cons
```

Healthcare

varsoc NV_Healthcare

Selection-order criteria
Sample: 2009m5 - 2016m8 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1962.23				1.4e+18*	44.6189*	44.6302*	44.6471*
1	-1961.58	1.302	1	0.254	1.4e+18	44.6268	44.6495	44.6831
2	-1960.66	1.8338	1	0.176	1.4e+18	44.6287	44.6628	44.7132
3	-1960.39	.55406	1	0.457	1.4e+18	44.6452	44.6905	44.7578
4	-1960.35	.0697	1	0.792	1.5e+18	44.6671	44.7238	44.8078

Endogenous: NV_Healthcare
Exogenous: _cons

varsoc GR_Healthcare

Selection-order criteria
Sample: 2009m6 - 2016m9 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	157.127				.001685*	-3.54835*	-3.53701*	-3.5202*
1	157.154	.05388	1	0.816	.001722	-3.52624	-3.50355	-3.46993
2	157.277	.24504	1	0.621	.001757	-3.50629	-3.47227	-3.42184
3	157.916	1.2777	1	0.258	.001772	-3.49809	-3.45272	-3.38548
4	158.02	.2076	1	0.649	.001808	-3.47772	-3.42101	-3.33696

Endogenous: GR_Healthcare
Exogenous: _cons

Consumer Services

varsoc NV_ConsumerServices

Selection-order criteria
Sample: 2009m5 - 2016m8 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2034.27				7.2e+18*	46.2562*	46.2675*	46.2843*
1	-2033.39	1.7662	1	0.184	7.2e+18	46.2589	46.2815	46.3152
2	-2033.2	.38478	1	0.535	7.3e+18	46.2772	46.3112	46.3617
3	-2032.94	.50424	1	0.478	7.5e+18	46.2942	46.3396	46.4068
4	-2031.69	2.5116	1	0.113	7.4e+18	46.2884	46.3451	46.4291

Endogenous: NV_ConsumerServices
Exogenous: _cons

varsoc GR_ConsumerServices

Selection-order criteria
Sample: 2009m6 - 2016m9 Number of obs = 88

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	143.249				.002309	-3.23293	-3.22159	-3.20478
1	146.068	5.6376	1	0.018	.002216	-3.27427	-3.25159*	-3.21797*
2	146.202	.2675	1	0.605	.00226	-3.25458	-3.22056	-3.17013
3	146.49	.57762	1	0.447	.002297	-3.23842	-3.19305	-3.12581
4	150.112	7.2423*	1	0.007	.002164*	-3.29799*	-3.24128	-3.15723

Endogenous: GR_ConsumerServices
Exogenous: _cons

Telecommunications

varsoc NV_Telecommunications

Selection-order criteria
Sample: **2009m5 - 2016m8** Number of obs = **88**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1997.14				3.1e+18*	45.4124*	45.4237*	45.4405*
1	-1997.06	.1655	1	0.684	3.2e+18	45.4332	45.4559	45.4895
2	-1996.84	.44674	1	0.504	3.2e+18	45.4509	45.4849	45.5353
3	-1996.36	.96139	1	0.327	3.2e+18	45.4627	45.508	45.5753
4	-1996.05	.60665	1	0.436	3.3e+18	45.4785	45.5352	45.6193

Endogenous: NV_Telecommunications
Exogenous: _cons

varsoc GR_Telecommunications

Selection-order criteria
Sample: **2009m6 - 2016m9** Number of obs = **88**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	122.74				.003681*	-2.76682*	-2.75548*	-2.73867*
1	123.617	1.7538	1	0.185	.003691	-2.76402	-2.74134	-2.70772
2	123.618	.0014	1	0.970	.003776	-2.74131	-2.70729	-2.65686
3	124.814	2.3927	1	0.122	.003759	-2.74577	-2.70041	-2.63317
4	125.062	.49568	1	0.481	.003824	-2.72868	-2.67197	-2.58792

Endogenous: GR_Telecommunications
Exogenous: _cons

Technology

varsoc NV_Technology

Selection-order criteria
Sample: **2009m5 - 2016m8** Number of obs = **88**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1789.99				2.8e+16	40.7043	40.7157	40.7325*
1	-1789.13	1.7223	1	0.189	2.8e+16	40.7075	40.7302	40.7638
2	-1786.24	5.7708*	1	0.016	2.7e+16*	40.6646*	40.6986*	40.7491
3	-1786.15	.18362	1	0.668	2.7e+16	40.6853	40.7306	40.7979
4	-1785.56	1.1864	1	0.276	2.8e+16	40.6945	40.7512	40.8353

Endogenous: NV_Technology
Exogenous: _cons

varsoc GR_Technology

Selection-order criteria
Sample: **2009m6 - 2016m9** Number of obs = **88**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	131.462				.003019*	-2.96505*	-2.9537*	-2.93689*
1	131.889	.85469	1	0.355	.003058	-2.95203	-2.92935	-2.89573
2	132.035	.29158	1	0.589	.003118	-2.93262	-2.89859	-2.84816
3	132.794	1.5178	1	0.218	.003136	-2.92714	-2.88177	-2.81453
4	132.815	.041	1	0.840	.003206	-2.90488	-2.84817	-2.76412

Endogenous: GR_Technology
Exogenous: _cons

APPENDIX D: ADF

Figure 25 ADF

Oil and Gas

```
. dfuller NV_OilsGas, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.735            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0001

. dfuller  GR_OilsGas, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.650            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Basic Materials

```
. dfuller NV_BasicMaterials, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.753            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0001

. dfuller  GR_BasicMaterials, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        89

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.883            -3.525            -2.899            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Industrials

```
. dfuller NV_Industrials, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.535            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
. dfuller GR_Industrials, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -9.031            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Consumer Goods

```
. dfuller  NV_ConsumerGoods, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.754            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0034
```

```
. dfuller  GR_ConsumerGoods, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.181            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Healthcare

```
. dfuller  NV_Healthcare, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.345            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

```
. dfuller  GR_Healthcare, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -10.355            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Consumer Services

```
. dfuller  NV_ConsumerServices, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.222            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

```
. dfuller  GR_ConsumerServices, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        90

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -7.293            -3.524            -2.898            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Telecommunications

```
. dfuller NV_Telecommunications, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -9.062            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller GR_Telecommunications, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -10.219            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Technology

```
. dfuller  NV_Technology, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.249            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller  GR_Technology, lags(0)

Dickey-Fuller test for unit root                   Number of obs   =        91

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -10.274            -3.523            -2.897            -2.584
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

APPENDIX E: Test of assumptions: cointegration

Figure 26 Johansen test for cointegration and lags

Oil and Gas

```
. varsoc NV_OilsGas GR_OilsGas
```

Selection-order criteria
Sample: 2009m6 – 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1848.24				1.0e+16	42.5343	42.5572	42.591
1	-1837.46	21.571*	4	0.000	8.7e+15*	42.3783*	42.4468*	42.5484*
2	-1836.05	2.8087	4	0.590	9.2e+15	42.438	42.5521	42.7214
3	-1835.64	.83361	4	0.934	1.0e+16	42.5204	42.6802	42.9172
4	-1834.67	1.9353	4	0.748	1.1e+16	42.5901	42.7955	43.1003

Endogenous: NV_OilsGas GR_OilsGas
Exogenous: _cons

```
. vecrank NV_OilsGas GR_OilsGas, trend(constant) lags(1)
```

Johansen tests for cointegration
Trend: constant Number of obs = 90
Sample: 2009m3 – 2016m8 Lags = 1

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	-1938.2653	.	31.2064	15.41
1	5	-1922.6621	0.29301	0.0000*	3.76
2	6	-1922.6621	0.00000		

Basic Materials

```
. varsoc NV_BasicMaterials GR_BasicMaterials
```

Selection-order criteria
Sample: 2009m6 – 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1903.81				3.6e+16	43.8118	43.8346	43.8685
1	-1881.19	45.241*	4	0.000	2.4e+16*	43.3837*	43.4522*	43.5538*
2	-1879.48	3.427	4	0.489	2.5e+16	43.4363	43.5504	43.7197
3	-1878.37	2.2147	4	0.696	2.7e+16	43.5028	43.6626	43.8996
4	-1878.11	.52962	4	0.971	2.9e+16	43.5887	43.7941	44.0988

Endogenous: NV_BasicMaterials GR_BasicMaterials
Exogenous: _cons

```
. vecrank NV_BasicMaterials GR_BasicMaterials, trend(constant) lags(1)
```

Johansen tests for cointegration
Trend: constant Number of obs = 90
Sample: 2009m3 – 2016m8 Lags = 1

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	-2037.0471	.	33.4276	15.41
1	5	-2020.3333	0.31024	0.0000*	3.76
2	6	-2020.3333	0.00000		

Industrials

