Volatility and Anomalies in the Johannesburg Securities Exchange Daily Returns

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ABSTRACT

Using three models that differ according to the degree to which they accommodate and allow risk to vary across days of the week, we examine whether anomalies exist in the Johannesburg Securities Exchange daily returns. Simultaneously, we also examine the relationship between risk and return across the different days of the week. We estimate the measure of time-varying market risk using an asymmetric GARCH model. While the results vary across the three models, we generally find that after allowing for risk to vary across the days of the week, anomalies exist in the JSE daily returns. More specifically, the JSE daily returns seem to exhibit significant positive returns early in the week and significantly negative returns later in the week. Furthermore, the relationship between risk and returns is contrary to the portfolio theory in later days of the week. We outline the investment implications of these findings.

1. INTRODUCTION

Many stock market anomalies have been documented within the past three decades including the January Effect (Keim, 1982), the Momentum Effect (De Bondt and Thaler, 1984), the Daylight Savings effect (Kamstra *et al.*, 2000) and numerous other such anomalies. The day-of-the-week effect is one of these anomalies. These effects are regarded as anomalies since they do not conform to the Efficient Market Hypothesis (EMH). This is due to the fact that their presence implies that an investor could get arbitrage profit by buying stocks on days when their returns are significantly negative and short them on the days when their prices are significantly positive.

The day-of-the-week effect was coined after it was noticed through empirical testing that the return of shares differs according to which day of the week it is. Numerous past empirical studies have observed differences in return between days of the week. Cross (1973: 69) noted that between 1953 and 1970, Fridays had a significantly higher mean return than Mondays. Subsequent studies have also measured the differing volatilities of indexes on different days of the week. US markets between 1973 and 1997 were found to exhibit the highest volatility

on Fridays and the least volatility on Wednesdays (Berument and Kiymaz, 2001: 181).

While there have been relevant studies on the South African equity market (cf. Bhana, 1985; Le Roux and Smit, 2001; Basher and Sadorsky, 2006; Mbululu and Chipeta, 2012), the effect of domestic risk on the day-of-the-week effect has not received attention. The current study attempts to fill this gap by investigating whether returns on the SA equity market exhibit the day-of-the-week effect and analysing whether this anomaly (if present) is influenced by time-varying market risk. We analyse both the aggregate market returns and sector-level returns.

The rest of the study is organised as follows: Section 2 reviews relevant theoretical and empirical literature. Section 3 describes data and methodology employed. In Section 4, the results are presented and analysed and finally Section 5 concludes the paper.

2. LITERATURE SURVEY

The Efficient Market Hypothesis postulates that stock markets are very efficient in determining the prices of securities (Fama, 1970). This hypothesis relies on the assumption that security prices are the product of all available information. Any new information which arises will immediately change the price of the security due to arbitrage, thus providing unbiased estimates of the underlying values (Basu, 1977: 663). For this reason it is argued that neither technical nor fundamental analysis would ever allow the investor to make profits which are in excess of the average market return over the long run (Malkiel, 2003: 59). The only possible way to consistently make excess profits would be if an investor possessed insider information, which is illegal.

In reality though, it is commonly held that there are three forms of market efficiency within the EMH. Firstly there is *weak form* efficiency in which the information set available to investors is made up only of past and present asset prices. In this form technical analysis would fail to predict future prices. Secondly there is *semi-strong form* efficiency in which all publicly available information is added to the information set of the w*eak form* efficiency. In this form both technical and fundamental analysis would fail to predict future prices. Lastly there is *strong form* efficiency in which the information set contains all public and privately held information as well as past and present asset prices (Timmerman and Granger, 2004: 17). In this form technical analysis, fundamental analysis and even insider trading would fail to provide a means of beating the market average.

Due its simplifying assumptions, the validity of the EMH has been questioned and many empirical studies have been done to this end. While early studies lent support to some of the forms of the EMH (see Jensen, 1978), there has been mounting evidence against this hypothesis. The existence of stock market anomalies is some of the evidence against of the EMH.

