



Modelling South African Currency Crises as Structural Changes in the Volatility of the Rand

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Abstract

This study tests the theory that currency crises are associated with sudden large changes in the structure of foreign exchange market volatility. Due to increases in market uncertainty, crisis periods exhibit abnormally high levels of volatility. By studying short-term changes in volatility dynamics, it is possible to identify the start- and end-dates of crisis periods with a high degree of precision. We use the iterative cumulative sum of squares algorithm to detect multiple shifts in the volatility of rand returns between January 1994 and March 2009. Dummy variables controlling for the detected shifts in variance are incorporated in a GARCH modelling framework. The analysis indicates that previously identified crisis periods in the rand coincide with significant structural changes in market volatility.

JEL Classification: F31, C60, C22

Keywords: *Currency crisis, exchange rate, volatility, ICSS algorithm, GARCH*

1 Introduction

This paper proposes a new method for timing the occurrence of currency crises under flexible exchange rate regimes. The method is based on the idea that currency crises, because they tend to be short-lived events, may be most accurately identified when they are modelled using frequent data observations. Therefore, in contrast to existing research, our investigation of currency crises is based on *daily* changes in foreign exchange market conditions.

Our model recognises the fact that heightened uncertainty is a fundamental characteristic of any crisis episode and a major driver of behaviour during periods of market turmoil. Under a flexible exchange rate regime the central bank allows the exchange rate to be determined by market forces. Given such a policy, changes in the level of uncertainty may indirectly be observed in the guise of time-varying exchange rate volatility. Hence, because of extreme uncertainty, we expect a crisis to be associated with a major spike in the short-term volatility of the market. In this respect, we suggest that points of transition between normal market conditions and those of crises should coincide with points of significant and large structural changes in the short-term volatility dynamics of exchange rate returns.¹

The applied methodology involves a two step procedure. The first step is to statistically detect the full set of possible structural change points in rand volatility during the sample period. This is achieved through implementation of Inclan and Tiao's (1994) iterative cumulative sum of

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¹In the context of this analysis, structural change refers to the occurrence of a sudden shift in variance, and not to a change in the domestic economic policy environment.

squares (ICSS) algorithm. By repeatedly evaluating the relative magnitudes of consecutive changes in squared returns with respect to a critical value, the ICSS algorithm locates multiple points of discontinuity in the variance process. Having identified potential structural changes in the volatility of the rand, the second step is devoted to testing for the significance and modelling the effects (if any) of these changes on the variance process. We apply Bollerslev's (1986) generalised autoregressive conditional heteroscedasticity (GARCH) model to capture the volatility in rand returns. The GARCH model has been shown to provide good approximations of the time-varying nature of volatility in financial returns (Diebold and Lopez, 1995), and is thus considered appropriate for our application. Two GARCH models are estimated and compared. The first is the GARCH(1,1) model. This standard GARCH specification assumes that there are no structural changes in the variance of returns. The second model augments the conventional GARCH(1,1) by incorporating a set of structural change dummy variables in the variance equation. Each dummy variable is constructed to measure the individual effect of one of the structural changes detected by the ICSS algorithm. In this way the structural change GARCH (SC-GARCH) model controls for changes in unconditional variance over time and allows for the measurement of these changes.

Our modelling approach is consistent with that of Wilson, Aggarwal, and Inclan (1996), Aggarwal, Inclan, and Leal (1999), Malik (2003), and Malik, Ewing and Payne (2005). All of these studies provide evidence of significant structural changes in the variance of financial returns. Furthermore, they consistently reach the conclusion that failing to control for detected structural changes leads to a misspecification of the variance process. Given the presence of significant breakpoints in variance, the GARCH(1,1) is liable to significant overestimation of volatility persistence (refer to Diebold and Pauly, 1987; Lastrapes, 1989; and Lamoureux and Lastrapes, 1990). The SC-GARCH model effectively addresses this limitation of the standard GARCH model.