```
. varsoc NV_Industrials GR_Industrials
```

Selection-order criteria
Sample: 2009m6 – 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1762.84				1.4e+15	40.571	40.5939	40.6277*
1	-1755.11	15.468*	4	0.004	1.3e+15*	40.4852*	40.5537*	40.6552
2	-1754.89	.4329	4	0.980	1.4e+15	40.5722	40.6863	40.8556
3	-1750.7	8.378	4	0.079	1.4e+15	40.5678	40.7276	40.9646
4	-1747.17	7.058	4	0.133	1.4e+15	40.5786	40.7841	41.0888

Endogenous: NV_Industrials GR_Industrials
Exogenous: _cons

```
. vecrank NV_Industrials GR_Industrials, trend(constant) lags(1)
```

Johansen tests for cointegration
Trend: constant Number of obs = 90
Sample: 2009m3 – 2016m8 Lags = 1

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	-1875.4681	.	42.1584	15.41
1	5	-1854.3889	0.37401	0.0000*	3.76
2	6	-1854.3889	0.00000		

Consumer Goods

. varsoc NV_ConsumerGoods GR_ConsumerGoods

Selection-order criteria
Sample: 2009m6 - 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1903.67				3.6e+16	43.8085	43.8314	43.8652
1	-1882.39	42.555*	4	0.000	2.4e+16*	43.4114*	43.4798*	43.5814*
2	-1880.7	3.3813	4	0.496	2.6e+16	43.4644	43.5786	43.7479
3	-1876.75	7.9115	4	0.095	2.6e+16	43.4655	43.6252	43.8623
4	-1874.65	4.1871	4	0.381	2.7e+16	43.5093	43.7147	44.0195

Endogenous: NV_ConsumerGoods GR_ConsumerGoods
Exogenous: _cons

. vecrank NV_ConsumerGoods GR_ConsumerGoods, trend(constant) lags(1)

Johansen tests for cointegration
Trend: constant Number of obs = 90
Sample: 2009m3 - 2016m8 Lags = 1

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	-2006.3904	.	23.0019	15.41
1	5	-1994.8894	0.22553	0.0000*	3.76
2	6	-1994.8894	0.00000		

Healthcare

. varsoc NV_Healthcare GR_Healthcare

Selection-order criteria
Sample: 2009m6 - 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1784.99				2.4e+15	41.0803	41.1032*	41.137*
1	-1779.44	11.105	4	0.025	2.3e+15	41.0446	41.1131	41.2147
2	-1777.44	4.0026	4	0.406	2.4e+15	41.0906	41.2047	41.374
3	-1771.09	12.706*	4	0.013	2.3e+15*	41.0365*	41.1963	41.4333
4	-1770.88	.41689	4	0.981	2.5e+15	41.1237	41.3291	41.6339

Endogenous: NV_Healthcare GR_Healthcare
Exogenous: _cons

. varsoc NV_Healthcare GR_Healthcare

Selection-order criteria
Sample: 2009m6 - 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1784.99				2.4e+15	41.0803	41.1032*	41.137*
1	-1779.44	11.105	4	0.025	2.3e+15	41.0446	41.1131	41.2147
2	-1777.44	4.0026	4	0.406	2.4e+15	41.0906	41.2047	41.374
3	-1771.09	12.706*	4	0.013	2.3e+15*	41.0365*	41.1963	41.4333
4	-1770.88	.41689	4	0.981	2.5e+15	41.1237	41.3291	41.6339

Endogenous: NV_Healthcare GR_Healthcare
Exogenous: _cons

Consumer Services

. varsoc NV_ConsumerServices GR_ConsumerServices

Selection-order criteria
Sample: 2009m6 - 2016m8 Number of obs = 87

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1868.99				1.6e+16	43.0113	43.0341	43.068
1	-1858.44	21.098	4	0.000	1.4e+16*	42.8607*	42.9292*	43.0308*
2	-1857.43	2.014	4	0.733	1.5e+16	42.9295	43.0437	43.213
3	-1856.18	2.5166	4	0.642	1.6e+16	42.9926	43.1523	43.3894
4	-1848.37	15.606*	4	0.004	1.5e+16	42.9051	43.1106	43.4153

Endogenous: NV_ConsumerServices GR_ConsumerServices
Exogenous: _cons

. vecrank NV_ConsumerServices GR_ConsumerServices, trend(constant) lags(1)

Johansen tests for cointegration
Trend: constant Number of obs = 90
Sample: 2009m3 - 2016m8 Lags = 1

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	-1993.899	.	53.1324	15.41
1	5	-1967.3327	0.44587	0.0000*	3.76
2	6	-1967.3327	0.00000		

Telecommunications

```
. varsoc  NV_Telecommunications GR_Telecommunications

   Selection-order criteria
   Sample:  2009m6 - 2016m8                          Number of obs      =       87
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1852.04				1.1e+16	42.6217	42.6445	42.6784
1	-1840.2	23.694*	4	0.000	9.3e+15*	42.4413*	42.5098*	42.6113*
2	-1837.05	6.2825	4	0.179	9.5e+15	42.461	42.5752	42.7445
3	-1836.67	.76438	4	0.943	1.0e+16	42.5442	42.704	42.941
4	-1835.69	1.9664	4	0.742	1.1e+16	42.6135	42.819	43.1237

```
   Endogenous:  NV_Telecommunications GR_Telecommunications
    Exogenous:  _cons

. vecrank   NV_Telecommunications GR_Telecommunications, trend(constant) lags(1)

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =      90
Sample:  2009m3 - 2016m8                                         Lags =       1
```

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	-1981.1901	.	60.2872	15.41
1	5	-1951.0465	0.48822	0.0000*	3.76
2	6	-1951.0465	-0.00000		

Technology

```
. varsoc NV_Technology GR_Technology

   Selection-order criteria
   Sample:  2009m6 - 2016m8                          Number of obs      =       87
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1640.49				8.6e+13	37.7585	37.7813	37.8152
1	-1631.37	18.251	4	0.001	7.6e+13	37.6407	37.7092	37.8107*
2	-1624.62	13.499	4	0.009	7.2e+13*	37.5775*	37.6916*	37.8609
3	-1622.66	3.9262	4	0.416	7.5e+13	37.6243	37.7841	38.0211
4	-1616.71	11.9*	4	0.018	7.2e+13	37.5795	37.7849	38.0896

```
   Endogenous:  NV_Technology GR_Technology
    Exogenous:  _cons

. vecrank NV_Technology GR_Technology, trend(constant) lags(2)

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =      89
Sample:  2009m4 - 2016m8                                         Lags =       2
```

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	-1705.9076	.	51.1723	15.41
1	9	-1680.3215	0.43728	0.0000*	3.76
2	10	-1680.3215	0.00000		

APPENDIX F: VEC fit of model and Granger-causality

Figure 27 VEC model

Oil and Gas

```
. vec NV_OilsGas GR_OilsGas
```

Vector error-correction model

Sample:	2009m4 - 2016m8	No. of obs	=	89
		AIC	=	42.82336
Log likelihood =	-1896.64	HQIC	=	42.9248
Det(Sigma_ml) =	1.11e+16	SBIC	=	43.07502

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_NV_OilsGas	4	8.5e+08	0.2960	35.73429	0.0000
D_GR_OilsGas	4	.129671	0.1114	8.786684	0.0667

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_NV_OilsGas						
_ce1 L1.	-.5474894	.1170807	-4.68	0.000	-.7769634	-.3180154
NV_OilsGas LD.	-.0650382	.1081949	-0.60	0.548	-.2770963	.14702
GR_OilsGas LD.	1.46e+08	6.70e+08	0.22	0.828	-1.17e+09	1.46e+09
_cons	-1.54e-07	9.02e+07	-0.00	1.000	-1.77e+08	1.77e+08
D_GR_OilsGas						
_ce1 L1.	-9.26e-12	1.78e-11	-0.52	0.604	-4.42e-11	2.57e-11
NV_OilsGas LD.	2.18e-11	1.65e-11	1.32	0.186	-1.05e-11	5.41e-11
GR_OilsGas LD.	-.3024999	.1020854	-2.96	0.003	-.5025836	-.1024161
_cons	.0011215	.0137451	0.08	0.935	-.0258185	.0280615

Basic Materials

```
. vec  NV_BasicMaterials GR_BasicMaterials
```

Vector error-correction model

Sample:	2009m4 - 2016m8	No. of obs	=	89
		AIC	=	44.22075
Log likelihood =	-1958.823	HQIC	=	44.32219
Det(Sigma_ml) =	4.49e+16	SBIC	=	44.47241

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_NV_BasicMate~s	4	2.9e+09	0.4223	62.12943	0.0000
D_GR_BasicMate~s	4	.078044	0.4577	63.58193	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_NV_Basic~s						
_ce1 L1.	-.6238636	.1029888	-6.06	0.000	-.825718	-.4220092
NV_BasicMa~s LD.	-.0841577	.0950486	-0.89	0.376	-.2704495	.1021341
GR_BasicMa~s LD.	-6.26e+08	3.05e+09	-0.21	0.837	-6.60e+09	5.34e+09
_cons	3.22e-07	3.11e+08	0.00	1.000	-6.09e+08	6.09e+08
D_GR_Basic~s						
_ce1 L1.	-1.38e-12	2.76e-12	-0.50	0.616	-6.79e-12	4.03e-12
NV_BasicMa~s LD.	-1.86e-12	2.55e-12	-0.73	0.465	-6.85e-12	3.13e-12
GR_BasicMa~s LD.	-.650678	.0816208	-7.97	0.000	-.8106519	-.4907041
_cons	.0019609	.0083228	0.24	0.814	-.0143514	.0182732

Industrials

