INDEX/SECTOR SEASONALITY IN THE SOUTH AFRICAN STOCK MARKET

STUDENT NAME: JUSTIN ROVIAN NAIDOO

STUDENT NUMBER: 0204588K

SUPERVISOR: DR ODONGO KODONGO

Declaration

I, Justin Rovian Naidoo, declare that this research report is my own work. Where someone else's work was used (whether from a printed source, the Internet or any other source) due acknowledgement was given and reference was made according to departmental requirements. It is submitted in partial fulfilment (50%) of the requirements for the degree of Master of Management in Finance and Investments at the Witwatersrand Business School.

Signed:

____

____

(Date)

Abstract

This paper aims to investigate the apparent existence of two anomalies in the South African stock market based on regular strike action, namely the month of the year effect and seasonality across specific sectors of the Johannesburg Stock Exchange.

Table of contents

1 Introduction

1.1 Background

This paper investigates the apparent existence of two anomalies in the South African stock market based on regular strike action, namely the month of the year effect and seasonality across specific sectors of the Johannesburg Stock Exchange. If these anomalies are found to be real, this would violate a fundamental pillar of finance theory– the Efficient Markets Hypothesis. The Efficient Markets Hypothesis (EMH) states that asset prices fully reflect all available information and that past priceinformation should allow for no prediction of future prices (Fama and French, 1988). The EMH is predicated on the Random Walk Theory,which postulates that future asset price changes cannot be predicted based on previous information and are indeed random.This study is inspired bypersonal observations as anequity stock and derivativestrader: each year at the Johannesburg Stock Exchange, it appears that fundsflow from theJohannesburg Stock Exchange's Resource Index(referred to as the RESI henceforth) intodual-listed stocks ahead of the anticipated South African strike season, namely from March onwards.As evidence of this, most bargaining council negotiations start in March and utilise industrial action as a means of leverage in these talks. In past years,industrial discussions have started in March but there is a notedincreasing impetus from unions to start negotiations earlier on in the year. Appendix 8, referenced from Statistics South Africa's Mining, Sales and Production review (2014), clearly graphs that from 2009 to 2012, mining production started declining from March onwards due to industrial action. They also note that the largest strike to hit the platinum mining sector ever started on 23 January 2014, resulting in a negative 6.5% loss in production year on year as of May 2014.The graph based on Statistics South Africa's industrial action analysis tracker clearly shows industrial action starting much earlier than in previous years. TheJohannesburg Stock Exchange RESI is constituted by the 10 largest resources shares by rand market capitalisation.

This paper has not investigated strike causality directly on share prices but ratherviewed it as an impetus to influence investor sentiment, and thus instead looked at why shares are bought and sold during this period, both pre-emptively and during the periods mentioned.Strike season is well known to South African investors and it would be expected that this seasonal pattern would be priced into securities ahead of strike season, but research by the likes of Becker and Olson (1986) show that this is not always the case.

The Annual Industrial Action Report (2013), published by the Department of Trade and Industry (DTI), presents the results of strike activities from January 2012 to December 2012. Overall, the year 2012 showed a comparably high increase when compared to the previous four years. A total of 99 strike incidents were recorded in 2012.There were 67 recorded strikes in 2011 and 74 in 2010. Going further back, there were 51 in 2009 and 57 in 2008. As a result of these strikes, the working days lost were 3 309 884 in 2012 (with 241 391 employees) as compared to 2806 656 in 2011 (with 203 138 employees).In addition, R6.7 billion was lost in 2012 in terms of wages, compared to R1.1 billion in 2011. More worrying is that 44% of strikes in 2012 were wildcat and thus unprotected, with 57.5% of total workers involved in the labour unrest from the mining sector where a wave of wildcat action was observed. Wildcat strikes are those where the striking takes place without permission or prior consent and are known for their documented violent nature in comparison to sanctioned strikes. The mining sector lost the most working days due to this strike action (82.4%), followed by the manufacturing (5.7%), community (4.1%) and agriculture (3.7%) sectors in 2012.The Annual Industrial Action Report (2013) shows that there has been an increase of 15.1% from 2012 to 2013 in terms of strikes recorded. The mining sector continued to be the most affected industry, with 515 971 days lost due to these strikes.

The mining sector is the primary sector for the focus of this research, in terms of the share price variations of constituent companies. The sector comprises resource shares, which are diversified across the various minerals and oils that amount to 50% of our export economy, as noted by Statistics South Africa (2014). These companies specialise in mining variousmineralsand provide coal, iron ore, copper, oils and their synthetic counterparts, characterised by Sasol Pty (SOL code on the Johannesburg Stock Exchange). Platinum was heavily hit by the 2014 strike actionand can be characterised by Anglo Platinum Pty (AMS-short code on the Johannesburg Stock Exchange). Gold can be characterised by Anglo American Pty (AGL -short code on the Johannesburg Stock Exchange)

Preliminary data supporting these observations ispresented in the discussion that follows.

1.1.1 Initial observation

Theinitial investigation to ascertain the possibility ofa relationship between month of the year effects and if there were any apparent seasonal movements between different stock sectorsisshown in Table 1. From the tables included, it is clear thatthe data points to there being a definite month of the year effect and indeed seasonal movements instocks sectors that warrants deeper investigation. Theinitial investigation was structured asfollows:The first step was tocreate an index based on the nine biggest dual-listed stocks by rand value market capitalisation. Thesenine specific stocks were chosen as they had sufficient data required for the research, as they had all been listed for at least 10 years. They were also the largest by rand market capitalisation and thus the big names in the mining industry, therefore the most targeted by labour unions for remuneration increases to workers. Their average monthly variation figures for 2013 were compared to The Johannesburg Stock Exchange's RESI to determine whether initial data showed any consistency with the hypothesis that come strike season (pre-emptively April/May), investment funds flow out of the RESI Index and its constituents and into "safe haven assets", namely dual-listed (or rand hedge) stocks.

The RESI comprises mining and resource stocks which, in theory, should all decline when industrial action starts.

Rand hedge stocks can be defined as companies listed on at leasttwo exchanges, at least one of which must be outside of South Africa. They must also incur a large proportion of their costs in South African rand,the bulk of whose revenue are denominated in foreign currency, such as U.S. dollars. Barrand Kantor(2005) go a step further and distinguish between rand hedge, rand leverage and pure randplay stocks.Barrand Kantor(2005) further expand by saying that rand hedge stocks have mostly U.S.dollar revenues and dollar costs. Rand leverage refers to companies with dollar revenues and rand costs, whilerand play stocks have most of their costs and revenues in rand value. The authors also state that few companies fall neatly into a specific category as most South African conglomerates have a mix of local and foreign assets. This definition of incurring the bulk of costs in South African Rand (ZAR) and generating the bulk of revenues in dollars/foreign currency will thus be used in the rest of this study. Table A1, contained in the appendices, shows the make-up of the Johannesburg Stock Exchange's Top 40 Index and how it is largely resource based. Table A2, contained in the appendices, shows the make-up of the Resource Index 10 (RESI). Table1 represents data on the monthly changes in the value of dual-listed stocks and the resource index for the period 2013.

Table 1: Variances of dual-listed stock vs. RESI

Monthly averaged data was used.The index starts at zero for the sake of clear movements from the baseline index, set at 0. Red signifies negative cumulative average variation, whilst black represents positive cumulative average variation. One year was chosen as an initial assessment of the initial theory, to see if it warranted deeper investigation. As 2013 was very labour dispute intensive, it is a prime year to test for patterns in stock movement and would warrant researching deeper into the last 10 years if significant evidence of patterns emerged from this initial research.

Variations in Index Levels													
Stock	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	CUM %
Anglo American plc	0	0.032293	-0.08563	-0.18234	0.107898	-0.01272	-0.0412	-0.03901	0.017812	0.019505	-0.03382	0.026649	-19.0560%
BHP Billiton plc	0	-0.01671	-0.06424	-0.13341	0.183321	-0.04937	0.058477	0.074032	-0.12125	0.295896	-0.04214	-0.18424	0.0346%
British American Tob plc	0	0.012993	0.022716	-0.11308	0.231535	-0.02088	0.099707	0.018679	-0.16156	0.266609	-0.03695	-0.18522	13.4543%
Compagnie Fin Richemont	0	0.036145	0.040868	-0.12283	0.22926	-0.0962	0.012531	0.139012	-0.09851	0.258076	0.083316	-0.11259	36.9083%
Firstrand Ltd	0	0.054439	0.039897	-0.14266	0.296087	0.002347	0.059989	0.029887	-0.16032	0.228647	0.028522	-0.16101	27.5820%
Naspers Ltd -N-	0	0.071912	0.047012	-0.06767	0.222144	-0.04057	0.02977	0.074395	-0.11358	0.329799	-0.03481	-0.18836	33.0031%
SABMiller plc	0	0.046307	0.016796	-0.11089	0.214252	-0.03957	0.119015	0.062585	-0.13936	0.235237	-0.01985	-0.15779	22.6727%
Sasol Limited	0	0.007187	-0.043	-0.1785	0.192941	-0.04429	0.001664	0.031346	-0.08702	0.214795	-0.04507	-0.20618	-15.6130%
Standard Bank Group Ltd	0	0.058638	0.01156	-0.13058	0.246818	-0.04355	0.029358	0.010265	-0.19028	0.192873	-0.02707	-0.18618	-2.8149%
Resource 10	0	-0.0003	-0.07048	-0.17111	0.184627	-0.04125	0.008795	0.0274	-0.11936	0.252653	-0.0524	-0.21116	-19.2578%

Table 1.2 : Cumulativeaverage variation results less non-mutually exclusive stocks

Performance 2013	
Other 6 dual-listed stocks	21.8009%
Resource 10	-19.2578%

Mutual stocks found in both indices have beenremoved for ease of reference.The table shows that when mutual stocks found in both indices are removed and there is thus no duality of data as mutual stocks such as Anglo American, BHP Billiton and Sasol have been eliminated from this paper, the returns are almost inversely correlated.This could indicate a direct flow from one JSE sector into another JSE sector.These stocks were removedwhen looking at movements, because they belong in both categories and thus investors might want to hold their positions in these stocks and trade the non-mutual stocks to exploit the rand hedge play. With these mutual stocks removed, you see an almost 1-to-1 inverse correlation(+21% vs -

19). Information is widely available to all investors, but the potential for these movements to have been actioned by sentiment can not be removed, whether rational or not.

Correlation:

A correlation exercise with these seven assets was run. These were the results as computed by Microsoft Excel:

Table 2:

	BTI	*CFR*	*FSR*	*NPN*	*SAB*	*SBK*	*RESI*
BTI	1						
CFR	0.959792	1					
FSR	0.934194	0.910183	1				
NPN	0.913511	0.910606	0.760651	1			
SAB	0.959622	0.945839	0.909113	0.9626	1		
SBK	0.68591	0.656168	0.43229	0.773685	0.673074	1	
RESI	0.619055	0.646032	0.613805	0.502413	0.509226	0.66891	1

As Table 2 shows, a number of these stocks have high correlation coefficients.1 shows perfect positive correlations as shown by BTI against BTI, equaling 1. A number of these stocks have correlations above 0.75, showing high positive correlation and may indicate a joint sector-based movement due to investor action, indicated in green.

1.2 Purpose of the study

The purpose of this study wasto investigate the existence of any month of the year effects on the JSE, specifically with regards to the RESI.Any effects may cause investmentRands to be moved from these resource/mineral and mining stocks into other stock sectors, such as the dual-listed sector. Muzenda (2012) replicated the work of Jegadeesh (1990) in the South African context. Muzenda(2012) tested individual stocks and twoportfolios comprised via return and market capitalisation, only to find thatthis method did notreliably predict returns on these stocks or portfolios. Darrat, Bin and Chung (2013) found no evidence of a “January” or “December” effect, but did find evidence of a “day of the week” effect, with Mondays and Tuesdays delivering significantly lower returns than on their benchmark of Wednesday.Alagidede (2012) found significantly higher returns in stocks preceding holidays and that month of the year effects are indeed present in African stock markets.

Ngidi (2011) states that the market reacts negatively from five days prior to an announced strike and continues on a downward trajectory up to five days post-strike. Persons (1995) conducted a detailed review on the effect of automobile strikes on the stock value of steel suppliers in the U.S. for the period 1965-1990. He stated that on announcement of automobile strikes, steel suppliers experienced statistically significant negative returns, about equal to the negative returns experienced by the actual automobile manufacturers. He concluded that researchers and policy-makers evaluating the private and social costs of strikes should consider the effects on the profitability of the stock of the strike-affectedindustries,as well as of the linked industries.

There has been a fair deal of research conducted on the South African stock market but there is a research gap as.While all the available research addresses seasonality across the entire JSE, it does not address seasonality or causality across indexes or categories of stock sectors. This is the gap this paper aims to address, as well as to substantiate whether there is seasonality/causality present across stock sectors, and whether this provides an above-market return opportunity for investors.

1.3 Research questions

1. Arethere seasonal changes in the RESI that provide arbitrage opportunities, which might be exploited by stock investors?
2. Arethere seasonalchanges in rand hedge stocksthat provide arbitrage opportunities, which might be exploited by stock investors?
3. Is there a relationshipbetween changes in the RESI and the changes in rand hedge stocks?

1.4 Research hypothesis

H_0^1: Returns on rand hedge stocks do not possess seasonal characteristics that may be exploited by investors
H_0^2: Returns on stocks in the RESI do not possess seasonal characteristics that may be exploited by investors

1.5 Research objectives

1. To determine whether there are month of the year effects on South African stocks.

2. To test for possiblerelationships betweentwo sectors of the South African stock market,namely the resource sector (with the RESI used as proxy) and the dual-listed rand hedge sector,comprising the nine stocks used in these tests.

1.6 Significance of study

This study will be highly beneficial to all stakeholders in the South African economy. It will benefit anyone investing in the local South African economy, either in equity or equity derivatives as it may prove or disprove the widelyknownrand hedgeasset safe haven hypothesis.It will also be beneficial to any short-term traders looking to profit from seasonality between different JSE stock sectors.

1.7 Limitations

A limitation is the effect of a volatile rand on the price of stocks, with a weakening rand also contributing to pushing up the price of rand hedge/dual-listed stocks (not entirely pure dollar income vs.dollar expenditure). This is because they pay their costs in rands but their exported goods get paid indollars, which means that a weaker rand results in more profits for them.

All of the above, namely investor action driven by sentiment and movements in the rand (listed as ZAR),mayin fact be caused by perceived negativity over strikes, but falls out of the scope of this study. It may well be a topic for further research.

Outline of the study

Aliterature reviewis conducted in the second chapter of this research. The literature review will be basedon journal articles, theses and papers covering existing work in this area of research. The third section will contain the research methodology used to analyse the data set and the information surrounding the hypothesis test. Results will be disclosed in the fourth chapter, with the fifth chapter comprising a conclusion drawn from the research results, as well as suggestions for how this research can be furthered in the future in the fifth chapter.

2. Literature review

2.1 Introduction

All material issues that have been proven tobe foundational with regards toaffecting shares prices have been included, as well as reviews on literature with specificattention on this study'sarea of focus. As mentioned regarding purpose of the study, there is no direct research on seasonality and causality between sectors on the Johannesburg Stock Exchange as of time of submitting this paper. The concepts and components of factors causing seasonality and causality will then be discussed in order to highlight the focused area of this research.

2.2 Factors influencing share prices

2.2.1 Economic factors

Gruber (1966) states that the price of a share should be equal to the present value of a stream of future benefits, discounted at a rate thatreflects both the stockholder's time preference and attitude towards risk. Benefits are future dividends, whilst the operating characteristics of the firm, financial structure, size and time path of dividends all affect the rate at which the stock would be discounted. Gruber (1966) found that the Discounted Cash Flow (DCF) fundamental valuation technique was successful in explaining an average of 87.5% of the variation of yearly stock prices. This leaves a substantial portion unaccounted for. The study concluded that (a) a rise in stock prices was usually accompanied by an increase in the stock holder's time horizon, as evidenced by the increased importance of growth, operating risk, financial risk and size, and the decreased importance of dividends; (b) that a fall in stock prices was usually accompanied by a decrease in the stockholder's horizon; and (c) that the stockholder's time horizon increased over the entire period.

Abdullah and Hayworth (1993) investigated the macro-economic factors affecting stock prices and found that stock returns are positively related to inflation and money growth and negatively to budget deficits, trade deficits and both short- and long-term interest rates. They further state that these factors, along with output growth and lagged information, account for substantial proportions of the forecast error variance of stock prices.

Timmermann (1993) focused on how learning creates excess volatility and predictability in stock prices and found that learning affected predictability of excess returns and the excess volatility of stock prices. Estimation uncertainty may therefore increase the volatility of stock prices andthe estimation of dividends growth lower than the ‘true’ value tends to increase dividend yields and capital gains. A key factor in the valuation of stock prices relates to parameters used in the dividend estimation process. Timmermann(1993) states that in a Rational Expectation model (RE), stock prices are proportional to dividends and so a dividend shock will be reflected in a proportional shock to the stock price.Learning also implies an additional effect on stock prices, as the estimated growth rate of dividends is also influenced by the dividend shock. Volatility may arise when stocks are valued by dividend growth rates different to their true dividend growth rates (estimation uncertainty). Analysts may thus have different valuations for stocks and traders may buy or sell stock based on these valuations, further fuelling volatility.

Gallagher and Taylor (2002) investigated the interaction between macro-economic shocks and stock price movements by investigating temporary and permanent aspects of these shocks. This study built on the initial work of Fama and French (1988), which investigated the mean reverting nature of stocks. Fama and French (1988) state that U.S. stock prices contain a slowly decaying temporary component and induce returns characterised by a large negative autocorrelation process for long return horizons of several years. Fama and French (1988) further showed that between 25% and 45% of the variation of three to five years stocks researched, appear to be predictable from past returns. Gallagher and Taylor (2002) showed that aggregate demand shocks had a temporary effect on stock prices, whilst supply side shocks may affect the real stock price permanently. They further allude to the market value of stocks deviating from theirfundamental value but reverting to their mean as non-random walks. This takes into account noise trading, fads and speculative bubbles.

