Impact of macroeconomic announcements on foreign exchange volatility: Evidence from South Africa

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Abstract

This study focuses on scheduled macroeconomic news announcements and evaluates their impact on the volatility of the South African rand (ZAR) and US dollar (USD) exchange rate using high frequency data. The following asymmetries are studied: news items by geographical location, no-news versus surprise news announcements and positive versus negative news announcements. We make the following findings in our empirical study: (i) After the release of a news announcement, the level of foreign exchange volatility rises. This is independent of whether the news item surprised the market or not. (ii) Both South African and US news items significantly impact USD/ZAR volatility, suggesting that the news items are being used to formulate investor expectations regarding the future prospects of the currency pair. (iii) Negative news appears to have a greater impact on exchange rate volatility relative to positive news. This result is also state dependent, as investors tend to behave differently to news depending on the economic climate at that point in time. Investor cognitive biases give rise to the asymmetric news effects on exchange rate volatility. Finally, investors do not always act in rational manner, especially when faced with multiple news items that are contradictory to each other.

Keywords: Exchange rates; macroeconomic news; high frequency data; market efficiency

JEL classification: C1; G0; F0

1 INTRODUCTION

Financial economists have spent a considerable amount of time during the past few decades trying to understand how information is incorporated into asset

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prices, especially in the foreign exchange market. Currencies are the most actively traded financial assets relative to equities and bonds, with trading activity amounting to US$5.3 trillion per day in April 2013 (Bank for International Settlements, 2013). A significant amount of literature studying exchange rate determination focuses on how the arrival of new information regarding the current state or future prospects of the economy affects exchange rates. This is partly attributed to the fact that the foreign exchange market is highly integrated with the macroeconomic fundamentals of an economy, resulting in exchange rates being mostly driven by the macroeconomic fundamentals and monetary policies of a country (Li, Wong, & Cenev, 2015).

Macroeconomic data has been widely used to test for informational efficiency in the foreign exchange market. Empirical literature examining the effects of macroeconomic news on exchange rates agree that macroeconomic news significantly affect exchange rates often resulting in a jump in the exchange rate level and a rise in volatility (Laakkonen, 2009). Since the acceptance of this hypothesis in modern day exchange rate literature, academic focus has shifted to examining the asymmetric effects of news on the exchange rate level and volatility. There is ample literature that evaluates the effects of macroeconomic announcements on exchange rates (see Anderson et al, 2003; Ehrmann and Fratzscher, 2005; Fatum and Scholnick, 2008). While a great deal of the literature examines the macroeconomic and monetary factors that drive exchange rates (see Dornbusch, 1986; Meese and Rogof, 1983; Engle and West, 2005; Ehrmann and Fratzscher, 2005; Fatum and Scholnick, 2008; Krugman & Obstfeld, 2011), recent studies have focussed on the market microstructure, particularly, on the imbalances between buy- and seller-initiated trades in the foreign exchange market. The vast majority of these studies (Bauwens et al (2003); Evans and Lyons, 2005, 2008; Vitale, 2007; Rime, 2000); Neely and Dey, 2010 and Vega, et al., 2015) analyse the transmission link between fundamental information and exchange rates and dealer perceptions regarding the economic prospects on the respective countries in the currency pair. Although sufficient strides have been made to cover the first camp, very few studies analyse how news asymmetrically affects exchange rate volatility, especially for emerging market currencies. While researchers such as Li et al. (2015), Joo et al. (2009) and Fedderke and Flamand (2005) have conducted studies on emerging markets currencies, their focus has been on the directional moves in the currency as opposed to its volatility. Moreover, the extant literature analyses exchange rates from the point of view of daily data with little or no inference to the differential impact of news on exchange rates. This study fills these gaps in the literature regarding the analysis of macroeconomic news on exchange rate volatility in South Africa. The use of high frequency data rather than daily data improves our understanding of the dynamic properties and drivers of volatility of the USD/ZAR. The study also assesses the presence of any asymmetric behaviour in the USD/ZAR currency pair to the arrival of macroeconomic news. The investigation focuses on how the exchange rate volatility reacts to the following variables: (i) domestic and international macroeconomic data (ii) surprise and no-news announcements (iii) positive and negative surprises. Given the changes in the microstructure of the foreign exchange market since the 2008 Global Financial Crisis, and the extreme swings in the South African rand against major international currencies in recent times, the study provides an updated report of the work done by Fedderke and Flamand (2005) and extends it by studying the effects on the exchange rate volatility and the efficiency of the foreign exchange market in South Africa.

The results of this study will provide guidance to foreign exchange market participants who trade USD/ZAR derivatives and asset managers who include currency derivatives in their portfolios to hedge their currency risk. Volatility is a key input in derivative pricing under Black-Scholes option pricing framework and understanding this subject matter will allow participants to make better informed decisions when trading such securities. It will also allow for improved risk management by derivative traders, attributable to a better understanding of the potential effects of macroeconomic news on the underlying volatility.

Section 2 details the data and methods employed and tease out the uniqueness of the techniques in relation to the research questions. The results are discussed thoroughly in section 3. A critical appraisal of the findings is carried out in section 4 and 5 concludes.

2 DATA AND RESEARCH METHODOLOGY

Our data set consists of 1-minute bid-ask quotes on USD/ZAR from 2 January 2014 to 31 December 2015. The data was obtained from HistData.com, a free online data provider of high frequency currency data. We use 10-minute data instead of 5-minute data that is used in most high frequency data studies. Given the inefficiencies of the USD/ZAR foreign exchange market relative to the EUR/USD market, this time-interval was appropriate as it is short enough to capture the asymptotic nature of the return series without much efficiency being lost. The prices are obtained from the Ninja Trader trading platform. Mid exchange rate prices, which is an average of the bid and ask quotes, are used in the study and returns are calculated as the differences of the logarithmic prices , $r_t = \ln(P_t) - \ln(P_{t-1})$ where r_t represents the return and P_t is the mid-price at time t.

The dataset consists of data for all the trading days, which is all the weekdays excluding New Year's day and Christmas day. However, due to a decrease in liquidity during the weekend and certain public holidays, we have excluded these days from the study to maintain consistency with previous literature by Andersen & Bollerslev (1998) and Laakkonen (2009). Andersen & Bollerslev (1998) define a day as starting at 21.05 GMT the night before to 21:00 GMT that evening. For this study, a day is defined as starting 00:10 South Africa Standard Time (SAST) to 00:00 SAST. This equates to 22.10 GMT the night before to 22:00 GMT that evening. The weekend is defined as the duration between 00: 00 SAST on Friday till 23:50 SAST on Sunday. The following holidays were excluded from the study: Christmas, News Years, Good Friday and Easter Monday. All other South Africa public holidays were included in the study as the market had sufficient liquidity on those days to conduct a meaningful experiment and some significant US news are released on those days, which significantly impacts the volatility on the currency pair. The data did have missing quotes at some time periods due to a lack of quotes, especially on South African or US public holidays. In cases where the time period of the missing data is less than an hour, a linear interpolation between the two end points was used to replace the missing data. If the time period of the missing data is more than an hour, these data points were excluded from our study.

The 10-minute return data series has the following statistical characteristics:

The statistical properties of the return series clearly show that USD/ZAR exhibits the fat tail distribution that is common to most financial assets. Due to the large kurtosis of the returns, the distribution is larger in the tails and thinner in the midrange than is implied by a normal distribution. The skewness in the returns highlights ZAR's tendency to depreciate rather than appreciate over the period of study. The minimum and maximum returns of -4.95% and 4.71% respectively, also highlights the volatile nature of USD/ZAR relative to other currency pairs such as EUR/USD which has a minimum and maximum of -1.35% and 2.79% respectively. The absolute returns, which are used as a proxy for intraday volatility, also support the notion that the currency pair is volatile.