```
. vec NV_Industrials GR_Industrials

Vector error-correction model

Sample:  2009m4 - 2016m8                         No. of obs      =        89
                                                 AIC             =  41.08211
Log likelihood = -1819.154                       HQIC            =  41.18355
Det(Sigma_ml)  =  1.95e+15                       SBIC            =  41.33377

Equation           Parms    RMSE     R-sq     chi2     P>chi2
----------------------------------------------------------------
D_NV_Industrials     4     1.0e+09   0.3648   48.81574   0.0000
D_GR_Industrials     4     .045242   0.2891   27.83039   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_NV_Indus~s |
        _ce1 |
         L1. |  -.7017336   .1313719    -5.34   0.000    -.9592177   -.4442494
             |
NV_Industr~s |
         LD. |  -.0209712     .10821    -0.19   0.846     -.233059    .1911166
             |
GR_Industr~s |
         LD. |  -1.09e+09   2.10e+09    -0.52   0.603    -5.21e+09    3.02e+09
             |
       _cons |   3.02e-07   1.09e+08     0.00   1.000    -2.14e+08    2.14e+08
-------------+----------------------------------------------------------------
D_GR_Indus~s |
        _ce1 |
         L1. |  -2.40e-12   5.77e-12    -0.42   0.677    -1.37e-11    8.90e-12
             |
NV_Industr~s |
         LD. |   1.17e-11   4.75e-12     2.47   0.014     2.42e-12    2.10e-11
             |
GR_Industr~s |
         LD. |   -.485255    .092204    -5.26   0.000    -.6659716   -.3045384
             |
       _cons |   .0022612   .0047969     0.47   0.637    -.0071406     .011663
------------------------------------------------------------------------------
```

Consumer Goods

```
. vec  NV_ConsumerGoods GR_ConsumerGoods
the parameters of the cointegrating equations are not identified by the sample
check your sample and the number of lags specified
r(498);

. vec NV_ConsumerGoods  GR_ConsumerGoods, lags(5) rank(1)

Vector error-correction model

Sample:  2009m7 - 2016m8                         No. of obs      =        86
                                                 AIC             =  43.75723
Log likelihood = -1860.561                       HQIC            =  43.99843
Det(Sigma_ml)  =  2.12e+16                       SBIC            =  44.35655

Equation           Parms    RMSE     R-sq     chi2     P>chi2
----------------------------------------------------------------
D_NV_ConsumerG~s    10     3.2e+09   0.3178   35.40611   0.0001
D_GR_ConsumerG~s    10     .051016   0.6192   120.0137   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_NV_Consu~s |
        _ce1 |
         L1. |  -.1962183   .1395648    -1.41   0.160    -.4697602    .0773236
             |
NV_Consum~ds |
         LD. |  -.3681351   .1594498    -2.31   0.021     -.680651   -.0556193
        L2D. |  -.3006708   .1609915    -1.87   0.062    -.6162083    .0148666
        L3D. |  -.1336426   .1457632    -0.92   0.359    -.4193332    .1520481
        L4D. |  -.2479347   .1386452    -1.79   0.074    -.5196743    .0238049
             |
GR_Consum~ds |
         LD. |   8.40e+09   7.00e+09     1.20   0.230    -5.31e+09    2.21e+10
        L2D. |   1.38e+10   1.00e+10     1.38   0.168    -5.84e+09    3.35e+10
        L3D. |   1.40e+10   9.83e+09     1.43   0.154    -5.25e+09    3.33e+10
        L4D. |   8.50e+09   6.90e+09     1.23   0.218    -5.02e+09    2.20e+10
             |
       _cons |  -1.24e-06   3.98e+08    -0.00   1.000    -7.80e+08    7.80e+08
-------------+----------------------------------------------------------------
D_GR_Consu~s |
        _ce1 |
         L1. |   2.22e-12   2.20e-12     1.01   0.313    -2.09e-12    6.54e-12
             |
NV_Consum~ds |
         LD. |  -3.25e-12   2.51e-12    -1.29   0.197    -8.17e-12    1.68e-12
        L2D. |  -4.69e-12   2.54e-12    -1.85   0.065    -9.67e-12    2.85e-13
        L3D. |  -1.77e-12   2.30e-12    -0.77   0.440    -6.28e-12    2.73e-12
        L4D. |  -2.82e-13   2.19e-12    -0.13   0.897    -4.57e-12    4.00e-12
             |
GR_Consum~ds |
         LD. |  -1.089437   .1103199    -9.88   0.000     -1.30566   -.8732142
        L2D. |  -.8010058   .1580936    -5.07   0.000    -1.110864   -.4911481
        L3D. |  -.3630052   .1550542    -2.34   0.019    -.6669058   -.0591045
        L4D. |  -.2333869   .1088075    -2.14   0.032    -.4466456   -.0201283
```

Healthcare

```
. vec NV_Healthcare GR_Healthcare

Vector error-correction model

Sample:  2009m4 - 2016m8                          No. of obs      =        89
                                                  AIC             =   41.4166
Log likelihood = -1834.039                        HQIC            =  41.51804
Det(Sigma_ml)  =  2.72e+15                        SBIC            =  41.66826

Equation           Parms    RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_NV_Healthcare      4     1.2e+09   0.4632   73.3575   0.0000
D_GR_Healthcare      4     .047203   0.3791  41.14257   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_NV_Healt~e |
        _ce1 |
         L1. |  -.7201412   .1427308    -5.05   0.000    -.9998884    -.440394
             |
NV_Healthc~e |
         LD. |  -.1690073     .10774    -1.57   0.117    -.3801737    .0421592
             |
GR_Healthc~e |
         LD. |  -2.94e+09   2.07e+09    -1.42   0.155    -6.99e+09    1.11e+09
             |
       _cons |  -1.64e-07   1.23e+08    -0.00   1.000    -2.40e+08    2.40e+08
-------------+----------------------------------------------------------------
D_GR_Healt~e |
        _ce1 |
         L1. |   5.22e-12   5.83e-12     0.90   0.371    -6.20e-12    1.66e-11
             |
NV_Healthc~e |
         LD. |   6.29e-12   4.40e-12     1.43   0.153    -2.33e-12    1.49e-11
             |
GR_Healthc~e |
         LD. |  -.5411921   .0843762    -6.41   0.000    -.7065663   -.3758179
             |
       _cons |  -.0001314    .005004    -0.03   0.979     -.009939    .0096763
------------------------------------------------------------------------------
```

Consumer Services

```
. vec NV_ConsumerServices GR_ConsumerServices

Vector error-correction model

Sample:  2009m4 - 2016m8                          No. of obs      =        89
                                                  AIC             =   43.3456
Log likelihood = -1919.879                        HQIC            =  43.44703
Det(Sigma_ml)  =  1.87e+16                        SBIC            =  43.59726

Equation           Parms    RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_NV_ConsumerS~s     4     2.7e+09   0.4408  67.01386   0.0000
D_GR_ConsumerS~s     4     .054863   0.4953  46.59946   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_NV_Consu~s |
        _ce1 |
         L1. |  -.9424782   .1431217    -6.59   0.000    -1.222992   -.6619649
             |
NV_Consum~es |
         LD. |   .1034176   .1152026     0.90   0.369    -.1223753    .3292105
             |
GR_Consum~es |
         LD. |   3.53e+09   4.02e+09     0.88   0.380    -4.35e+09    1.14e+10
             |
       _cons |   6.47e-07   2.82e+08     0.00   1.000    -5.53e+08    5.53e+08
-------------+----------------------------------------------------------------
D_GR_Consu~s |
        _ce1 |
         L1. |   4.67e-12   2.95e-12     1.58   0.113    -1.11e-12    1.04e-11
             |
NV_Consum~es |
         LD. |   3.54e-12   2.37e-12     1.49   0.136    -1.11e-12    8.19e-12
             |
GR_Consum~es |
         LD. |  -.5651375   .0828114    -6.82   0.000    -.7274449   -.4028302
             |
       _cons |   .0010705   .0058158     0.18   0.854    -.0103284    .0124693
------------------------------------------------------------------------------
```

Telecommunications

```
. vec NV_Telecommunications GR_Telecommunications

Vector error-correction model

Sample:  2009m4 - 2016m8                        No. of obs      =        89
                                                AIC             =  43.21268
Log likelihood = -1913.964                      HQIC            =  43.31411
Det(Sigma_ml)  =  1.64e+16                      SBIC            =  43.46434