Adrangi, Chatrath and Todd (1999) investigated the relationship between stock returns and the inflation rate in industrialised economies. They built on the proxy effect cited by Fama and French (1988), which states two propositions. Proposition A states that contrary to the suggestion of the Phillips curve, there is a negative relationship between inflation and real economic activity. Proposition B states that stock returns are directly related to real economic activity.

Adrangi,Chatrath and Todd (1999) state that the negative relationship between real stock returns and inflation rate persists even after the negative relationship between inflation and real activity is purged. They conclude that real stock price may be adversely affected by inflation because inflationary pressures may threaten future corporate profits, and that nominal discount rates rise under inflationary pressures, reducing the current value of future profits and thus stock returns. A key point is that the research put forth by Adrangi,Chatrath and Todd(1999) points to supporting the proxy effect in the long run but not in the short term.

Furthermore,Balcilar (2004) addresses long-term memory persistence inflation. He found that numerous countries have experienced very long periods ofinflation and that the inflation reproduces itself in the absence of new shocks. For example, the inflation process in Turkey was found to be highly persistent and the feedback mechanism was so strong that current supply shocks such as oil price hikes automatically translated into permanent increases in the rate of inflation. Monetary and fiscal policies failed to curb this inflation because inertia had rendered it unresponsive to demand. This supports the findings of Adrangi, Chatrath and Todd(1999) as well asFama and French (1998), in that it shows that inflation negatively affects real activity and thus negatively affects stock prices.

Pearce and Roley (1985) investigated the effect of news on stock prices, particularly regarding the Consumer Price Index (CPI), Producer Price Index (PPI) and the Federal Reserve's discount rate. They concluded that new information related to monetary policy/supply directly affects stock prices. In particular, money announcement surprises have a significant negative effect on stock prices. PPI announcements were found to have significant effects (whether positive or negative) on the day but these faded in one week. The researchers also concluded that anticipated components of economic announcements had no significant impact on stock prices because these would have already been priced into the stock.

All of the above-mentioned factors are seminal work in the area of stock price valuations and share price prediction. These are largely technical issues with regard to valuations and macro-economic with regard to over-arching impact on share price. Mentioning the above authors puts into perspective the amount of literature in existence when trying to understand, track and predict share pricemovements. The above body of work shows that macro-economic determinants can be used to predict themajority of a stock's movement but not its entire movement, as the debate between random walk theory and whether stocks are mean reverting continues. This alludes to the fact that even with all the available science and literature,and while stocks are to a large degree predictable, a big margin of variationexists for them to move, thus rendering prediction difficult.The remaining portion that affects a stock's movement must be made up of soft,non-macro-economic factorslike behavioural finance, mentioned below such as investor sentiment, as well as further issues, which also follow below.

2.2.2 Politics/labour unrest and the stock market

Asteriou and Siriopolous (2000) found a significantly negative relationship between socio–economic uncertainty and economic growth. In another paper, Asteriouand Price (2000) delved deeper into this topic, stating that political instability encompasses governments, regimes such as trade unions and communities within a nation. They assert that socio-political instability has two effects, namely of creating uncertainty concerning the political and legal environment and secondly of disrupting market activities and labour relations, resulting in significant adverse effects on production. They state that this instability will reduce the available factors of production and subsequent investment of physical capital will be affected.

Beaulieu and Cosset (2005) investigated the topic of political risk on the volatility of stock returns.They found that unfavourable news of political risk had a more significant impact on stock price returns than did positive news. They also show that stock return volatility varies with a firm's exposure to political risk, structure of assets and the extent of foreign involvement. A sovereign nation's risk profile will affect its probability of default, credit rating and spreads as well as capital flight to and from that country. Furthermore, political instability often leads to depreciation of that country's currency. All of these factors directly influence investor confidence of the stocks listed in those countries and subsequently affect their actions.

2.2.3 Industrial action

Phang(2004) quotes the Monetary Authority of Singapore (MAS), stating that there are significant economic costs related to industrial relation events such as strikes, slow-downs or work stoppages. Evidence from factors such as firm level measures of output and output per worker is strong in this regard. Phang (2004)investigated the effect of unrest at Caterpillar during 1999, between Caterpillar and the United Auto Workers Union (UAW). This research found that product quality is linked to effort and Phang(2004) concluded that the temporal patterns of resale prices, appraisal reports, resale rates and list prices for equipment all declined. He addsthat pieces of equipment produced in facilities undergoing unrest were resold more often, received worse appraisal reports and had lower list prices. Furthermore, equipment produced in the entire U.S. during the dispute period were discounted by 5%, which can be attributed to a reduction in salvage value, reduced productivity of the equipment or increased operating expenses.

Dinardo and Hallock (2002) investigated the impact of strikes on financial markets for the period 1925 to1937. They mentionthat news generated by typical strikes seems to register in share prices very early in the strike, but that there were also fairly large stock price reactions to news only fully revealed at the end of the strike. They conclude that longer strikes, violent strikes, strikes won by unions, strikes leading to union recognition, industry-wide strikes and strikes leading to wage increases affected industry stock prices more than strikes with other characteristics.

Linked to this, Davidson, Worrell and Garrison, (1988) put forward that the market reacts negatively and significantly to a strike’s onset and positively but statically insignificantly to a strike’s end. Becker and Olson (1986) further discuss howthe market consistently underestimates the effects of strikes in the pre-strike period. This is evidenced by the fact that two thirds of the total decline in returns occurs after the announcement of strikes. Davidson, Worrell and Garrison, (1988) concludethat there appears to be a permanent loss to the shareholders of companies that experience strikes.

Britt and Galle (1974) investigated the structural components of a strike. They found the concentration of workers and degree of unionisation to be twokey factors affecting the structure of strikes.More heavily unionised industries tend to be characterised by broader, shorter and more frequent strikes. They also observed that breadth and duration are critical determinants of strike shape and that effective strike shape does not change as the union becomes larger. The probability of a strike does increase as the union becomes larger, in thatlarger unions have access to larger funds, thus affecting the probability of a strike occurring.

In the local context, themost accurate source of industrial action-related data is the Department of Labour's annual Industrial Action Report. The 2013 edition summarises the past four years and notes the increase of industrial action, citing 51 incidents in 2009, 74 in 2010, 67 in 2011, 99 in 2012 and 114 recorded in 2013.It notes an increase in wages lost in 2013 amounting to 6.7 billion rand, up from 6.6 billion rand in 2012, with the average wage increase at 8%, a level above inflation. Added to this, the South African Transport and Allied workers Union (SATAWU) and National Union of Mineworkers (NUM) had the biggest participation strike rate of members and, due to sheer volume size, were able to negotiate a 25.7% and 17.4% wage increase respectively. The Departmentelaborates on this by stating that low wages, rising inequality and tough economic conditions had led analysts to predict toughnegotiations in 2013. This was also influenced by above-average wage increases granted in 2012. It was found that the mining, manufacturing and community industries were hardest hit, case in point being the manufacturing industry, which contracted 6.6%, forcing car giant producer BMW to stop its expansion projects in South Africa and look for new manufacturing locations overseas. There's a 25% unemployment rate in the mining, manufacturing and community sectors, which is set to continue to negatively affect the economy in the next two to three years.

The above literature reviewed on industrial action is of vital focus for this research,as it shows the widely known extent of the negativemacro-economic result of industrial action in South Africa. Industrial action has been proven to be increasing in both duration as well as volume of incidents, thus increasing the negative spill over into production costs for mining firms. Savvy investors would be cognisant of the data and act to find a way to benefit from this. Interestingly, the Efficient Markets Hypothesis states that an efficient market would render this information useless.This conversely raises the issue of whether investors are indeed able to find a way to benefit from this yearly cycle of strike action and if seasonality does in fact exist.

2.3 Stock return seasonality

Beaulieu and Cosset (2005) investigated the topic of political/event risk on the volatility of stock returns. They found that unfavourable political risk news had a more significant impact on stock price returns than did positive news. This researchwill not investigate the causality of mining unrest on indexes but rather focus on proving or disproving whetherstock return seasonality does in fact exist in different South African sectors.

Corhay and Hawaini (1987) found that there is seasonality in risk premiums of stocks across the U.S., France, the U.K. and Belgium. This in turn influenced portfolio returns, which can be attributed to an increase or decrease in consumer appetite for these risk and reward levels. This builds on the work of Gultekin and Gultekin (1983), which observed this same phenomenon in multiple stock exchanges around the world. Patton and Verardo (2012) further expanded this concept by stating that betas increase on earnings announcement days and revert to their average levels two to five days later. They also foundthat the increase in betas is greater for announcements that have larger positive or negative surprises.

Furthermore, Heston and Sadka (2010) assert that stocks that outperform the domestic market in a particular month continue to outperform the domestic market in that same calendar month for up to four years. They also notethat global trading strategies based on seasonal predictability outperform similar non-seasonal strategies by over 1% per month. They found thatthese abnormal seasonal returns persist even after controlling for size, betas and value.

Saad (2004) further emphasised this by investigating seasonality in the Kuwait stock market. Kuwait has no taxation and thus new factors must be considered as the taxation effect is normally attributed to seasonal effects on stocks. This expands the work of Wachtel (1942) who first observed seasonality on the New York Stock Exchange (NYSE). He observed bullish tendencies from December to January for 11 of the 15 years studied,and attributes this to year-end tax-loss selling. The tax-loss selling hypothesis is that Capital Gains Taxation incentivises investors to realise losses at the end of the year and this puts downward pressure on these stocks that are sold. This downward pressure passes with the coming of a new tax year and these over-sold stocks rebound, causing high returns in January, known as the January effect.

Saad (2004) also picked up seasonality in the absence of taxation in Kuwait. July seasonality was detected in his research. He attributed this to August being holidayseason (Ramadan) in Kuwait, with investors investing idle cash and rebalancing their portfolios during July. Husain (1998) also investigates the seasonal effect of Ramadan. People are well aware of this annual event but seasonal effects still persist. Seasonality is evident not so much in reduced returns but more so in reduced volatility attributed to investors taking less risky gambles/trades during this holy month. Husain (1998) posits that investors may benefit during this known time period from the reduction in volatility. Savvy investors may well change their strategies during this time period to benefit from a more predictable set of returns by moving funds to more risky or less risky investments for this time period, depending on their risk appetite. These investments may be more risky, but this seasonal effect renders them more predictable and less volatile. Investors may then switch out of these investments at the end of Ramadan.

Per Hylleberg(1992), seasonality is the systematic,although not necessarily regular,intra-year movement caused by the changes of the weather, the calendar, and timing of decisions, directly or indirectly through the production and consumptions decisions made by the agents of the economy. These decisions are influenced by endowments, the expectations and preferences of the agents and the production techniques available in the economy.Granger (1979) wrote the seminal work on seasonality, definingfour distinct classes of seasonality, namely:

<u>Calendar:</u>Certain public holidays, such as Christmas and Easter, affect data related to productions. The number of monthly working days may affect flow variables, such as imports and productions.

<u>Timing of decisions</u>: Seemingly uneconomically related events, such as school holidays, company dividends payments dates andtax year-end all cause seasonal affects as they occur at the same time every year. They are very deterministic and cause pronounced seasonal components, such as employment rates.

<u>Weather</u>: Actual changes in temperature, rainfall rate and the like have direct effects on agricultural production, construction and transportation and can directly affect the economy.

<u>Expectation</u>: Expectation can lead to plans that in go on to cause seasonality and perpetuate seasonality, such as with seasonal holidays.

Deterministic seasonality is defined as when the “process started”. The opposite of the deterministic approach is the seasonal random walk model. This poses that the seasonal cycle is persistent but also changes persistently, variance is thus increasing and the process is therefore not stationary.

2.4 Investor psychology/sentiment and capital markets

2.4.1 Psychology

Alter and Oppenheimer (2006) address a psychological factor pertaining to stock prices. They address fluency, which is that people tend to prefer easily processed information, implying that simple cognitive approaches to modelling human behaviour sometimes outperform more typical, complex alternatives such as valuations. This is of potential benefit in that itshows investors like to stick to what they know and may in fact cause them to follow seasonal patterns to their trading strategies. In an event with negative ramifications for a stock, such as an insider trading scandal or strike, analysts may be able to predict where investor funds may flow to from the affected company.Vissing-Jorgensen (2003) states that investor expectations about future market returns depend strongly on the investor's own investment experience and that the expectation of certain variables does affect portfolio choice.The dependence of beliefs on own experience remains strong for high wealth investors, suggesting that information costs are not a likely explanation.

2.4.2 Sentiment

SrivastavaandRao (2014) showjust how important the concept of sentiment is in the modern economy. We have more information readilyavailable at a second's notice through various conventional financial systems, such as Bloomberg and Reuters, and new age social media, such as Facebook and Twitter. Srivastava and Rao(2014) focus on the impact of social mediaplatforms on stock markets. They note that there is growing interest from trading firms and hedge funds in mining social media to gauge public opinion to drive investment decisions. Never has there been a time when information has been so easily available, with people able to make and execute investment/trading decisions in seconds.

Although the speed of sentiment-related activity has changed, this concept is not new. Kamstra, Kramer and Levi (2003),wrote the boldly titled*Winter Blues: A Sad Stock Market Cycle*. Thisis a foundational paper in the field of psychology affecting investor behaviour. In particular, they investigated the effects of Seasonal Affect Disorder (SAD). SAD is a well-researched medical disorder, which proves that people's happiness (depression) levels are influenced by the shortness of days and exposure to sunlight. They proved that SAD levels were higher at higher latitude levels where the days are shorter and thus exposure to sunlight is lessened, causing depression. Depression results in symptoms such as trouble concentrating, loss of interest in sexual activity, social withdrawal, loss of sleep and weight gain. They proved that this depression of mood leads to risk aversion in investors. They observed unusually low investor returns before the winter solstice and higher returns following it.

Bakerand Wurgler(2006)go a step further and examine investor sentiment on different classes of stocks. They state that some stocks are more vulnerable to speculation, which could in turn result in investor action not in line with fundamentals and allow for arbitrage opportunities. A key concept is that vulnerable stock has highly subjective valuations. They state that concepts such as earnings, age of the company and dividends open up the stock to speculation from investors with higher risk appetites, who will either buy or sell these stocks in line with their sentiment-based view of future performance.

Cochrane (2003)considers that sentiment causes people to hold their money in stocks, as opposed to currency. Cochrane (2003) noted that IPOs were happening at regular intervals, with stock prices rising rapidly after their listing. These stocks were all over-valued and eventually caused the ‘dotcom’ bubble to burst.

In fact, sentiment plays such a great role that it has become an indicator of fear. The Chicago Board Options Exchange Volatility Index (VIX) has become the benchmark for sentiment in terms of whether people are fearful to invest or not. It measures the 30-day stock market volatility of the S&P 500 Index’s implied expectations. It is based on index points – the higher the number, the higher the perceivedvolatility, which in turn is perceived as fear and affects investor behaviour.

Sentiment has been established to be a real and proven motivator of investor behaviour and its impact on the South African economy cannot be discounted when you take into consideration the highly violent and proficient nature of our industrial action season.

2.5 Safe haven theory

Bauer and McDermott (2010) confirmed that gold is seen as the standard medium or asset by investors, acting both as a hedge and as a safe haven asset. A hedge is defined as an asset that is negatively correlated with another asset or portfolio. Safe haven then is defined as an asset that is negatively correlated with an asset or portfolio in certain periods. The distinguishing feature of these two definitionsis the length of time covered. In another paper, this time by Bauer and Lucey (2010), they make the case that gold is a safe haven asset for stocks for only 15 days after an extremely negative shock.

They also note that a hedge can co-move with stocks in negative periods due to herd behaviour or contagion versus safe haven assets, which always hold their value. They found this to be more strongly correlated to U.S. and European markets and that gold acts as a stabilising force for the economy by reducing losses in the face of extremely negative market shocks. Since the financial crash of late 2007/2008,the price of gold had risen 42%. They go on to define a safe haven asset as an asset that holds its value in the face of adverse markets conditions. This phenomenon is usually experienced on a short-term basis as the investor seeks to protecthis or her wealth when unexpected negative shocks arise and then switches out when markets conditions return to normal. Theresearch, however, points to gold not been proven to be econometrically significant as a safe haven asset in emerging markets like South Africa. Gold is seen as a universal hedge except in emerging markets, thus proving that personal trader observations about rand hedge stocks used as hedges does merit investigation if gold is proven not to be the benchmark hedge in South Africa.

Ciner,Gurdgiev andLucey(2013) explore work in the field of safe haven assets from a behavioural analysis viewpoint, in discussing investors making decisions under risk. Theystate that investors will exhibit extreme loss aversion in exceptional circumstances and move quickly between assets to minimiselosses. Thisadds rationale to why safe haven assets only comeinto play in extremely negative market conditions.

Bodington (2014), in her thesis specificallyinvestigatinggold as a safe haven for South African stocks, found via various econometric calculations that gold does not act as a safe haven for international or dual-listed stocks. This is of paramount importance in that the local equity market as a whole in the South African context has been bearish on gold as an investment over the last three to five years. Savvy investors encompassing the entire spectrum from equity funds to short-term arbitrage traders would know that stocks are the best performing asset class over the last 30 years and invest in shares found to be safe havens compared to the current asset portfolios in times of adverse market conditions.

2.6 Chapter summary and conclusions

In conducting thisliterature review, many factors affecting the price of stocks were investigated. Mostof these foundational papers address the role of fundamental analysis or the valuation of the firm's underlying assets in relation to a stock's price. Gruber (1966) points out that 87.5 % of the variation in stock prices can be based on fundamental analysis, but that still leaves a sizable percentage unaccounted for. Thesubsequent reviews of literature discussed issues that may fill in the missing chunk, namely: learning, macro-economic shocks (such as noise, fads and bubbles), the effect of news, human psychology and sentiment encompassed by behavioural finance, political risk, the effects of strikes and seasonality. The amount of material reviewed on the issue of seasonality piquedinitial interest in this concept and identified a gap in the local South African market context. Occurrences such as tax selling, Ramadan and strikes do occur frequently and are well known but the literature review shows that the market has still not completely factored these into stock prices and that the potential does exist to benefit from these events.