The intraday volatility pattern exhibits strong periodicity due to events such as market opens and closes and macroeconomic data announcements being made at particular times of the day. In Figure 2, we plot the average intraday volatility pattern in a day by computing the mean absolute returns per 10-minute interval. The figure clearly shows that the opening and closing of the various major markets around the world have a significant bearing on market volatility. The level of volatility rises at various points in the day due to different trading times of the various markets:

- 02:00 – Asian Market
- 09:00 – South African Market
- 10:00 – European Market
- 15:00 – United States Market

It is worth noting that there is a spike in volatility around 15:30 SAST; this can be attributed to the fact that most US macroeconomic announcements are usually released around this time – which seems to significantly increase the volatility. The sporadic spike in volatility at 02:00 SAST is due to the flash crash of most emerging market currencies on 24 August 2015 sparked by fears over the economic health of China, causing ZAR to depreciate by 4.71% within a 10-minute interval. This figure skewed the average volatility at this point and a similar incident can be said for the spike at 09:00 SAST. These spikes in volatility are a result of public information being disseminated into the market, in form of both scheduled and unscheduled news announcements.

Overall, it is evident USD/ZAR is most volatile during South African market open. This volatility increases even more during the overlap between the South

African and US trading times, which is between 15:00 and 17:00 SAST. The local foreign exchange market also exhibits lunchtime effects, as we can see a decline in volatility between 12:00 and 14:00 SAST. Volatility seems to peter out as the market nears its closing time, which is around 17:00 for the South African market.

The U-shape autocorrelation of the 10-minute USD/ZAR returns in Figure 3 shows that the volatility pattern is repeated on a daily basis, which is consistent with the findings of Andersen & Bollerslev (1998) on EUR/USD volatility. The autocorrelation that's present in the return data series will require to be de-trended before it is analysed, as the presence of autocorrelation will violate the key assumptions of the linear regression model. Laakkonen (2009) evaluates a range of popular methods that are used to remedy the seasonality issue often experienced with high frequency financial market data. She evaluates the advantages and the shortcomings of using the Flexible Fourier Form (FFF) model, Locally Weighted Scatterplot Smoothing method (LOWESS) and the Intraday Average Observations Model (IAOM). While Laakkonen (2009) and Andersen & Bollerslev (1998) utilise the FFF model to filter the periodicity in the return series as it yields superior results most scenarios, we utilise IAOM as it is an equally as robust, easily computed and capable of filtering out the periodicity in volatility.

2.1 Macroeconomic news data

The macroeconomic news data used in this study is sourced from Bloomberg's World Economic Calendar platform. The platform contains a calendar of all the scheduled economic news that is set to be announced, stating both the date and time of the announcement and any market analyst expectations for the economic data print. In this study, we collect all the scheduled macroeconomic news from the 1^{St} January 2014 and 31^{st} December 2015. The market forecasts are median expectation by analysts from the survey conducted by Bloomberg. While forecasts are available for a wide range of data prints, less supervised data prints often lack forecasts. Since this is a point in time study, we use the original data print that is announced when computing the surprise component instead of using the revised figure, if the figured is revised at a later point in time.

We isolate the study to news announcements released out of South Africa and the US, which amounts to 728 and 3229 news announcements respectively. While this is the total number of news announcements that are released during our observation period, the number of unique news variables during this period amount to 42 and 216 for South Africa and the US respectively. The reason behind the number of unique observations being significantly lower is because most data prints are released on a monthly and quarterly basis i.e. some data such as non-farm payrolls could contribute 24 news announcements to the total number of US announcements over the observation period.

To test the asymmetrical news effects, the news announcements are divided into different categories. Given our research questions, the data was separated according into the following groups:

- Positive surprise news
- Negative surprise news
- No news announcements
- Consistent news
- Contradictory news

As mentioned earlier, not all news announcements have available forecasts, resulting in only 546 and 2507 news announcements from South Africa and the US being eligible for our asymmetrical news effects analysis. A positive news announcement is defined as a data print that exceeds what is expected by the market, except when considering macroeconomic variables such consumer price index (CPI), producer price index (PPI) and unemployment figures. In the CPI instance, a news item that is lower than the market forecast would be considered as a positive news announcement. This statement is also conditional on CPI being in positive territory in the region, as an increase in CPI above market expectations in a country with negative CPI changes would be regarded as positive by market agents. Negative news items are defined as news items where the market had been overly optimistic about the actual news announcement i.e. actual news item is lower than market expectations. This definition is consistent with most literature, but questions are still being raised whether survey forecasts serve as a good proxy for market expectations (Laakkonen (2009) and Andersen & Bollerslev (1998)). No-news announcements, which are defined as news items that are in line market expectations, only amounted to 49 and 326 news items for South Africa and the US respectively.

In instances where more than one news item is released at a specific date and time, we evaluate whether the news items are contradictory or consistent with each other. Contradictory news items occur when a positive and negative news announcement is released at the same date and time, while consistent news items occur when the multiple news items that are released at the same time are either all positive or negative. This provides insight into how investors process multiple news items that are disseminated at the same time. This will also contribute to the work done by Damodaran (1985) regarding information processing biases, which he attributed to market agents being under pressure to respond very quickly to new information. Market agents could also act in an irrational manner due to contradictory news items being very hard to interpret.

The frequency table clearly indicates that market agents are frequently exposed to multiple news announcements at the same time. This is largely due to announcements being released at certain times in a day. South African data is usually released at 10:00 and 11:00 SAST and US news are usually released at 15:30 and 17:00 SAST. The Bloomberg world economic calendar also splits certain macroeconomic variables in multiple news items i.e. CPI is split into Headline CPI, Core CPI, CPI MoM and CPI YoY. This characteristic results in there being a lot more news items occurring at the same time.

2.2 Seasonality Filtering

The intraday volatility of 10-minute USD/ZAR returns exhibit strong periodicity that needs to be filtered in order to remove the seasonality. Microstructure literature states that news announcements, opening and closing of markets and days of the week can lead to cyclical seasonality into many foreign exchange variables such as volatility (Omrane & de Bodt, 2004). While a wide variety of filtration methods have been proposed throughout literature, there is no one method that has been unanimously accepted.

The intraday seasonality can either exhibit a deterministic or stochastic nature – in some cases it may be both. Where the seasonality is deterministic, classic methods such as the intraday average observation method (IAOM) perform well in fitting the cyclicality. It is only when the seasonality exhibits stochastic characteristics that these models fall short. The stochastic seasonality component can be induced by a change in the times in which macroeconomic news items are released (Omrane & de Bodt, 2004). Andersen & Bollerslev (1998) and Laakkonen (2007) adopt a linear model to estimate the periodicity component. The FFF model uses sinusoids as exogenous variables to capture the periodicity.

Two broad categories exist in seasonality adjustment methods. The first method is a one-step procedure that aims to remove the periodicity through a regression model that contains exogenous variables that capture the seasonality component (Omrane & de Bodt, 2004). The second method is a two-step method which first aims to adjust the raw return data in such a way that the periodicity is filtered out. Once the seasonality component of the return series is filtered, a regression model is used to model the adjusted returns against a set of exogenous variables.

In all the seasonality adjustment methods that were evaluated by Laakkonen (2007), the models were consistent in this regard: The model produced an estimate of intraday volatility, which we represent using $v_{t,n}$. This estimate is then normalized such that the mean of the normalized intraday volatility equals one. The normalised intraday volatility is calculated as follows:

$$\tilde{v_{t,n}} = \frac{T.v_{t,n}}{\sum_{t=1}^{T/N} \sum\limits_{n=1}^{N} v_{t,n}} \tag{1}$$

where T = number of observations in whole sample, N is the number of intervals in a day and T/N denotes the total number of days under observation.

To calculate the set of adjusted returns, the original return series, $r_{t,n}$, is divided by normalized estimate of intraday volatility $\tilde{v_{t,n}}$ i.e. $\tilde{r_{t,n}} = \frac{r_{t,n}}{\tilde{v_{t,n}}}$. This method reduces volatility during periods of high volatility and increases volatility during periods of low volatility.