The focus of the analysis is on modelling recent crisis episodes in the South African foreign exchange market. Specifically, we evaluate the ability of the SC-GARCH model to detect rand crises that have previously been identified in the literature. According to Bhundia and Ricci (2005), rand crises are observed during 1998 and 2001. Similarly, Knedlik and Scheufele (2008) provide evidence of crises in 1998 and 2001, but also of crises in 1996 and 2006. Our chosen data sample spans the period between January 1994 and March 2009, thus providing us with four previously identified crisis episodes to be modelled. In addition, our sample includes the latter stages of 2008. From August to October of 2008, a period that has yet to be documented in the South African currency crisis literature, the rand exhibited substantial volatility and ultimately a depreciation of over 35 percent. We evaluate the volatility features of the 2008 depreciation and analyse whether this event should be considered as a currency crisis in the rand.

Our results indicate that, using high frequency financial time series, the SC-GARCH model has the ability to identify currency crises. The SC-GARCH model is more precise than that of Knedlik and Scheufele's (2008) MS model in identifying crisis periods. Moreover, we identify the 2008 crisis beginning on 26/9/2008 and ending on 5/11/2008.

The remainder of this study is structured as follows. Section 2 provides a brief review of the South African currency crisis literature and the motivation for our study. In Section 3, we discuss our methodology, and in particular, the detection and implications of structural changes in the variance of financial returns. This is followed by data analysis in Section 4 and our empirical results in Section 5. Section 6 concludes.

2 Motivation

At the heart of asset pricing theory lies the prediction that on average the market rewards investors in proportion to the systematic riskiness of their asset portfolios (Perold, 2004). The extent of price volatility that we observe for a given asset indirectly reflects the degree of uncertainty that agents

associate with that asset's expected future payoff.² By studying and characterising the dynamics of volatility, it is possible to obtain a measure of market uncertainty as it evolves over time.

Consistent with this view, neoclassical theory proposes that exchange rate volatility be a reflection of exogenous uncertainty regarding fundamentals (Frankel and Rose, 1994). Thus, a currency crisis is associated with exceptional uncertainty in the foreign exchange market. The increased uncertainty is the consequence of economic or political developments, in either domestic or international affairs, which the market perceives in an unusually negative light. The bad 'news' is typically unforeseen, and for this reason, its arrival has the effect of shocking the market. The shock causes agents to sharply revise their expectations, leading to a sudden loss of demand for the afflicted currency at current market rates.

Recently, Kurz (1994) put forward the theory that the effects of exogenous uncertainty on market volatility are in fact far outweighed by those of endogenous uncertainty. At times of crisis, heterogeneous behaviour results in extreme asymmetry in the distribution of market-wide expectations, leading to a cycle of aggressive adjustment in the exchange rate. In the context of the current analysis, Kurz's view is consistent with the so-called 2nd generation models of currency crisis (Obstfeld, 1986). These models propose that the foreign exchange market may at times be pulled into situations of crisis by endogenously driven and self-fulfilling speculation, even when economic fundamentals are relatively sound.

However, whether volatility is assumed to arise from exogenous or endogenous sources is immaterial to our analysis. In either of these cases, theory associates a crisis period with a phase of intensive price discovery, beginning initially with an unexpected, rapid and considerable loss in market value.³

The motivation for our study is the claim that time-varying volatility dynamics of exchange rate returns should form an important element of our understanding of currency crises, particularly when such crises occur under floating exchange rate regimes. This is supported by Abiad (2003: 45), who points out that a well specified volatility model may provide the kind of information that has yet to be fully exploited in the currency crisis literature.

A prominent example of how volatility dynamics are successfully being incorporated in crisis modelling is through application of Markov-switching (MS) models (Hamilton, 1989, 1990) with time-varying transition probabilities (Lee 1991; Diebold, Weinback and Lee 1994). The MS model specifies two unobservable state variables to represent periods of tranquillity and crisis. The main distinguishing characteristic of the crisis state is a high degree of exchange rate volatility (Abiad, 2003: 45). It is assumed that the state variables determine the behaviour of economic fundamentals. Consequently, the transition between the two different states of the economy is indirectly inferred and conditioned on observations of changes in the fundamentals. The onset of a crisis period is endogenously identified in the MS model as the point of transition from the tranquil state to the crisis state. Similarly, the end of the crisis is identified as the transition back from the crisis state to the tranquil state.