Papers that showed the negative effects of strikes on shareholder wealth as well as the importance of unions in the industrial dispute context were also reviewed. Becker and Olson (1986) discuss that the market consistently underestimates the effects of strikes in the pre-strike period. This is evidenced by the fact that two thirds of the total decline in returns occurs after the announcement of strikes.Another aspect of the literature review involved an investigation into the persistence of seasonality in both developed and emerging markets, as well as the major role that sentiment has shown to play. Both these factors are important in the context of thisstudy in that strike action is seasonal in South Africa and many sources were referenced that showed the persistence and power of sentiment-driven investor action. What happens in times of strife was another major factor to consider, mainly through the safe haven asset theory, which has proven to be significant in developed economies but not emerging ones such as South Africa. But South Africa does indeed experience strife, so where do these investors place their money to minimise risk if it is not in gold? Papers referenced in the literature review indicate that it is usually placed in stocks over bonds. This means that if stocks are already part of a portfolio and they come under pressure, investors are more likely to move into another stock sector than an entire new asset class, such as commodities or bonds. Most trading platforms have evolved to specialise in either equity or specific asset classes to minimise transaction costs, and most day traders or those specialising in short-term strategies would only have access to equity markets, thus by necessity need to move into another equity sector.

Therefore, this paper willstudythis issue in the South African market context and explorewhether capital flight from seasonally, possiblystrike-affected companies, actually benefits companies as they are thought to be safer rand-hedge options.

3. Methodology

3.1. Introduction

This chapter discusses the research approach and the methodology used to achieve the research objectives, in which they will be analysed to answer the research questions of this study. The main aim of the chapter is to explore and present the estimation procedures used in analysing the direction of causality between stock market prices/indices. In it, the presence of monthly seasonality in stock market prices will also be questioned. Section 3.2 covers model specification and estimation of the Vector Autoregressive (VAR) model, including a description of the variables used. Unit root tests are discussed in Section 3.3. Section 3.4 discusses the Granger-Causality test under the VAR framework, with Section 3.5 covering the correlation matrix, variance decomposition and impulse response functions. Section 3.6 features a regression with autoregressive integrated moving average (ARIMA) errors modelling framework for modelling the month of the year effect in the data.

3.2 The Vector Autoregressive (VAR) model

The VAR model discussed in this project incorporates six stock market indices. All variables in a VAR model enter the model as endogenous variables. The purpose of the VAR model is to allow the incorporation of feedback in the model, in which all the seven variables in each model are allowed to affect each other and hence the interaction of all seven variables will be captured. The VAR model is given as:

$$\begin{aligned}\mathrm{RDF}_t = \alpha_0 &+ \sum_{i=1}^{p} \alpha_{1i}\mathrm{RDF}_{t-i} + \sum_{i=1}^{p} \alpha_{2i}\mathrm{CFR}_{t-i} + \sum_{i=1}^{p} \alpha_{3i}\mathrm{SBK}_{t-i} + \sum_{i=1}^{p} \alpha_{4i}\mathrm{SAB}_{t-i} + \sum_{i=1}^{p} \alpha_{5i}\mathrm{NPN}_{t-i} \\ &+ \sum_{i=1}^{p} \alpha_{6i}\mathrm{FSR}_{t-i} + \sum_{i=1}^{p} \alpha_{7i}\mathrm{RESI}_{t-i} + \varepsilon_{1t} \qquad (1)\end{aligned}$$

$$\begin{aligned}\mathrm{RCH}_t = \beta_0 &+ \sum_{i=1}^{p} \beta_{1i}\mathrm{RDF}_{t-i} + \sum_{i=1}^{p} \beta_{2i}\mathrm{CFR}_{t-i} + \sum_{i=1}^{p} \beta_{3i}\mathrm{SBK}_{t-i} + \sum_{i=1}^{p} \beta_{4i}\mathrm{SAB}_{t-i} + \sum_{i=1}^{p} \beta_{5i}\mathrm{NPN}_{t-i} \\ &+ \sum_{i=1}^{p} \beta_{6i}\mathrm{FSR}_{t-i} + \sum_{i=1}^{p} \beta_{7i}\mathrm{RESI}_{t-i} + \varepsilon_{2t} \qquad (2)\end{aligned}$$

$$\mathrm{SBK}_t = \gamma_0 + \sum_{i=1}^{p} \gamma_{1i}\mathrm{RDF}_{t-i} + \sum_{i=1}^{p} \gamma_{2i}\mathrm{CFR}_{t-i} + \sum_{i=1}^{p} \gamma_{3i}\mathrm{SBK}_{t-i} + \sum_{i=1}^{p} \gamma_{4i}\mathrm{SAB}_{t-i} + \sum_{i=1}^{p} \gamma_{5i}\mathrm{NPN}_{t-i} + \sum_{i=1}^{p} \gamma_{6i}\mathrm{FSR}_{t-i} + \sum_{i=1}^{p} \gamma_{7i}\mathrm{RESI}_{t-i} + \varepsilon_{3t} \quad (3)$$

$$\mathrm{SAB}_t = \vartheta_0 + \sum_{i=1}^{p} \vartheta_{1i}\mathrm{RDF}_{t-i} + \sum_{i=1}^{p} \vartheta_{2i}\mathrm{CFR}_{t-i} + \sum_{i=1}^{p} \vartheta_{3i}\mathrm{SBK}_{t-i} + \sum_{i=1}^{p} \vartheta_{4i}\mathrm{SAB}_{t-i} + \sum_{i=1}^{p} \vartheta_{5i}\mathrm{NPN}_{t-i} + \sum_{i=1}^{p} \vartheta_{6i}\mathrm{FSR}_{t-i} + \sum_{i=1}^{p} \vartheta_{7i}\mathrm{RESI}_{t-i} + \varepsilon_{4t} \quad (4)$$

$$\mathrm{NPN}_t = \varphi_0 + \sum_{i=1}^{p} \varphi_{1i}\mathrm{RDF}_{t-i} + \sum_{i=1}^{p} \varphi_{2i}\mathrm{CFR}_{t-i} + \sum_{i=1}^{p} \varphi_{3i}\mathrm{SBK}_{t-i} + \sum_{i=1}^{p} \varphi_{4i}\mathrm{SAB}_{t-i} + \sum_{i=1}^{p} \varphi_{5i}\mathrm{NPN}_{t-i} + \sum_{i=1}^{p} \varphi_{6i}\mathrm{FSR}_{t-i} + \sum_{i=1}^{p} \varphi_{7i}\mathrm{RESI}_{t-i} + \varepsilon_{5t} \quad (5)$$

$$\mathrm{FSR}_t = \tau_0 + \sum_{i=1}^{p} \tau_{1i}\mathrm{RDF}_{t-i} + \sum_{i=1}^{p} \tau_{2i}\mathrm{CFR}_{t-i} + \sum_{i=1}^{p} \tau_{3i}\mathrm{SBK}_{t-i} + \sum_{i=1}^{p} \tau_{4i}\mathrm{SAB}_{t-i} + \sum_{i=1}^{p} \tau_{5i}\mathrm{NPN}_{t-i} + \sum_{i=1}^{p} \tau_{6i}\mathrm{FSR}_{t-i} + \sum_{i=1}^{p} \tau_{7i}\mathrm{RESI}_{t-i} + \varepsilon_{6t} \quad (6)$$

$$\mathrm{RESI}_t = \delta_0 + \sum_{i=1}^{p} \delta_{1i}\mathrm{RDF}_{t-i} + \sum_{i=1}^{p} \delta_{2i}\mathrm{CFR}_{t-i} + \sum_{i=1}^{p} \delta_{3i}\mathrm{SBK}_{t-i} + \sum_{i=1}^{p} \delta_{4i}\mathrm{SAB}_{t-i} + \sum_{i=1}^{p} \delta_{5i}\mathrm{NPN}_{t-i} + \sum_{i=1}^{p} \delta_{6i}\mathrm{FSR}_{t-i} + \sum_{i=1}^{p} \delta_{7i}\mathrm{RESI}_{t-i} + \varepsilon_{7t} \quad (7)$$

WhereRDF represents Redefine Income Fund Ltd, CFR represents Richemont Securities Dr, SBK represents Standard Bank Group Ltd, SAB represents SAB Miller Plc, NPN represents Naspers Ltd, FSR represents FirstRand Ltd and RESI represents the Resource Index.

3.3 Data and data sources

The data has been obtained directly from the JSE. Data points will be analyseddaily to investigate foundational statistical properties of mean, standard deviations, skewness, kurtosis and outliers. The daily data will be converted to monthly averages to counteract noisy trading, when actual models are used to test for seasonality. Time periods are from 1 January

2003 to 31 December 2012, which amounts to 3650 daily observations /520 weekly and 120 monthly observations.This time period was chosen as it encompasses a number of prominent and headline-grabbing strikes. Saad (2004) claims that indices are the bestindicators of seasonality. Therefore the Resource Index (RESI) will be a proxy for the strike-affected mining industry and I will use the nine largest dual-listed stocks, as determined by market capitalisation, to represent the dual-listed industry. These will be used as proxy for the rand hedge category, which will amount to six stocks, once mutual stocks are excluded. These stocks are located in different sectors but are all deemed good rand hedges because of their overseas revenue streams.

3.4 Unit root tests and test for cointegration

3.4.1 Unit root tests

Gujarati (2004) found that financial time series data tends to follow an upward or downward trend. This normally leads to the problem of non-stationarity. Non-stationarity is due to the moments of a distribution, which are time-varying, as described by Gujarati (2004). Spurious regressions usually arise when there are ‘correlated time trends’, which appear to be attractive at face value but without any ‘meaningful economic relationship’, as found by Granger and Newbold(1986). Gujarati (2004) adds that if a non-stationary variable is regressed on another non-stationary variable; the results obtained will be spurious. In order to test for non-stationarity, unit root tests arecarried out and where the series is non-stationary, differencing is usually done until the series become stationary. In this project, the Augmented Dickey-Fuller (ADF) tests are used to investigate whether the variables are stationary or not. In equation (8), which represents the Augmented Dickey-Fuller specification, the unit root test is carried out as follows(Gujarati, 2004):

$$\Delta y_t = \beta_1 + \beta_2 t + \delta y_{t-i} + \sum_{i=1}^{m} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{8}$$

wherey_t represents the variable under consideration, Δ represents the first difference operator, and t stands for the time trend. The null hypothesis is that there is a unit root, i.e. $\delta = 0$ meaning the time series is not stationary. The alternative is that the time series is stationary, i.e. δ is less than zero.

3.4.2 Test for cointegration

Having checked the order of integration of the variables through carrying out of unit root tests, it is also necessary to check for the possibility of cointegration amongst given non-stationary variables (Engle and Granger, 1987; Gujarati, 2004; among others). The existence of such a long-running relationship typically occurs because of the relations of the stochastic trends of the given variables (Enders, 1995). As such, the variables may deviate from each other in the short run but eventually show affinity in the long run. Enders (1995) explained three important points with regards to the existence of cointegration:

a) Cointegration refers to a linear combination of non-stationary variables and the linear combination of the given non-stationary variables should necessarily be stationary.
b) For cointegration to exist, all the variables in a given model should be integrated of the same order. However, it does not necessarily follow that all variables that are integrated of the same order are cointegrated.
c) If a given vector, say H_t has n variables, there can be at most $n-1$ linearly independent cointegrating vectors and the number of cointegration vectors gives the cointegration rank.

Therefore, the fundamental aspect preceding the carrying out of any cointegration tests is that the variables should be integrated of the same order. If the variables are not integrated of the same order, then tests for cointegration cannot proceed. In addition, if variables are cointegrated, this will justify the use of error-correction models (ECMs) or the Vector Error Correction Models (VECMs) so as to test for the direction of causality. In this project, the unrestricted VAR model is used, with return series data for the stocks, which are all first difference stationary.

3.5 The Granger-Causality Model

The causality between stock market indices is one of the main hypotheses of the study. In this project, the concepts of causality as defined by Granger (1979) will be adopted. Granger (1979) explained causality as the case where Y_t is causingX_t, denoted as$Y_t \rightarrow X_t$. This is the instance where the use of the information set containing Y_t yields results that lead to a better explanation of X_t than if Y_t is excluded. Granger (1979) also explained the concept of feedback, denoting as $Y_t \leftrightarrow X_t$ and arising when the two variables cause each other and the inclusion of each of the variables in the prediction of the other variable leads to the yielding of better results; as well asthe concept of instantaneous causality, denoted as$Y_t \rightarrow X_t$. This is when the inclusion of the present value of Y_t leads to better results from X_t than if Y_t had not been incorporated in the estimation.

In this project, the return series data of the stocks will be used to test for Granger-causality. That is, if y_t and x_t are stationary time series, then the null hypothesis states that x_t does not Granger-cause y_t. Consider the regression model with lagged values of y_t and x_t given in equation (9).

$$y_t = a_0 + \sum_{i=1}^{m} a_i y_{t-i} + \sum_{j=1}^{k} b_j x_{t-j} + \eta_t \tag{9}$$

where $a_i, i = 0, \ldots, m,\ b_j, j = 1, \ldots, k$ are constants and η_t is an error term. Only lagged values of $x_t$thatare statistically significant are kept in the regression model. The decision rule using p-values will be to reject the null hypothesis that x_t does not Granger-cause y_t if the level of significance denoted by α (5% level of significance will be used in this project) is greater than the p-value.

3.6 The correlation matrix, impulse response and variance decomposition functions

The correlation matrix is employed in the study so as to investigate the relationship, i.e., either positive or negative and the interaction between stock market indices. The impulse response functions will also be employed in the study. These are used to capture the sensitivity of the long-run response of stock market indices. The variance decomposition function is important in that it explains the extent to which fluctuations in stock market indices can be explained by theirown variance and the extent to which they are explained by the variance of other variables. These impulse analysis models are very important in the sense that they enable us to analyse the financial markets in South Africa using the variables used in the Granger-causality tests. Variance decomposition analysis is useful in clarifying the percentage of variance of the forecasted variables (stock market indices) that can be attributed to its own variance. These results are expected to be consistent with the results from the Granger-causality.

3.7 Volatility and Regression with ARIMA errors

3.7.1Volatility modelling

The spread of asset returns is a major concern to stock brokers and risk managers in financial markets. This spread is referred to as volatility and is measured using the standard deviation of returns, the population standard deviation is usually not given and as a result an estimate is used, which is the sample standard deviation. This is calculated as:

$$\hat{\sigma} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(r_t - \hat{\mu})^2} \tag{10}$$

Where $\hat{\mu}$ is the estimated average return over the n-month period and r_t is the return calculated as:

$$r_t = 100\ln\frac{P_t}{P_{t-1}} = 100\big(\ln(P_t) - \ln(P_{t-1})\big) \tag{11}$$

With P_t and P_{t-1} as the current and one lagged stock prices on month t and $t-1$ respectively. The volatility of the return series is generally modelled using GARCH type models. GARCH models are an extension of the ARCH models developed by Engle (1982). Bollerslev (1986) extended the ARCH models to GARCH models. The GARCH model is given as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\,\varepsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i\,\sigma_{t-i}^2 \tag{12}$$

Where p is the order of GARCH process, q is the order of ARCH, α_0,α_i and β_i are constants, $\sigma_t^2$is the conditional variance of ε_t, ε_{t-i}^2 is the news about the volatility from the i^{th} period and σ_{t-i}^2 is the i^{th} forecast error variance.

3.7.2 Regression with autoregressive errors

In order to capture monthly seasonality in the stock prices, the regression model will be used with autoregressive (AR) errors given in equation (13). The model in equation (13) assumes that the error terms are auto-correlated.

$$r_t = \omega_0 + \sum_{i=2}^{12}\omega_i \mathrm{M}_{it} + u_t$$

$$\left(1-\sum_{i=1}^{p}\phi_i B^i\right)u_t = \varepsilon_t \tag{13}$$

Where r_t is the return series as defined in equation (10), ω_0, ω_i, ϕ_i, θ_i are parameters, u_t is a stochastic disturbance term (error term), which is assumed to follow an autoregressive model of order p (AR(p)), i.e. the error terms are autocorrelated, ε_t is assumed to be an uncorrelated error term, i.e. it is white noise, B is a backward shift operator ($Bu_t = u_{t-1}$), M_{it} are dummy variables representing the months February up to December. The variable M_{it} takes value 1 if the t observation belongs to month i, where $i = 2$ represents February, $i = 3$ represents March up to $i = 12$ representing December and 0 otherwise. The month of January is taken as a base month in order to avoid the problem of multicollinearity, which affects the stability of the regression coefficients when dummy variables are used to denote different periods in regression models (Makridakis, Wheelwright and Hyndman,1998).

For example, if u_t follows an AR(1) model we can write equation (13) as

$$r_t = \omega_0 + \sum_{i=2}^{12}\omega_i \mathrm{M}_{it} + u_t$$

$$(1-\phi_1 B)u_t = \varepsilon_t$$

$$u_t - \phi_1 u_{t-1} = \varepsilon_t$$

$$u_t = \phi_1 u_{t-1} + \varepsilon_t$$

Therefore, the final model will be written as:

$$r_t = \omega_0 + \sum_{i=2}^{12}\omega_i \mathrm{M}_{it} + \phi_1 u_{t-1} + \varepsilon_t \tag{14}$$

In this project, equation (14) will be used. In order to account for the monthly seasonality effect in the variance equation (volatility model), the model given in equation (15) will be used.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\,\varepsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i\,\sigma_{t-i}^2 + \sum_{i=2}^{12}\omega_i \mathrm{M}_{it} \tag{15}$$

Assuming a GARCH(1,1) process equation (14) reduces to:

$$\sigma_t^2 = \alpha_0 + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{i=2}^{12}\omega_i \mathrm{M}_{it} \tag{16}$$

In this project, the parameter estimates of the GARCH models are obtained by the Berndt, Hall, B.H., Hall, R.E., Hausman(1974) algorithm using numerical derivatives.

4: Data analysis

4.1. Introduction

In this chapter,the data will be analysed using the steps and techniques described in chapter three. The statistical packages used in data analysis are Eviews, R and MINITAB. Microsoft Excel is also used for simple calculations and some graphical plots.

4.2 Descriptive statistics and stationarity results

A summary of the descriptive statistics for the six stocks including the RESI are shown in Table 4.1, while the summary statistics of monthly returns (r_t) are given in Table 2. The values in parentheses under the Jarque-Bera test for normality are p-values. Asthe monthly stocks and the RESI increase with time, the return series summary statistics are used to test for normality astheir distributions are stationary.