2.2.1 Models

In this study we employ the two-step approach of modelling the periodicity of the 10-minute USD/ZAR return series. We use the IAOM method to filter out the seasonality in the original return data, followed by a FFF consistent model to regress the intraday exchange rate volatility against a set of exogenous variables. The two processes are explained in details below:

2.2.2 The Intraday Average Observation Model

The Intraday Average Observation Model (IAOM) fits under the average observations category of seasonality adjustment models. Omrane & de Bodt (2004) finds that this method successfully estimates the periodicity without estimation error. However, it falls short when the seasonality contains both a deterministic and stochastic component.

The estimate of intraday volatility $v_{t,n}$ is computed by averaging the squared returns per each intraday interval and then taking the square root. The computation is defined as follows:

$$v_{t,n} = (\frac{1}{W}\sum_{w=1}^{w} r_{w,d,n}^2)^{0.5} \tag{2}$$

where W denotes the number of weeks in the dataset, d= 1,2,3,4,5, denotes the weekday and n=1,2,. . . ,N denotes the intraday interval. In this study we define Monday as the start of the week, resulting in Monday being equal to 1 and Sunday being equal to 7.

In Figure 4, we clearly see that the IOAM decreased the volatility of returns during periods of high volatility and increased the volatility during periods of high returns. While we applied the IAOM to the whole dataset, the method can be applied to different subsets of the dataset. The model can be separately applied to weekly, quarterly and yearly datasets (see Laakkonen (2009)), with the amount of periodicity being filtered out increasing when the subsets are shortened. While this may filter out the periodicity of the returns, it could also filter out the news effect that we are trying to study.

The IAOM has sufficiently managed to filter out the cyclicality in the autocorrelation of the original absolute return data series (see Figure 5). While there is still some periodicity present, we wanted to strike a balance between the filtering out the periodicity and maintaining the news effect in the return data. The sporadic spikes in the autocorrelation function were also filtered out, resulting in much smoother changes in correlation.

Since the returns data has been adjusted for seasonality, the statistical properties should change accordingly, to reflect those changes. The mean and standard deviation of the original and filtered returns data are relatively the same. The kurtosis of the filtered returns data has decreased significantly, suggesting that the tails of the distribution have been reduced. This can also be seen by the drastic reduction in the maximum and minimum for the filtered returns data.

The skewness of the filtered returns has dropped meaningfully compared to the original returns data.

This highlights that seasonality adjustment methods do not affect the mean and variance, but rather the third and fourth moment of the returns data. This is consistent with Laakkonen's (2009) findings across the three filtering methods that she used - FFF model, LOWESS and IAOM respectively.

2.2.3 Fourier Form model

The Flexible Fourier Form (FFF) model is a linear projection technique that was popularised by Andersen & Bollerslev (1998) in his intraday volatility study. This method uses sinusoids to capture the periodicity in high frequency return data. The model takes the following form:

$$r_{t,n} - \overline{r}_{t,n} = \sigma_{t,n}.\, v_{t,n} Z_{t,n} \tag{3}$$

where $r_{t,n}$ denotes the 10-minute USD/ZAR returns, $\overline{r}_{t,n}$ is the expected 10-minute returns, $v_{t,n}$ represents calendar and news announcements effects on intraday volatility, $\sigma_{t,n}$ denotes the remaining volatility component that is usually captured by ARCH-type models and $Z_{t,n}$ is an independent and identically distributed (i.i.d) variable. All the returns are assumed to be independent.

Without applying further restrictions, the component of equation above cannot be separated into distinct variables. By squaring and taking logs of the equation, we are able to separate the news announcement effects variable $v_{t,n}$ and express it as an independent variable in the equation,

$$\begin{aligned} 2\ln\left(|r_{t,n} - \overline{r}_{t,n}|\right) - \ln\left(\sigma_{t,n}^2\right) &= \ln\left(v_{t,n}^2\right) + \ln?({Z_{t,n}}^2) \\ 2\ln\left(|r_{t,n} - \overline{r}_{t,n}|\right) - \ln\left(\sigma_{t,n}^2\right) &= c + \ln\left(v_{t,n}^2\right) + e_{t,n} \end{aligned} \tag{4}$$

where $c = E[\ln\left({Z_{t,n}}^2\right)]$ and $e_{t,n} = \ln\left({Z_{t,n}}^2\right) - E[\ln\left({Z_{t,n}}^2\right)]$.The price and volatility reaction will reflect the news effect, the dispersion of beliefs by market agents and all other market conditions at the time of the release (Anderson and Bollerslev, 1998). It is assumed that $\ln(\sigma_{t,n})$ is strictly stationary and has an unconditional mean, $E[\ln(\sigma_{t,n})]$. To calculate $\sigma_{t,n}$, we use its estimator $\sigma_{t,n} = \frac{\sigma_t}{\sqrt{N}}$ where $\sigma_t$denotes daily volatility and N is the number of 10-minute intervals in a day. The daily volatility σ_t is estimated using a standard GARCH(1,1) model. Andersen & Bollerslev (1998) suggests a parametric representation for the regressor $\ln\left(v_{t,n}^2\right)$ and uses a flexible functional form using trigonometric functions to estimate the cyclical pattern. The FFF regression model is defined as follows,

$$f_{t,n} = c + \mu_0 + \sum_{l=1}^{L} \lambda_l I_{l;t,n} + \sum_{p=1}^{P} (\gamma_{c,p} \cos\left(\frac{p2\pi}{N} n\right) + \gamma_{s,p} \sin\left(\frac{p2\pi}{N} n\right)) + \varepsilon_{t,n} \tag{5}$$

where $f_{t,n} = 2\ln\left(|r_{t,n} - \overline{r}_{t,n}|\right) - \ln\left(\sigma_{t,n}^2\right) = 2ln\frac{|r_{t,n} - \overline{r}_{t,n}|}{\sigma_{t,n}} = 2ln\frac{|r_{t,n} - \overline{r}_{t,n}|}{\frac{\sigma_t}{\sqrt{N}}}$, $I_{l;t,n}$ is an indicator variable that denotes the event l on interval n of day

t and μ_0, λ_l, $\gamma_{c,p}$ and $\gamma_{s,p}$ are fixed coefficients. The estimate for intraday volatility $\tilde{v_{t,n}}$ is obtained in the following manner,

$\tilde{v_{t,n}} = \exp\left(\frac{\check{f_{t,n}}}{2}\right)$, where $\check{f_{t,n}}$ is the models estimate of $f_{t,n}$. The estimate $\tilde{v_{t,n}}$ is normalized using the following equation, $\widehat{v_{t,n}} = \frac{T.\tilde{v_{t,n}}}{\sum_{t=1}^{T/N}\sum\limits_{n=1}^{N}\tilde{v_{t,n}}}$, such that the mean of the periodicity estimate $\widehat{v_{t,n}}$ equals 1.

Since we employ a two-step method, we use the following equation to study the news effects on exchange rate volatility,

$$f_{t,n} = \mu_1 + \sum_{l=1}^{L}\phi_l I_{l;t,n} + \varepsilon_{t,n} \tag{6}$$

where $f_{t,n} = 2ln\frac{|\check{r_{t,n}} - \overline{r}_{t,n}|}{\frac{\sigma_t}{\sqrt{N}}}$ is our measure of exchange rate volatility, μ_1 denotes the intercept and $\check{r_{t,n}}$ denotes the filtered returns which replace the original returns $r_{t,n}$.Since the original returns $r_{t,n}$ are filtered using IAOM to remove the periodicity, there is no need to estimate the cyclical component using trigonometric functions resulting in the omission of the trigonometric terms. Furthermore, the indicator variable $I_{l;t,n}$ will take on the value 1 to denote an event l on interval n of day t or 0 otherwise.