In a recent study, Knedlik and Scheufele (2008) – hereafter referred to as KS – compare the performance of the more traditional signals- and probit/logit approaches with that of an MS model in identifying currency crises in South Africa. Based on their constructed exchange market pressure (EMP) index, they determine the following crisis periods in the rand: May-June 1996, April-July 1998, December 2001, and June 2006. Their findings indicate that the MS approach compares favourably with the competing approaches, successfully identifying each of the suspected crisis peri-

²In markets that are characterised by effective price controls the relationship between uncertainty and volatility will be less than perfectly observed. Under fixed or managed exchange rate regimes, the central bank actively intervenes in the foreign exchange market in order to achieve a desired target for the exchange rate. Given such a policy, changes in uncertainty will be reflected not only in changes in exchange rate volatility, but also in changes in reserves and in short-term interest rates. Therefore, because neither reserves nor interest rates feature in our model, an important proviso of our analysis is that of a flexible exchange rate regime.

³At the time of writing, there is still no universally accepted definition of currency crisis. However, according to Knedlik (2006: 6), significant depreciation of the domestic currency is a common element of most crisis definitions.

ods. Specifically, KS’s MS model identifies December 1995 to December 1996 (excluding September 1996), May to October of 1998, and December 2001 as respective episodes of rand crisis. Furthermore, the MS approach is found to be successful in forecasting the 2006 crisis in the rand.

The SC-GARCH model, which is discussed in the following section, is conceptually similar to the MS model. As in the case of the MS model, the SC-GARCH treats volatility as being time-varying and uses this feature of the data to endogenously identify crisis periods. The main difference between these approaches is that, whereas the MS model uses macro fundamentals to identify crises, the SC-GARCH represents a pure time-series approach. Although the fundamentals are undoubtedly important to our understanding of crises, fundamental models are in some respects difficult to implement empirically. A notable problem is that of low frequencies in the reporting of fundamental data. This makes it difficult for MS models to accurately estimate the timing of currency crises – especially since crises tend to be short-lived events. In contrast, financial volatility processes can be reliably estimated in data-driven models using data that is readily available in daily (or sometimes higher) frequencies. In this paper, we investigate whether application of the SC-GARCH allows for greater precision in crisis identification than that of the MS model. We use the crisis dates identified by KS’s MS model as a benchmark for our analysis.

3 Methodology

3.1 GARCH Modelling of Time-Varying Volatility Dynamics

Even though the GARCH model is certainly not the only model of its kind, it is generally regarded as the benchmark approach to volatility modelling.⁴ In general, financial volatility models like the GARCH are classified as pure time-series models in the sense that they are primarily designed to closely mimic the volatility process of returns, and not necessarily with reference to economic theory. Although they are technically different, most volatility models are based on similar principles. The majority of these models provide a measure of volatility persistence, a concept which is important to our analysis.

Regardless of the chosen model, a fundamental problem in measuring volatility is that it is a latent or unobservable variable. Hence, typically applied measures such as realised variance or standard deviation of returns may at best be considered proxies of true volatility. For this reason it is easy to obtain misleading results when modelling financial volatility. Furthermore, difficulties in modelling volatility are compounded by the stylized features of financial data. The typical distribution of financial returns displays fat tails, volatility clustering and, in some cases, asymmetry.⁵ Thus, a prerequisite for volatility approximation is that the specified model should account for non-normality where this presents itself in the data.

Despite these measurement difficulties, the GARCH has been shown to provide a good approximation of the time-varying nature of volatility in financial returns (Diebold and Lopez, 1995: 8). A typical GARCH(1,1) specification takes the following form

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \tag{1}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \quad \omega > 0, \quad \alpha, \beta \geq 0, \quad \alpha + \beta < 1 \tag{2}$$

where r_t denotes the 1st difference of the period t exchange rate, or in other words, the percentage geometric return realised in period t .⁶ Returns are modelled as being dependent on μ , their (zero) mean observation.⁷ It is assumed that the error term, ε_t , is conditioned on past information, Ω_{t-1} ,

⁴For a recent survey of volatility modelling, refer to Poon and Granger, 2003.

⁵We do not investigate possible asymmetry in the volatility of the rand. This represents a topic for future research.

⁶Mathematically, $r_t = s_t - s_{t-1}$, where s_t refers to the natural logarithm of the period t exchange rate.