Table 4.1: Summary statistics of monthly stocks and the RESI

	CFR	FSR	NPN	RDF	RESI	SAB	SBK
Mean	3099.604	1722.756	20196.265	604.862	40724.2	17171.2	8258.88
Median	2884.333	1780.95	17074.944	666.143	45317.2	16566.6	8944.29
Maximum	6762.222	3043.889	54775.818	954.722	73818.2	39161.5	11474.3
Minimum	1070.421	685.25	2115.947	232.952	15464.8	4880.85	2761.55
Std. Dev.	1287.877	546.796	13925.457	209.443	15034.7	8242.08	2548.94
Skewness	0.268	-0.005	0.666	-0.53	-0.237	0.629	-0.737
Kurtosis	2.098	2.536	2.46	1.977	1.989	2.943	2.3689
Jarque-Bera	5.557 (0.065)	1.07 (0.586)	10.235 (0.006)	10.757 (0.005)	6.184 (0.045)	7.853 (0.020)	12.757 (0.002)
Observations	119	119	119	119	119	119	119

The skewness is negative for all the returns as shown in Table 4.2. The negative values of skewness suggest greater probability of large decreases in stock returns during the sample period. In all cases, the values of the kurtosis are very high and greater than three, except for RDF, indicating that they are fat-tailed, i.e. their distributions are leptokurtic. The high values of kurtosis for the returns also suggest that extreme price changes occurred more frequently during the sampling period, from 2003 to 2012. The distributions of NPN, RDF and SBK are approximately normally distributed, as shown by the Jarque-Bera test for normality in Table

4.2. Under the Jarque-Bera test for normality, the null hypothesis is that the distribution is approximately normally distributed. Using the level of significance of 5% the decision rule is to reject the null hypothesis if the level of significance is greater than the p-values, which are given in parentheses in Table 4.2 under the Jarque-Bera test.

Table 4.2: Summary statistics of monthly returns (r_t)using Equation 11

	CFR	**FSR**	**NPN**	**RDF**	**RESI**	**SAB**	**SBK**
Mean	1.240	1.196	2.589	1.077	0.817	1.583	1.102
Median	1.94	2.1	2.97	1.62	1.68	2.14	1.27
Maximum	15.14	12.02	19.73	12.69	15.03	11.93	10.96
Minimum	-51.4	-17.39	-18.68	-12.27	-27.93	-15.06	-14.67
Std. Dev.	7.980	5.525	6.366	5.191	6.175	4.488	4.877
Skewness	-3.125	-0.939	-0.255	-0.460	-0.983	-1.109	-0.4085
Kurtosis	19.975	4.005	3.384	2.823	6.055	5.124	3.470
Jarque-Bera	1622.4 (0.000)	22.5 (1.3E-05)	2.0 (0.365)	4.4 (0.113)	65.5 (6.1E-15)	46.8 (6.9E-11)	4.4 (0.111)
Observations	119	119	119	119	119	119	119

Table 4.1 shows original values, whilst Table 4.2 shows returns as defined by equation (11)

The time series plots of the stocks, the RESI and the return series plots are given in Figures 4.1 and 4.2 respectively. The time series plots of the stocks and the RESI show that the monthly stock prices are not stationary while the plots for the returns are stationary, as shown in Figures 4.1 and 4.2. All the stocks were affected by the worldwide economic recession (2008/2009) as shown by the time series plots in Figures 4.1 and 4.2. The recession had a huge impact on the CFR stock in particular, as shown by Figure 4.1 panels (c) and (d).

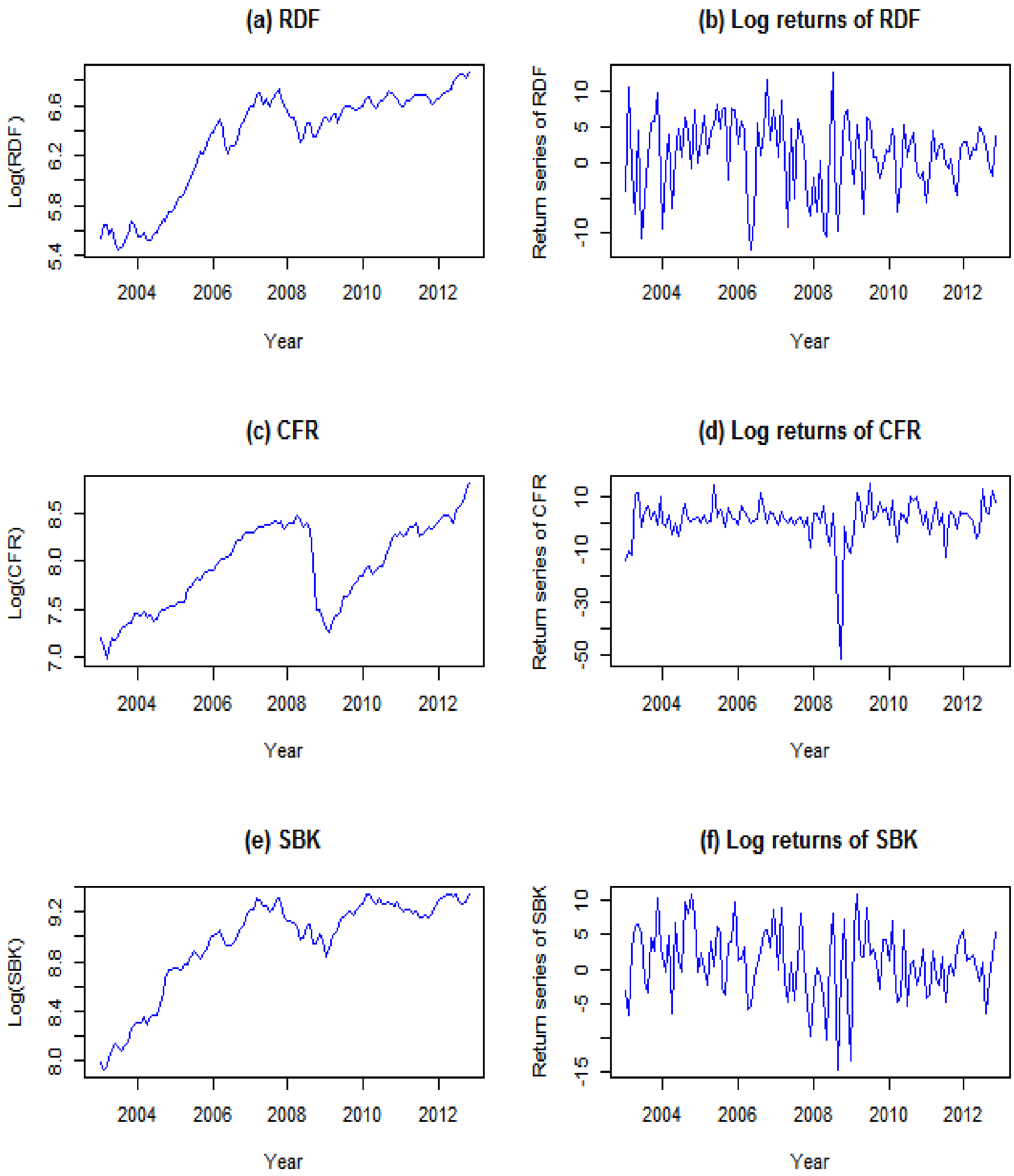


Figure 4.1: Time series plots of the stocks, including the return series

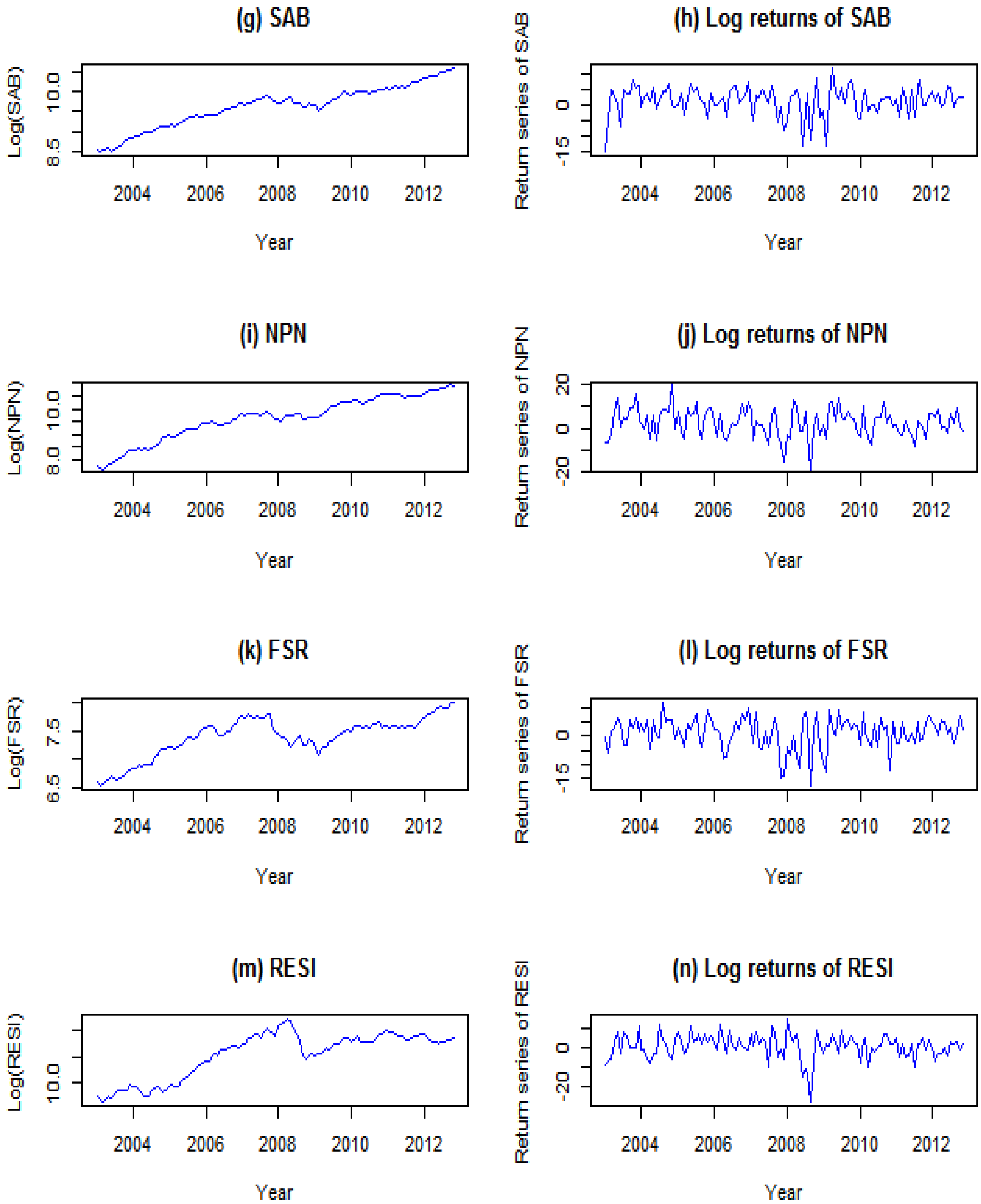


Figure 4.2: Time series plots of the stocks, including the return series

The time series plots of the stocks including the RESI in Figure 4.1 (a), (c), (e) and Figure 2 (g), (i), (k), (m) show that the stocks are increasing with time. Formal unit root tests are carried out using the Augmented Dickey-Fuller (ADF) tests. The results of these ADF tests are summarised in Table 4.3. Using the absolute values, the calculated ADF statistic (t-statistic) figures given in column 2 of Table 4.3 are all less than the critical absolute value at 5% level of significance. The null hypothesis of non-stationarityis thus not rejected, and the conclusion is that all the time series are integrated of order one, meaning that they are all not stationary. It should be noted that even at 1% and 10%, all the time series are not stationary (see Table 4.3). The logs of stock prices are stationary after taking the first differences, as discussed in Chapter 3, given in equation (10), which is $r_t = 100\ln\frac{P_t}{P_{t-1}}$. The absolute values of the calculated ADF statistic (t-statistic) given in column 4 of Table 4.3 are all greater than the critical absolute value at 10% level of significance, showing that the return series data is stationary. The conclusion thus is that all the stocks are stationary after the first difference of the logged data.

Table 4.3: Unit root tests

	Level		First Difference	
	t-statistic	t-test at 5%*	t-statistic	t-test at 5%
CFR	-0.370	-2.886	-6.944	-2.886
FSR	-0.755	-2.886	-8.757	-2.886
NPN	1.784	-2.886	-8.439	-2.886
RDF	-0.843	-2.886	-8.406	-2.886
RESI	-1.790	-2.886	-8.056	-2.886
SBK	-1.730	-2.886	-5.300	-2.886
SAB	2.130	-2.886	-9.408	-2.886

*Critical values at 1% level and 10% level are -3.487 and -2.580 respectively.

4.3 Correlations

The correlation matrix for the monthly stocks is given in Table 4.4. The table summarises the relationship among the stocks and the RESI. The correlation matrix shows that there is a strong to very strong positive linear relationship between pairs of stocks. A number of these stocks have correlations above 0.75, showing high positive correlation and may indicate a joint movement due to investor action.

Table 4.4: Correlation matrix for the monthly stocks

CFR	CFR	FSR	NPN	RDF	RESI	SAB	SBK

FSR	0.858	1	0.799	0.895	0.71	0.852	0.905
NPN	0.721	0.799	1	0.862	0.687	0.976	0.818
RDF	0.776	0.895	0.862	1	0.857	0.888	0.961
RESI	0.802	0.71	0.687	0.857	1	0.735	0.859
SAB	0.798	0.852	0.976	0.888	0.735	1	0.847
SBK	0.76	0.905	0.818	0.961	0.859	0.847	1

4.4 Interpretation of the Granger-Causality results

One of the main objectives of empirical economics is that of causal relationships among variables. Table 4.5 below shows the pairwise Granger causality tests among variables used. In each of the pairs, a null hypothesis is stated and the F-statistic together their corresponding p-values are given. The null hypothesis is rejected if the level of significance, which is 0.10 in this study, is greater than the p-value. For example, the null hypothesis that FSR does not Granger-cause CFR is rejected, as 0.10 is greater than 0.007438 level of significance, but the null hypothesis that CFR does not Granger-cause FSR is accepted, as 0.10 is less than 0.162042. This shows that Granger-causality for the two stocks is unidirectional. The phrase 'unidirectional' implies that a specific stock has Granger-causality on another specific stock but not the other way around. In modern application, it could mean that an oil-based stock such as Sasol could have an impact and causality on another stock such as Super Group,which is an automotive industry share counter affected by petrol price,, but not that Super Group would have any effect on Sasol. Specifically to this research, this would mean that mining shares might affect dual-listed shares but not vice versa.

Table 4.5: Pairwise Granger-Causality tests

Pairwise Granger-Causality Tests		
Date: 11/01/14 Time: 22:39		
Sample: 2003:02 2012:12		
Lags: 4		
Null Hypothesis:	F-Statistic	Probability

RTFSR does not Granger-Cause RTCFR	3.6923806	0.007438
RTCFR does not Granger-Cause RTFSR	1.6714426	0.162042
RTNPN does not Granger-Cause RTCFR	2.6989314	0.034543
RTCFR does not Granger-Cause RTNPN	0.2170351	0.928442
RTRDF does not Granger-Cause RTCFR	1.8033693	0.133592
RTCFR does not Granger-Cause RTRDF	3.0128728	0.021297
RTRESI does not Granger-Cause RTCFR	5.0457074	0.000922
RTCFR does not Granger-Cause RTRESI	0.8358347	0.505371

The Akaike Information Criterion (AIC) was used to make the choice of lags employed (4). AIC is a measure of the relative quality of a statistical model for a given set of data

4.5 The estimated VAR model

4.5.1 The VAR estimates

The results of the estimated VAR model are presented in Appendix 2. According to Gujarati (2004), it is not necessary to give detailed explanations of the individual coefficients and their signs and significance because they are likely to be inaccurate. Instead, emphasis should be placed on commenting on the impulse response functions and variance decomposition, as these provide useful and valid inferences about the whole system of equations. Hence, this project is focused on the impulse response functions and variance decompositions.

4.5.2 Impulse response functions

The use of impulse functions is meant to show how each endogenous variable responds over time to innovations or shocks to each of the endogenous variables. As such, impulse response functions show how innovations to given endogenous variables spread through each and every endogenous variable and eventually how it affects the original variable itself.

The results from the impulse response functions are presented in Appendix 3. The results show the impulse response functions of the six stocks to a permanent shock in the RESI and to each of the other stocks, where the response of these variables has been divided by the standard errors of their residuals. It is important to note that the results from the impulse response functions depend on the ordering of the variables. In this study, the Cholesky decomposition was used.

The first row of the table in appendix 3 shows the sensitivities of the long run response of CFR to the other stock, including the RESI. For example,if a positive shock of one standard deviation is given to the RESI (1^{st} row 5^{th} panel); there will be an increasing positive response to CFR in the first four months and a decline thereafter.
In specifically analysingthe effect of shocks to the RESI on the other stocks, it is apparent that shocks to the RESI result in a majority positive increase in the other stocks. Row 5(appendix 3) shows these results are only negative for CFR and NPN, whereas shocks to the RESIare positive for the remaining sharesi.e. FSR, RDF, SAB and SBK. FSR stands for First Rand Bank and SBK for Standard Bank, and these two banking shares have the highest positive outcome. It is interesting to note that RDF or Redefine International, a property stock, also benefits from a shock to the resource sector. This indicates that investors seek safe havens such as dual-listed banking shares or even innovation in the form of property stocks in adverse conditions. Via analysis of the graph, it becomes apparent that these effects are visible for at least three months on all positively affected stocks, thus possibly creating a nice trading window of opportunity to work with.