The seminal paper on stock market anomalies was by Cross (1973: 67). This study investigated the movement of share prices in US markets on Fridays and

the following Mondays. Cross (1973) found that between 1953 and 1970 stock prices rose most often on Fridays (64.6% of observations), and rose least often on Mondays (43% of observations), compared with other days in the week. The difference between these two days was found to be statistically significant. Furthermore, it was noted that the chances of prices increasing on Mondays were dependent to a significant degree on whether the share price had increased or decreased on the preceding Friday. When the stock price had increased on Friday there was a 49% chance that the following Monday would also see an increase. On the occasions when the stock price had dropped on Friday there was only a 24% chance that the price would increase on the following Monday. This relationship between Friday and Monday was found to be significantly different from the relationships between other successive days of the week, i.e. Monday to Tuesday; Tuesday to Wednesday and so forth.

Following in the same field was French (1980), who studied whether the returns generating process was continuous. The hypothesis was that if returns occurred continuously then the returns for Monday would be three times higher than those for other days since investors would require returns for three full days including for Saturday and Sunday when the market is closed. French termed this the 'calendar-time hypothesis'. Alternatively, if returns occurred only during trading, French argued that Monday's mean return would be no different to the return earned on any other day of the week and he termed this the 'trading time hypothesis'. Using data for the US stock market, French (1980) surprisingly found that Monday's returns were significantly negative in each of the four sub-periods studied. Furthermore it was found that Monday's return was significantly different to all other days of the week. Thus, the results appeared to contradict both the calendar-time and the trading time hypotheses. The only sub-period during which he failed to reject the two hypotheses was during the period from 1973 to 1977, the most recent sub-period in his study, illustrating the possibility that the trend for stock market anomalies diminishes over time. This is logical given that when studies are published revealing anomalies, investors might rebalance their portfolios or alter their investment strategies, in an attempt to exploit super-normal profits emanating from these anomalies. As the information spreads to an increasing number of investors it is expected that the excess returns which once existed will now diminish or disappear due to arbitrage (Marquering *et al.*, 2006: 291). Therefore it can be said that "Once the market 'discovers' a trading opportunity, it should not persist for long, unless the anomaly is due to the limits of arbitrage" (Jones and Pomorski, 2005: 3). This serves to show that that the existence of these studies on inefficiency actually increases the efficiency of the market (Schwert, 2003: 939).

Early investigation of stock market anomalies tended to be predominantly centred on stock exchanges in developed countries. This is largely due to the higher degree of transparency of the stock exchange institutions in developed markets and consequently the greater availability of appropriate data (Ayogu, 1997: 298). Much fewer studies have focused on emerging economies. In more recent times however there have been some studies which have investigated

stock market anomalies in developing countries. There has been an increased amount of research in Asia and some in South America. Africa has received comparatively little attention.

The earliest study of daily seasonality in South African markets was by Bhana (1985). Using a multiplicative random walk model and daily data on the Rand Daily Mail 100 index (RDM 100) and the JSE Overall Actuaries Index (OAI) for the periods 1978–1983, the author tested whether the mean returns of the SA stock market exhibited day-of-the-week trends. Both the trading time and the calendar-time hypothesis were rejected. Monday returns were significantly negative and Wednesday returns were the highest not significantly affected. In line with French (1980), the author interpreted Monday returns as being caused by some sort of weekend effect.

Le Roux and Smit (2001) investigated whether several seasonal anomalies which had been documented on South African markets were still present. The seasonalities examined included the week-of-the-month effect, turn-of-the-year effect and day-of-the-week effect. Data for indices divided into sub periods were used: periods 1978–1989 and 1990–1998, and ANOVA F-tests and Kruskal-Wallis tests were used to test the presence of the day-of-the-week effect in each period. In the period 1978–1989, a negative mean return for Monday existed in the All Share, the Industrial and the All Gold indices. However, although Monday still had the lowest mean return in the period 1990–1998, these returns were now positive and insignificant for the three indices but negative and significant in the Financial Index. Instead the All Gold Index now had negative insignificant returns for Tuesday. It was therefore concluded that the day-of-the-week effect had disappeared in the All Share Index, the All Gold Index and the Industrial Index.

More recently, Mbululu and Chipeta (2012) show that there is no evidence of the day-of-the-week on the JSE using measures of the third (skewness) and the fourth (kurtosis) moments. However, their study does not address the risk-return relationship, an important cornerstone of the portfolio theory. Typically, a positive relationship between risk and return would entail that risk is priced. As such, it is possible to interpret the non-existence of the day-of-the-week effect as implying that the excess returns in any day of the week are matched by excess risk during that particular day of the week.