Equation           Parms    RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_NV_Telecommu~s     4    1.7e+09   0.4912   82.04755   0.0000
D_GR_Telecommu~s     4    .077169   0.3588   30.41889   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_NV_Telec~s |
        _ce1 |
         L1. |  -1.052205    .150427    -6.99   0.000    -1.347036   -.7573734
             |
NV_Telecom~s |
         LD. |   .1151453   .1138585     1.01   0.312    -.1080133    .3383039
             |
GR_Telecom~s |
         LD. |   2.53e+09   2.13e+09     1.18   0.236    -1.66e+09    6.71e+09
             |
       _cons |  -1.09e-06   1.85e+08    -0.00   1.000    -3.63e+08    3.63e+08
-------------+----------------------------------------------------------------
D_GR_Telec~s |
        _ce1 |
         L1. |   1.15e-11   6.64e-12     1.72   0.085    -1.56e-12    2.45e-11
             |
NV_Telecom~s |
         LD. |   1.48e-12   5.03e-12     0.30   0.768    -8.36e-12    1.13e-11
             |
GR_Telecom~s |
         LD. |  -.5195697   .0942247    -5.51   0.000    -.7042468   -.3348926
             |
       _cons |   .0023245   .0081841     0.28   0.776    -.0137161    .0183651
------------------------------------------------------------------------------
```

Technology

```
. vec  NV_Technology GR_Technology

Vector error-correction model

Sample:  2009m4 - 2016m8                        No. of obs      =        89
                                                AIC             =  37.96228
Log likelihood = -1680.321                      HQIC            =  38.06372
Det(Sigma_ml)  =  8.59e+13                      SBIC            =  38.21394

Equation           Parms    RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_NV_Technology      4    1.6e+08   0.4782   77.90261   0.0000
D_GR_Technology      4    .061784   0.4374   30.00797   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_NV_Techn~y |
        _ce1 |
         L1. |  -1.106026   .1381118    -8.01   0.000    -1.376721   -.8353322
             |
NV_Technol~y |
         LD. |   .2877859   .1081881     2.66   0.008     .0757411    .4998307
             |
GR_Technol~y |
         LD. |   2.75e+08   2.21e+08     1.25   0.213    -1.58e+08    7.07e+08
             |
       _cons |  -1.34e-08   1.69e+07    -0.00   1.000    -3.32e+07    3.32e+07
-------------+----------------------------------------------------------------
D_GR_Techn~y |
        _ce1 |
         L1. |   3.98e-12   5.34e-11     0.07   0.941    -1.01e-10    1.09e-10
             |
NV_Technol~y |
         LD. |   1.36e-10   4.19e-11     3.25   0.001     5.39e-11    2.18e-10
             |
GR_Technol~y |
         LD. |  -.4672358   .0853692    -5.47   0.000    -.6345564   -.2999152
             |
       _cons |   .0018811   .0065496     0.29   0.774    -.0109559    .0147181
------------------------------------------------------------------------------
```

APPENDIX G: Stability check

Figure 28 Vecstable command - stability check

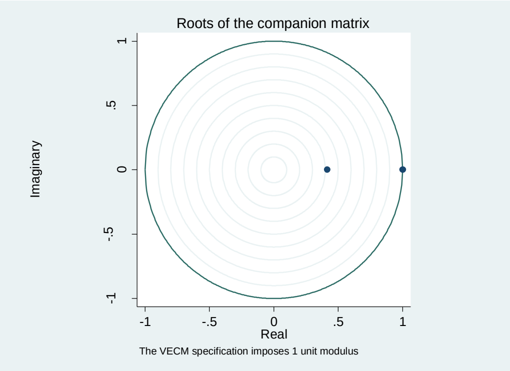
Oil and Gas

```
. vecstable, graph

   Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
.4147374	.414737

The VECM specification imposes a unit modulus.



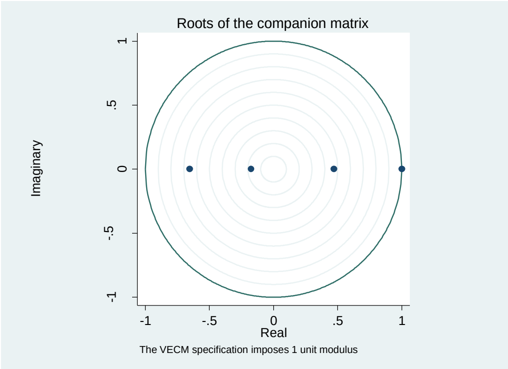
Basic Materials

```
. vecstable, graph

   Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
-.6553257	.655326
.4704646	.470465
-.1738382	.173838

The VECM specification imposes a unit modulus.



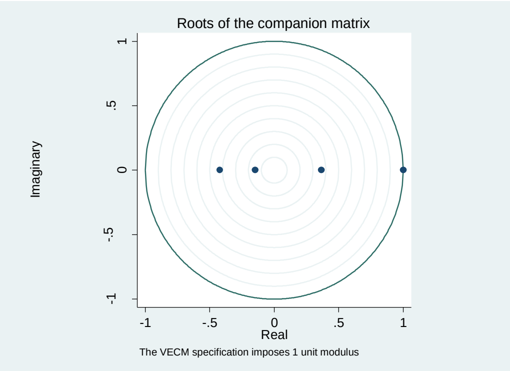
Industrials

```
. vecstable, graph

   Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
-.4229411	.422941
.3643088	.364309
-.1493275	.149327

The VECM specification imposes a unit modulus.



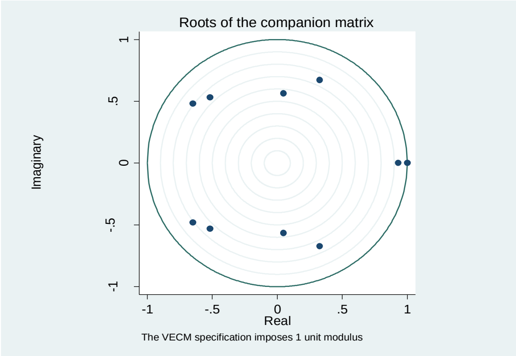
Consumer Goods

```
. vecstable, graph

   Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
.931047	.931047
-.6506036 + .4801419*i*	.808592
-.6506036 - .4801419*i*	.808592
.3260276 + .6735249*i*	.748285
.3260276 - .6735249*i*	.748285
-.5167185 + .531862*i*	.741536
-.5167185 - .531862*i*	.741536
.04887556 + .5649328*i*	.567043
.04887556 - .5649328*i*	.567043

The VECM specification imposes a unit modulus.



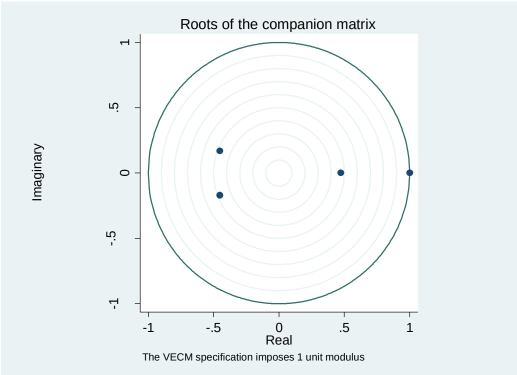
Healthcare

```
. vecstable,graph

  Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
−.4517684 + .1682813*i*	.482093
−.4517684 − .1682813*i*	.482093
.4731962	.473196

The VECM specification imposes a unit modulus.



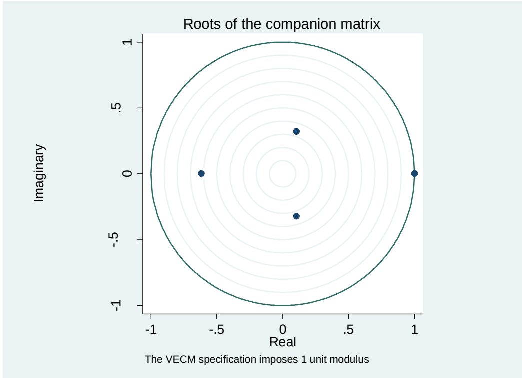
Consumer Services

```
. vecstable,graph

  Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
−.6171477	.617148
.1064748 + .3218574*i*	.339012
.1064748 − .3218574*i*	.339012

The VECM specification imposes a unit modulus.



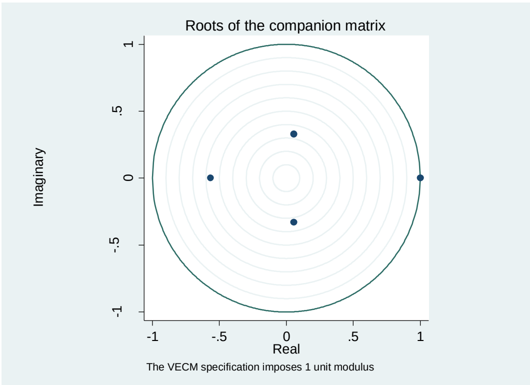
Telecommunications

```
. vecstable,graph

  Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
−.5667877	.566788
.05507923 + .3303679*i*	.334928
.05507923 − .3303679*i*	.334928

The VECM specification imposes a unit modulus.