2.2.4 Decay structure model

It is well documented that the effects of news announcements on exchange rate volatility usually have a long –lasting effect, rather than being a short-lived event. Andersen & Bollerslev (1998) finds that the news effect usually last for an hour or two, and could even last longer in an underdeveloped market where new information takes longer to be fully incorporated into the exchange rate. Volatility instantaneously spikes after the news announcement is disseminated but gradually diminishes and converges to the mean level of volatility.

We model the decay structure of volatility after a news announcement by assuming that it steadily decreases to zero after 2 hours, maintaining consistency with literature by Andersen & Bollerslev (1998) and Laakkonen (2009). In Figure 7, we can clearly see that this an appropriate assumption as the average volatility, which is presented by the mean absolute returns, converges to its overall average volatility 1 hour 50 minutes to 2 hours after the announcement. To fit the average news impact decay structure, we calculate the average absolute returns at each 10-minute interval post a news announcement minus the mean absolute return from the whole sample. A third order polynomial is then used to fit the average news effect pattern, resulting in following in following OLS regression equation,

$$\lambda_k = 0.049747 \left(1 - \left(\frac{k}{12}\right)^3\right) - 0.013444 \left(1 - \left(\frac{k}{12}\right)^2\right) k + 0.001913 \left(1 + \frac{k}{12}\right) k \tag{7}$$

Where $k = 1, 2, 3 \ldots 12$ denotes the 10-minute intervals after the news announcement. The regression model smoothly fits the decay structure of the news impact and also forces the average news impact to converge to zero after 2 hours (see Figure 8). The results of the independent variable λ_k are greater than zero for $k = 1, 2, 3 \ldots 12$and zero otherwise.

Once the average decay structure of volatility is estimated, we can use results from our regressions model λ_k and coefficients ϕ_l from our news announcement indicator variable to calculate the news impact on volatility. The volatility impact of news announcement l, k intervals after the news announcement can be calculated with following equation,

$$M_{l,k} = \exp(\frac{\phi_l . \lambda_k}{2}) \tag{8}$$

where $M_{l,k}$ denotes the volatility impact of news announcement l, k intervals after the news announcement.

3 EMPIRICAL ANALYSIS

This section presents the findings from our empirical study on the impact of news announcements on USD/ZAR volatility. The results are presented in a manner, which answers the research questions regarding asymmetric news effects. The subsections categorise the different news announcements as follows; all macroeconomic news announcements, news announcements from different countries, no-news announcements, positive and negative news.

3.1 *Macroeconomic news announcements*

While it is well documented that the release of macroeconomic news results in a significant rise in volatility, we test this theory on USD/ZAR volatility as most studies have focused on developed market currencies. Our analysis is limited to news announcements from South Africa and the US. While news announcements out of China and the Euro area could have a meaningful bearing on USD/ZAR volatility as exhibited in some events during our period of study, we assume that only US news announcements have a significant bearing on volatility as found in the study by Laakhonen (2007). Therefore, we use US and South Africa news items as a proxy for all news announcements. The regression model is defined as follows,

$$f_{t,n} = \mu_1 + \phi_{news} I_{news;t,n} + \varepsilon_{t,n} \tag{9}$$

where $I_{news;t,n}$ denotes all the macroeconomic news announcements that we consider in this study and ϕ_{news} is the coefficient of the news variable.

In Table 7 below, the results from the regression equation clearly show that news announcements in general result in a significant increase in USD/ZAR volatility. While news announcements increase volatility, the increased volatility deteriorates over time, as the uncertainty associated with the announcement is resolved. The average decay structure after a news announcement also supports this notion (see Figure 7). On average, volatility increases by 142% in the first 10-minute interval after the release of a news announcement. This can be attributed to the surprise component - good or bad- of the news announcement which market participants haven't factored into their price quotes. Bauwens, et al. (2003) also finds that volatility increases prior to a scheduled news announcement as traders who expect negative figures adjust their quotes in order to avoid significant price jumps that may go against their positions.

3.2 Country news

Earlier we found that macroeconomic news announcements lead to a rise in volatility, however it is not all news announcements that lead to a significant rise in volatility. Instead of analysing this asymmetry using individual news items, we use the origin of the announcement. By testing the news effect by different countries, we are able to ascertain which countries drive the foreign exchange market. In our study, we focus only on South African and US news announcements as mentioned above. The regression model is defined as follows,

$$f_{t,n} = \mu_1 + \phi_{SA} I_{SA;t,n} + \phi_{US} I_{US;t,n} + \varepsilon_{t,n} \tag{10}$$

where $I_{SA;t,n}$ and $I_{US;t,n}$ denotes news announcements from South Africa and the US respectively.

We find that both South African and US news have a significant impact on volatility. US news are statistically more significant in increasing volatility post a news announcements than the South African news, with t-statistics of 4.04 and 5.67 respectively. The results also show that South African news result in a far greater increase in volatility relative to US news. Volatility increases by 186% and 130% in the first 10-minute interval after the news announcement from South Africa and the US respectively. This result contradicts findings by Fedderke & Flamand (2005), who found that US news events impact USD/ZAR exchange rate with greater strength than South African events. In fact, they find little evidence that South African news significantly impacts USD/ZAR daily rates. The conflict in results may be due to the fact that we used high-frequency data in our study, instead of end of day data. By using high-frequency data, we are able to get a much deeper understanding of the underlying dynamics of USD/ZAR, which may not necessarily be captured by end of day data. Fedderke & Flamand (2005) highlights that news events are time varying, therefore the news variables used in their study may not have been significant at that point in time but may be significant during our period of study. South Africa's macroeconomic fundamentals were relatively weak during our observation period, resulting in wide range swings in the currency that may have demanded traders to pay close attention to variables driving the currency.

3.3 *No news announcements*

Fama's (1970) EMH states that current exchange rate quotes reflects all publicly available information. This premise is based on the fact that investors are continuously exposed to information, which allows them to develop expectations regarding future asset prices and trade on these convictions. Due to this process, asset prices should reflect the marginal investor's current expectations and asset prices should only react to the surprise component of announcement (Neely & Dey, 2010). We test whether this theory holds for USD/ZAR volatility. The result from this analysis will provide insight into the informational efficiency of the USD/ZAR exchange rate market. We define our regression models as follows,

$$f_{t,n} = \mu_1 + \phi_{No-news} I_{No-news;t,n} + \phi_{Surprise} I_{Surpise;t,n} + \varepsilon_{t,n} \tag{11}$$

where $I_{No-news;t,n}$ denotes no-news announcements while $I_{Surpise;t,n}$ denotes all news announcements with a positive or negative surprise component.

Our results are consistent with the Fama's (1970) EMH, suggesting that no-news effects do not necessarily result in a statistically significant rise in volatility. This is not to say that exchange rate volatility does not rise on average after a no-news announcement, in fact it increases by 72% in the first 10-minutes interval after the news announcement. The standard error of the impact of no-news announcements is relatively high, highlighting how some no-news may result in a negligible increase in volatility while others could significantly increase volatility. Laakhonen (2007) suggests that one reason why no-news events increase exchange rate volatility is because no-news announcements do not necessarily mean that the news weren't bad or good. Surprise news announcements result in a significant rise in volatility at 5% significant level, increasing volatility by 136% in the immediate 10-minute interval. This finding is consistent with general exchange rate determination theory, highlighting that investors adjust their quotes accordingly in light of new information. This process results in the increase in volatility after the surprise news announcement. In Laakhonen's (2007) empirical study, she reports that no-news announcements have a far greater impact on volatility than surprising news. It is found that no-news announcements result in a 65% jump in EUR/USD volatility in the first 5-minute interval after the announcement, while surprise news only increase volatility by 36%. This contradicts conventional thinking, as one would expect the surprise component to result in a greater rise on volatility even though Laakhonen (2007) suggests that the increase in trading volumes after a scheduled announcement, whether or not the announcement surprised, can be attributed to the discrepancy.