In a sample comprising of 21 emerging economies, Basher and Sadorsky (2006) considers the role of risk in the day-of-the week effect. Their measure of volatility is proxied by the MSCI world stock market index rather than the volatilities of the individual stock markets. The results showed no evidence of daily anomalies in South African stock returns if volatility is not incorporated. However, once risk was taken into account, Monday was found to exhibit significant negative returns. This result highlights the need to take market volatility into account when analysing stock market anomalies. If the return is high whilst volatility is simultaneously high, then the findings cannot be regarded as being anomalous as the increased return is likely to simply be compensation for the increased level of risk. Conversely if returns are significantly low whilst

volatility is increased, as in the above case of the JSE, there may be a significant day-of-the-week effect which is not at first apparent if volatility is ignored.

The current is in the same spirit with Basher and Sadorsky (2006). However, unlike these authors, our main contributions are twofold. Firstly, unlike Basher and Sadorsky (2006), our measure of risk is based on time-varying domestic stock market volatility. A key advantage of domestic time-varying volatility over the MSCI world stock market index is that the former measure account for the response of the JSE to both domestic and global innovations, while the latter measure only account for the JSE's response to global innovations. Although the South African financial markets have made strides towards integration into the global markets, there is evidence suggesting that that volatility in the South African financial markets is still dominated by domestic innovations (see for example, Chinzara and Aziakpono, 2009; Kambadza and Chinzara, 2012). Our second contribution is that we examine both aggregate market and sector-level returns. Our decision to focus on these two main aspects turns out to be an important contribution in the sense that we yield some striking differences and additional findings relative to previous studies. We outline these findings in the sections that follow.

3. DATA AND METHODOLOGY

Daily closing price data was collected for the 16 year period from 1 January 30 1995 to 31st December 2010 for the All Share Index and four other indices which represent the more prominent sectors of the JSE. All data collected was sourced from Thompson DataStream. The four sectors chosen were the FTSE/JSE indices of Industrials (IND), General Retailers (RET), Mining (MIN) and Financials (FIN). These particular sectors were selected so as to represent a broad range of South African activities as well as a mix of traditional South African strongholds, i.e. Mining, and sectors which have become increasingly significant in more recent years, including Financials, Retail and Industrials.

Continuously compounded returns were calculated for each series for each day of the trading week, which in South Africa runs from Monday to Friday, through the use of equation [1].

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) X\ 100 \qquad [1]$$

where R_t is the daily compounded percentage return and P_t is the price of the index at closing at time t.

In accordance with many other studies within this field (e.g. Chukwuogor, 2008), all weeks during which the market closed for any day for any reason other than a normal weekend were removed from the dataset. This was done in order to limit the observations to normal 5-day trading weeks and therefore act as a control. The most common reason for such a market closure would be public

holidays. This resulted in the data set being reduced from 3652 data points per index to a total of 2977 points for each index. General descriptive statistics of the returns were computed and are reported in Table 1.

The largest mean returns, 0.027% per day, were found on the industrials and mining sectors, while the general retail sector has the least mean return of about 0.009%. The standard deviations suggest that the mining sector has the most volatile returns with the industrial sector having the least volatile returns. This is not surprising considering the mining industry's large reliance on the underlying price of individual commodities, which is often highly dependent on the state of world markets, and their large exposure to foreign exchange fluctuations. A large range was found to exist across all indices between the maximum and minimum daily returns earned. The largest range, 23.5%, was found on the mining sector. All returns show evidence of leptokurtic distribution. Except for the mining sector, all sectors show evidence of negative skewness. Jacque-Bera tests on each of the indices reveal that there is significant evidence of non-normality of the distribution of the returns. Generally, these returns show the features that are common with financial returns data (Brooks, 2008: 162).