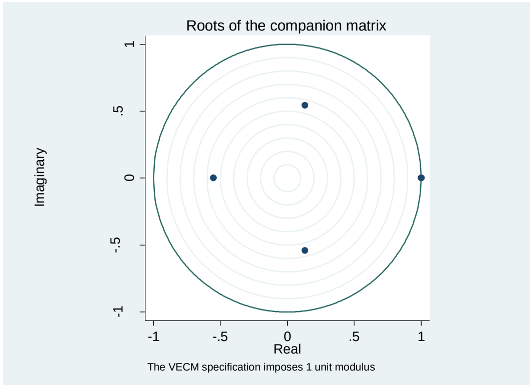
Technology

```
. vecstable,graph

  Eigenvalue stability condition
```

Eigenvalue	Modulus
1	1
.1331526 + .5418841*i*	.558004
.1331526 − .5418841*i*	.558004
−.5517815	.551782

The VECM specification imposes a unit modulus.



APPENDIX H: Normality of errors

Figure 29 Normality of errors

Oil and Gas

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_oilsGas	10.826	2	0.00446
D_GR_oilsGas	837.223	2	0.00000
ALL	848.049	4	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_oilsGas	-.62639	5.755	1	0.01644
D_GR_oilsGas	.46125	3.120	1	0.07732
ALL		8.875	2	0.01182

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_oilsGas	4.176	5.071	1	0.02433
D_GR_oilsGas	18.083	834.103	1	0.00000
ALL		839.174	2	0.00000

Basic Materials

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_BasicMaterials	24.997	2	0.00000
D_GR_BasicMaterials	1.362	2	0.50613
ALL	26.359	4	0.00003

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_BasicMaterials	-.74095	8.144	1	0.00432
D_GR_BasicMaterials	.14912	0.330	1	0.56575
ALL		8.473	2	0.01445

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_BasicMaterials	5.1318	16.853	1	0.00004
D_GR_BasicMaterials	2.4724	1.032	1	0.30967
ALL		17.885	2	0.00013

Industrials

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_Industrials	68.451	2	0.00000
D_GR_Industrials	2.271	2	0.32125
ALL	70.722	4	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_Industrials	-.74956	8.334	1	0.00389
D_GR_Industrials	.24001	0.854	1	0.35529
ALL		9.188	2	0.01011

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_Industrials	7.0263	60.117	1	0.00000
D_GR_Industrials	2.3819	1.417	1	0.23397
ALL		61.533	2	0.00000

Consumer Goods

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_ConsumerGoods	249.249	2	0.00000
D_GR_ConsumerGoods	4.457	2	0.10770
ALL	253.706	4	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_ConsumerGoods	-1.9433	54.126	1	0.00000
D_GR_ConsumerGoods	.54428	4.246	1	0.03934
ALL		58.372	2	0.00000

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_ConsumerGoods	10.379	195.123	1	0.00000
D_GR_ConsumerGoods	3.2424	0.211	1	0.64628
ALL		195.334	2	0.00000

Healthcare

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_Healthcare	712.766	2	0.00000
D_GR_Healthcare	1.697	2	0.42807
ALL	714.463	4	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_Healthcare	-2.9209	126.555	1	0.00000
D_GR_Healthcare	.32978	1.613	1	0.20404
ALL		128.168	2	0.00000

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_Healthcare	15.573	586.211	1	0.00000
D_GR_Healthcare	2.8498	0.084	1	0.77235
ALL		586.295	2	0.00000

Consumer Services

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_ConsumerServices	45.353	2	0.00000
D_GR_ConsumerServices	2.634	2	0.26794
ALL	47.987	4	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_ConsumerServices	-.61433	5.598	1	0.01798
D_GR_ConsumerServices	.41797	2.591	1	0.10744
ALL		8.190	2	0.01666

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_ConsumerServices	6.2742	39.755	1	0.00000
D_GR_ConsumerServices	3.1071	0.043	1	0.83653
ALL		39.797	2	0.00000

Telecommunications

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_Telecommunications	11.150	2	0.00379
D_GR_Telecommunications	5.619	2	0.06023
ALL	16.769	4	0.00214

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_Telecommunications	-.64774	6.224	1	0.01261
D_GR_Telecommunications	.40278	2.406	1	0.12084
ALL		8.630	2	0.01337

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_Telecommunications	4.1526	4.926	1	0.02645
D_GR_Telecommunications	3.9308	3.213	1	0.07307
ALL		8.139	2	0.01709

Technology

. vecnorm, jbera skewness kurtosis

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_NV_Technology	2807.082	2	0.00000
D_GR_Technology	0.066	2	0.96764
ALL	2807.148	4	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_NV_Technology	4.1082	250.342	1	0.00000
D_GR_Technology	.0084	0.001	1	0.97419
ALL		250.343	2	0.00000

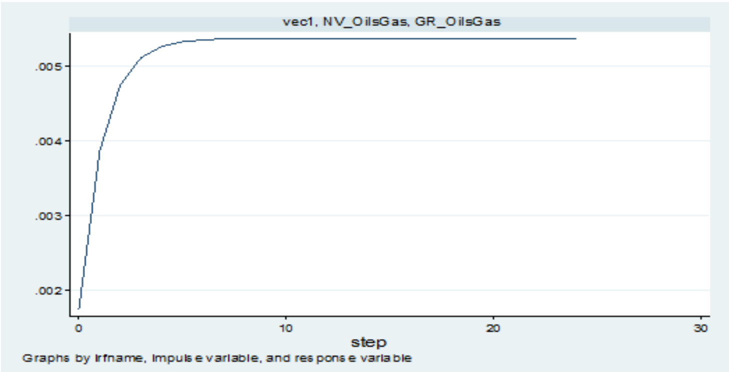
Kurtosis test

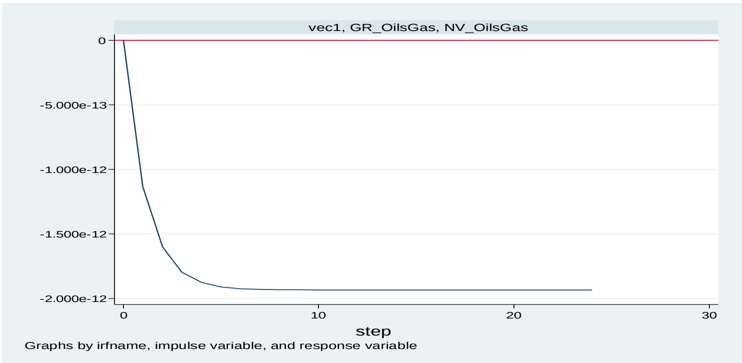
Equation	Kurtosis	chi2	df	Prob > chi2
D_NV_Technology	29.258	2556.740	1	0.00000
D_GR_Technology	2.8679	0.065	1	0.79916
ALL		2556.805	2	0.00000