The Wald-test, which is used to test relationships between data items, shows that the effects of surprise news on USD/ZAR volatility are insignificantly different from the effects of no-news. The p-value of nearly 0.5 shows on all three test statistics, namely t-test, F-statistic and Chi-squared test, that we cannot reject the null hypothesis that the coefficient of no-news announcement is the same as the coefficient of surprise announcements at 5% and 10% significance level. This supports the assumption that no-news announcements do not necessarily mean that the news was neither good nor bad.

Instead of bundling all no-news and surprise news from South Africa and the US, we decompose these news items by their country of origin. The regression model is defined as follows,

$$f_{t,n} = \mu_1 + \phi_{SA:No-news} I_{SA:No-news;t,n} + \phi_{SA:Surprise} I_{SA:Surpise;t,n} + \phi_{US:No-news} I_{US:No-news;t,n} + \phi_{US:Surprise} I_{US:Surpise;t,n} + \varepsilon_{t,n} \quad (12)$$

The decomposed regression provide mixed results, reporting that SA no-news announcements have a far greater impact on USD/ZAR volatility than surprise news from the region, increasing volatility 395% and 157% respectively. Beyond the reasons provided by Laakhonen (2007) as to why no-news events could result in greater volatility than surprise news, we think that the negative investor sentiment on South Africa during this period of study could have attributed to greater volatility. The no-news announcements could have actually been perceived as negative news given the weak macroeconomic fundamentals. The South African no-news variable also consisted of only 34 no-news events, which may be considered as an inadequate sample size to generate an informed view regarding the impact of South African no-news announcements on volatility.

The Wald-test results in Table 12 and Table *13* are consistent with the results found in the overall analysis. This suggests that the impact of no-news announcements on volatility is not significantly different to that of surprise news. As we have mentioned above, no-news announcement don't necessarily represent a non-event, as market participants could perceive this information as good or bad, resulting in as much volatility as a surprise announcement. The statistical tests produce a p-value of 0.51 and 0.29 for South Africa and US respectively.

3.4 Negative versus positive news

As illustrated above, surprise news significantly affects USD/ZAR volatility while no-news announcements result in a small or negligible rise in volatility. Investor cognitive biases make it vital to decompose the surprise component into negative and positive surprises, as asymmetries may exist in their effects on volatility. Laakhonen (2009) reports two ways of calculating positive and negative news. One could use Bloomberg forecasts or use the sign of the return following the news announcement to determine whether the news were positive or negative. We adopt the market forecast methodology as consistent with most literature. We test the asymmetric news effect on exchange rate volatility using the following equation,

$$f_{t,n} = \mu_1 + \phi_{Positive} I_{Positive;t,n} + \phi_{Negative} I_{Negative;t,n} + \varepsilon_{t,n} \tag{13}$$

where $I_{Positive;t,n}$ and $I_{Negative;t,n}$ denote positive and negative news announcements respectively.

The regression model results suggest that it is only negative news that result in a significant rise in volatility. This is consistent with Laakhonen's (2007) finding on EUR/USD volatility. She also finds that positive news are insignificant at 5% significance level and only increases EUR/USD volatility by 18% in the first 5-minute interval after a positive news release. Positive news announcements result in a 5% increase in volatility, while negative news result in a 140% increase in the first 10-minute interval after the news release in this study. This highlights the presence of cognitive biases in the manner in which investors react to news. The assumption that underpins most financial theories, which is that investors act in a rational manner is not always true, as behavioural finance proves that investors do sometimes overreact to news, especially negative news. This also highlights that negative news have a far greater impact on investors' psychology than positive news. The fact that negative news increase volatility far greater than positive news suggests that investors strongly prefer to avoid losses than to acquire gains. The manner in which investors react to good and bad news is also dependent on the state of the economy. Veronesi (1999) finds that investors often hedge against uncertainty regarding the state of the economy, resulting in overreaction to bad news in good times and underreaction to good news in bad times.

The Wald test results (see Table 15) support earlier conclusions regarding the effects of positive and negative news effects on volatility. The effect of negative news on volatility is significantly different to that of positive news, with a p-value of 0.03.

To gain a deeper understanding of the source of the asymmetries, we categorised the negative and positive surprise variables by country. The regression equation is defined as follows,

$$\begin{aligned} f_{t,n} = \mu_1 &+ \phi_{SA:Positive} I_{SA:Positive;t,n} + \phi_{SA:Negative} I_{SA:Negative;t,n} + \\ &\phi_{US:Positive} I_{US:Positive;t,n} + \phi_{US:Negative} I_{US:Negative;t,n} + \varepsilon_{t,n} \end{aligned} \tag{14}$$

Results above are still consistent with previous findings regarding negative and positive news effects. Positive news from both South Africa and the US do not lead to a meaningful rise in volatility, suggesting that investors do underreact to good news especially South African good news. Positive news surprises out of South Africa and the US lead to a 2% and 11% rise in volatility respectively.

These asymmetries can also be attributed to informational biases such as incorrectly processing the information. This often arises when market participants have a short timeframe to act or multiple news announcements, which may be contradictory, are released at the same time.

Since informational biases can contribute to news effect asymmetries, we studied the difference between contradictory and consistent news effects on volatility. Single news announcements accounted for only 26% and 21% of scheduled news announcements out of South Africa and the US respectively. Therefore market participants often have to process more than one news item at a time, which could lead them into irrationally reacting to the news i.e. underreacting to positive news when released at the same time as negative news. We define the regression model as follows,

$$\begin{aligned} f_{t,n} &= \mu_1 + \phi_{One} I_{One;t,n} + \phi_{Contradict} I_{Contradict;t,n} \\ &\quad + \phi_{Consistent} I_{Consistent;t,n} + \varepsilon_{t,n} \end{aligned} \tag{15}$$

where $I_{One;t,n}, I_{Contradict;t,n}$ and $I_{Consistent;t,n}$ denote single new announcements, multiple announcements that are contradictory and multiple announcements that are consistent respectively.

Statistical results show that all the variables defined above significantly increase volatility. Consistent news induce the most volatility, increasing volatility by 228% in the first 10-minute interval after the news release. Consistent news are easy for investors to interpret as there is no conflicting information, resulting in investors being able to quickly act on the information with minimal informational biases. Even though the information may be consistent, there is still scope for investors to act irrationally, especially if they believe that the data is incorrect as assumed in the study by Veronesi (2000).

In comparison, contradictory news resulted in the least rise in volatility, only increasing volatility by 121% in the first 10-minute interval after the news release. This is inconsistent with Laakkonen's (2009) results, who found that contradictory news lead to the highest volatility increase. Laakkonen (2009) reports that in cases where market agents are not given a clear positive and negative sign, they will mostly likely find it hard to evaluate the effects of the news and this causes excess volatility. However, this could also deter market agents from acting quickly on the information resulting in lower volatility. This supports the notion that the clarity of the news announcement matters. Once market agents are able to get a broader picture of state of the economy, they are able to act accordingly. Zhang (2006) finds that the degree of incompleteness of the market reaction increases monotonically with the level of information uncertainty. As a result, investors tend to underreact to new information when there is ambiguity with respect to the implications for firm value. The same can be said about the foreign exchange market, where the economy can be inferred to be the firm and the currency value represents its underlying firm value. This explains the positive relation between the news effect on volatility and the level of ambiguity of the news i.e. consistent news result in the highest volatility. Single news announcements increase volatility by 142% in the first 10-minute interval after the news release and are significant at 5% significance level.