Table 1: General Descriptive Statistics of Returns

	ALSI	FIN	IND	MIN	RET
Mean	0.02	0.008	0.027	0.027	0.009
Median	0.057	0.024	0.0634	0.021	0.049
Maximum	7.423	8.113	7.687	11.616	6.598
Minimum	-12.69	-13.312	-13.616	-11.966	-8.906
Std. Dev.	1.329	1.403	1.32	1.928	1.339
Skewness	-0.509	-0.47	-0.531	0.028	-0.409
Kurtosis	9.538	10.038	9.324	7.711	6.609
Observations	2977	2977	2977	2977	2977
Jacque-Bera p-values	0.00	0.00	0.00	0.00	0.00

Source: Thompson DataStream (2010) and Author's own estimates

Following Brooks and Persand (2001) and Basher and Sadorsky (2006), this study employs dummy variable-based models to examine for the existence of the day-of-the-week effects. Three regressions are estimated. The simplest model does not include volatility as an explanatory variable and is shown in [2]:

$$R_t = \sum_{j=1}^{5} \delta_j D_{jt} + \varepsilon_{1t} \qquad [2]$$

where R_t is as defined in [1], D_{1t},. . .D_{5t}. represents the day-of-the week (0, 1) dummy variables for Monday, . . . , Friday and ε_t is an independently and identically distributed and *white noise* error term. The coefficients of the dummy variables, δ_1,...,δ_5, represent both the magnitude and direction which each individual day exerts on the mean return of the index. Statistical significance of any one of these coefficients indicates the presence of a day-of-the-week effect

since it implies that the day's return is high/low enough to be significantly different to the other days of the week.

In order to examine the effect of volatility on daily anomalies, equation [2] is augmented in two ways. Firstly, volatility is included as an explanatory variable but volatility is set constant across all days of the week. However a possible weakness with this approach is that it keeps the risk-return relationship constant over all days of the week when volatility could be significantly different across the days of the week, thereby exerting different influences each of the day's returns. Thus a second augmentation involves allowing volatility to vary for each individual day of the week by multiplying volatility by interactive dummies (D1,..., D5,). The two augmented models are respectively shown by [3] and [4] where V_t is time-varying conditional volatility for each of the indices being analysed and all other terms are as defined in [1]:

$$R_t = \sum_{j=1}^{5} \delta_j D_{jt} + \gamma_i V_t + \varepsilon_{2t} \qquad [3]$$

$$R_t = \sum_{j=1}^{5} \delta_j D_{jt} + \sum_{j=1}^{5} \gamma_j (D_j V_t) + \varepsilon_{3t} \qquad [4]$$

V_t was estimated using an appropriate GARCH model. This process involved analysing volatility of the aggregate market returns using the GARCH, exponential GARCH and GJR GARCH models and then selecting the most appropriate one. The selection criteria are based on the stationarity of the model, its ability to fully capture heteroscedasticity in the data and its ability to capture asymmetry in volatility. GARCH models have recently received considerable attention in analysing financial market data. This is due to the fact that financial market series are often characterised by properties such as heteroscedasticity, non-normality and volatility clustering, which cannot be captured by time series models.

Independently developed by Bollerslev (1986) and Taylor (1986), the GARCH model employs the maximum likelihood procedure and allows the conditional variance to be dependent upon previous own lags and it is specified as follows:

$$r_t = \mu i + a r_{t-1} + \varepsilon_t \qquad [5]$$

$$h_t = \omega + \alpha \varepsilon^2{}_{t-1} + \beta h_{t-1}\ ,\ \alpha + \beta < 1 \qquad [6]$$

where equation [5] is an autoregressive mean equation and equation [6] is the volatility equation. This is a GARCH (1, 1) model. ε_t in the mean equation should be unserially correlated. h_t is the conditional variance, ω is a constant, α is the coefficient of lagged squared residuals, $\varepsilon^2{}_{t-1}$ is the lagged squared residual from the mean equation and β is the coefficient for the lagged GARCH component which is the lagged conditional variance. Since variance cannot be negative, the

coefficients α and β are required to be positive. The condition $\alpha + \beta < 1$ ensures that the GARCH model is stationary. Usually the GARCH (1, 1) is considered sufficient to capture volatility clustering in the data and studies rarely use higher order GARCH models.

Nevertheless, the GARCH model has some weaknesses, the main one of which is that it cannot capture asymmetry in volatility. Asymmetry in volatility occurs when the size of response of volatility to positive and negative shocks differ significantly. This is normally attributed to leverage effects[1]. Thus a number of extensions to the GARCH model have been suggested, for instance the exponential GARCH (EGARCH) and the threshold GARCH (TARCH/GJR GARCH) models.

