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Full Length Research Paper

Implied volatility of foreign exchange options: A leading indicator for currency crisis identification

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In 2001, the commission of inquiry into the rapid depreciation of the exchange rate attributed the rapid 72.4% depreciation of the South African Rand from June to December 2001 to the excessive volatility caused by market participants' expectations. This paper investigates whether the market participants' expectations implicit in foreign exchange options can provide a signal for currency crises. To achieve this, and to capture the dynamics of nonlinearity of implied volatility in foreign exchange options, the paper uses the Markov regime switching GARCH with time varying probabilities. We find that, using implied volatility in foreign exchange options, the technique manages to identify the crisis dates identified by previous literature and to some extent offers an early signal of the crisis before it occurs.

Key words: Currency crisis, foreign exchange, market participants' expectations, implied volatility, Markov regime switching, generalized autoregressive conditional heteroscedastic (GARCH), market microstructure, Black-Scholes model, options, European options, at the money, option maturities.

INTRODUCTION

This paper investigates the use of implied volatility of foreign exchange rates in identifying the currency crises in South Africa. The excessive volatility of foreign exchange that we have witnessed recently in currency markets remains an important concern not only for policy makers in emerging economies but also for firms that are involved in international transactions. In South Africa, the rand has been particularly volatile over the course of the 1990s: it weakened 15.6% to the dollar in 1996, recovered, collapsed once more in 1998, plunged to a record low of R13.85 to the dollar in 2001 and rose back to around R6.00 to the dollar in 2004 (Fedderke and Flamand, 2005).

The rapid 72.4% depreciation of the Rand from June to December 2001 can be seen as a currency crisis and can be analyzed within the framework of currency crisis as defined in the literature. A currency crisis is an episode in which there is a sharp depreciation of the currency, a large decline in foreign reserves, a dramatic increase in domestic interest rates or combination of these elements (Bhundia and Ricci, 2005). The question this paper attempts to answer is whether currency crises can be detected earlier so as to allow governments to adopt pre-emptive measures?

Knedlik and Scheufele (2008) for example use a Markov switching regression with constant variance and constant transition probabilities in order to detect currency crisis in South Africa. They identify the following currency crisis periods for the South African rand: May to June 1996, April to July 1998, December 2001, and June 2006. Although their model has a good out-of-sample predictive ability to identify high transition probabilities as a signal for upcoming crises; it is often criticized for assuming constant volatility within each regime (Brunetti et al., 2008) and constant transition probabilities.

This paper uses implied volatility as a proxy for future realized volatility in order to identify potential currency crises by making use of Markov switching regression model with time varying volatility and time varying transition probabilities. We estimate a Markov Switching GARCH regression model and find the presence of two distinct regimes: - the low volatility regime and the high volatility regime characterized by abrupt movement of the

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South African rand volatility around the period between June and December 2001. During our sample period our model identifies the following crisis periods: the last month of 3rd Quarter 2001, 4th Quarter 2001 and 2nd Quarter 2002, 2nd Quarter 2003, 4th Quarter 2005 and late 2008. These results are consistent with those identified by Knedlik and Scheufele (2008) and Duncan and Liu (2009), except for the false signal registered in 2003.

Recently a large number of research papers that use implied volatility as proxy for future realized volatility has been publish in the literature (Giot, 2003; Canina and Fegliwsky, 1993, Magrebi, 2007) in order to model and understand the behavior of expected volatility. For example, Giot (2003) investigates whether a regime switch in volatility for the stock markets in the United States and Germany occurred around the summer of 1997. He applies the U.S VIX and German VDAX implied volatility indices to a Markov switching regression model. His findings show that the volatility of the U.S S&P 100 index and German DAX index switched from a low volatility state to a high volatility state around the events of the Japanese financial crisis that is, mid to end of 1997.

Similarly, Maghrebi et al. (2007) developed an implied volatility index for the Korean KOSPI200 in order to examine its informational content and nonlinear dynamics by making use of Markov switching regression. They find that the expected level of volatility in the Korean stock market has been steadily falling since the inception of options trading and the onset of the Asian financial crisis. They highlight the fact that implied volatility is able to reflect useful information on future volatility that is not contained in the history of observed returns even after allowing for leverage. They show that nonlinearity in volatility identified by the Markov regime-switching model is not only driven by asymmetric impact of news but, also by regime dependencies in the realignment mechanism adjusting for forecast errors.