4.6 Monthly seasonality of stock returns

4.6.1 Results from the time series regressions

Table 4.6 presents a summary of the regression estimates of the variables of equation (14). The p-values are given in parentheses. Equation (14) can be written as

$$r_t = \omega_2\text{Feb} + \omega_3\text{Mar} + \cdots + \omega_{12}\text{Dec} + \phi_1 u_{t-1} + \varepsilon_t \qquad (17)$$

In order to test whether a variable should be included in the regression model given in equation (17), it is important to test for each of the regression coefficients, with the null hypothesis that the regression coefficient takes the value zero against the null hypothesis that it is not equal to zero. The decision rule is to reject the null hypothesis if the level of significance, α (α =0.10 for this study) is greater than the p-value. For the CFR, only September has a significant regression coefficient.

TheLjung-Box Q-statistics are used to test for autocorrelation and also to test for heteroscedasticity. The null hypothesis is that there is no serial autocorrelation in the residuals up to lag order $l(=5$ in this study). An alternative test is that of the Breusch-Godfrey Serial Correlation LM Test. For the CFR regression model, there is no serial autocorrelation at lag 5, but there is evidence of heteroscedasticityasthe Q^2statistic at lag 5 has a p-value ($p = 0.000$), which is less than the 10% level of significance. The GARCH model is used so as to capture this heteroscedasticity.

All the Ljung-Box Q-statistics on standardised residuals in Table 4.6 are insignificant up to lag 5 at the 10% level, indicating that there is no excessive autocorrelation left in the residuals. However, the Ljung-Box Q-statistics on squared standardised residuals are significant up to lag 5 at the 10% level for the following stocks: CFR, RDF, SBK and SAB. This indicates that there is heteroscedasticity in the residuals for these stocks. There can be some improvement on the current models for these four stocks. This improvement is implemented through volatility modelling. The results of the monthly seasonality of stock returns in mean and volatility are presented in Table 4.7. From Table 4.6, there is no evidence of monthly seasonality in the RESI. The monthly p-values for the coefficients of February, September and November are all significant for the FSR stock, indicating the presence of monthly seasonality in this stock for these months. For NPN, monthly seasonality is present in the months of February, November and December.

Table 4.6: Monthly seasonality of stock returns

	CFR	FSR	NPN	RDF	RESI	SBK	SAB
ϕ	0.400	0.223	0.269	0.230	0.283	0.256	0.105

	(0.085)	(0.031)	(0.004)	(0.018)	(0.021)	(0.004)	(0.109)
February	-0.450 (0.764)	-0.605 (0.673)	2.315 (0.029)	-0.624 (0.644)	2.075 (0.419)	-1.053 (0.537)	-0.680 (0.427)
March	0.951 (0.547)	-1.378 (0.445)	-1.235 (0.481)	1.940 (0.240)	-0.459 (0.767)	0.413 (0.782)	-1.025 (0.537)
April	1.802 (0.319)	2.924 (0.064)	3.896 (0.068)	3.076 (0.009)	1.398 (0.448)	3.120 (0.023)	3.200 (0.000)
May	2.772 (0.211)	-0.896 (0.586)	3.138 (0.146)	-2.909 (0.067)	-0.368 (0.844)	-0.967 (0.513)	3.004 (0.014)
June	1.997 (0.374)	-0.872 (0.602)	1.519 (0.410)	-2.728 (0.177)	1.524 (0.350)	-1.116 (0.490)	1.707 (0.140)
July	-0.147 (0.929)	3.032 (0.011)	0.920 (0.636)	2.115 (0.307)	-1.193 (0.546)	2.874 (0.013)	0.576 (0.765)
August	3.127 (0.247)	0.811 (0.554)	3.341 (0.091)	2.365 (0.173)	0.690 (0.800)	0.060 (0.967)	2.272 (0.062)
September	4.240 (0.049)	3.563 (0.021)	3.166 (0.024)	2.617 (0.030)	1.769 (0.402)	0.683 (0.646)	3.688 (4.08E-06)
October	-0.371 (0.914)	0.457 (0.846)	3.916 (0.158)	2.134 (0.142)	0.353 (0.902)	0.933 (0.657)	2.022 (0.225)
November	-1.025 (0.820)	3.217 (0.004)	3.995 (0.020)	0.674 (0.644)	0.566 (0.725)	1.768 (0.181)	2.548 (0.057)
December	2.002 (0.422)	1.738 (0.499)	5.051 (0.036)	2.163 (0.211)	0.481 (0.724)	3.457 (0.013)	2.275 (0.049)
Model diagnostics							
$Q(5)$	(7.065) 0.132	4.921 (0.295)	0.614 (0.961)	5.707 (0.222)	4.761 (0.313)	5.453 (0.244)	7.597 (0.107)
$Q^2(5)$	(35.727) 0.000	1.803 (0.772)	2.555 (0.635)	11.399 (0.022)	6.838 (0.145)	14.272 (0.006)	21.114 (0.000)
R-Squared	0.194	0.135	0.140	0.181	0.100	0.151	0.125

Table 4.6 is used to tabulate the results of the seasonality test.A complete analysis shows FSR has seasonality on April, July, September and November. NPN displays seasonality in February, April, August, September, November and December. RDF displays seasonality in April and September only. SBK displays seasonality in April, July and December. SAB displays seasonality in April, May, August, September November and December. The key months that stick out are April (4), September (4), November (3) and December (3).

Table 4.7: Monthly seasonality of stock returns in mean and volatility

	CFR	FSR	NPN	RDF	RESI	SBK	SAB
Mean Equation							
ϕ	0.166			0.215		0.218	0.111

	(0.0702)			(0.002)		(0.000)	(0.048)
February	1.010 (0.233)			-0.998 (0.215)		-0.900 (0.438)	-0.361 (0.680)
March	2.048 (0.053)			1.681 (0.101)		0.980 (0.373)	-0.832 (0.267)
April	2.900 (0.014)			3.109 (6.00E-05)		2.877 (0.009)	2.566 (0.005)
May	1.817 (0.168)			-1.670 (0.049)		-0.940 (0.434)	2.201 (1.14E-05)
June	3.243 (0.052)			-1.626 (0.114)		-0.468 (0.706)	1.398 (0.144)
July	-0.371 (0.780)			2.747 (0.025)		2.680 (0.003)	0.471 (0.678)
August	2.210 (0.290)			1.669 (0.044)		-0.564 (0.638)	2.223 (0.033)
September	5.580 (0.001)			2.607 (0.010)		0.050 (0.965)	3.596 (1.69E-08)
October	0.425 (0.844)			2.033 (0.012)		0.524 (0.680)	2.234 (0.010)
November	2.401 (0.153)			-0.127 (0.868)		1.373 (0.116)	2.492 (0.013)
December	1.864 (0.045)			1.522 (0.140)		2.946 (0.003)	1.420 (0.072)
Variance equation							
α_0	45.784 (0.003)			-2.118 (0.673)		22.432 (0.040)	15.140 (0.059)
α_1	0.323 (0.031)			-0.059 (0.367)		-0.083 (0.003)	-0.083 (0.002)
α_2				0.301 (0.001)		0.249 (0.003)	0.246 (2.40E-05)
β_1	0.411 (0.001)			0.672 (4.63E-22)		0.685 (1.95E-09)	0.620 (1.44E-09)
February	-64.102 (0.004)			1.141 (0.886)		-29.519 (0.118)	-23.677 (0.065)
March	-35.654 (0.030)			1.608 (0.784)		-23.869 (0.050)	-6.358 (0.475)
April	-48.674 (0.003)			-2.270 (0.664)		-24.183 (0.044)	-11.886 (0.243)
May	-33.616 (0.046)			15.311 (0.038)		-14.601 (0.234)	-21.08 (0.017)
June	-14.577 (0.524)			16.073 (0.147)		-10.659 (0.492)	-6.518 (0.463)
July	-59.276 (0.001)			-0.475 (0.967)		-33.305 (0.013)	6.572 (0.681)

August	-0.687 (0.981)			-9.058 (0.221)		-15.982 (0.167)	-18.705 (0.148)
September	-48.689 (0.020)			2.579 (0.682)		-17.767 (0.163)	-23.454 (0.004)
October	44.188 (0.490)			1.869 (0.740)		-7.989 (0.606)	-7.556 (0.411)
November	-79.035 (0.011)			2.892 (0.581)		-33.549 (0.010)	-5.624 (0.602)
December	-49.702 (0.002)			14.261 (0.129)		-19.472 (0.116)	-17.737 (0.069)
Model diagnostics							
$Q(5)$	6.245 (0.182)			6.363 (0.174)		1.043 (0.903)	3.113 (0.539)
$Q^2(5)$	3.759 (0.440)			4.556 (0.336)		2.969 (0.563)	7.132 (0.129)
R-Squared	0.111			0.168		0.143	0.116

All stocks in this table failed the Ljung Box test for second order serial correlation (test for constant variance). This indicates that there is heteroscedasticity in the residuals for these stocks. This was corrected by making use of GARCH models, as in Table 4.7.

4.6.2 Time series decomposition

In order to have a better understanding of the performance of the six stocks and the RESI on a monthly basis, time series decomposition was carried out for the each of the stocks using the statistical package MINITAB. Figures 4.4 and 4.5 present graphical plots of the seasonal indices for RDF stock and the RESI. The plots of the seasonal indices of the other stocks are given in appendix 5. From Figure 4.4, the stock price of RDF was above average in January, February, April, September, October and December.

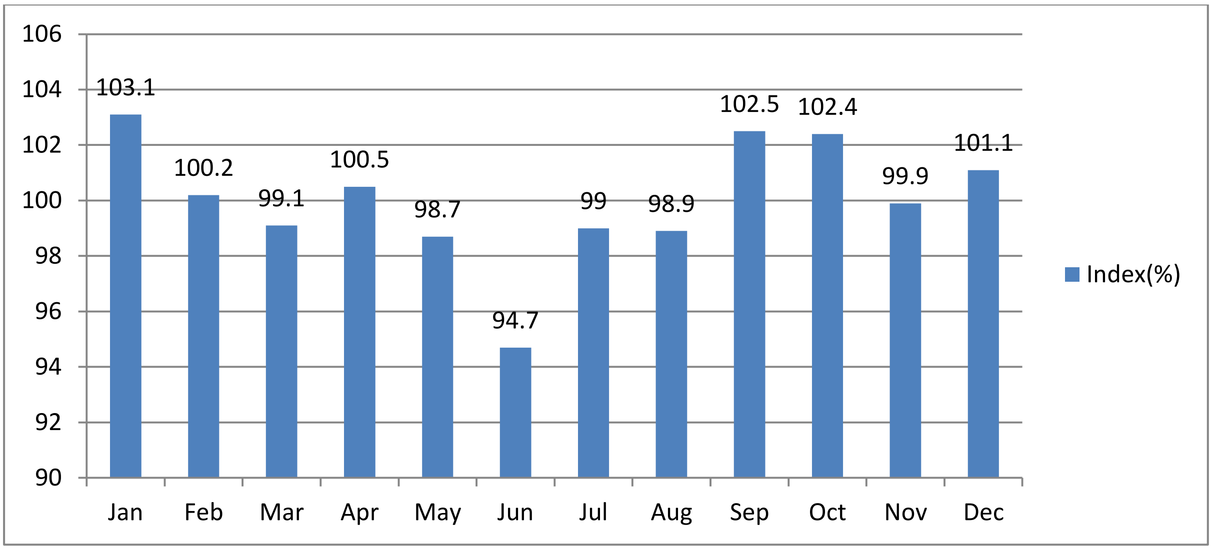


Figure 4.4: Plot of seasonal indices of RDF stock

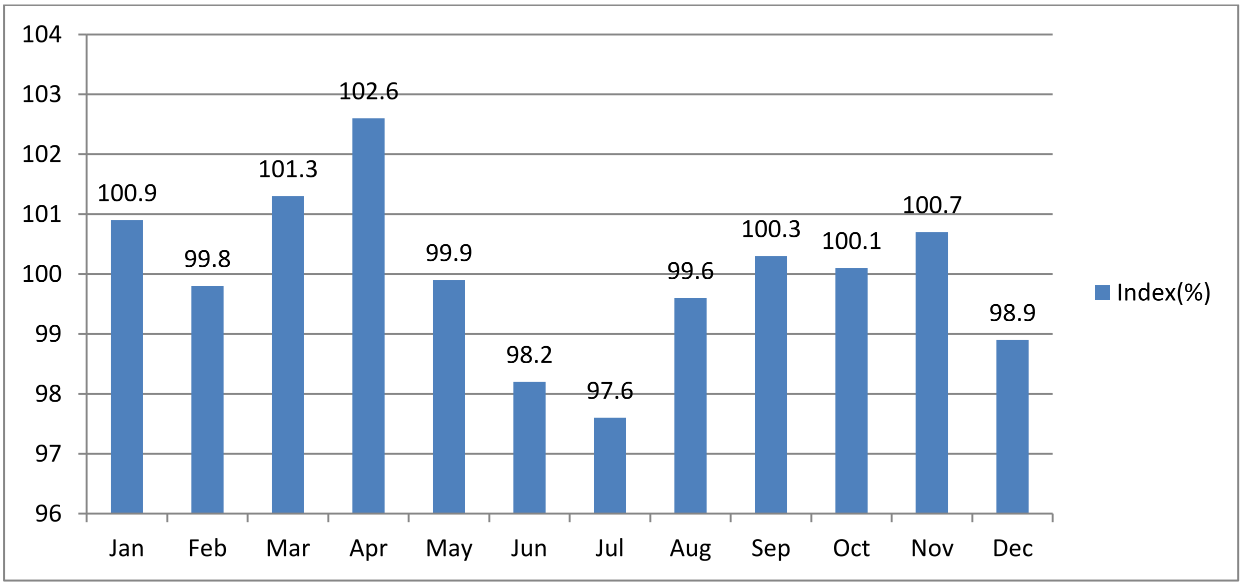


Figure 4.5: Plot of seasonal indices of the RESI

5: Interpretation and further study

5.1 Interpretation

The VAR model used does infact show seasonality present in thesix dual-listed stocks, but none in the RESI. The Granger-Causality test, when analysed in conjunction with the correlation co-efficient and the time series decomposition/impulsetest, does show casualty between many stocks, including the RESI on dual-listed stock (see appendix 4.4).The effect of shocks (via impulse test) to the RESI and subsequent ramifications for the banking shares SBK and FSR in particular, as well as property stock RDF, shows that there is in fact causality present on the Johannesburg Stock exchange. The key months that stick out are April (4), September (4), November (3) and December (3). This clearly indicates that the effect of mining induced seasonality can be found in that the major months as evidenced in my literature review states that the most frequent months for commencement of strikes are April and September. April is pronounced because that is when strike season usually commences. September is pronounced in that this is the most watched month by investors as strikes either get resolved or more pronounced industrial action is called for by unions.Past analysis of data shows that September is usually when strike season ends with unions and mining houses having reached an end to negotiations. November and December also rank highly and could indicate the laggard after effects of the strikes in continued monetary flow movement after the effects of the September industrial action. If the dispute has been resolved – investors that sold their shares in resource stocks and entered positions in dual listed stocks may choose to sell their positions in the dual listed stocks and re- enter positions in resources stocks as they would be driven up by the end in labour disputes. They would pick up resource stocks at much lower levels then before the April strikes and look to play the same strategy for the next year i.e. to switch in between the dual listed shares and resource stocks timed by the periodization caused by industrial dispute. Seasonality in November and December also tie in with the end of year tax selling hypothesis wherein which, investors realise losses for tax benefits.

As Bauer and McDermott (2010)said, hedges can co-move with stocks in negative periods due to herd behaviour or contagion versus safe haven, which always hold their value. Thus,these rand hedge stocks cannot be excluded as hedges, as their value increases in these times but the theory that they are safe haven assets must be rejected, because not all of them hold their value. These dual-listed stocks were proven to be statistically leptokurtic and prone to large movements and thus the domain of the more risk-attracted investor – their seasonal components do imply that there must be similar thinking and joint investor action in these stocks to induce these seasonal components, which leads to the conclusion that there is a large degree of joint sentiment-driven investment present. Therefore:

H_0^1 is rejected, because it was statistically proven that seasonality is present in these stocks

H_0^2 is accepted, because seasonality in this index could not be proved, although there is indeed causality present between this index and the other rand hedge stocks, which could be used to obtain above-market returns.

5.2 Further research

The research has established that dual-listed stocks do possess seasonality and, for certain stocks, causality. If these stocks are rand sensitive and seasonal, that must imply a seasonal component to the rand currency. Further research could delve deeper into what causes this seasonality in the form of:

a)Exploring the macro-economic stimuli that affect the rand;

b) Deeper investigation into labour sentiment gauges (similar to the VIX Index) or other factors influencing the rand's apparent seasonality.

c) SAB, NPN and RDF are vastly different stocks in terms of their core functions and could have been chosen due to this diversification being seen as an effective hedge. FSR and SBK – both banking stocks also show seasonality and further research could be done to investigate what sets them apart from other banking stocks such as ABSA – now Barclays Africa (BGL) and Nedbank (NED).Further research should also be conducted on stocks proven via the Granger-causality test, as this could lead to opportunities for above-market returns.

Summary : My research has proven via econometric tests that seasonality does in fact exist in dual listed shares on the Johannesburg stock exchange. Months where identified with significant seasonal properties and savvy investors may well benefit from implementing a strategy aligned to these yearly market movements to obtain above the market returns.