The EGARCH model was proposed by Nelson (1991). It takes the same mean equation as [5] and its conditional variance equation is specified as follows:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \alpha\left[\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}} - \sqrt{2/\pi}}\right], \qquad [7]$$

$\delta + \beta < 1; \gamma < 0$, if volatility is asymmetric.

where α and β are still interpreted as they are in the GARCH (1, 1) model and γ is an asymmetry coefficient. If $\gamma < 0$ and significant then there is asymmetry in volatility (Brooks, 2008:406). Another advantage of the EGARCH model over the pure GARCH model is that the former does not require a non-negativity assumption on the parameters since it is based on a logarithmic functional form. The GJR GARCH model also captures asymmetry although, like the GARCH model, it does not guarantee the 'non-breach' of the non-negativity assumption. Proposed by Zakoian (1990) and Glosten *et al*. (1993), this model is simply a re-specification of the GARCH (1, 1) model with an additional term to account for asymmetry as follows:

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_t^2 + \beta h^2_{t-i} + \gamma \varepsilon^2_{t-1} I_{t-1}, \qquad [8]$$

where $I_{t-1} = 1$ *if* $\varepsilon_{t-1} < 0$

$= 0$ *if otherwise*

I_{t-1} is the asymmetry component and γ is the asymmetry coefficient. If leverage effects and asymmetry exist in volatility, then the coefficient of asymmetry will be positive and significant (i.e. $\gamma > 0$).

Assuming conditional normality of residuals, the GARCH models specified above can be estimated by maximizing the following log-likelihood function:

[1] For more insight into asymmetry in volatility see Chinzara and Aziakpono (2009).

$$l = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}(r_t - \mu - \phi r_{t-1})^2 / \sigma_t^2 \quad [9]$$

where T is the number of the observations and other variables are as defined earlier. In this study, estimation was done by applying the Marquardt algorithm on the above log-likelihood function.

4. RESULTS

4.1. Analysis of volatility

The GARCH and its extensions were estimated for the aggregate market data and the results are reported in Table 2 (see Appendix). As evident from γ in both EGARCH and TARCH models, volatility on the SA stock market exhibits evidence of asymmetry. This implies that bad news has a larger impact on the volatility of the SA stock market than good news of the same magnitude. For instance, news about a 2% decrease in economic growth in SA would have a greater impact on volatility than would news about a 2% increase in economic growth. For this reason, the standard GARCH model is inappropriate since it does not capture asymmetry. Although the EGARCH captures asymmetry, it seems to violate the stationarity condition and does not fully capture ARCH effects. For this reason, the TARCH model is the most appropriate of the three in all the cases. Using the TARCH model, we then estimated conditional volatility series, which we now use as our measure of the aggregate risk (V_t) of the JSE.

Table 2: Comparing GARCH models

	Ω	α	B	α + β	Γ	F-LM	AIC	SIC
GARCH (1, 1)	0.01***	0.11***	0.89***	1	NA	0.01	3.05	3.06
EGARCH (1, 1, 1)	0.16***	0.21***	0.98*	1.19	-0.08***	0.05	3.04	3.05
TARCH (1, 1, 1)	0.02***	0.05***	0.89*	0.94	0.095***	1.04	3.04	3.05

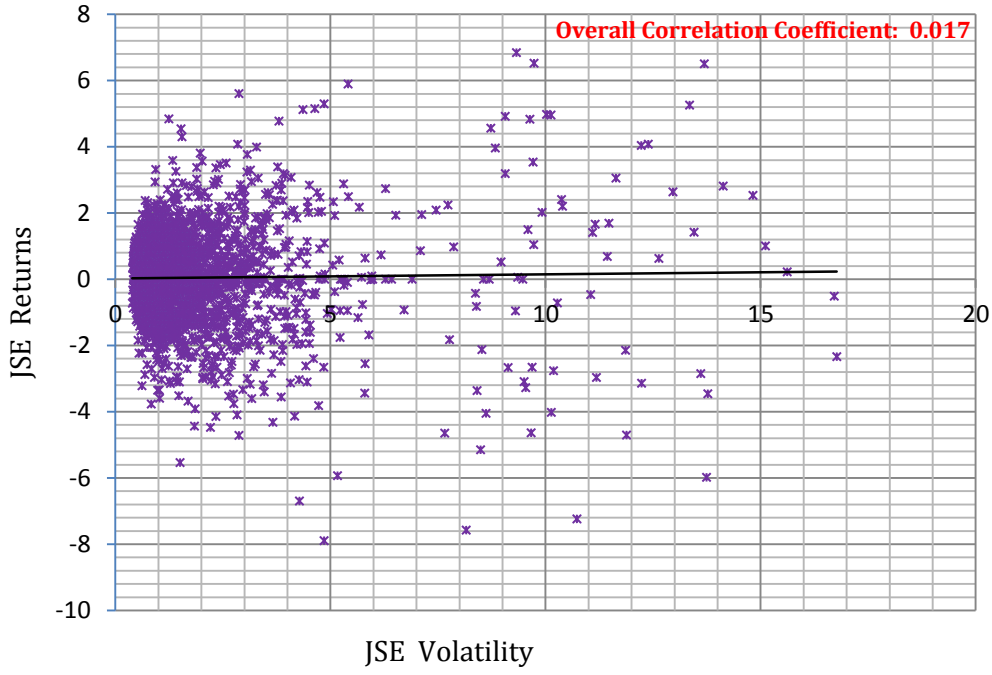
Source: Thompson DataStream (2010) and Author's own estimates