⁷In the event that the returns series is found to exhibit significant autocorrelation, it is customary to replace μ with one or more autoregressive operators.

and normally distributed, with zero mean and conditional variance of h_t .⁸ Variance is set conditional on its own lagged value, and on the square of the error term realised in period $t - 1$, ε_{t-1}^2 .

The true process underlying the volatility of returns is approximated in the model's three estimated coefficients. The unconditional component of variance is given by the quotient, $\omega/(1 - \alpha - \beta)$. Conditional variance is captured in the α and β coefficients, where α measures the 'ARCH effect' – the sensitivity of the market's reaction to breaking news – and β the 'GARCH effect' – the extent to which current price changes are influenced by historically observed volatility. The sum of α and β represents the degree of persistence that shocks have in influencing the volatility process over time. If α and β sum to a value close to one, it is concluded that the volatility process has long-memory.

In their survey of ARCH-type modelling, Bera and Higgins (1993) report high persistence as a widespread finding of empirical research pertaining to financial volatility. With respect to the domestic economy, Farrel (2001) applies the GARCH to estimate volatility in various measures of the commercial and financial rand exchange rates between 1983 and 1998. He reports $\alpha + \beta$ values ranging between 0.931 and 0.998. This indicates that the volatility of the rand is highly persistent (or at least, that this was the case during the period sampled by Farrel).

However, Berra and Higgins (1993: 342) note that "... the consistent finding of very large persistence in variance in financial time series is perplexing because currently no theory predicts that this should be the case". This finding is at odds with the efficient market hypothesis, which proposes that 'news' is instantly and fully reflected in prices (see, for example, Hallwood and MacDonald, 2000: 294-99). According to this theory, shocks should result in immediate, not persistent, market volatility.

Diebold and Pauly (1987), Lastrapes (1989), and Lamoureux and Lastrapes (1990), pose a convincing argument that the degree of volatility persistence is often over-estimated in applications of the GARCH approach. The standard GARCH specification is unable to account for structural changes in volatility. This is because all the GARCH coefficients are, by construction, assumed to remain fixed over time. In contrast, a structural change implies a shift in unconditional variance and therefore a change in the magnitude of ω , the intercept of the GARCH variance equation. With ω fixed, structural change tends to create a positive bias in the estimates of α and β .

This indicates that the standard GARCH model is open to misspecification, especially when applied to time series that exhibit unusually high volatility or outlying observations. Naturally, this is an important concern when modelling the volatility associated with sample periods that include currency crises. To account for the structural changes in volatility, we employ the SC_GARCH model in the paper, in which the structural changes in the volatility are detected by the ICSS algorithm. The ICSS methodology is documented in the following subsection.

3.2 *Detecting Shifts in Unconditional Variance*

Two approaches predominate in locating structural changes in variance. The first is to select break-points in the variance process on *a priori* grounds. For example, Lastrapes (1989) introduces shifts in unconditional variance as coinciding with changes in monetary regime. The second approach involves endogenous detection of break-points. The latter approach is arguably the more sophisticated of the two, and is thus preferred in this analysis. Endogenous detection holds the advantage that breakpoints are estimated using statistical techniques. This allows for more accurate estimates of the timing of structural changes.

The most commonly applied method for endogenous detection of breakpoints in variance is the ICSS algorithm, developed by Inlan and Tiao (1994). The ICSS procedure is a retrospective test which analyses relative variations in variance over time. A break in the variance process is assumed to result from the occurrence of a sudden, large and unexpected economic or political shock. When,

⁸Robust standard errors (Bollerslev and Wooldridge, 1992) are calculated to account for non-normality in financial data.

following such a shock, the degree of variability from historically observed variance is sufficiently high, this implies that market volatility has undergone a structural change.

The primary advantage of using the ICCS methodology instead of a traditional cumulative sum of squares (CUSUM) type test is that it has the power to detect multiple breakpoints in a variance series. The algorithm thus allows for complete classification of structural changes in the data and the subsequent identification of distinctive intervals of time-varying unconditional variance in the market.