There is still no consensus in the literature on whether implied volatility can provide completely useful information contained in future realized volatility. For example using the S&P100 index options; Canine and Fegliwsky (1993) find implied volatility to be a poor of realized volatility.

The ultimate objective of this paper is to determine whether implied volatility of foreign exchange options (used as a proxy for market participants' expectations of future realized volatility) provides useful information in identifying currency crisis in South Africa. The use of implied volatility from option prices is motivated by their ability to infer market participants' expectations and by the fact that they are inherently forward-looking in nature.

The rest of the paper is structured as follows; methodology used in the paper that is, the Markov switching GARCH regression model; data used in the study; discussion of our findings; conclusion.

METHODOLOGY

In most of the empirical literature, currency crises are estimated by using a linear function. However, an important shortcoming of estimating a linear function is that it ignores the possibility that shifts in market participants' expectations and beliefs might also cause crises (Fratzscher, 2002). Thus, using a Markov switching model GARCH might be helpful in that it assumes that observed time-series depend on unobservable state variables.

Our approach consists of modelling the conditional mean and the conditional variance of exchange rate returns with the first- and second-order moments of changes in exchange rate returns driven by the Markov process. The underlying assumption within this process is quite simple. We assume that there are two regimes: the tranquil and the turbulent regime. A "tranquil" regime is characterized by low volatility – that is, small exchange rate movements due to stable variables – while a "turbulent" regime is characterized by high volatility due to large depreciations of exchange rates, falling reserves, and/or interest rate hikes.

The two regimes can be represented in a two state Markov chain, s_t, where $s_t = 1$ denotes a tranquil state and $s_t = 0$ denotes a turbulent or crisis state. In this case of the series being modelled that is, implied volatility represented as vix_t, will be different in each regime. For example,

$$vix_t = \Phi_{00} + \Phi_{10} vix_{t-p}.\beta_{00} + \varepsilon_{to} \text{ ; if } s_t = 0$$

$$vix_t = \Phi_{01} + \Phi_{11} vix_{t-p}\beta_{01} + \varepsilon_{t1} \text{ ; if } s_t = 1 \qquad (1)$$

where $\varepsilon_{t,j} \sim \text{iid } N(0, \sigma^2)$, vix_t follows an AR (p) process with the density of vix_t conditional on the regime s_t and the history Ω_{t-1} is normally distributed with mean equal to $\Phi_{1S_t} + \Phi_{1S_t} vix_{t-1} + \ldots + \Phi_{pS_t} vix_{t-p}$ and the variance of σ^2.

Following Hamilton (1989), we assume that s_t is a first-order Markov process, which means that the current regime (s_t) depends only on the regime one period ago (s_{t-1}) (Franses and van Dijk, 2000).

The model is completed by defining the transition probabilities of moving from one regime to another (referred to as 'the transition probabilities'):

$$Pr[S_t = 0 | S_{t-1} = 0] = P,$$
$$Pr[S_t = 0 | S_{t-1} = 1] = (1 - P),$$
$$Pr[S_t = 1 | S_{t-1} = 1] = Q,$$
$$Pr[S_t = 1 | S_{t-1} = 0] = (1 - Q). \qquad (2)$$

Thus, $P_{i,j}$ is equal to the probability that the Markov chain moves from state *i* at time *t-1* to state *j* at the time t. For $P_{i,j}$ to define proper probabilities, probabilities should be non-negative and add up to one $(P_{1\,1} + P_{1\,2} + P_{2\,1} + P_{2\,2} = 1)$. This version of the model is characterized by the transition probabilities that are time-invariant, called the fixed transition probabilities model. This kind of assumption may be costly from an empirical point of view (Diebold et al., 1994), as it assumes that the expected durations of the tranquil and turbulent periods are constant.

This implies that exogenous shocks, macroeconomic policies, changes in market expectation and an economy's own internal propagation mechanisms do not affect the expectation of how long a regime will last (Filardo and Stephen, 1998). Hence, in this paper we opt for a model that incorporates time-varying transition probabilities as proposed by Diebold et al. (1994), a model that incorporates time-varying transition probabilities by using a specification for the transition probabilities that reflect information change in market expectations.