Appendices

Appendix 1: Time series plots of stocks and the logarithmic returns

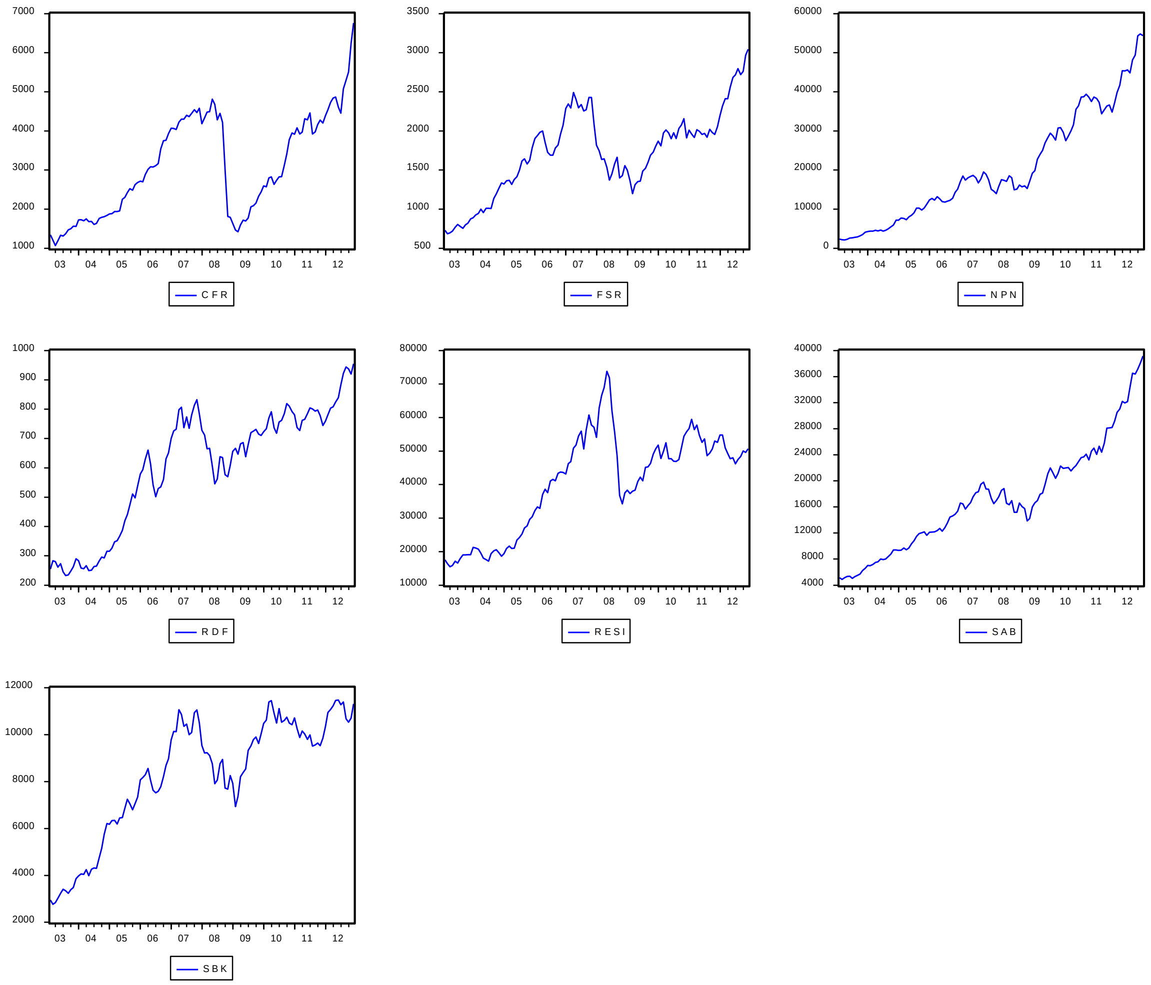


Fig 1.1: Time series plots of raw data

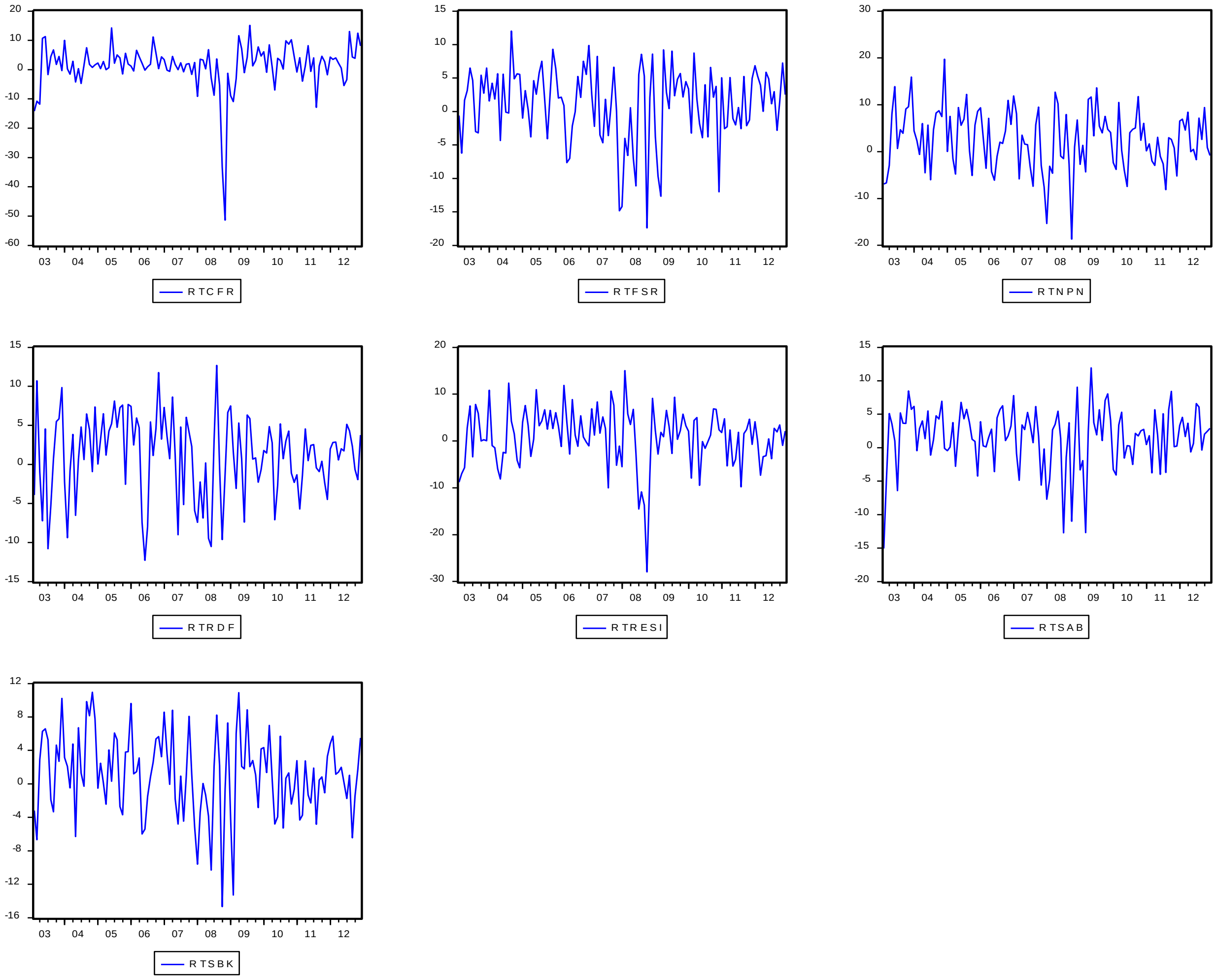


Fig 1.2: Time series plots of return series

Appendix 2: VAR models (Vector Autoregression Estimates)

Vector Autoregression Estimates							
Date: 10/23/14 Time: 15:35							
Sample(adjusted): 2003:06 2012:12							
Included observations: 115 after adjusting endpoints							
Standard errors in ( ) & t-statistics in [ ]							
	RTCFR	RTFSR	RTNPN	RTRDF	RTRESI	RTSAB	RTSBK
RTCFR(-1)	0.1935669	-0.07208	-0.10234	-0.03876	0.02628	-0.1371	-0.03605
	0.1298893	0.113807	0.133753	0.097753	0.12035	0.0792	0.099005
	[1.49025]	[-0.63331]	[-0.76517]	[-0.39651]	[0.21833]	[-1.73050]	[-0.36416]
RTCFR(-2)	-0.073851	0.082472	0.044123	-0.19693	-0.01032	0.1142	-0.0828
	0.1274289	0.111652	0.131219	0.095901	0.11807	0.0777	0.09713
	[-0.57955]	[0.73866]	[0.33625]	[-2.05352]	[-0.08741]	[1.46934]	[-0.85242]
RTCFR(-3)	0.0178574	0.089079	-0.06927	-0.04785	-0.0752	-0.0349	0.152172
	0.1301089	0.114	0.133979	0.097918	0.12055	0.0794	0.099172
	[0.13725]	[0.78140]	[-0.51706]	[-0.48869]	[-0.62380]	[-0.43948]	[1.53441]
RTCFR(-4)	0.1791772	0.179396	0.07352	0.101028	0.20149	0.2626	-0.04974
	0.1143755	0.100214	0.117778	0.086077	0.10597	0.0698	0.08718
	[1.56657]	[1.79013]	[0.62422]	[1.17369]	[1.90137]	[3.76367]	[-0.57057]
RTFSR(-1)	0.0485959	-0.17136	-0.01843	0.206217	-0.11177	0.1879	-0.10112
	0.2310775	0.202467	0.237951	0.173905	0.2141	0.141	0.176133
	[0.21030]	[-0.84638]	[-0.07746]	[1.18580]	[-0.52202]	[1.33276]	[-0.57412]
RTFSR(-2)	-0.263564	0.02325	-0.08353	0.170878	-0.46655	-0.0587	0.059467
	0.2273624	0.199212	0.234125	0.171109	0.21066	0.1387	0.173302
	[-1.15922]	[0.11671]	[-0.35677]	[0.99865]	[-2.21472]	[-0.42299]	[0.34314]

RTFSR(-3)	0.1969208	-0.16721	-0.17504	-0.00559	-0.14648	-0.1585	-0.1258
	0.2258467	0.197884	0.232565	0.169969	0.20926	0.1378	0.172146
	[0.87192]	[-0.84499]	[-0.75266]	[-0.03288]	[-0.70000]	[-1.15030]	[-0.73077]
RTFSR(-4)	-0.075035	-0.13115	-0.03417	-0.09249	-0.01322	-0.0876	-0.09226
	0.2295913	0.201165	0.236421	0.172787	0.21272	0.1401	0.175001
	[-0.32682]	[-0.65198]	[-0.14452]	[-0.53529]	[-0.06216]	[-0.62555]	[-0.52722]
RTNPN(-1)	0.3286794	0.13522	0.113851	-0.04855	0.20549	0.0787	-0.01232
	0.1600322	0.140218	0.164792	0.120438	0.14828	0.0976	0.121981
	[2.05383]	[0.96436]	[0.69087]	[-0.40308]	[1.38587]	[0.80562]	[-0.10102]
RTNPN(-2)	-0.092295	-0.00318	0.022612	-0.00768	-0.24324	-0.1036	0.085002
	0.1561314	0.1368	0.160776	0.117502	0.14466	0.0953	0.119007
	[-0.59114]	[-0.02327]	[0.14064]	[-0.06538]	[-1.68146]	[-1.08783]	[0.71426]
RTNPN(-3)	-0.297606	-0.09596	-0.19709	0.016581	-0.25136	-0.1314	-0.15365
	0.1590811	0.139385	0.163813	0.119722	0.14739	0.0971	0.121256
	[-1.87078]	[-0.68848]	[-1.20314]	[0.13849]	[-1.70535]	[-1.35428]	[-1.26718]
RTNPN(-4)	0.1353503	0.108197	0.073144	0.131716	0.07425	-0.0098	0.101878
	0.1574849	0.137986	0.162169	0.118521	0.14592	0.0961	0.120039
	[0.85945]	[0.78412]	[0.45103]	[1.11133]	[0.50885]	[-0.10237]	[0.84871]
RTRDF(-1)	0.0385338	0.024917	0.033148	0.183373	0.05183	0.0071	0.098995
	0.1704136	0.149314	0.175483	0.128251	0.15789	0.104	0.129894
	[0.22612]	[0.16687]	[0.18890]	[1.42980]	[0.32828]	[0.06827]	[0.76212]
RTRDF(-2)	0.0614369	-0.0327	0.025243	-0.03126	0.18273	0.0763	-0.13087
	0.1692409	0.148287	0.174275	0.127368	0.15681	0.1033	0.129
	[0.36301]	[-0.22050]	[0.14484]	[-0.24539]	[1.16532]	[0.73938]	[-1.01447]
RTRDF(-3)	-0.012899	0.158058	0.176724	0.183837	0.17551	0.0346	0.204567
	0.1548266	0.135657	0.159432	0.11652	0.14345	0.0945	0.118013
	[-0.08331]	[1.16513]	[1.10846]	[1.57773]	[1.22347]	[0.36650]	[1.73343]
RTRDF(-4)	-0.150981	-0.10161	-0.24744	-0.29778	0.09838	-0.0586	-0.08723
	0.1511587	0.132443	0.155655	0.11376	0.14005	0.0922	0.115217
	[-0.99883]	[-0.76717]	[-1.58964]	[-2.61765]	[0.70245]	[-0.63545]	[-0.75711]
RTRESI(-1)	0.1954494	0.011602	-0.03185	0.052471	0.15262	0.0033	0.043386
	0.1485356	0.130145	0.152954	0.111786	0.13762	0.0906	0.113218
	[1.31584]	[0.08915]	[-0.20820]	[0.46939]	[1.10897]	[0.03678]	[0.38321]

RTRESI(-2)	0.3008981	-0.06917	0.119843	0.05731	0.12078	0.0411	-0.02394
	0.146106	0.128016	0.150452	0.109957	0.13537	0.0891	0.111366
	[2.05945]	[-0.54031]	[0.79655]	[0.52120]	[0.89223]	[0.46153]	[-0.21493]
RTRESI(-3)	0.3492566	-1.20E-01	0.135636	-0.00777	0.13881	0.1982	0.037302
	0.1458232	1.28E-01	0.150161	0.109744	0.13511	0.089	0.11115
	[2.39507]	[-0.93885]	[0.90327]	[-0.07080]	[1.02740]	[2.22743]	[0.33560]
RTRESI(-4)	-0.197896	-0.15734	0.04635	0.079702	-0.26788	-0.1869	-0.0027
	0.1572249	0.137758	0.161902	0.118325	0.14567	0.0959	0.119841
	[-1.25868]	[-1.14212]	[0.28628]	[0.67358]	[-1.83892]	[-1.94859]	[-0.02250]
RTSAB(-1)	-0.215335	-0.08788	0.029622	-0.20005	-0.09142	0.0655	-0.143
	0.2128541	0.1865	0.219186	0.160191	0.19722	0.1299	0.162243
	[-1.01166]	[-0.47119]	[0.13515]	[-1.24880]	[-0.46357]	[0.50457]	[-0.88139]
RTSAB(-2)	0.011535	0.216308	-0.00587	0.124891	0.11194	-0.193	0.179938
	0.2095818	0.183633	0.215816	0.157728	0.19419	0.1279	0.159749
	[0.05504]	[1.17794]	[-0.02721]	[0.79181]	[0.57645]	[-1.50966]	[1.12638]
RTSAB(-3)	0.3084723	0.34064	0.274568	0.235141	0.26562	0.1005	0.258378
	0.2043054	0.17901	0.210383	0.153757	0.1893	0.1246	0.155727
	[1.50986]	[1.90291]	[1.30509]	[1.52930]	[1.40321]	[0.80652]	[1.65917]
RTSAB(-4)	0.0334042	0.077089	-0.24939	-0.03475	-0.04546	-0.1403	0.07085
	0.1923104	0.1685	0.198031	0.14473	0.17818	0.1173	0.146584
	[0.17370]	[0.45750]	[-1.25934]	[-0.24009]	[-0.25512]	[-1.19620]	[0.48334]
RTSBK(-1)	0.0595052	0.384524	0.376164	0.071274	-0.05052	0.0102	0.388679
	0.2446911	0.214395	0.25197	0.184151	0.22672	0.1493	0.18651
	[0.24318]	[1.79353]	[1.49289]	[0.38704]	[-0.22282]	[0.06834]	[2.08396]
RTSBK(-2)	-0.139501	-0.21994	-0.08214	-0.30965	0.31067	0.0432	-0.21641
	0.2341136	0.205127	0.241078	0.17619	0.21691	0.1428	0.178448
	[-0.59587]	[-1.07223]	[-0.34073]	[-1.75745]	[1.43221]	[0.30231]	[-1.21272]
RTSBK(-3)	-0.069278	0.075591	0.13817	0.000117	0.30483	0.1231	0.153037
	0.2427983	0.212737	0.25002	0.182726	0.22496	0.1481	0.185067
	[-0.28533]	[0.35533]	[0.55263]	[0.00064]	[1.35502]	[0.83108]	[0.82693]
RTSBK(-4)	0.1723032	0.024656	0.089003	0.061951	0.13175	0.1747	-0.08141
	0.2529496	0.221631	0.260474	0.190366	0.23437	0.1543	0.192805

	[0.68118]	[0.11125]	[0.34169]	[0.32543]	[0.56215]	[1.13234]	[-0.42224]
C	0.1760866	0.091441	2.227413	0.603282	0.3791	1.8668	0.379492
	0.8633988	0.756499	0.889081	0.649781	0.79997	0.5268	0.658105
	[0.20395]	[0.12087]	[2.50530]	[0.92844]	[0.47389]	[3.54404]	[0.57664]
R-squared	0.4948551	0.247829	0.190604	0.342849	0.30711	0.3671	0.25323
Adj. R-squared	0.3303893	0.002936	-0.07292	0.128892	0.08151	0.1611	0.010095
Sum sq. resids	3467.1507	2661.744	3676.484	1963.737	2976.44	1290.5	2014.375
S.E. equation	6.349465	5.563318	6.538334	4.77851	5.883	3.8738	4.839728
F-statistic	3.0088635	1.011988	0.72329	1.602423	1.36132	1.7817	1.04152
Log likelihood	-359.0319	-343.832	-362.403	-326.344	-350.257	-302.21	-327.808
Akaike AIC	6.7483811	6.48403	6.807005	6.179897	6.59578	5.7601	6.205357
Schwarz SC	7.4405814	7.17623	7.499205	6.872098	7.28798	6.4523	6.897557
Mean dependent	1.5094783	1.254696	2.752174	1.127217	1.00783	1.7351	1.145913
S.D. dependent	7.7593607	5.571503	6.312239	5.119842	6.1385	4.2293	4.864343
Determinant Residual Covariance		4.33E+08					
Log Likelihood (d.f. adjusted)		-2285.71					
Akaike Information Criteria		43.28198					
Schwarz Criteria		48.12738					