Let period x represent a volatility interval denoted by I_x , $x = 0, 1, \dots, N$. In a sample comprising T data observations, and N structural changes in volatility, we denote the locations of the ICSS detected points of variance shifts by sc_j , $j = 0, 1, \dots, N$. Here, sc_0 coincides with the first observation in the time series. The volatility profile calculated through application of the ICSS algorithm is represented as follows

$$sc_0 \leq I_0 < sc_1 \leq I_1 < sc_2 < \dots < sc_N \leq I_N \leq T \quad (3)$$

The estimate of unconditional variance during volatility interval I_x is then denoted by $\hat{\sigma}_x^2$.

We briefly explain how the CUSUM method may be applied to detect a single breakpoint in variance. Let $C_k = \sum_{i=1}^k \varepsilon_i^2$ denote the CUSUM of returns innovations. Now, let

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, k = 1, \dots, T, \text{ with } D_0 = D_T = 0 \quad (4)$$

be the centred CUSUM statistic. In order to normalise the output from (4), the estimated D_k series is multiplied by $\sqrt{(T/2)}$.

Inclan and Tiao (1994: 914) show that D_k fluctuates around zero for time-series that exhibit a high degree of homoscedasticity. They state that, in contrast, “when there is a sudden change in variance, the plot of D_k will exhibit a pattern going out of some specified boundaries with a high probability”. This allows for the calculation of critical values for normalised D_k beyond which we reject the null hypothesis of no significant shifts in variance. In this paper, we apply a critical value of $D_{.01}^{SC} = 1.628$. The finding that $\sqrt{(T/2)} |D_k| > 1.628$ indicates, at a confidence level of 99 percent, the occurrence of a significant shift in variance. In the case that the critical value is exceeded, the exact location of a shift in variance coincides with the value of k at which the absolute value of D_k is maximised.

Where it is of interest to detect only a single breakpoint in variance, the analysis ends here. However, when the objective is to test for the possibility of multiple structural changes in volatility, simple application of the D_k function often leads to omission of significant variance shifts. This is because, relative to a large shift in variance, small shifts have less impact on D_k . The possibility arises that a small – but nevertheless, significant – shift in variance may escape the detection of a CUSUM test. Inclan and Tiao (1994: 916) refer to this possibility as a “masking effect” in the D_k function.

To avoid masking effects, Inclan and Tiao propose an iterative application of the CUSUM test. Following the identification of one or more break-points using the CUSUM method, a new D_k series is estimated for each interval of unconditional variance. This process is repeated until $\sqrt{(T/2)} |D_k| < 1.628$ for all data points in each of the identified volatility intervals. Thus, the ICSS algorithm tests for the presence of additional structural changes in variance between the initially detected structural change points.

3.3 Accounting for Structural Changes in the GARCH Modelling Framework

As discussed previously, a structural change in the market’s volatility process implies a discrete shift in the level of unconditional variance. Following their detection, structural changes should be

incorporated in the chosen volatility model to avoid misspecification of the variance process.⁹

In this analysis, we apply two GARCH models to estimate volatility dynamics in the rand and compare the respective results. In the first case, the model takes the form of the typical GARCH(1,1) specification, and thus ignores the effects of potential structural changes on the variance process. In the second model, the SC-GARCH, the traditional GARCH approach is augmented to include structural change dummy variables in the variance equation. The SC-GARCH(1,1) takes the following form

$$h_t^{SC} = \omega + \nu_1 D_1 + \dots + \nu_N D_N + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^{SC} \quad (5)$$

where h_t^{SC} denotes the structural change augmented conditional variance of returns, and D_1, \dots, D_N is a set of dummy variables taking a value of one from each point of coinciding structural change, sc_1, \dots, sc_N , and zero elsewhere (consistent with Malik, et al. 2005). In this specification, ν_1, \dots, ν_N are a set of structural change coefficients (hereafter referred to as SC-coefficients) which measure the magnitude, direction, and significance of identified shifts in variance.

The SC-GARCH specification has the flexibility to ensure that shifts in the average level of volatility do not impact on the estimation of α or β , the coefficients governing conditional variance. Hence, because the effects of structural changes are measured separately in the SC-GARCH model, it should be possible to obtain a closer approximation of the true volatility process by applying this method in place of the conventional GARCH approach. Wilson, et al. (1996), Aggarwal, et al. (1999), Malik (2003), and Malik, et al. (2005), consistently report a reduction in GARCH estimated volatility persistence when the SC-GARCH specification is applied.