In contrast with the time-invariant transition probabilities, the time-varying transition probabilities (TVTP) are

$$Pr = \begin{Bmatrix} P_{00}(z_t) & 1 - P_{11} \\ 1 - P_{00}(z_t) & P_{11}(z_t) \end{Bmatrix} \quad (3)$$

where z_t is the information variable(s) upon which the evolution of the unobserved regime will depend. A popular way to model TVTP is to incorporate a simple logistic function (Filardo and Stephen, 1998). These probabilities are estimated as logistic functions of a conditioning matrix z_{t-1}, as shown in the following equation:

$$Pr[S_t = 1 | S_{t-1} = 1] = P = \frac{\exp(\alpha_1 + \beta_1 s_t)}{1 + \exp(\alpha_1 + \beta_1 s_t)}$$

$$Pr[S_t = 2 | S_{t-1} = 2] = Q = \frac{\exp(\alpha_2 + \beta_2 s_t)}{1 + \exp(\alpha_2 + \beta_2 s_t)} \quad (4)$$

By allowing transition probabilities to vary over time, we can model the mechanics underlying shifts from tranquil to turbulent regimes explicitly. In particular, we use this framework to determine whether expectations have any effect in bringing about shifts to speculative attack regimes.

Further, as stated earlier, we realize that the volatility of these variables in two regimes is not constant over time, hence the reason for using the GARCH approach. The GARCH class of models will be able to capture the volatility dynamics of these variables. This approach is termed the time-varying probabilities Markov switching GARCH models.

The model popularized by Gray (1996) in modelling the conditional distribution of interest rates (y_t) is written as:

$$y_t |\ \phi_{t-1} = \phi_{0\,1} + \phi_{1\,1}\ y_{t-p}\ h_{i\,t} \qquad \text{If} \quad s_{t=0}$$

$$y_t |\ \phi_{t-1} = \phi_{0\,2} + \phi_{1\,2}\ y_{t-p}\ h_{i\,t} \qquad \text{If} \quad s_{t=1}$$

$$h_{it} = b_{0i} + b_{1i}\varepsilon^2{}_{t-1} + b_{2i}h_{t-1} \quad (5)$$

The h_t represents an aggregate of conditional variances from both regimes and can now be used to specify the conditional variances $h_{1\,t-1}$ and $h_{2\,t-1}$ for each regime in a GARCH (1, 1) model and under the assumption that the ε_t are normally distributed (conditional upon the history ϕ_{t-1}).

From this setting, the next step would be to estimate the parameters, mean (ϕ_0, ϕ_1) (β_0, β_1), and variance by using the maximization of the likelihood, that is, estimating the unknown parameters in such a manner that the probability of observing the given y_t is as high as possible. In most applications the probability of observing y_t is set against certain thresholds, which are equal to 1 if the crisis probability exceeds a certain threshold and 0 otherwise. In this paper the threshold is set in line with studies done by Berg and Pattillo (1999) and Knedlik and Scheufele (2008) – that is, as equal to 50%, meaning that whenever the probability lies above the threshold, the model forecasts a crisis period.

A Markov switching regime GARCH model with time-varying probabilities as developed in Gray (1996) allows for forecasting the conditional probability of being in a given regime (i, j) at time t+1 given the information available at time t. Denote $\xi_{t|t}$ by the (N×1) vector of conditional probabilities of being in state (0, 1) at time t, conditional on the data until date t. Define ηt as the (N×1) vector of the density of y_t conditional on s_t. Following Franses and van Dijk (2000), the optimal forecast for each t is computed by iterating the following two equations:

$$\xi_{t|t} = \frac{(\xi_{t|t-1} \odot \eta t)}{1'(\xi_{t|t-1} \odot \eta t)} \quad (6)$$

$$\xi_{t+1|t} = P_{t+1} \cdot \xi_{t|t} \quad (7)$$

For t = 1, ….., n, unit vector, P_{t+1} is the (N×N)Markov transition probability matrix and $\odot$ denotes the element -by- element multiplication.

DATA AND DISCUSSION OF RESEARCH FINDINGS

The model in this paper is estimated using daily data drawn from the over-the-counter markets in which most currency option dealing takes place. In over-the-counter currency option markets, dealers quote implied volatilities rather than option prices denominated in currency units. These markets use conventions based on the Black and Scholes (1973) model to express the terms and prices of currency options. The data used for the estimation was sourced from the Bloomberg database, where historical[1] and implied volatility time series for one-week, one-month, and two-month of the South African rand to the U.S dollar (USDZAR) European-style at-the-money options, and the daily spot rates were used. The option maturities used are the most liquid available.