These results show that the asymmetric news effects that arise due to negative and positive news cannot be evaluated in isolation as other variables can also affect these results. The number of news released at that point in time and whether they were consistent with each other or not will have a significant bearing on the news effect on volatility. The greater the quality of information that is dissimilated to investors, the higher the chances of them acting in a rational manner – an assumption that underlies EMH. The magnitude of the surprise and the type of announcement released will also play a role in the magnitude of the increase in volatility, suggesting that it is not entirely correct to evaluate the effects of positive and negative news on volatility without considering the size of the surprise. While reasonable inferences can be made from our results, the dominance of highly important data figures in the negative or positive surprise news item could also skew the results. We know that the importance of data figures to investors is time varying, therefore the same analysis could produce conflicting results during a different observation period (Fedderke & Flamand, 2005).

4 DISCUSSION

In this empirical study we explored the asymmetric news effects on USD/ZAR volatility, evaluating news from different geographical locations, positive and negative news, surprise news that are consistent and contradictory with one another and no-news announcements. One clear point that has been consistent in the study is that the release of macroeconomic news results in an increase in volatility, irrespective of whether the news surprised or not. This highlights that it is the news announcement itself that results in a significant rise in volatility rather than the surprise component.

While one would expect volatility to decrease after the release of a news announcement, as the uncertainty surrounding the news announcement would be resolved, this is not the case as highlighted above. This could be attributed to investors waiting for the uncertainty to be resolved before taking any positions in the market. If the news announcement surprises the market, this would result in investors adjusting their positions to reflect the new information. Another point that has been highlighted is that no-news announcements do not necessarily imply that the news announcement was neither good nor bad. A no-news announcement could have the same bearing as surprise news, emphasizing that no-news could be interpreted as either good or bad by market participants. This contradicts Fama's (1970) EMH, which proposes that current prices should reflect all publically available information. Due to the process of investors adjusting their positions to reflect their expectations regarding the state of the economy, asset prices should reflect the marginal investor's expectations. Since investor's current expectations have already been factored into price quotes, it is the only surprise component of the news announcement that should result in an increase in the volatility. The shortcoming of this premise is that it assumes that market agents are rational, which has been proved on many occasions that it is not entirely the case. Cognitive biases by investors can be attributed to the asymmetric news effect on volatility.

The manner in which investors react to news announcements is not always rational and this was acknowledged by John Maynard Keynes with the following, "Markets can remain irrational longer than you can remain solvent". Investors often suffer from cognitive biases such as overreacting/underreacting to surprise news, informational and representative biases. Due to these biases, they often exhibit irrationality in their expectations. This is often exhibited in the manner in which they react to positive and negative news surprises. If investors were rational, the sign of the surprise component would be insignificant. However, we find that negative news tend to have a greater impact on volatility relative to positive news. This finding is consistent with empirical studies by Anderson, et al. (2003) and Laakhonen (2007), while Pearce & Solakoglu (2007) argues that there is no asymmetry with respect to the sign of the surprise news. One explanation for the different results is that the reaction by investors to surprise news is dependent on the state of the economy. Therefore, the period of study will influence the results. Laakhonen (2009) highlights that negative news increased volatility more than positive news only when the economy was in its expansionary phase. This economic state dependency was explained by Veronesi (1999), who argued that due to investors' willingness to hedge against uncertainty about the state of the economy, they tend to overreact to bad news in good times and underreact to good news in bad times. The South African economy is going through a stagflation period during our period of study, which can be used to explain the underreaction of investors to positive news – suggesting that economic state dependency could also apply to our results.

Economic state dependency could also explain the difference in findings between our study and Fedderke and Flamand (2005), regarding whether South African news have a significant impact on USD/ZAR exchange rate. Fedderke and Flamand (2005) find that US news announcements impact USD/ZAR with greater strength than South African news and there is little evidence that South African news has a significant impact on USD/ZAR. It is important to note that their study was conducted during the recovery period post the 9/11 recession. Given the risk-averse nature of investors and investor fears over the state of the US economy at the time, focus would have been on US news. In our study, the US economy is in a boom phase while South Africa is in a stagflation environment; therefore attention has switched to South Africa given investor concerns over the state of the economy. But this is not to say that US news items are insignificant, its impact on volatility is just at a lower scale relative to South African news announcements.

Market agents are often exposed to more than one news announcement at a time, which often results in uncertainty when interpreting the news announcement. When investors are exposed to multiple news items that are consistent with each, investors have an improved and clearer understanding of the economy and this results in the most volatility increase relative to a single announcement or multiple announcements that are contradictory to each other. This is attributed to the lack of ambiguity, which decreases the probability of investors underreacting to the news. Zhang (2006) finds that the degree of incompleteness of the market reaction increases monotonically with the level of information uncertainty. Multiple news announcements that contradict each other often confuse investors, resulting in some investors taking longer to respond to the new information or incorrectly interpreting the information. Investors could also choose to focus on a few news items that are perceived as important at that point in time, resulting in only a fraction of the information being regarded when adjusting their quotes. In the study by Laakkonen (2009), it is stated that contradictory news items result in the most volatility while consistent news items result in the least volatility increase in some cases. When multiple news items are contradictory to each other, investors occasionally process the information inaccurately given the short time frame in which they have to react, leading to a rise in excess volatility. While we accept that incorrectly interpreting the news announcement could result in excess volatility in some occasions, it could also lower volatility as market participants underreact to this information.

Cognitive biases play a crucial role in accounting for news effect biases that are often experienced in the foreign exchange market. Investors could suffer from anchoring bias where they evaluate news items not only on their current merits, but anchor their decision to the previous data prints when evaluating the data. When positive (negative) news persistent for some time, followed by a negative (positive) news item, it may be hard for investors to evaluate whether this signals a turning point or not. Therefore, they may underact to the surprise news. Conversely, if positive or negative news surprises persist, investors could overreact to the information as they may perceive this information as a clear sign that the economy is in contractionary or expansionary phase.

While our results provide in-depth insight into the asymmetric effects of news on USD/ZAR, we are cognisant of the time-varying nature in which markets react to information. This idea was first highlighted by Laakkonen (2009) and Fedderke & Flamand (2005), who found that the manner in which investors react to positive and negative news is economic state dependent and that news events that significantly impact the market change over time – suggesting that traders only focus on a few variables at any given point in time. This highlights that the results should be considered in the context of the economic environment.

5 CONCLUSION

The key finding of the study after the release of a news announcement, the level of foreign exchange volatility rises. The occurrence of the increase in volatility is independent of whether the news item surprised the market or not. No-news announcements also have a meaningful bearing on volatility, suggesting that no-news announcements do not necessarily mean that the news were neither good nor bad. We do not find any asymmetric news effects on USD/ZAR volatility with regards to the country of the news. Negative news announcements appear to have a greater impact on exchange rate volatility relative to positive news. Negativity bias and loss aversion can be attributed to the underreaction by investors to positive news.

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Table 1: Statistical properties for 10-minute USD/ZAR returns and their corresponding absolute return

	Mean	**St. dev**	**Kurtosis**	**Skewness**	**Min**	**Max**
Returns	0.0006	0.0800	439	0.3296	-4.954	4.710
Absolute returns	0.0474	0.0645	988	16.290	0.000	4.954

Table 2: Number of macroeconomic announcements in the different countries

Region	**Number of News**	**Number of unique news**
South Africa	728	42
United States	3 229	216

Table 3: Frequency of news announcements at the same time

Frequency	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
South Africa	190	172	9	39	1	1										
United States	662	280	96	81	42	49	32	20	8	21	10	6	1	1	0	1

Table 4: Number of macroeconomic news items per asymmetric category

News item	**South Africa**	**United Sates**	**Total**
All news	728	3229	3957
Forecast available	546	2461	3007
Forecast not available	182	768	950
Positive news	251	984	1235
Negative news	246	1151	1397
No-news	49	326	375
One announcement	190	662	852
Contradictory	91	418	509
Consistent	127	207	334