3.4 Identifying Currency Crises in the SC-GARCH Model

The SC-GARCH model provides an effective method for estimating volatility dynamics in time-series that are characterised by discrete shifts in variance. The model is thus particularly useful in analysing currency crises. This is due to the general finding that crises are associated with substantial spikes in market volatility. In this sense, because an unusually high level of volatility is a distinguishing feature of the most crises, the SC-GARCH model may be applied to identify the beginning- and end-points of crisis periods. The SC-GARCH model identifies the beginning of a crisis as a point in time at which unconditional variance displays a large positive shift away from its initial value. Such a shift represents a structural change in market volatility.

A practical problem in our application of the SC-GARCH model is that not all significant shifts in variance need signal the occurrence of a currency crisis. Small shifts in variance indicate small variations in market uncertainty. Slight fluctuations in short-term pricing dynamics are not unusual in foreign exchange markets, and thus minor changes in volatility are indicative of normal market behaviour. It is necessary to discern between normal- and abnormal shifts in market volatility.

The identification problem is solved by specifying a threshold level for volatility that is unlikely to be exceeded under normal market conditions. The beginning of a crisis period is identified as a point of significant structural change in variance which results in the volatility threshold being exceeded. Similarly, the end of the crisis period coincides with a significant shift in variance to a below the volatility threshold. Selection of an appropriate threshold for crisis identification is regarded as an empirical issue. We choose a crisis threshold for the rand that is broadly consistent with KS's crisis identifications, but that, at the same time, is reflective of the volatility features of past crises in the rand.¹⁰

⁹An alternative treatment involves the removal of outliers from the data (see, for example, Kearns and Pagen, 1993). However, this method is not appropriate when modelling the volatility associated with currency crisis, and thus it is not applied in this paper.

¹⁰For detailed discussion, see subsection 5(c)

4 Data Analysis

As stated previously, the objective of this analysis is to provide precise identifications of start- and end-dates for recent crises in the South African foreign exchange market. We argue that the precision with which crises may be identified depends to a large extent on the data frequency that is being modelled. Trade in foreign currencies is continuous; with the result that exchange rates often exhibit considerable volatility on a daily, or sometimes even hourly, basis. Hence, models that rely on low frequency data (for example, weekly or monthly time-series) suffer from substantial losses of information. This is particularly true at times when market volatility is pronounced – as is generally the case during currency crises.

In order to avoid losses of information, we use daily data to estimate the short-term volatility dynamics of the rand. Moreover, the choice of a daily frequency is also motivated by the fact that the accuracy of GARCH estimation is known to improve with increased data observations, especially when the model is applied to non-normal data (Engle, 2001: 158). Our sample period comprises a total of 3794 consecutive observations, beginning on 3 January 1994 and ending on 31 March 2009.¹¹ The sample has been chosen to overlap with the period studied by KS, and therefore includes the four rand crises identified using their MS model; specifically, December 1995 to December 1996 (excluding September 1996), May to October of 1998, December 2001 and April to June of 2006. This allows for the comparison of respective crisis dates identified by the MS- and SC-GARCH approaches.

The analysis is based on the volatility of the rand relative to the US dollar. The dollar continues to be the most significant currency in the world economy. According to the Bank for International Settlements (2007), 86.3 percent of all foreign exchange market transactions involve the dollar. Similarly, the South African foreign exchange market is dominated by trade involving the dollar. Since the rand/dollar is the most significant exchange rate from the perspective of domestic market participants, our analysis is based on the volatility of this currency pairing.¹²

Figure 1 provides a plot of the daily rand/dollar exchange rate for the period under investigation. The start- and end-dates of the crises identified by KS have been indicated on the graph. Each of the crises is associated with a loss of value in the rand relative to the dollar. However, the pattern of depreciation varies considerably for different crisis episodes. For example, whereas the 1996 (and to a lesser extent, the 1998) crisis is characterised by a relatively gradual depreciation in the rand, the 2001 crisis represents a very sudden adjustment in market value. This indicates that, due to changes in the South African Reserve Bank's (SARB) exchange rate policy, the rand was far more volatile during (and following) 2001 than it was in either 1996 or 1998.