The time series spans the period February 1999 to April 2009 with a continuous sample of 2590 observations. Ideally, the sample chosen would have been the same as that used in Knedlik and Scheufele (2008), and Duncan and Liu (2009) – the period between January 1994 and March 2009 – for easier comparison with all currency crises identified. However, as a result of data limitations on option contracts, the sample spans from 1999. The chosen sample includes the three rand crises, December 2001 to January 2002, April to June of 2006 and September to November 2008 as per the and

[1] We refer interested reader to the www.bloomberg.com for more details about the definition and calculation methodologies used for these indices.

Table 1. Descriptive statistics.

Statistics	ZARimp1W	ZARimp1M	ZARimp2M	ZARspot
Mean	0.0148	0.0103	0.0091	0.0044
Median	0.0000	0.0000	0.0000	0.0013
Standard deviation	4.3867	2.6119	2.1126	0.5072
Kurtosis	36.4965	18.3543	11.9733	7.0191
Skewness	-0.0842	1.5216	0.5820	0.3196
Minimum	-47.7121	-16.9751	-13.8495	-4.1908
Maximum	48.1622	29.7569	21.7015	4.0050
Sum	36.8752	25.8058	22.6614	10.9637
Count	2495	2495	2495	2495

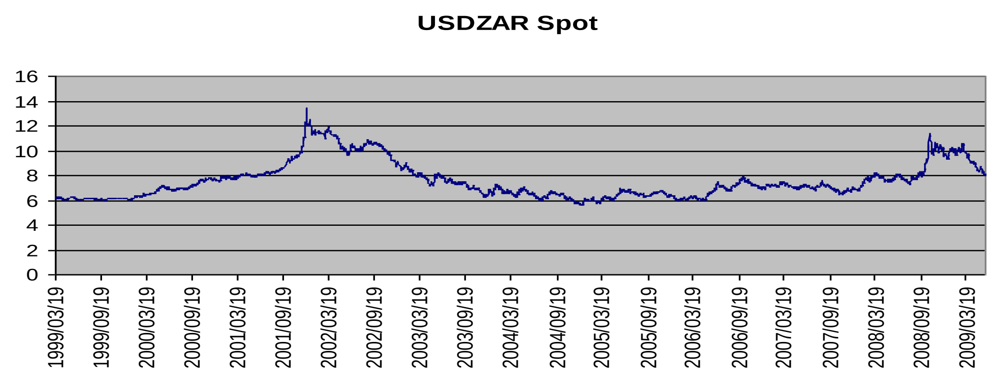

Figure 1. Spot rate USDZAR for the period 1999 to 2009.

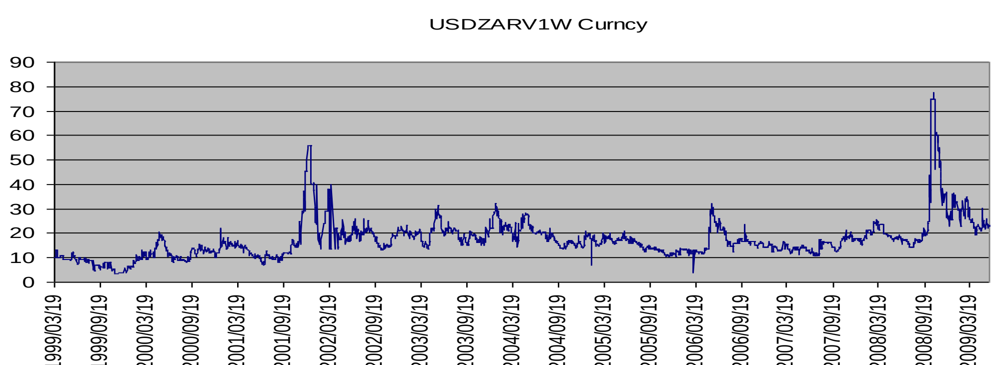

Figure 2. One week implied volatility of USDZAR for the period 1999 to 2009.