Table 5: Largest volatility swings

Date	Time	Weekday	Absolute Return	Event
14-Dec-15	00:00	Mon	4.954	Hiring of Pravin Gordhan
24-Aug-15	02:00	Mon	4.710	China's 'Black Monday'
09-Dec-15	21:00	Wed	2.426	Removal of Finance Minister
28-Oct-15	21:10	Wed	1.473	FOMC Rate Decision
29-Jun-15	00:20	Mon	1.469	China Fears - Risk off
29-Jan-14	15:30	Wed	1.325	SARB Announce Interest Rate
06-Nov-15	15:40	Fri	1.312	Nonfarm Payrolls
06-Mar-15	15:40	Fri	1.303	Nonfarm Payrolls
24-Aug-15	02:30	Mon	1.246	China's Black Monday
09-Dec-15	20:30	Wed	1.244	Removal of Finance Minister

Table 6: Statistical properties of the original and filtered returns

	Mean	St. deviation	Kurtosis	Skewness	Min	Max
Original Returns	0.0006	0.0800	439	0.3296	-4.954	4.710
Filtered Returns	0.0008	0.0700	8.24	0.0916	-0.619	0.658

Table 7: Regression model results: All macroeconomic news

Variable	Coefficient	Std. Error	t-Statistic	Probability	$M_{l,1}$
$I_{news;t,n}$	46.37	6.81	6.81	0.00	242%

Table 8: Regression model results: News by country

Variable	Coefficient	Std. Error	t-Statistic	Probability	$M_{l,1}$
$I_{SA;t,n}$	55.22	13.68	4.04	0.00	286%
$I_{US;t,n}$	43.77	7.72	5.67	0.00	230%

Table 9: Regression model results: Surprise vs. No-news announcements

Variable	Coefficient	Std. Error	t-Statistic	Probability	$M_{l,1}$
$I_{No-news;t,n}$	28.57	20.73	1.38	0.17	172%
$I_{Surpise;t,n}$	44.98	7.15	6.29	0.00	236%

Table 10: Wald test results: Surprise vs. No-news announcements

Equation: $\phi_{No-news;t,n} = \phi_{Surpise;t,n}$

Test Statistic	Value	DF	Probability
t-statistic	-0.69	65658	0.49
F-statistic	0.48	(1, 65658)	0.49
Chi-square	0.48	1	0.49

Table 11: Regression model results: Surprise vs. No-news announcements by country

Variable	Coefficient	Std. Error	t-Statistic	Probability	$\boldsymbol{M_{l,1}}$
$I_{SA:No-news;t,n}$	83.96	48.14	1.74	0.08	495%
$I_{US:No-news;t,n}$	15.91	22.99	0.69	0.49	135%
$I_{SA:Surpise;t,n}$	49.51	14.13	3.50	0.00	257%
$I_{US:Surpise;t,n}$	43.96	8.15	5.40	0.00	231%

Table 1: Wald test results: South African Surprise vs. No-news announcements

Equation: $I_{SA:No-news;t,n} = I_{SA:Surpise;t,n}$

Test Statistic	Value	DF	Probability
t-statistic	0.65	65656	0.51
F-statistic	0.43	(1, 65656)	0.51
Chi-square	0.43	1	0.51

Table 2: Wald test results: US Surprise vs. No-news announcements

Equation: $I_{US:No-news;t,n} = I_{US:Surpise;t,n}$

Test Statistic	Value	DF	Probability
t-statistic	-1.06	65656	0.29
F-statistic	1.12	(1, 65656)	0.29
Chi-square	1.12	1	0.29

Table 3: Regression model results: Positive versus negative news

Variable	Coefficient	Std. Error	t-Statistic	Probability	$\boldsymbol{M_{l,1}}$
$I_{Positive;t,n}$	2.83	10.79	0.26	0.79	105%
$I_{Negative;t,n}$	45.82	10.57	4.33	0.00	240%

Table 4: Wald test results: Positive vs. Negative news announcements

Equation: $I_{Positive;t,n} = I_{Negative;t,n}$

Test Statistic	**Value**	**DF**	**Probability**
t-statistic	-2.20	65658	0.03
F-statistic	4.84	(1, 65658)	0.03
Chi-square	4.84	1	0.03

Table 5: Regression model results: Positive vs. Negative news announcements by country

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**	$\boldsymbol{M_{l,1}}$
$\phi_{SA:Positive}$	1.03	20.41	0.05	0.96	102%
$\phi_{SA:Negative}$	54.37	20.25	2.68	0.01	282%
$\phi_{US:Positive}$	5.50	12.52	0.44	0.66	111%
$\phi_{US:Negative}$	41.97	12.26	3.42	0.00	223%

Table 6: Wald test results: South African Positive vs. Negative news announcements

Equation: $I_{SA:Positive;t,n} = I_{SA:Negative;t,n}$

Test Statistic	Value	DF	Probability
t-statistic	-1.47	65656	0.14
F-statistic	2.17	(1, 65656)	0.14
Chi-square	2.17	1	0.14

Table 7: Wald test results: US Positive vs. Negative news announcements

Equation: $I_{US:Positive;t,n} = I_{US:Negative;t,n}$

Test Statistic	Value	DF	Probability
t-statistic	-1.60	65656	0.11
F-statistic	2.55	(1, 65656)	0.11
Chi-square	2.55	1	0.11

Table 8: Regression model results: Consistent vs. Contradictory news

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**	$\boldsymbol{M_{l,1}}$
$I_{Consistent;t,n}$	62.30	0.15	4.12	0.00	328%
$I_{Contradict;t,n}$	41.60	12.28	3.39	0.00	221%
$I_{One;t,n}$	46.30	9.56	4.84	0.00	242%

Figure 1: 10-minute USD/ZAR return histogram

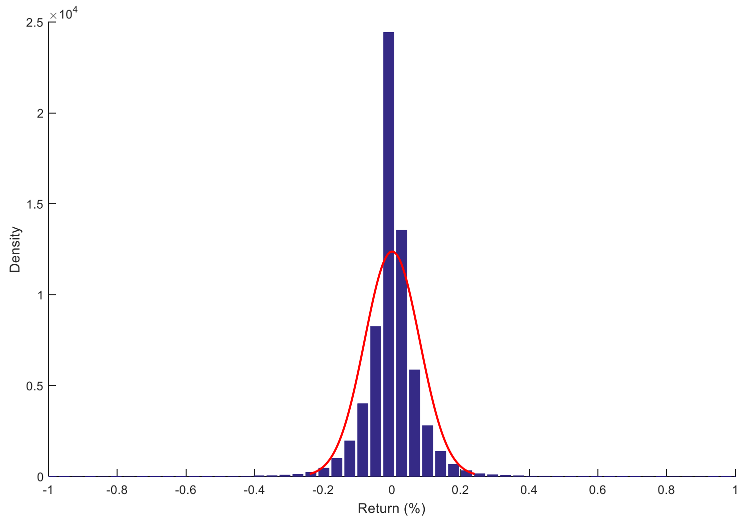

Figure 2: The average intraday USD/ZAR volatility over the period January 2014 and December 2015.