[INSERT FIGURE 1]

During 1996 and 1998, the SARB intervened heavily in the forward exchange market to support the value of the rand, and thus dampen market volatility. The policy of continuously defending the rand from market forces had the negative consequence that the SARB was forced to accumulate a very large net open forward position (NOFP). The NOFP amounted to USD23.2 billion by the end of September 1998 (Myburgh Commission 2002). The costliness of defending the rand during the 1990's may be regarded as a primary motivation for the change in policy stance that occurred in 2000. With the advent of inflation targeting, the SARB effectively abandoned the policy of consistently intervening in the foreign exchange market. Consequently, when pressure mounted against the rand in the latter parts of 2001, domestic market volatility increased substantially.

The effect of the policy change on market volatility can be observed in the plot of squared rand/dollar returns, given in Figure 2. The graph illustrates the increase in rand volatility following 2000, and in particular following the 2001 crisis. It is also evident from the graph that, with the

¹¹The data was obtained from the I-Net Bridge databank.

¹²We gratefully acknowledge Brian Kahn from the South African Reserve Bank for his suggestion that we focus on modelling the volatility of the rand / dollar exchange rate.

exception of June 2006, each of the periods identified by KS is centred on what appears to be a large spike in volatility relative to the periods leading up to and following crisis. Analysis of the data suggests that, in general, rand crises are indeed characterised by changes in domestic market volatility.

[INSERT FIGURE 2]

From the perspective that past crises were associated with heightened levels of volatility, Figure 2 is indicative of a rand crisis occurring during the latter stages of 2008. The rand exhibited far greater volatility during 2008 than it did during any other part of the sample period. In the following section, we apply the SC-GARCH model in order to determine start- and end-dates for previously established crisis periods in the rand, and to test for the occurrence of a crisis in 2008.

5 Empirical Results

In what follows, we summarise the results of our investigation. Subsection 5(a) discusses the application of the ICSS algorithm to the time-series of rand/dollar returns. As discussed in subsection 2(c), the SC-GARCH model controls for the structural changes detected in the ICSS methodology. Accordingly, subsection 5(b) provides a comparison of the results of GARCH and SC-GARCH models of rand volatility. Subsection 5(c) evaluates whether the detected structural changes have a significant effect on the volatility of the rand. We discuss the selection of a volatility threshold used to identify structural changes associated with crisis periods in the rand. This is followed by a comparison of crisis periods identified by KS's MS model with those identified by the SC-GARCH approach.

5.1 *Detection of break-points in the variance of rand returns*

The ICSS algorithm is applied to the time series of innovations in rand/dollar returns. The locations of the endogenously detected breakpoints in variance are summarised in Table 1.

[INSERT TABLE 1]

Application of the ICSS methodology indicates, at a confidence level of 99 percent, the occurrence of 19 significant shifts in the volatility of the rand during the sample period. A shift in rand volatility occurs on average once in every 190 trading days – a period of roughly nine months. This indicates that the domestic foreign exchange market exhibits a great deal of instability, especially in comparison to other studies of shifting variance in exchange rate returns. For instance, Malik (2003), who uses the ICSS algorithm to investigate shifts in variance in foreign exchange markets between 1990 and 2000, reports only two shifts in the respective variances of returns to the French franc, Canadian dollar, and German mark, and three shifts in the Japanese yen and British pound. Relative to these markets for major world currencies, the rand is characterised by exceptionally high volatility, implying a great deal of uncertainty in international transactions that involve the rand.

5.2 *Comparison of GARCH and SC-GARCH Models of Rand Volatility*

The results of our modelling of rand volatility during the sample period are reported in Table 2. Panel (A) represents the standard GARCH(1,1) estimation of the variance process underlying rand returns. The results suggest some cause for concern regarding model specification. The first problem is that the estimated ω coefficient does not differ significantly from zero, implying that we are unable to calculate the unconditional variance of the rand using a simple GARCH approach. Of greater concern, is that, although α and β are both highly significant, they sum to a value of greater than 1.