Markov switching model by Knedlik and Scheufele (2008) and the SC-GARCH approach by Duncan and Liu (2009). Table 1 report the descriptive statistics of the percentage changes in implied volatility for one-week, one-month, and two-month USDZAR European-style at-the-money options, and the daily spot rates of the South African rand to the U.S dollar respectively. The presence of higher kurtosis for all these time series is an indication of the likelihood of large swings of volatility in the South African rand. The magnitude of the standard deviation is inversely proportional to the maturity of the implied volatility; short maturities have larger standard deviation while long maturities have small standard deviations. In other words, implied volatility in the short run is more volatile than in the long run. Furthermore, the presence of negative skewness in shorter maturity (the one week implied volatility) is an indication that the likelihood of large negative changes in shorter maturity is higher than in longer maturities.

Figures 1 and 2 displays the spot rate and the one-

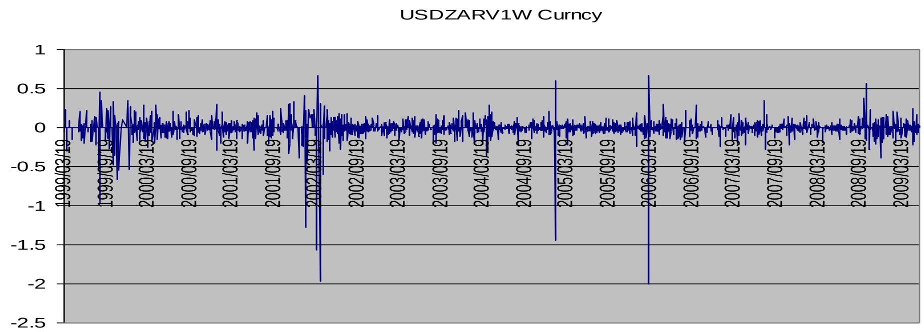

Figure 3. Returns of USDZAR for the period 1999 to 2009.

Table 2. Testing of unit root using Dickey-Fuller root test.

Parameter	T- Statistic
USDZARH1W	-10.8507
USDZARH1M	3.4889
USDZARH2M	-2.1750
USDZAR	-1,9165
USDZARV1W	-6.6914
USDZARV1M	-5.0722
USDZARV2M	-2.2155

week implied volatility of the USDZAR exchange rate during the period under consideration. At first sight, it is noticeable that in 2001 the one week implied volatility of USDZAR in Figure 2 started to increase sharply a month (2001/09/09) ahead of the increase in the USDZAR spot price (2001/12/03) in Figure 1; indicating that the one week implied volatility of USDZAR is a leading indicator of the USDZAR spot price.

Implied volatility tends to decline as the spot market rises and increase as the spot market falls. When implied volatility increases, risk increases and returns decrease (Figure 3).

The graph indicates that periods of high volatility (February 2002 and end of March 2002, and March 2006) are followed by periods of extreme losses. This means that implied volatility predicts extreme losses before they occur; we argue that implied volatility is an unbiased estimator of future realized volatility.

Testing the unbiasedness of implied volatility

In line with most literature (for example Day and Lewis, 1992; Lamoureux and Lastrapes, 1993; Jorion, 1995) we use the regression analysis to test whether implied volatility is an unbiased estimator of the realized volatility. It is established from this literature that if implied volatility reflects market participants' expectations of future realized volatility and that if the market participants' expectations are rational, then the expected value of realized volatility corresponds to implied volatility (Lyons, 2001). This can be represented formally as:

$$E\left[\sigma_{t,\tau} / \Omega_t\right] = \mathrm{vix}_{t,\tau} \tag{8}$$

where Ω_t denotes the set of information available to market participants at time t, and $\mathrm{vix}_{t,\tau}$ is the implied volatility at time t. The expected deviation from the expected value equals zero under this information set, therefore

$$\sigma_{t,T} = E\left[\sigma_{t,T} | \Omega_t\right] + \varepsilon_t\ ,\ E[\varepsilon_t | \Omega_t] = 0 \tag{9}$$

If the assumptions of Equations 9 and 10 hold, this implies that the implied volatility is approximately the conditional expectation of realised volatility $\sigma_{t,T}$. The testable inference of this unbiasedness hypothesis in the following linear regression

$$\sigma_{t,\tau} = \alpha + \beta_1 \mathrm{vix}_{t.\tau} + \varepsilon_t \tag{10}$$

can be analyzed by testing the conditions that α=0; β_1=1; deviation from these values is evidence of biasedness. Consequent to that, we will be able to say that implied volatility has useful informational content for predicting exchange rate movement.