Note: *, ** and *** denote significance at 10%, 5% and 1% levels respectively

4.2. Risk-return Relationship: A Graphical Analysis

We begin by analysing the relationship between risk and return. Figure 1 shows a plot of the correlation between the two. It is evident that overall, the correlation between risk and return is weakly positive. Figure 2 plots the relationship between risk and returns in different days of the week.

Figure 1: Overall Correlation between Daily Returns and Volatility: (1995 – 2010)



4.3. Analysis of the day-of-the-week effect

Equations [2], [3], [4] were estimated and the results are reported in Tables 3, 4 and 5 respectively. From Table 3 it is evident that significant day-of-the-week effects are exhibited in three of the five sectors. The All Share and the Industrials sector both exhibit significant positive returns on Mondays. The Retail sector is found to exhibit a significant negative mean return on Fridays. These significant positive returns for Monday and significant negative returns for Tuesday could be due to differences in volatilities for these days. This justifies the inclusion of risk/volatility in the model. Only if the effect persists once volatility has been taken into account is it possible to conclude the existence of these anomalies.

Table 3: Regression 1 results –No risk included

	ALL SHARE	FINANCIALS	MINING	RETAILS	INDUSTRIALS
MONDAY	**0.1104****	0.0372	0.0978	0.0617	**0.0993***
TUESDAY	0.0009	0.062	-0.0908	0.0350	0.0649
WEDNESDAY	-0.0353	0.0444	-0.0557	-0.0078	-0.0064
THURSDAY	0.02	-0.0482	0.0752	0.0590	0.0381
FRIDAY	0.0022	-0.0531	0.1093	**-0.1008***	-0.0628

Source: Thompson DataStream (2010) and Author's own estimates
Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively

Table 4 reports the results from equation [3], in which time-varying risk is set as a constant throughout the week. The significantly positive Monday returns noted in equation [2] for the All Share and Industrials sectors are still present although with reduced economic and statistical significance. The Retail sector no longer exhibits the significant negative Friday returns. Instead Retail joins the All Share and Industrials indices in exhibiting significant positive Monday effects. In addition to this, the Retail sector also exhibits significantly positive returns for Thursday. The persistence of significantly positive Monday returns in the All Share and Industrials indices might illustrate that the average volatility experienced during the week is not sufficient in explaining the return earned on that particular day. Alternatively, the fact that new effects are noted, which were not initially present in the first model, indicates that those days' returns which initially appeared to be normal were in fact significantly different once volatility had been accounted for. It is interesting to note that the retail sector also exhibits a significantly negative volatility coefficient. This implies that an increase in volatility in the Retail sector exerts a negative influence on returns. This is surprising since it is not in line with Portfolio theory as propounded by Markowitz (1952), wherein it is postulated that an investor would require an increased return when risk, measured by volatility, is higher.