Figure 3: Five day autocorrelation of 10-minute USD/ZAR absolute returns

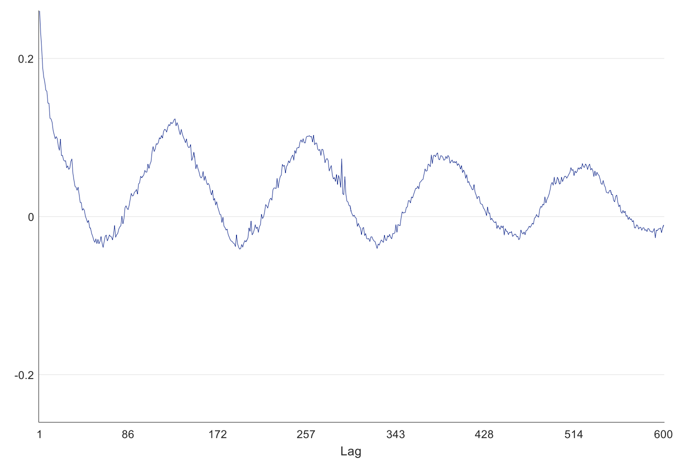

Figure 4: Unfiltered and filtered 10-minute return after applying the IAOM

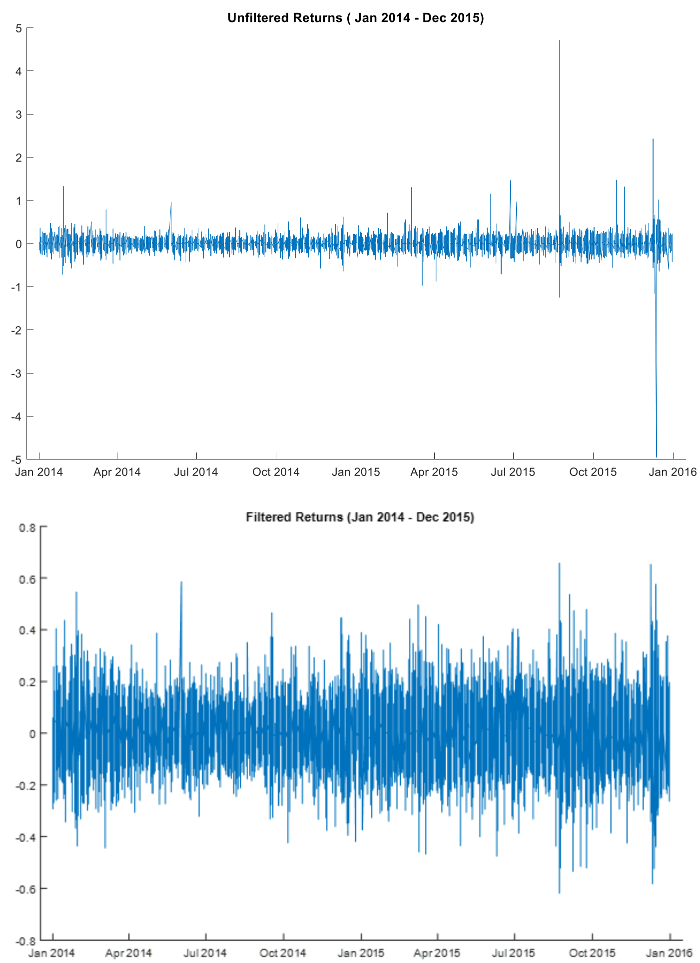

Figure 5: Autocorrelation of original and filtered absolute return data

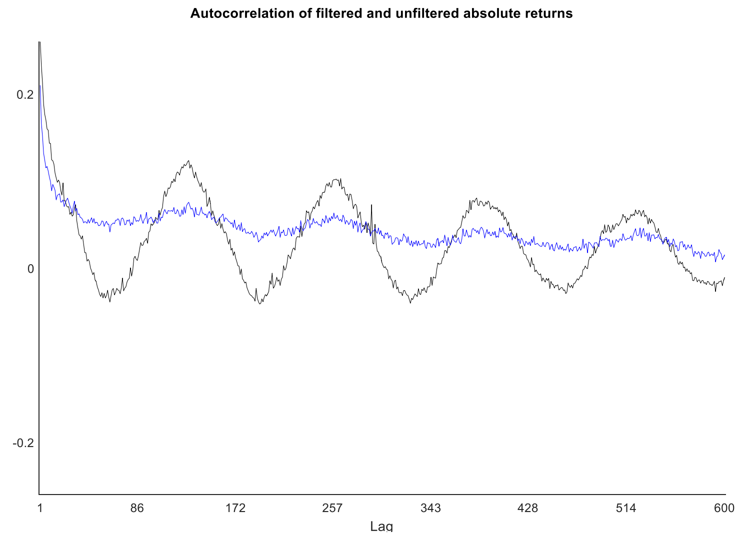

Figure 6: Filtered 10-minute USD/ZAR return histogram

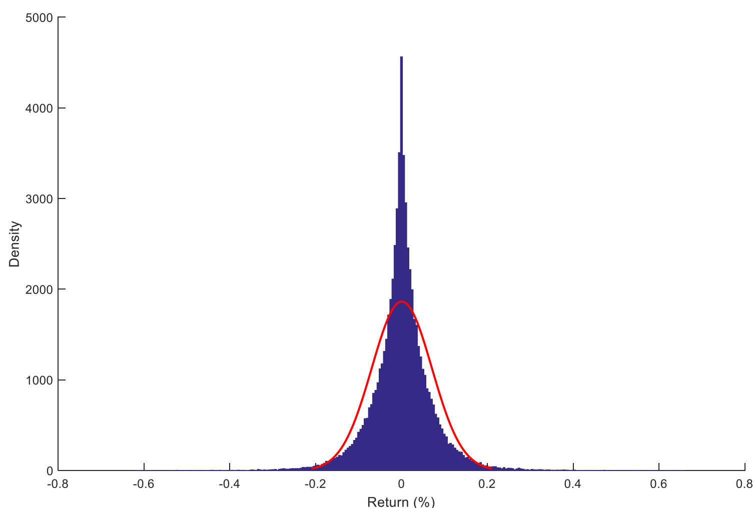

Figure 7: Average decay structure of volatility after a news announcement

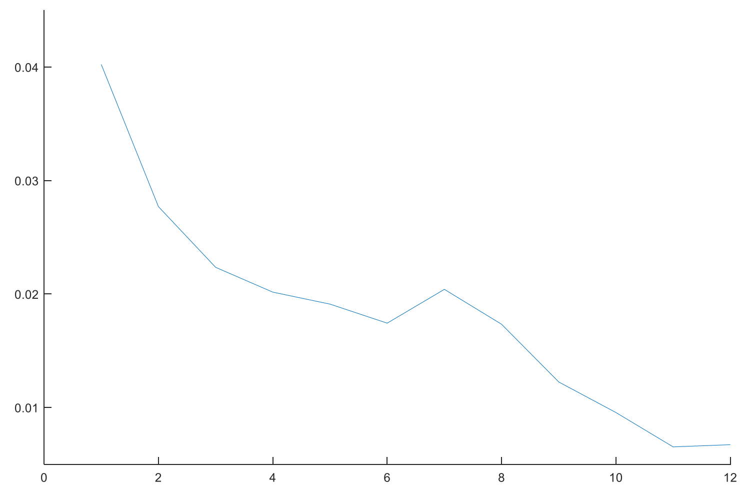

Figure 8: Actual and fitted decay structure of volatility after a news announcement

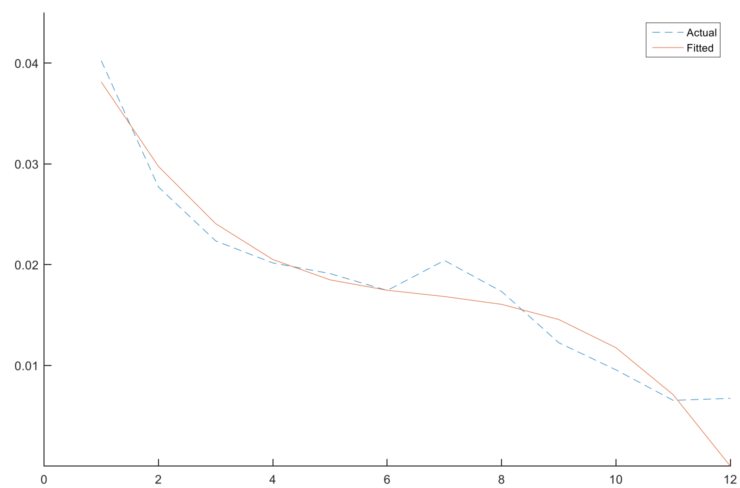

Figure 9: Estimated news impact: Surprise vs. No-news announcements