The following volatilities: one week (USDZARH1W), one month (USDZARH1M), two month (USDZARH2M) historical volatilities, and one week (USDZARV1W), one month (USDZARV1M), and two month (USDZARV2M) implied volatilities were used in testing the unbiasedness hypothesis using Equation 10. These time series were first individually tested for unit roots using the Augmented Dickey-Fuller Root test in order to ensure that they are stationary, as the econometric consequences of non-stationary time series are very severe in that estimators and t-statistics are unreliable. Furthermore, such time series are very difficult to analyze effectively and may lead to spurious results. Time series with unit root will be differenced until it becomes stationary. Table 2 shows

Table 3. The coefficient of estimated model (p-values).

Horizon	Parameter	
	α	β_1
1 week	0.0004 (0.9959)	0.5288 (0.0000)
1 month	0.0037 (0.8670)	0.1374 (0.0000)
2 month	0.0033 (0.7988)	0.0556 (0.0000)

that the spot rate USDZAR contains unit root although it does not enter explicitly the regression model in Equation 10.

In order to establish the unbiasedness of implied volatility, we estimate the regression model in Equation 10, using implied volatility as an explanatory variable and historical volatility as the dependent variable. The results are given in Table 3.

Looking at the results from the estimation, we can conclude that in the majority of forecast horizons, implied volatility seems to contain useful information related to future realized volatility. The coefficients of implied volatility differ from zero up to the 2-month horizon. However, with the lengthening of the forecast horizon, the coefficients decrease from 0.5288 in one week to 0.0556 in two months. This is most likely due to the fact that the longer-maturity USDZAR options market is undeveloped compared to the short-term maturity of the USDZAR options market. Hence, in testing the efficiency of the information content of implied volatility below, we opted to use the one-week horizon, as it has the highest coefficient.

The efficiency test is carried out using the Markov regime switching GARCH models as described earlier. This test was chosen, also as explained before, because of the non-linearity of the models, and the ability of these models to account for the possibility that the implied volatility that generates the crisis risk may undergo a finite number of changes over the sample period. We consider both Markov regime switching with constant variance (CV-MS) and Markov regime switching with GARCH (MS-GARCH) models; the parameter estimates for these models appear in Table 4.

The first column of this Table 4 reports estimates of the CV-MS model, and most of the conditional mean parameters of the model reach statistical significance. The significance of conditional mean parameters confirms the symmetry across regimes. The “turbulent” regime (s_t = 0), a regime characterized by high means and high volatility, has the implied long-run mean of 6.83% $(-\phi_0/\phi_1)$ per annum, whereas the “tranquil” regime (s_t = 1), which is characterized by a low mean and low volatility, has the implied long-run mean of 0.6845% per annum.

Presented also in the first column is the matrix of transition probabilities for the CV-MS model computed from Equation 3. The transition probabilities P (s_t = 0) = 0.7891 and P (s_t = 1) = 0.2108 show that there is persistency in the “tranquil” regime (s_t = 0), with its probability exceeding 0.7. It appears that the regime s_t = 0 is much more persistent than the regime s_t = 1. Table 4 also includes the Ljung–Box (LB) statistics relating to the squared standardized residuals of the CV-MS model. As expected, the CV-MS model does a poor job of modelling the volatility of the series, with the Ljung–Box (LB) statistics indicating that there is serial correlation in the squared standardized residuals. These results all point towards time-varying conditional variances.

Hence, in our next estimation we relax the assumption of constant variances within each regime and allow the conditional variance to be GARCH process by the inclusion of the GARCH term. The new model with the GARCH process has the Ljung–Box (LB) statistics relating to the squared standardized residuals for the MS GARCH, Q (1) =0.0356, Q (5) = 1.6047 and Q (15) = 9.1653. Corresponding p-values are 0.8502, 0.9007 and 0.8687 respectively, indicating no remaining serial correlation in the squared standardized residuals. Thus the model appears adequate, as it captures much of the volatility.

The higher volatility regime (s_t = 0) is characterized by more sensitivity to shocks $(\beta_{01} > \beta_{02})$ and high persistence $(\beta_{11} > \beta_{12})$ than the low volatility regime (s_t = 1). This indicates that during periods of high volatility, the effect of individual shocks has a magnitude that dies out very slowly, while it does so quickly in a low volatility regime. This indicates that a large shock will be out of the market very soon after a switch to the low volatility regime. This is in contrast to GARCH models, where shocks appear to take too long to die down to the average variance, as all of the persistence in volatility is thrown into the persistence of the shock other than being associated with a specific regime.