Table 4: Regression 2 results –Constant risk variable included

	ALL SHARE	FINANCIALS	MINING	RETAILERS	INDUSTRIALS
MONDAY	**0.1074***	0.0474	0.084	**0.1012***	**0.0713***
TUESDAY	-0.0041	0.0721	-0.1096	0.0747	0.0648
WEDNESDAY	-0.0402	0.0546	-0.0733	0.0319	-0.0065
THURSDAY	0.0150	-0.0381	0.0575	**0.0988***	0.0379
FRIDAY	-0.0028	-0.0430	0.0917	0.0610	-0.0630
VOLATILITY	0.0027	-0.0049	0.0046	**-0.0213****	0.0001

Source: Thompson DataStream (2010) and Author's own estimates

Note: *, ** and *** indicate significance at the 10, 5 and 1% levels respectively

Table 5: Regression 3 results – Daily time-varying risk variables included

	ALL SHARE	FINANCIALS	MINING	RETAILERS	INDUSTRIALS
MONDAY	0.0236	0.0102	-0.0331	-0.03	0.0353
TUESDAY	-0.0924	-0.0137	**-0.2118****	-0.046	0.0137
WEDNESDAY	-0.0705	-0.0799	0.0038	0.001	**-0.1299***
THURSDAY	**0.1643****	**0.1534****	**0.2178****	**0.200*****	**0.2315*****
FRIDAY	0.0348	0.0425	0.0806	0.0466	-0.0132
MON VOL	**0.0481****	0.0233	**0.0352****	0.0173	0.0376
TUES VOL	**0.0502****	**0.0372***	**0.0313***	**0.0435****	0.0291
WED VOL	0.0189	**0.0605*****	-0.0136	-0.0041	**0.0699*****
THURS VOL	0.0771	**0.0982***	**0.0171***	**-0.0458****	**0.0378***
FRI VOL	**-0.0175****	**-0.0465****	**-0.0075****	**-0.0796*****	**-0.0281*****

Source: Thompson DataStream (2010) and Author's own estimates

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively

A possible concern with the above result is that volatility is unlikely to be constant throughout the week because investors are likely to receive new information every day. This new information may manifest from the fact the trading timing between stock markets are different. For instance, news from stock markets of Japan, Australia, China, and USA do not affect South Africa contemporaneously, but on a lagged or lead basis. To address this issue, we estimate equation [4], which allows for differences in volatility across days of the week. The results are reported in Table 5.

Once volatility is allowed to vary across all the days of the week, the previously statistically significant positive Monday returns become insignificant and their economic significance is reduced. This implies that these excess returns are explained by their corresponding excess time-varying volatilities. The most noticeable trend is the fact that all returns now exhibit very significant positive mean returns on Thursdays. This implies that the excess returns earned on Thursdays are not explained by the level of volatility experienced on Thursdays.

With respect to the coefficients of time-varying volatility, it is evident that daily time-varying market risk seems to have a significant positive impact on returns early in the week (i.e. Monday to Wednesday) and significant negative impact on returns late in the week (Friday). Most outstanding sectors in this regard are the Mining and Industrial sectors, which show significant evidence of excess negative returns on Tuesdays and Wednesdays respectively and significantly evidence positive returns on Thursdays. This strongly suggests the existence of potentially profitable arbitrage opportunities in these two sectors.

The relationship between risk and return is negative on Fridays. This finding is not uncommon in empirical analysis of daily data. While Chou *et al*. (1992), Whitelaw (1994), Lettau and Ludvigson (2004) demonstrate that such a finding may be due to misspecification of the time-varying nature of the risk-return relationship, LeBaron (1989) and Balios (2008) attribute this finding to non-synchronisation of trading when the market is characterised by illiquidity and thin trading, forcing investors to forgo risk-premium in pursuit of a successful transaction. Since GARCH models have been widely credited for their ability to appropriately model time-varying risk, the latter explanation is most likely in the context of the current study.

5. CONCLUSIONS

This study tested for the presence of the day-of-the-week effect on the SA stock market using both aggregate market data and sector level data. Three types of models were using ranging from the simplest, which did not accommodate the impact of risk on returns, to one that allows risk to vary across the days of the week. Unlike previous studies (e.g. Brooks and Persand, 2001; Basher and Sadorsky, 2006) our measure of market risk was estimated from aggregate domestic market returns using an asymmetric GARCH model. The three models seem to produce different results. Before allowing risk to vary across the days of

the week, Monday effects tend to exist in the market. However after allowing for risk to vary across the week, significant evidence of positive returns for Thursday effects is detected for all the sectors. The results seem to show that risk significantly and positively impacts on returns early in the week and negatively later during the week.

The implication of the results is that arbitrage opportunities exist to *long* the Mining and the Industrial index on Wednesday and Thursday respectively when their returns are significantly low and *short* them on Thursday when their returns are significantly high. Further research should examine the reasons for the negative risk-return relationship found in some of the days of the week. This could be done by linking the risk-return relationship with changes in daily trading volumes, market capitalizations and turnover velocities.