APPENDIX I: Effect of shocks

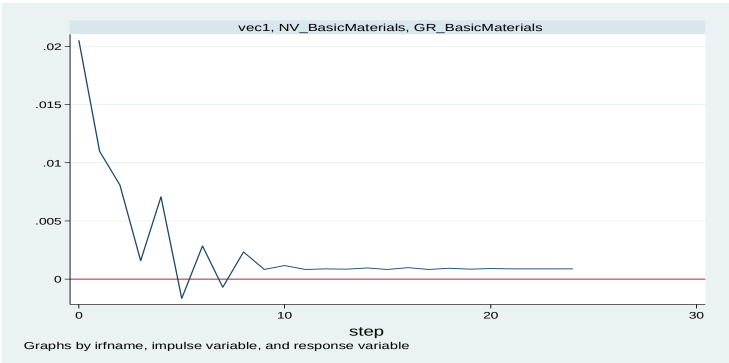
Figure 30 IRF

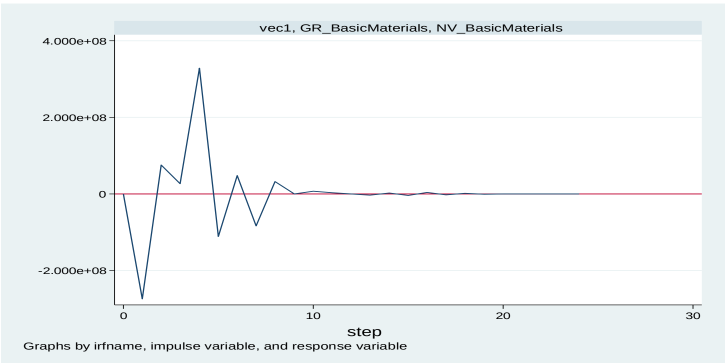
Oil and Gas



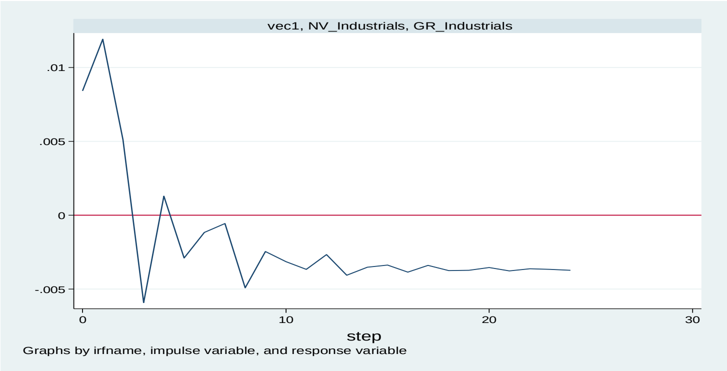


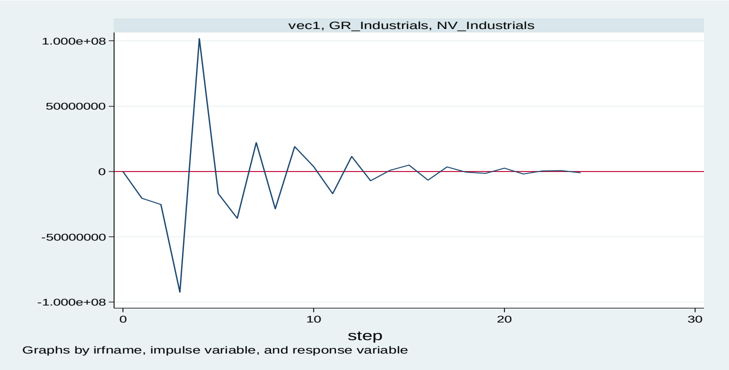
Basic Materials



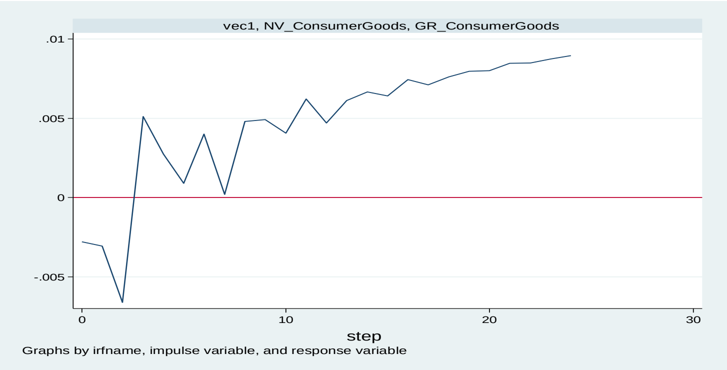


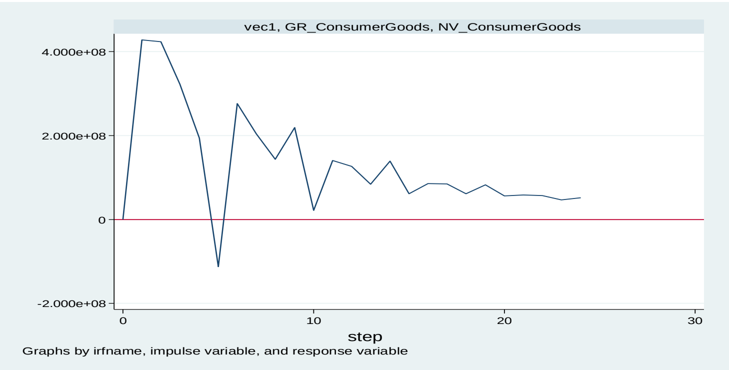
Industrials



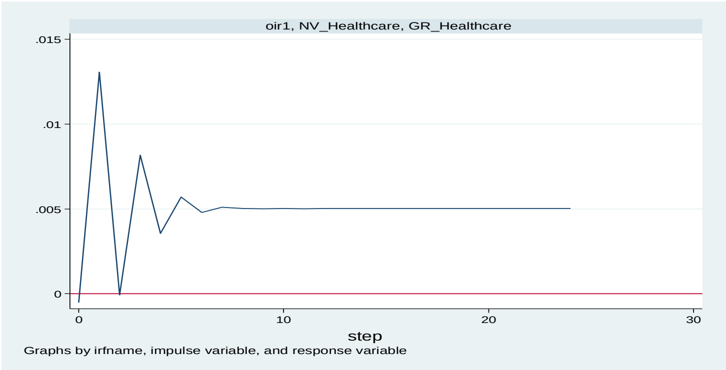


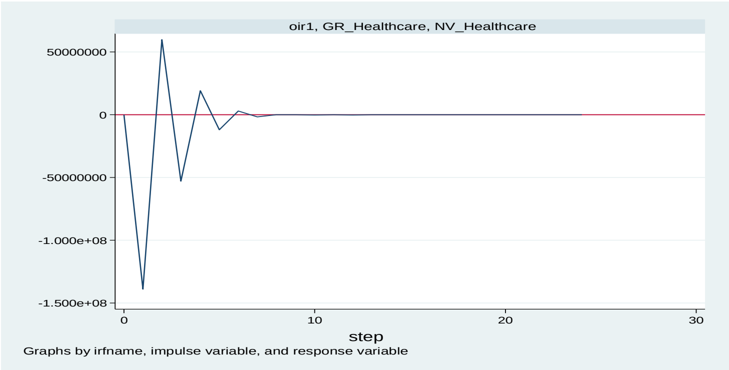
Consumer Goods



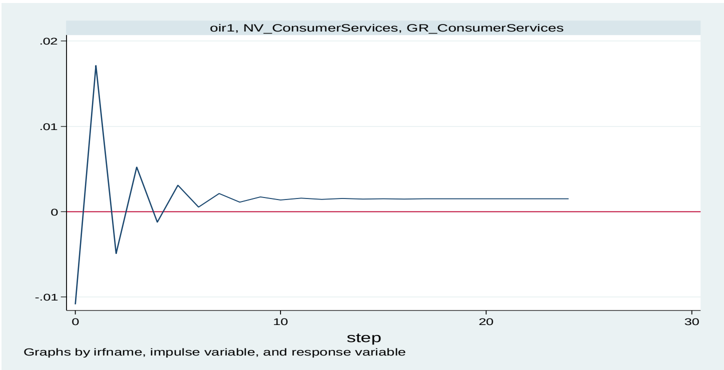


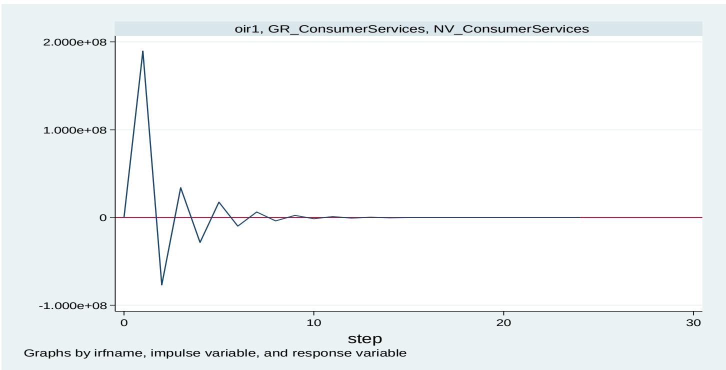
Healthcare



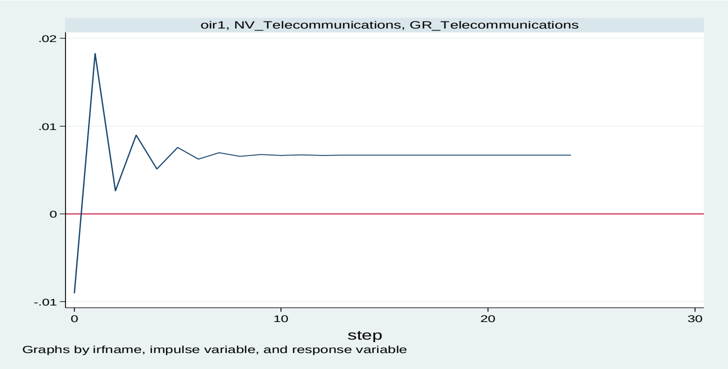


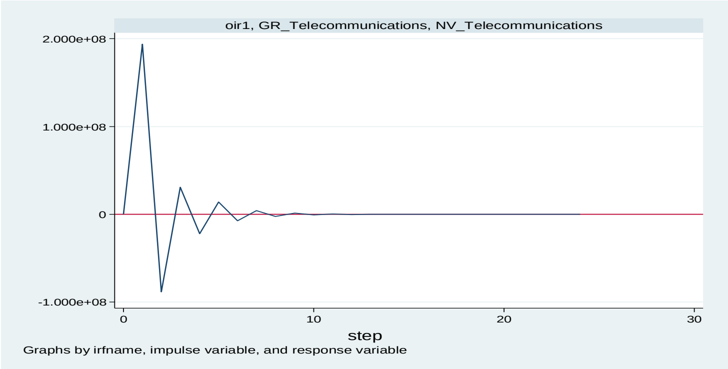
Consumer Services



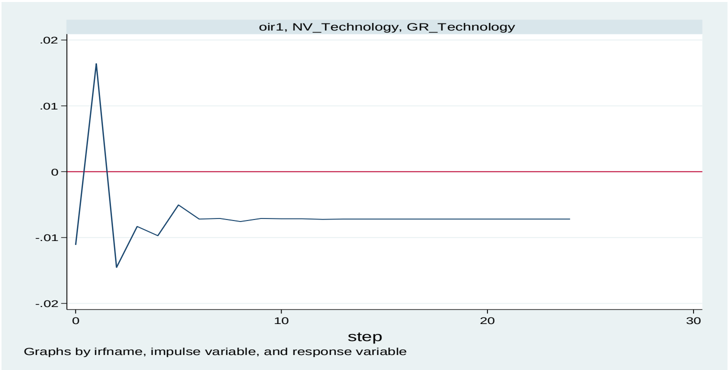


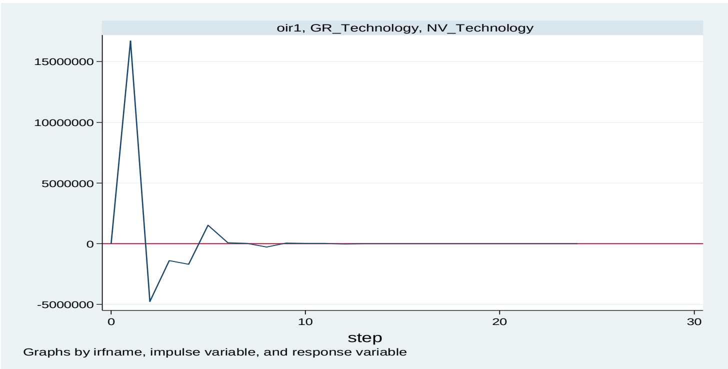
Telecommunications