The use of Markov regime switching model allows for GARCH effects in each regime to provide a richer characterization of the conditional variance rather than in the regime-switching with constant variance. This allows for capturing of variance dynamics of each regime and the individual shocks, which is also indicated by the low probabilities of moving through regimes, P (s_t = 0) = 0.5096 and P (s_t = 1) = 0.3615. This indicates that as you introduce the GARCH term, the probability of moving into regime s_t = 0 and (s_t = 1) is lower, as a result of less persistence in individual shocks.

In estimating regime switching models, two different conditional probabilities are of interest: the ex-ante probability, Pr [s_t = 1| ϕ_{t-1}], and the smoothed probability Pr [s_t = 1| ϕ_T]. The former is of interest in forecasting, based on the evolving information set, while the latter is of interest in determining if and when regime switches occur. Gray (1996) develops an efficient way of determining these conditional probabilities, using a

Table 4. Parameter estimates and related statistics for the Markov Switching and Markov Switching GARCH models.

Parameter	Markov switching (CV - MS)		Markov switching GARCH (MS – GARCH)	
	Estimate	p-value	Estimate	p-value
ϕ_{01}	0.2255	0.1103	0.1181	0.0011
ϕ_{02}	-0.0486	0.0000	-0.0505	0.0000
ϕ_{11}	-0.0330	0.4267	-0.1809	0.0000
ϕ_{12}	-0.0710	0.0002	-0.0531	0.0002
β_{01}	2.9611	0.0000	0.1466	0.0000
β_{11}	0.4839	0.0000	0.1770	0.0003
β_{21}			1.8834	0.0000
β_{02}			0.0268	0.0003
β_{12}			0.0007	0.6786
β_{22}			0.1446	0.0000
P	0.7486	0.0000	0.5096	0.0000
Q	0.0590	0.0000	0.3615	0.0000
Ljung – Box statistics				
$LB^2{}_1$	3.9066	0.0481	0.0356	0.8502
$LB^2{}_2$	6.0256	0.0492	0.4194	0.8108
$LB^2{}_3$	28.3014	0.0000	0.4469	0.9304
$LB^2{}_5$	47.2068	0.0000	1.6047	0.9007
$LB^2{}_{10}$	230.5312	0.0000	8.2393	0.6055
$LB^2{}_{15}$	258.6497	0.0000	9.1653	0.8687

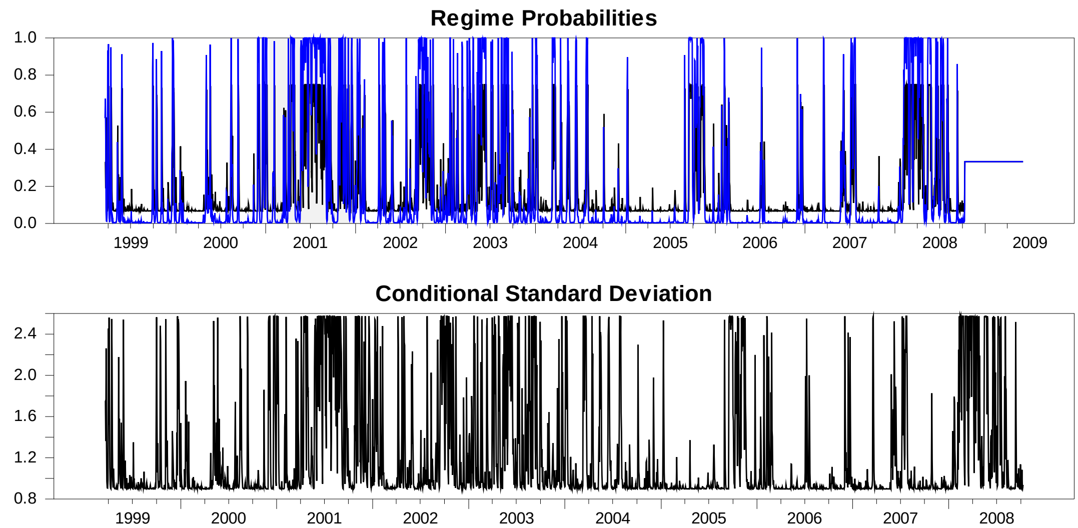

Figure 4. Regime probability of implied volatility one week.

smoothing algorithm. This technique is forward-looking and directly links these two conditional probabilities.