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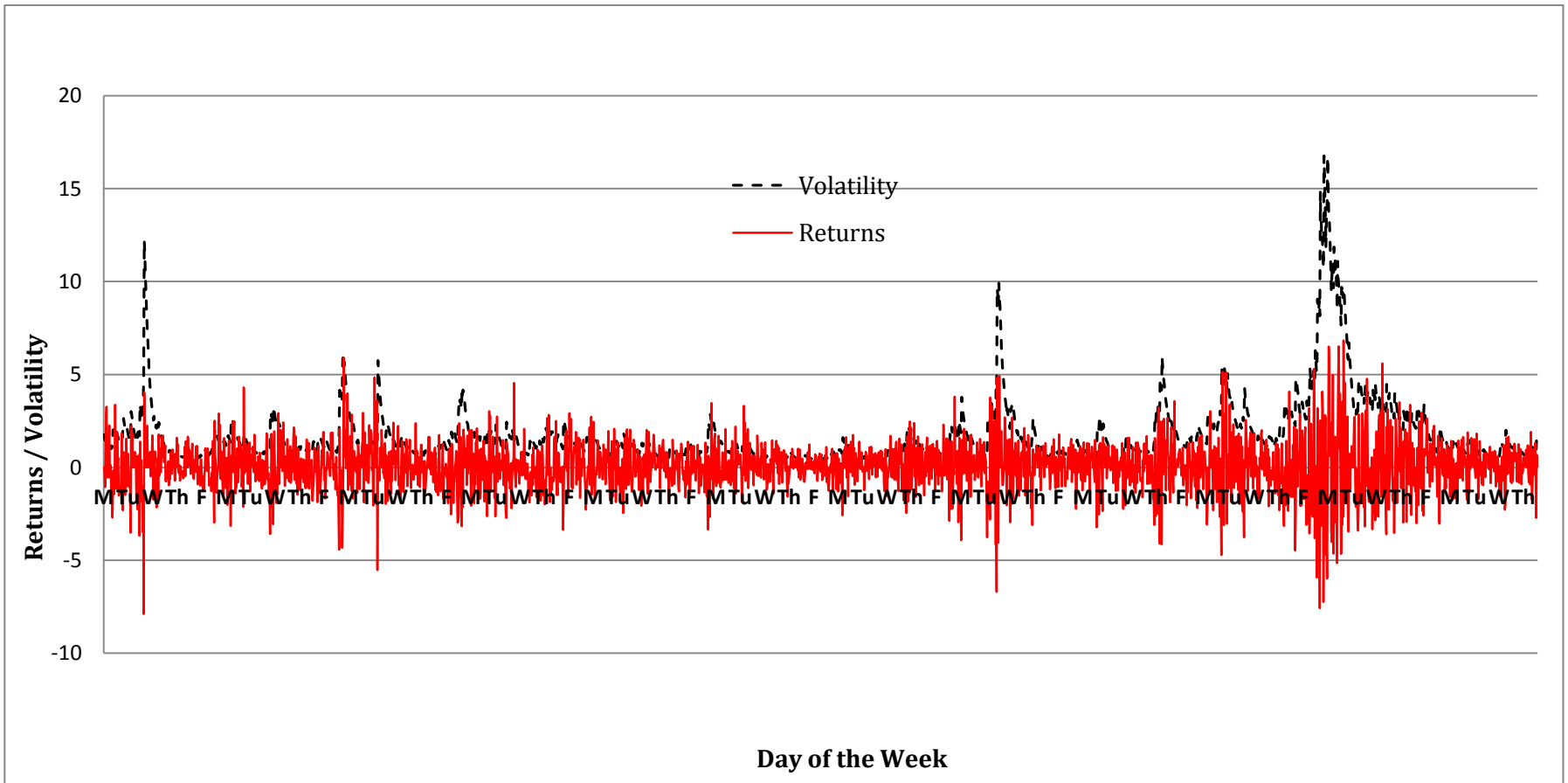
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Figure 2: Returns-Volatility Relationship in Different Days of the Week


20
15
10
5
0
-5
-10
Returns / Volatility
Volatility
Returns
M Tu W Th F M Tu W Th F M Tu W Th F