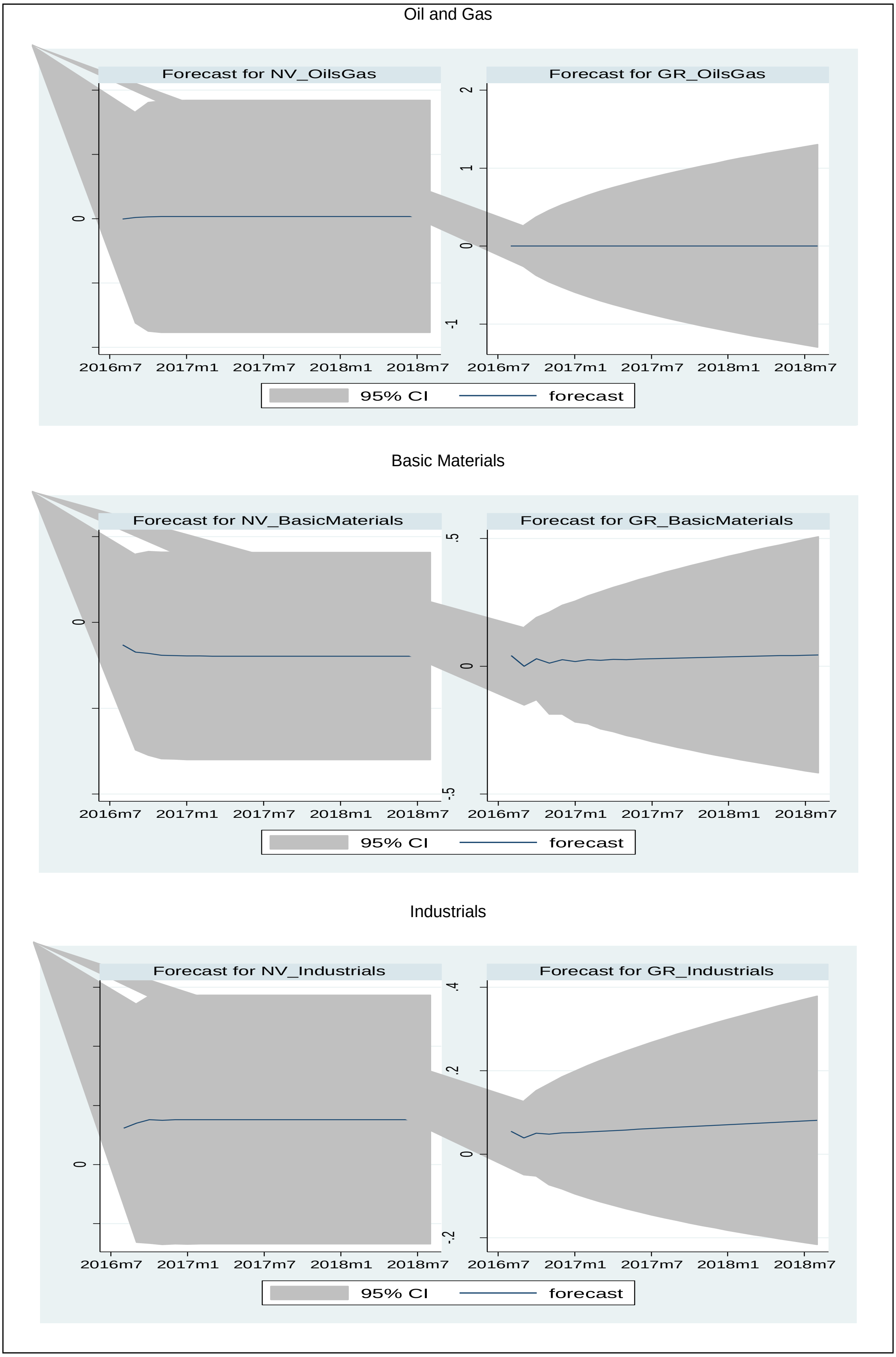
Technology



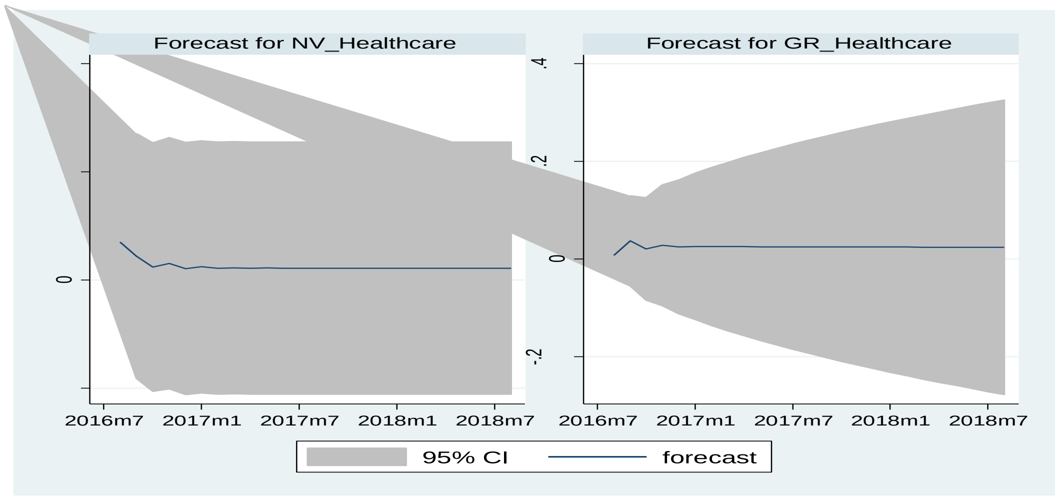


APPENDIX J: Forecasting

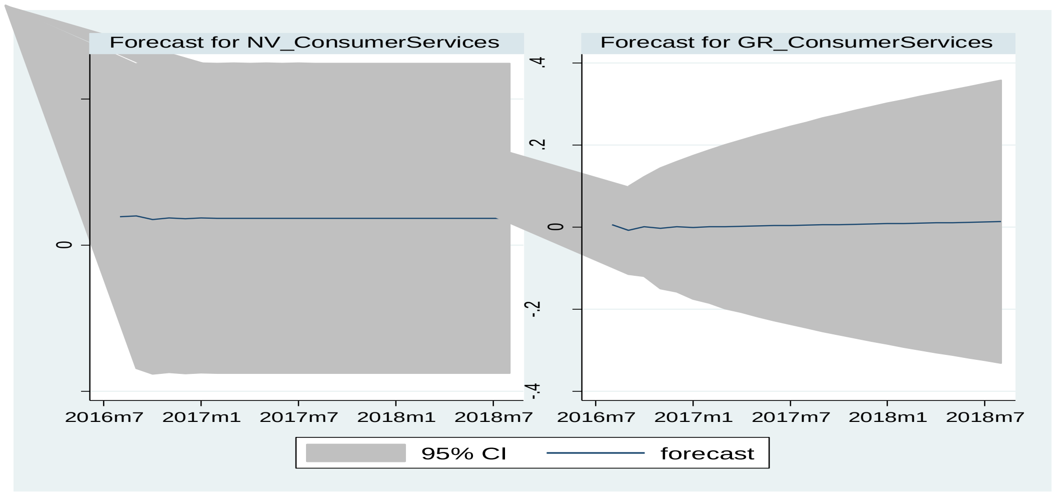
Figure 31 Forecasting



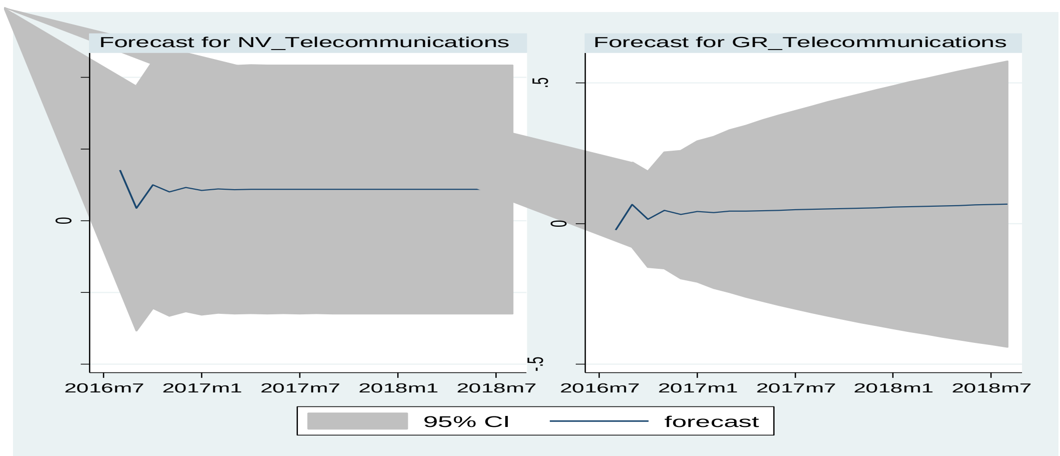
Healthcare



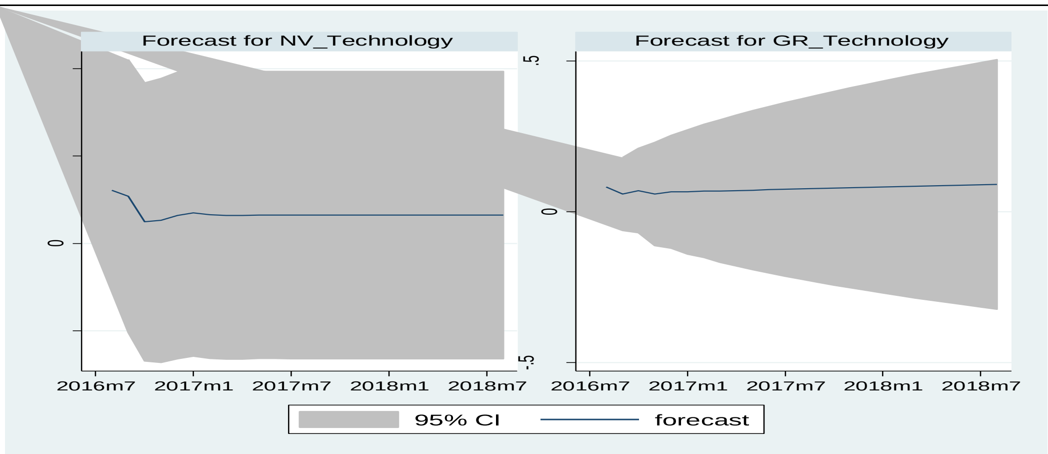
Consumer Services



Telecommunications

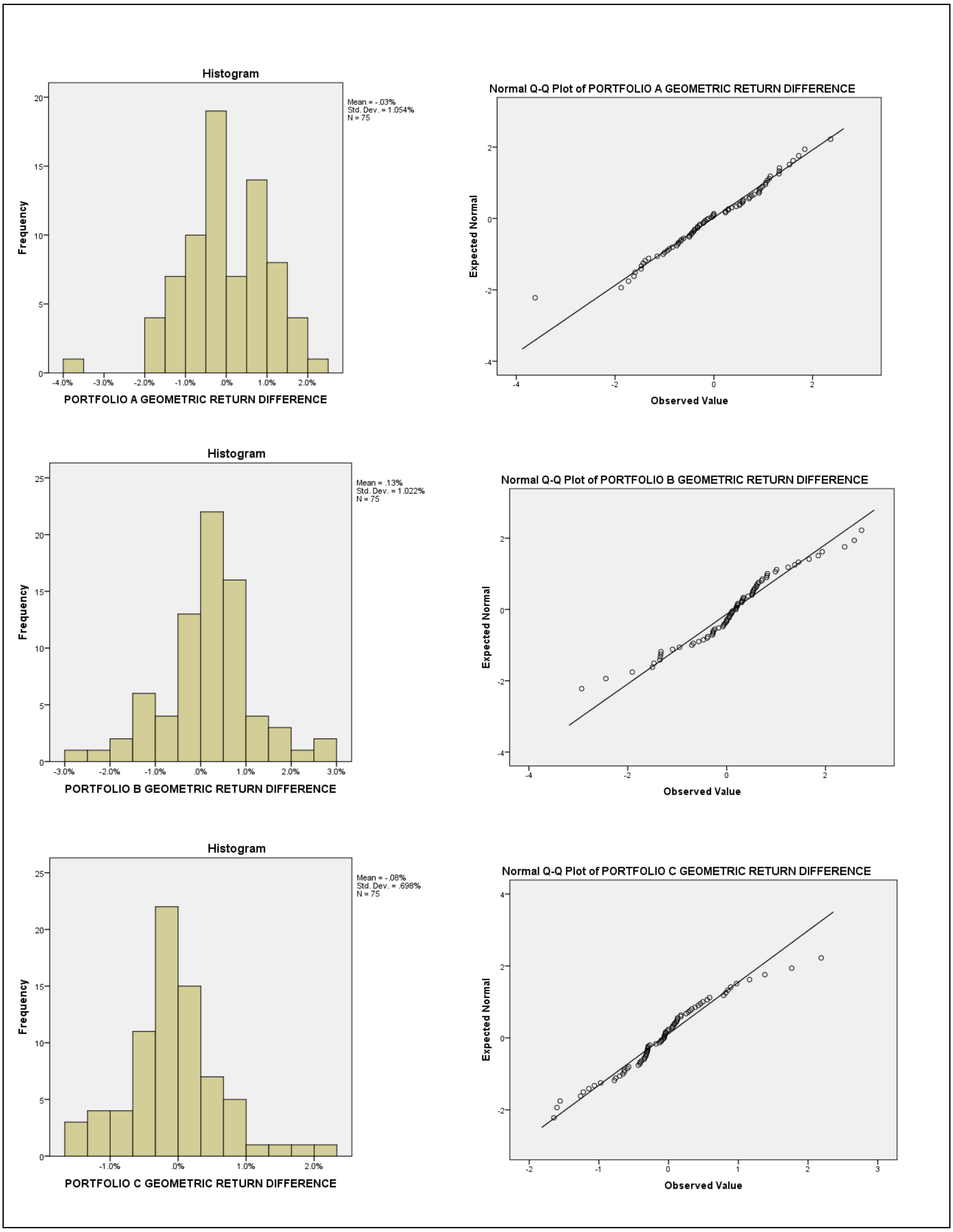


Technology


Forecast for NV_Technology
Forecast for GR_Technology
0
.5
-.5
2016m7
2017m1
2017m7
2018m1
2018m7
95% CI
forecast

APPENDIX K: PDF and QQ plots

Figure 32 PDF and QQ plots for portfolio return differences to May 2015



APPENDIX L: Tests for normality

Table 15 Kolmogorov-Smirnov and Shapiro Wilk tests

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PORTFOLIO A GEOMETRIC RETURN DIFFERENCE	.057	75	.200*	.981	75	.336
PORTFOLIO B GEOMETRIC RETURN DIFFERENCE	.112	75	.020	.962	75	.023
PORTFOLIO C GEOMETRIC RETURN DIFFERENCE	.103	75	.049	.966	75	.041

APPENDIX M: T-test

Table 16 Paired sample t-test for portfolio A return difference

		Paired Differences	t	df	Sig. (2-tailed)
		95% Confidence Interval of the Difference			
		Upper			
Pair 1	PORTFOLIO A GEOMETRIC RETURN - BENCHMARK GEOMETRIC RETURN	0.2168%	-.211	74	.833

APPENDIX N: Wilcoxon tests

Table 17 Wilcoxon tests for portfolios B and C return differences

	BENCHMARK GEOMETRIC RETURN - PORTFOLIO B GEOMETRIC RETURN	BENCHMARK GEOMETRIC RETURN - PORTFOLIO C GEOMETRIC RETURN
Z	-1.705[b]	-1.371[c]
Asymp. Sig. (2-tailed)	.088	.170