The top panel of Figure 4 contains a time series plot of the ex-ante (thin line) and smoothed (bold line)

Table 5. Comparison of crisis date identified by our Markov Switching GARCH with those dates identified by the Knedlik and Scheufele (2008) Markov Switching model and the Duncan and Liu (2009) SC GARCH model.

Knedlik and Scheufele (2008) (MS Model)	Duncan and Liu (2009) SC GARCH	MS GARCH
4th Quarter 2001 – 2nd Quarter 2002	4th Quarter 2001 – 1ST Quarter 2002	Last month of 3rd Quarter 2001, 4th Quarter 2001 and 2nd Quarter 2002
	----------------------------	4th Quarter 2005
	3rd Quarter 2008 – 4th Quarter 2008	3rd Quarter 2008 – 4th Quarter 2008

probabilities of the one week implied volatility. The ex-ante probability is based on information available at time t (Pr [s_t = 1| ϕ_{t-1}]), while the smoothed probability is based on the entire sample (Pr [s_t = 1| ϕ_T]).

Figure 3 (ex-ante and smoothed probabilities of the one week implied volatility) points toward two periods during which the process was in high mean and high volatility regime: last month of 3rd Quarter 2001, 4th Quarter 2001 and 2nd Quarter 2002, 2nd Quarter 2003, 4th Quarter 2005 and late 2008. These periods are indicated by conditional probabilities higher than the threshold probability of 0.5: the conditional probabilities are in the ranges of 0.6 to 0.7 last month of 3rd Quarter 2001, in the range of 0.65 to 0.8 in 2003 and 4th Quarter 2005, and in the range of 0.65 to 0.8, and 0.7 and 0.8 in 1st Quarter 2008.

The periods identified, except 2003, have quite an intuitive explanation in the context of this particular regime switching model. The first of these periods (last month of 3rd Quarter 2001, 4th Quarter 2001 and 2nd Quarter 2002) was attributed to the announcement by the South African reserve bank that it would tighten the enforcement of exchange controls. A number of observers, including some who testified before the Myburgh Commission, argued that this announcement reduced market liquidity and thereby contributed to the sharp rand depreciation. Lastly, the 2008 result corresponds to the financial turmoil around the world.

For the sake of comparison, we compare the crisis date identified by our model with the dates identified by the Knedlik and Scheufele (2008) and Duncan and Liu (2009) models.

From the comparison in Table 5, there are some notable similarities between crisis dates identified in the Knedlik and Scheufele (2008) Markov switching model and our Markov switching GARCH model, the only difference being in 2001, when our model identifies a crisis date ahead of 4th quarter 2001 (that is, in last month of 3rd Quarter 2001) as compared with 4th Quarter 2001 identified by Knedlik and Scheufele (2008) and Duncan and Liu (2009). This is indicative of a fact that implied volatility can be a good signal of an imminent crisis.

Conclusion

The purpose of this paper was to investigate whether implied volatility in foreign exchange options, being a proxy of market participants' expectations, can provide a signal for currency crisis identification. Our Markov switching GARCH model identifies two distinct exchange rate regimes, and a kind of abrupt movement from a low to a high volatility regime. The paper finds that the South African rand exchange rate is subject to several shifts in expectations over time; especially during the last month of 3rd Quarter 2001, 4th Quarter 2001 and 2nd Quarter 2002, 2nd Quarter 2003, 4th Quarter 2005 and late 2008.

This switching is theoretically from a low to a high volatility regime and is higher than the common threshold of 0.5, hence indicative of a crisis looming. The paper also identifies crisis periods consistent with those identified by Knedlik and Scheufele (2008) and Duncan and Liu (2009), except for the false signal registered in 2003.

The paper argues that shifts in market expectations had an important influence on the occurrence of the currency crisis in 4th Quarter 2001 to 2nd Quarter 2002 and 4th Quarter 2008 in South Africa. The paper highlights the importance of implied volatility of foreign exchange options as a reliable leading indicator for regime changes in currency market. The paper finds that in South African currency market higher implied volatilities are indicative of a forthcoming turbulent regime, while lower implied volatilities are indicative of a forthcoming tranquil regime.

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