Appendix 3: Impulse response functions

Figure 3.1: Impulse response functions

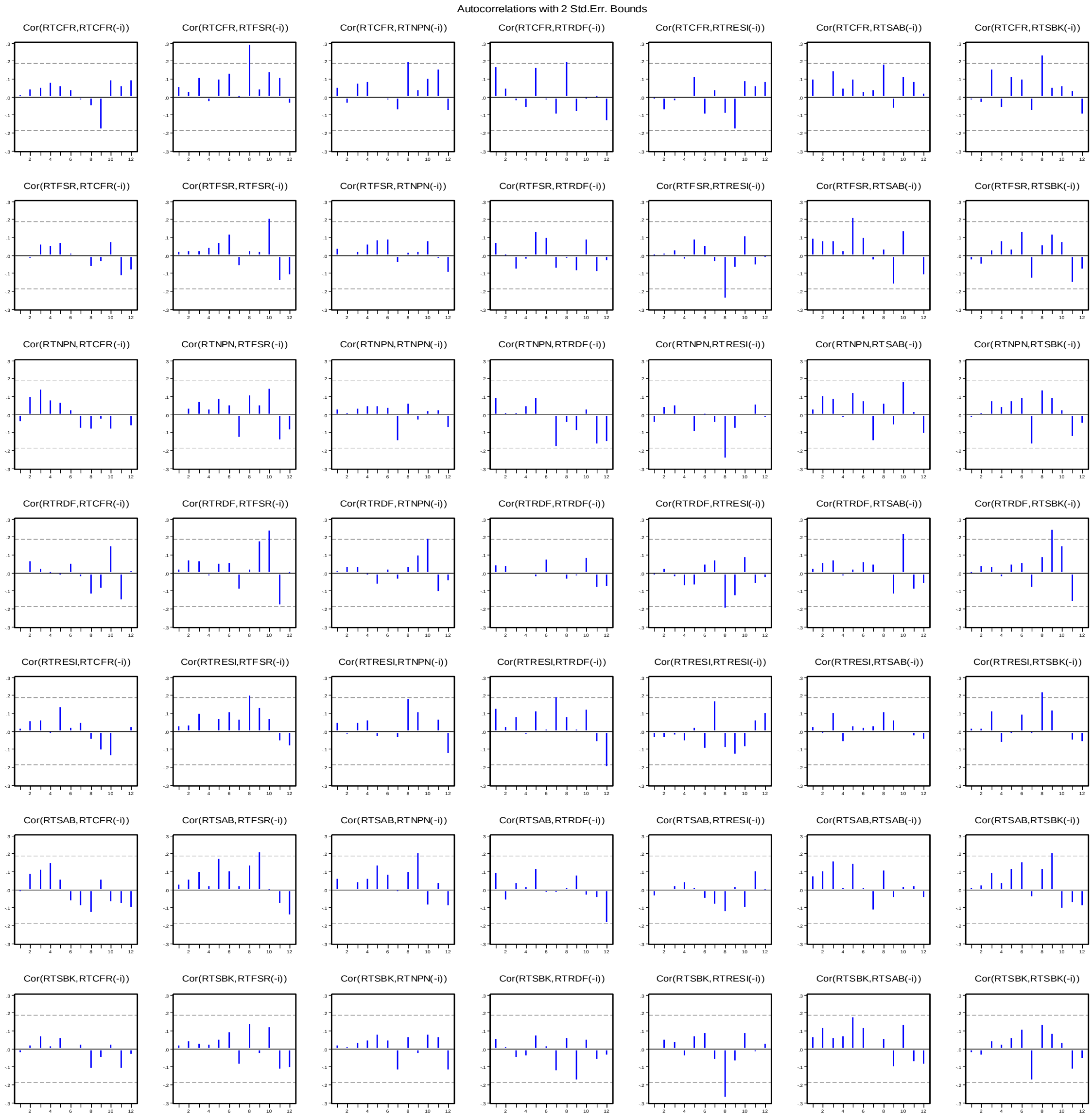
Appendix 4: Pairwise Granger-Causality Tests

Table 4.1: Pairwise Granger-Causality Tests

Pairwise Granger-Causality Tests			
Date: 11/01/14 Time: 22:39			
Sample: 2003:02 2012:12			
Lags: 4			
RTSAB does not Granger-Cause RTCFR	115	1.3142613	0.269436
RTCFR does not Granger-Cause RTSAB		3.5091424	0.00988
RTSBK does not Granger-Cause RTCFR	115	3.5469922	0.009318
RTCFR does not Granger-Cause RTSBK		1.2090358	0.311358
RTNPN does not Granger-Cause RTFSR	115	0.4527613	0.770179
RTFSR does not Granger-Cause RTNPN		0.4776257	0.752079
RTRDF does not Granger-Cause RTFSR	115	0.4544917	0.768921
RTFSR does not Granger-Cause RTRDF		1.8234093	0.129705
RTRESI does not Granger-Cause RTFSR	115	0.1728802	0.951853
RTFSR does not Granger-Cause RTRESI		2.6759294	0.035784
RTSAB does not Granger-Cause RTFSR	115	1.6063451	0.178076
RTFSR does not Granger-Cause RTSAB		2.1801169	0.076156
RTSBK does not Granger-Cause RTFSR	115	1.3608355	0.252513
RTFSR does not Granger-Cause RTSBK		0.0864311	0.986479
RTRDF does not Granger-Cause RTNPN	115	0.6454763	0.631282
RTNPN does not Granger-Cause RTRDF		1.5317976	0.198231
RTRESI does not Granger-Cause RTNPN	115	0.8812282	0.477872
RTNPN does not Granger-Cause RTRESI		2.0564438	0.09172

RTSAB does not Granger-Cause RTNPN	115	0.7158374	0.58292
RTNPN does not Granger Cause RTSAB		1.1096624	0.355922
RTSBK does not Granger-Cause RTNPN	115	0.8015397	0.526837
RTNPN does not Granger-Cause RTSBK		0.4040344	0.805376
Pairwise Granger-Causality Tests			
Date: 11/01/14 Time: 22:39			
Sample: 2003:02 2012:12			
Lags: 4			
RTRESI does not Granger-Cause RTRDF	115	0.479551	0.750676
RTRDF does not Granger-Cause RTRESI		1.9772072	0.103253
RTSAB does not Granger-Cause RTRDF	115	1.6423333	0.169038
RTRDF does not Granger-Cause RTSAB		0.6298242	0.642281
RTSBK does not Granger-Cause RTRDF	115	2.9286999	0.024252
RTRDF does not Granger-Cause RTSBK		0.4835922	0.747731
RTSAB does not Granger-Cause RTRESI	115	0.5972245	0.665427
RTRESI does not Granger-Cause RTSAB		1.1021968	0.359473
RTSBK does not Granger-Cause RTRESI	115	1.3115087	0.270467
RTRESI does not Granger-Cause RTSBK		0.8187067	0.516019
RTSBK does not Granger-Cause RTSAB	115	1.3225632	0.266349
RTSAB does not Granger-Cause RTSBK		2.2092678	0.072878

Appendix 5: Residuals for VAR model



Appendix 6: Plots of seasonal indices

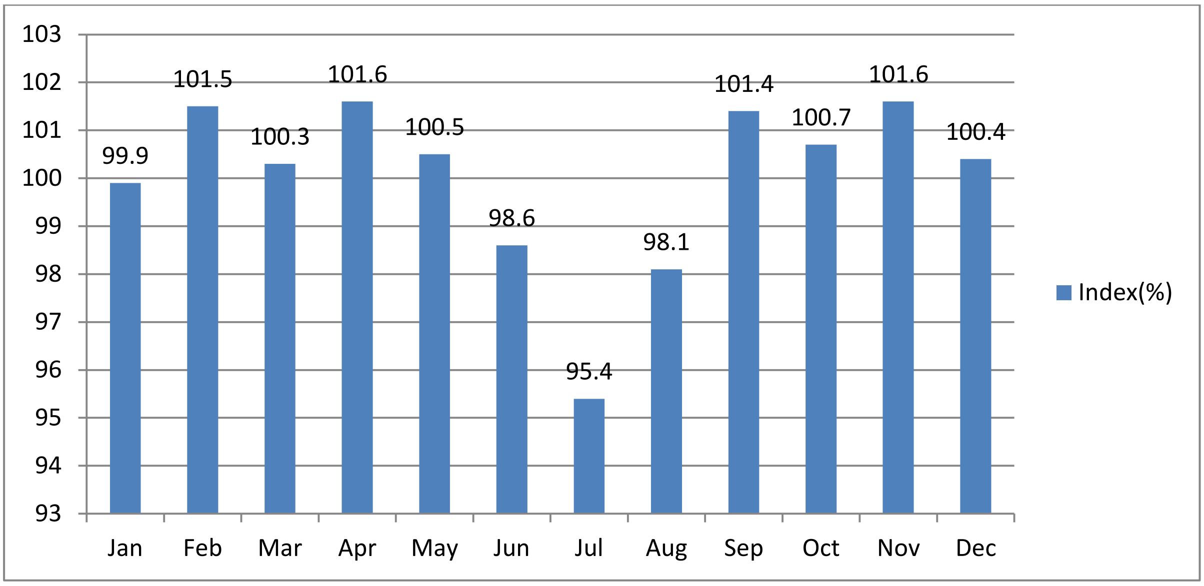


Figure 6.1: Plot of seasonal indices of CFR stock

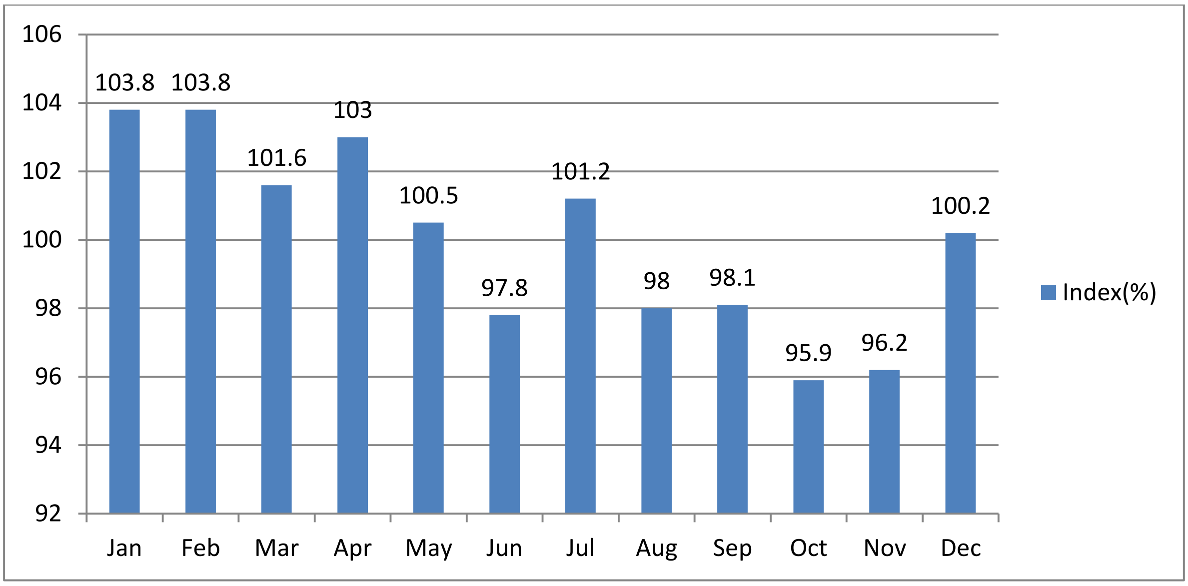


Figure 6.2: Plot of seasonal indices of SBK stock

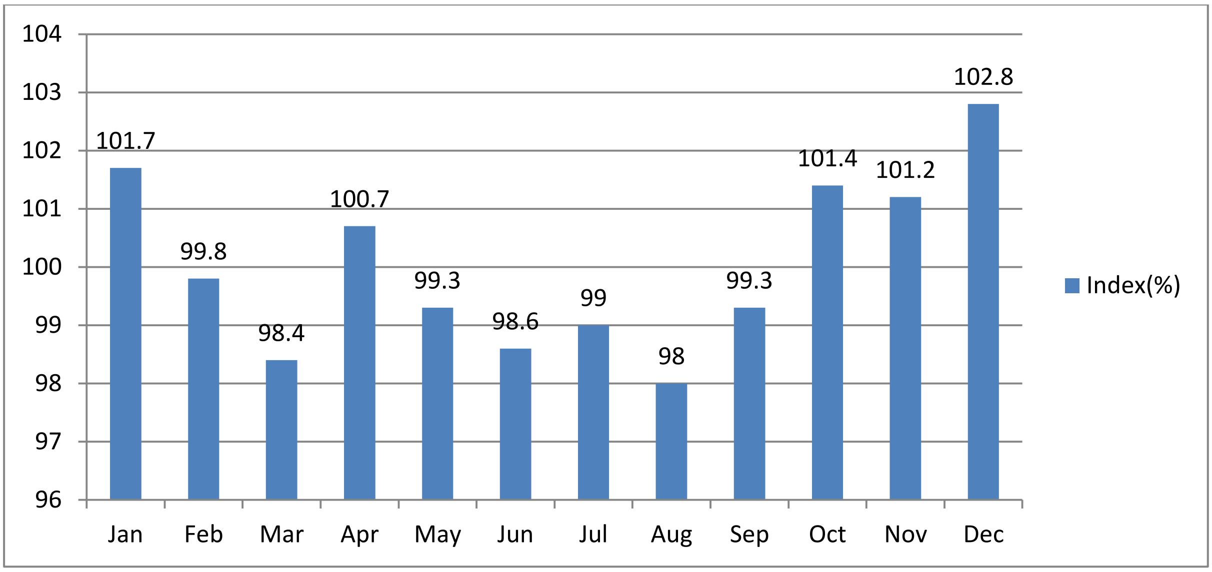


Figure 6.3: Plot of seasonal indices of SAB stock

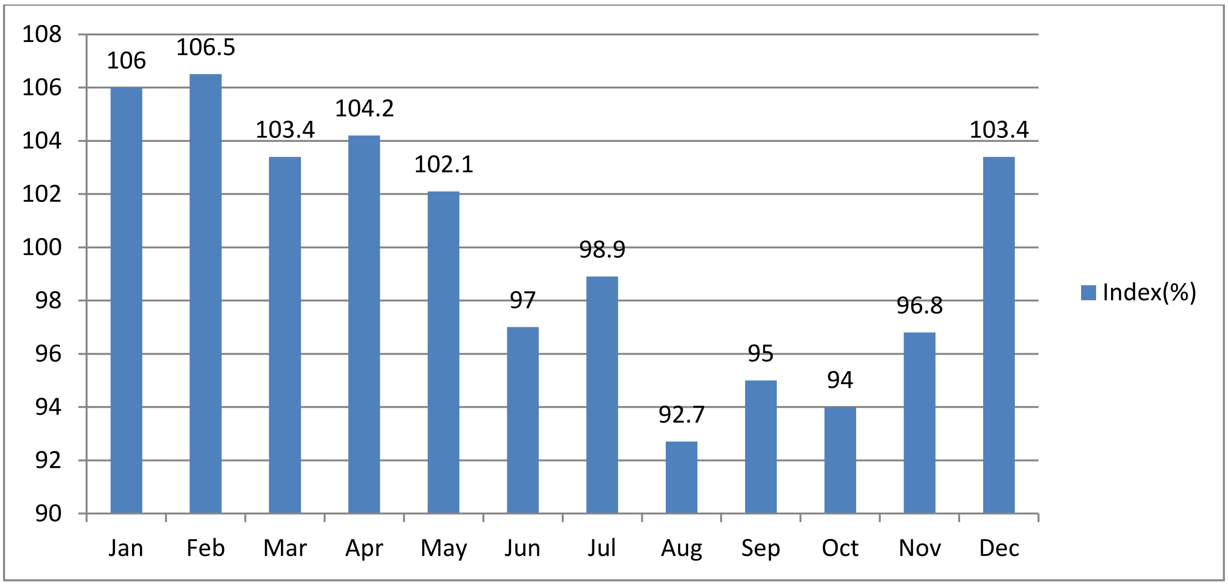


Figure 6.4: Plot of seasonal indices of NPN stock

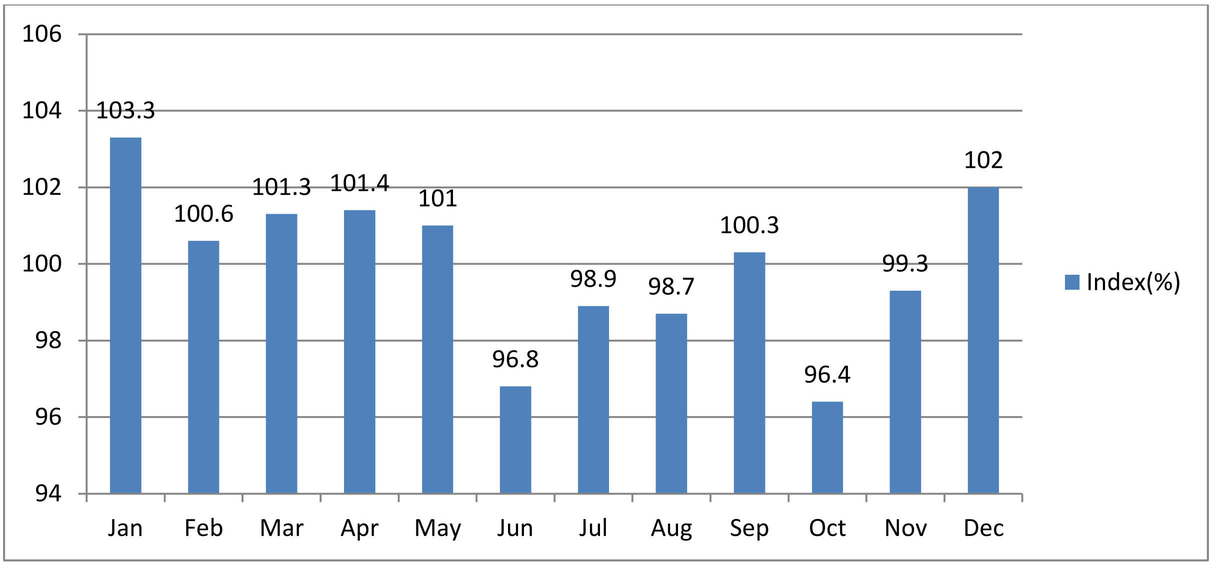


Figure 6.5: Plot of seasonal indices of FSR stock

Appendix 7:Topic index tables

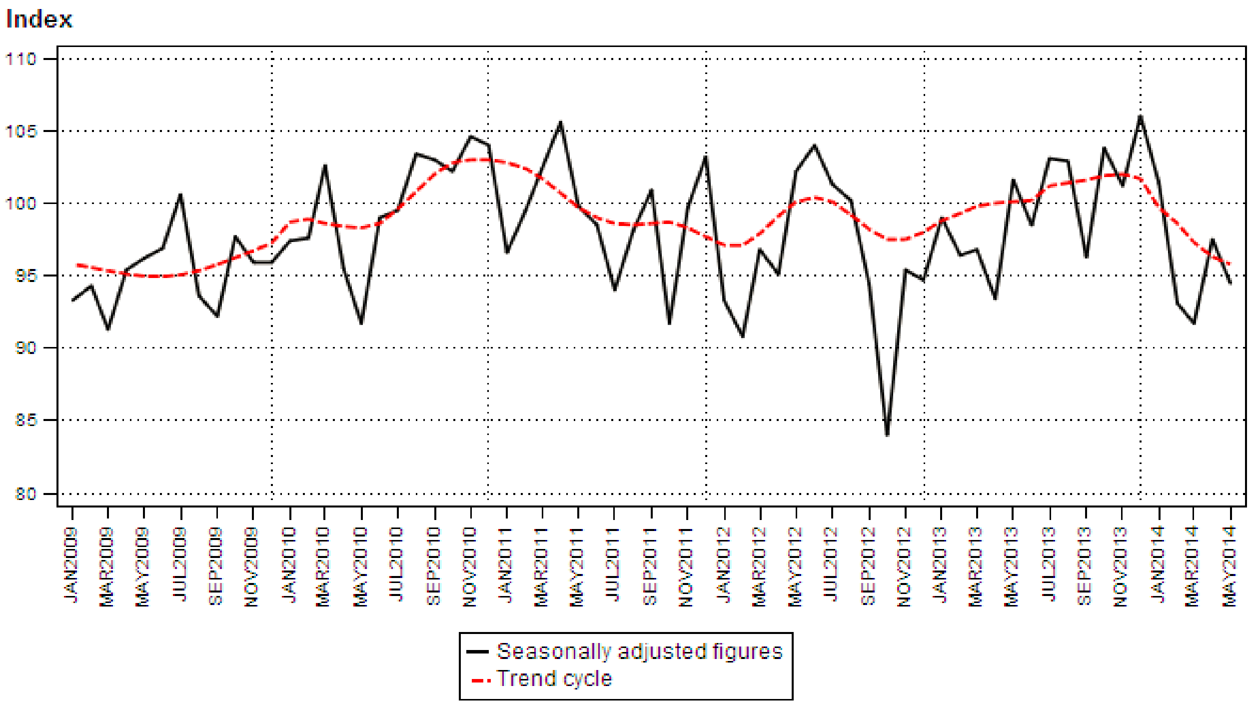
7.1 Table A1Constituents of the Top 40 Index

IndexCode	IndexName	NumberofConstituents	MarketCapitalisation	Alpha	InstrumentName	Price	MCap Gross	Weight
J200	Top 40	42	5,684,649,114,342	AGL	Anglo American	259.58	364827.9915	6.03270853
J200	Top 40	42	5,684,649,114,342	AMS	Anglo American Platinum	476.7	128557.3551	0.497526189
J200	Top 40	42	5,684,649,114,342	ANG	Anglogold Ashanti	172.41	69360.63507	1.22013925
J200	Top 40	42	5,684,649,114,342	APN	Aspen Pharmacare Holdings	305	138707.7344	1.634827061
J200	Top 40	42	5,684,649,114,342	ARI	African Rainbow Minerals Ltd	185.29	39929.91329	0.32311159
J200	Top 40	42	5,684,649,114,342	ASR	Assore Ltd	347.96	48577.65172	0.205089816
J200	Top 40	42	5,684,649,114,342	BGA	Barclays Africa Group Ltd	160.52	136080.939	0.909656089
J200	Top 40	42	5,684,649,114,342	BIL	BHP Billiton	338.21	722479.2824	12.70930303
J200	Top 40	42	5,684,649,114,342	BTI	British American Tobacco PLC	650	1316875.55	3.474820144
J200	Top 40	42	5,684,649,114,342	BVT	Bidvest Group	286.04	95179.75937	1.590613063
J200	Top 40	42	5,684,649,114,342	CCO	Capital & Counties Properties PLC	58.3	43907.35092	0.20081998
J200	Top 40	42	5,684,649,114,342	CFR	Compagnie Financiere Richemont AG	111.06	579733.2	9.790294191
J200	Top 40	42	5,684,649,114,342	DSY	Discovery Ltd	93.01	54660.36328	0.480771655
J200	Top 40	42	5,684,649,114,342	EXX	Exxaro Resources	140.5	50283.59207	0.318438179
J200	Top 40	42	5,684,649,114,342	FSR	Firstrand Limited	41.1	230717.6018	2.11047596
J200	Top 40	42	5,684,649,114,342	GRT	Growthpoint Prop Ltd	24.25	51582.59123	0.834809378
J200	Top 40	42	5,684,649,114,342	IMP	Impala Platinum Hlds	112.62	71051.87061	1.024909941
J200	Top 40	42	5,684,649,114,342	INL	Investec Ltd	96.51	27306.01139	0.413097965
J200	Top 40	42	5,684,649,114,342	INP	Investec PLC	96.35	58324.37556	1.025997812
J200	Top 40	42	5,684,649,114,342	IPL	Imperial Holdings	199.5	41887.87067	0.611593292
J200	Top 40	42	5,684,649,114,342	ITU	Intu Properties Plc	56.28	69971.73328	0.861622456
J200	Top 40	42	5,684,649,114,342	KIO	Kumba Iron Ore	334.02	107025.0454	0.338886495
J200	Top 40	42	5,684,649,114,342	LHC	Life Healthcare Group Holdings	40.16	41855.14356	0.647929636
J200	Top 40	42	5,684,649,114,342	MDC	Mediclinic International	80.2	66324.79634	0.583367548
J200	Top 40	42	5,684,649,114,342	MND	Mondi Ltd	193.09	22844.53544	0.401863598
J200	Top 40	42	5,684,649,114,342	MNP	Mondi Plc	193.2	70950.92353	1.248114388
J200	Top 40	42	5,684,649,114,342	MTN	MTN Group	229	431224.6003	7.206484728
J200	Top 40	42	5,684,649,114,342	NED	Nedbank Group	232.4	118571.4972	0.813469451
J200	Top 40	42	5,684,649,114,342	NPN	Naspers	1235	513192.2199	8.486023974
J200	Top 40	42	5,684,649,114,342	OML	Old Mutual	35.9	174715.3336	2.950520196
J200	Top 40	42	5,684,649,114,342	REI	Reinet Investments	26	50944.73436	0.672135606
J200	Top 40	42	5,684,649,114,342	REM	Remgro	223.19	107378.1307	1.88891396
J200	Top 40	42	5,684,649,114,342	RMH	RMB Holdings	52.93	74721.45133	0.617788036
J200	Top 40	42	5,684,649,114,342	SAB	SABMiller	627.36	1043588.23	10.83122359
J200	Top 40	42	5,684,649,114,342	SBK	Standard Bank Group	146	234386.7433	3.09236426
J200	Top 40	42	5,684,649,114,342	SHF	Steinhoff International Holdings	54.88	111672.9242	1.964464682
J200	Top 40	42	5,684,649,114,342	SHP	Shoprite	159	90722.13414	1.212894948
J200	Top 40	42	5,684,649,114,342	SLM	Sanlam	61.66	129486	2.050036821
J200	Top 40	42	5,684,649,114,342	SOL	Sasol	638.62	411108.1228	6.147114753
J200	Top 40	42	5,684,649,114,342	TBS	Tiger Brands	315.99	60000.77273	0.823280413
J200	Top 40	42	5,684,649,114,342	VOD	Vodacom Group	127.5	189714.135	0.734207316
J200	Top 40	42	5,684,649,114,342	WHL	Woolworths Holdings	78.59	66535.87932	1.018290027

7.2: Table A2Constituents of RESI Index:

IndexCode	IndexName	NumberofConstituents	MarketCapitalisation	Alpha	InstrumentName	Price	MCap Gross	Weight
J258	SA Resources	17	1,723,784,593,240	AGL	Anglo American	259.58	364827.9915	19.89449919
J258	SA Resources	17	1,723,784,593,240	AMS	Anglo American Platinum	476.7	128557.3551	1.640728095
J258	SA Resources	17	1,723,784,593,240	ANG	Anglogold Ashanti	172.41	69360.63507	4.023741443
J258	SA Resources	17	1,723,784,593,240	AQP	Aquarius Platinum	4.37	6199.081015	0.129463343
J258	SA Resources	17	1,723,784,593,240	ARI	African Rainbow Minerals Ltd	185.29	39929.91329	1.065548456
J258	SA Resources	17	1,723,784,593,240	ASR	Assore Ltd	347.96	48577.65172	0.676339518
J258	SA Resources	17	1,723,784,593,240	BIL	BHP Billiton	338.21	722479.2824	41.91238773
J258	SA Resources	17	1,723,784,593,240	EXX	Exxaro Resources	140.5	50283.59207	1.050136613
J258	SA Resources	17	1,723,784,593,240	GFI	Gold Fields	38.9	29973.14701	1.738798869
J258	SA Resources	17	1,723,784,593,240	HAR	Harmony	30.81	13410.18603	0.669037189
J258	SA Resources	17	1,723,784,593,240	IMP	Impala Platinum Hlds	112.62	71051.87061	3.379919633
J258	SA Resources	17	1,723,784,593,240	LON	Lonmin PLC	45.3	25647.23369	1.130761795
J258	SA Resources	17	1,723,784,593,240	NHM	Northam Platinum	45.64	18145.82915	0.915826224
J258	SA Resources	17	1,723,784,593,240	PAN	Pan African Resource	2.46	4496.627267	0.219120586
J258	SA Resources	17	1,723,784,593,240	RBP	Royal Bafokeng Platinum	73.79	13157.22741	0.228982684
J258	SA Resources	17	1,723,784,593,240	SGL	Sibanye Gold	24.88	18150.13744	1.052923754
J258	SA Resources	17	1,723,784,593,240	SOL	Sasol	638.62	411108.1228	20.27178487

Appendix 8 – Volume of mining production (base 2010=100)



References

Abdullah, D., & Hayworth, S. (1993).‘Macro econometrics of Stock Price Fluctuations’.*Quarterly Journal of Business and Economics, 32(1),* pp. 50-67.

Adrangi, B., Chatrath, A., &Todd, M. (1999).Inflation, output and stock prices: evidences from Latin America.*Managerial and Decision Economics*, 20(2), pp. 63-74.

Alagidede, P. (2012).Month of the Year and pre-holiday effects in African Stock Markets.*South African Journal of Economic and Management Sciences :S. Afr. j. econ. manag. sci. vol.16 n.1 Pretoria Jan. 2013*

Alter, A., &Oppenhiemer, D.(2006). Predicting Short-Term Stock Fluctuations by Using Processing FluencyProceedings of the National Academy of Sciences of the United States of America, *103(24),* pp. 9369-9372.

Asteriou, D. & Price, S. (2000). Political instability and economic growth: UK times series evidence.

Asteriou, D., &Siriopolous, C. (2000). The role of political instability in the stock market development and economic growth: the case of Greece.

Baker, M., &Wurgler, J. (2006).Investor Sentiment and the Cross Section of Stock Returns.

Balcilar, M. (2004). Persistence in Inflation: Does Aggregation cause long Memory. *Emerging Market Finance and Trade*,40(5),pp. 25-56.

Barr, G.D.I. & Kantor, B.S. (2005).The Impact of the Rand on the value of the JSE, *Journal in Economics and Econometrics,* 29(2), pp. 77-95.

Bauer, D. &Lucey, B. (2010). Is Gold a Hedge or a Safe Haven: An Analysis of Stocks, Bonds and Gold.

Bauer, D., &McDermott, T. (2010). Is Gold a Safe Haven? International Evidence.*Journal of Banking and Finance,* Elsevier.

Beaulieu, M., & Cosset, J. (2005). The Impact of Political Risk on the Volatility of Stock Returns: The Case of Canada. *Journal of International Business Studies*,36(6),pp. 701-718.

Becker, B., & Olson, C. (1986).The Impact of Strikes on Shareholder Equity.*Industrial and Labor Relations Review, 39(3),*pp. 425-438.

Berndt, E.K., Hall, B.H., Hall, R.E., &Hausman, J.A., (1974). Estimation and inference in nonlinear structural models.*Annals of Economic and Social Measurement*, 4,pp. 653-665.

Britt, D., &Galle, O. (1974). Structural Antecedents of the Shape of Strikes: A Comparative Analysis.*American Sociological Review,*39(5),pp. 642-651.

Bodington, L. (2014).Gold in the South African market – a safe haven or hedge?

Research report – Wits 2014

Bollerslev, T.(1986).Generalized autoregressive conditional heteroscedasticity.*Journal of Econometrics*,31, pp. 307-327.

Cochrane, J. H.*(*2003).Stocks as money: Convenience yield and the tech-stock bubble, in William. C Hunter, George G. Kaufman, and Michael Pomerleano, (eds).:*Asset Price Bubbles*. (MIT Press, Cambridge).

Corhay, A., &Hawaini, G. (1987). Seasonality in the Risk-Return Relationship: Some International Evidence.*The Journal of Finance*, 42(1), pp. 49-68.

Ciner, C.,Gurdgiev, C., &Lucey, B.M.(2013).Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis – Elsevier.*

Darrat, A.F., Bin, L., & Chung, R.Y.(2013). Seasonal Anomalies: a Closer Look at the Johannesburg Stock Exchange.

Davidson, W., &Worrell, D., &Garrison, S. (1988).Effect of Strike Activity on Firm Value.*The Academy of Management Journal*,31(2), pp. 387-394.

Department of Labour: Industrial action Annual review 2012.

Department of Labour: Industrial action Annual review 2013.

Dinardo, J., &Hallock, K. (2002).When Unions "Mattered": The Impact of Strikes on Financial Markets, 1925-1937.Industrial and Labor Relations Review,55(2), pp. 219-233.

Enders, W. (1995).Applied Econometric Time Series.New York, John Wiley and Sons, Inc.

Engle, R.F., (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom Inflation.*Econometrica*, 50, pp. 987-1008.

Engle, R.F., & Granger, C.W.J. (1987).Cointegration and Error Correction: Representation, Estimation and Testing. *Econometrica*,55(2),pp. 251 – 276.

Fama, F. & French, K. (1988).Permanent and Temporary Components of Stock Prices.*Journal of Political Economy*,96(2).

Gallagher, A., & Taylor, M. (2002). Permanent and Temporary Components of Stock Prices: Evidence from Assessing Macroeconomic Shocks.*Southern Economic Journal*, 69(2), pp. 345-362.

Granger, W.J. (1979).Seasonality: Causation, Interpretation, And ImplicationSeasonal Analysis of Economic Time Series.

Granger, C.W.J. and Newbold, P. (1986).*Forecasting economic time series*, (2nd ed.), Academic Press.

Gruber, M. (1966).Determinants of Common Stock Prices.*The Journal of Finance*,21(4), pp. 747-748.

Gujarati, D.N. (2004).*Basic Econometrics*.(4th Ed.)New York: Tata Graw Hill Publishing Company Ltd.

Gultekin, M., &Gultekin, N. (1983). Stock Market Seasonality: International Evidence.*Journal of Financial Economics,* 12(4).

Hylleberg, S. (1992). *Modelling Seasonality*.Oxford University Press.

Heston, S., &Sadka, R. (2010). Seasonality in the Cross Section of Stock Returns: The International Evidence. *The Journal of Financial and Quantitative Analysis, 45(5), pp. 1133-1160.*

Husain, F. (1998).A Seasonality in the Pakistani Equity Market: The Ramadhan Effect. *The Pakistan Development Review,* 37(1), pp. 77-81.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns.*Journal of Finance,* 45, pp. 881-898.

Kamstra, M.,Kramer, M., Levi, L. (2003). Winter blues: a SAD stock market cycle.

Makridakis S, Wheelwright S, Hyndman R. (1998). *Forecasting methods and applications*.(3rd ed.) New York: Wiley.

Muzenda, S. (2012). Analysis of Predictable behaviour of security returns on the JSE.

Ngidi, N. (2011).Market Reactions to Industrial Action in South Africa.

Research report – Wits 2014

Patton, A., &Verardo, M. (2012). Does Beta Move with News? Firm-Specific Information Flows and Learning about Profitability. *The Review of Financial Studies,25(9),* pp. 2789-2839.

Pearce, D., &Roley, V. (1985).Stock Prices and Economic News.*The Journal ofBusiness,* 58(1), pp. 49-67.

Persons, O. (1995).The Effects of Automobile Strikes on the Stock Value of Steel Suppliers.

Industrial and Labor Relations Review,49(1),pp. 78-87.

Phang, S. (2004). House Prices and Aggregate Consumption: Do They Move Together? Evidence from Singapore.*Journal of Housing Economics,* 13(2),pp. 101-119.

Timmermann, A. (1993). How Learning in Financial Markets Generates Excess Volatility and Predictability in Stock Prices.*The Quarterly Journal of Economics*,108(4), pp. 1135-1145.

Saad, K. (2004).Seasonality in the Kuwait Stock Exchange.*Savings and Development*,*28(4), pp. 359-374.*

Statistics South Africa (May 2014). Mining:Production and Sales, Statistical release.pp. 2041.

Srivastava, S. &Rao, T. (2014).*Twitter sentiment analysis: How to hedge your bets in the stock markets.*

Vissing-Jorgensen, A.(2003). Stock Market Participation, Intertemporal Substitution and Risk Aversion. *The American Economic Review,* 93(2).

Wachtel, S. B. (1942). Certain observations on seasonal movements in Stock Prices.*The Journal of Business of the University of Chicago*, 15, pp. 184-193.