This violates the coefficient restrictions of the model and implies that the variance process estimated by means of a GARCH(1,1) model follows a non-stationary process over time.

Panel (B) represents the same GARCH coefficients and specification tests reported in panel (A). However, in this case, we have applied the SC-GARCH(1,1) specification in order to account for the effects of structural changes on the variance process. In contrast to the GARCH model, the estimated ω, α and β coefficients of the SC-GARCH specification are all significant and obey the coefficient restrictions of the model. Furthermore, the error term of the SC-GARCH does not show any significant signs of heteroscedasticity.

The above comparison indicates that, because the SC-GARCH introduces dummy variables that measure discrete shifts in variance over time, it improves on the standard GARCH specification of exchange rate volatility. Furthermore, it calls into the question the validity of previous studies of volatility in the rand. For example, Farrel (2001) estimates various GARCH models to capture rand volatility between 1983 and 1998. His results suggest a very high degree of persistence in rand volatility, with reported $\alpha + \beta$ values ranging between 0.931 and 0.998. Estimation of the SC-GARCH model indicates far less persistence in rand volatility, with α and β summing to a value of only 0.69. This finding is consistent with the empirical literature relating to financial volatility (see, for example, Malik, et al. 2005). In comparison to the standard model, the measure of volatility persistence declines significantly when the GARCH(1,1) is augmented to include structural change dummy variables in the variance specification, indicating that the GARCH(1,1) overestimates the degree of volatility persistence in financial time series.

[INSERT TABLE 2]

5.3 *Applying the SC-GARCH Model to Identify Crisis Periods in the Rand*

The significant SC-coefficients estimated for the SC-GARCH(1,1) model of rand volatility are reported in Table 3. Of the 19 possible variance shifts detected by the ICSS algorithm, 16 are modelled as having a significant influence on the variance process of the rand at a 90 percent confidence level.

[INSERT TABLE 3]

In order to correctly interpret the magnitudes of the SC-coefficients, we need to convert them into measures of unconditional variance. This is done by summing the estimate of ω , which measures unconditional variance prior to the first structural change, with each of the respective significant SC-coefficients, ν_x , and dividing by the complement of $\alpha + \beta$. This calculation takes the following form

$$\sigma_x^2 = \frac{\omega + \nu_x}{1 - \alpha - \beta}, \quad x = 0, 1, \dots, N \quad (6)$$

where, as before, σ_x^2 denotes the unconditional variance associated with volatility interval x .¹³

As discussed in subsection 3(d), our application of the SC-GARCH model requires a volatility threshold to facilitate the identification of crisis periods. Selection of an appropriate threshold is an empirical issue. The threshold should be chosen in relation to periods of normal market volatility. Thus, the threshold needs to be high enough to prevent the false identification of non-crisis periods. At the same time, the threshold should not be so high as to exclude the correct identification of known periods of crisis. Finally, the threshold should be dynamically calculated so that it evolves over time to reflect changes in factors (for example, market structure or exchange rate policy) that determine the amount of volatility that we expect to observe.

¹³All of the insignificant SC-coefficients (in this case, ν_3, ν_6 , and ν_{10}) are assumed to have a magnitude of zero.

Given the above requirements, the crisis threshold proposed in this analysis is specified relative to the weighted average of unconditional variance *preceding* the various points of structural change.¹⁴ We denote average unconditional variance by $\bar{\sigma}_{x-1}^2$. Next, we evaluate the importance of individual structural changes observed in rand volatility. To do so, we calculate the ratio of individual shifts in variance relative to average unconditional variance. That is, we divide the level of unconditional variance observed during each volatility interval by average unconditional variance preceding that interval. The calculation takes the following form

$$\rho_x = \frac{\sigma_x^2}{\bar{\sigma}_{x-1}^2} \quad (7)$$

where ρ_x denotes the ratio of unconditional variance preceding and following structural change sc_x .

The unconditional variance estimated for each of the 20 detected volatility intervals that make up the sample period are summarised in Table 4. The weighted averages- and ratios of unconditional variance are also reported in Table 4. Crisis labels are attached to those volatility intervals that overlap with the crisis periods identified by KS. Remarkably, 9 of the 14 volatility intervals that coincide with the sample period studied by KS include an identified crisis episode. This overstatement of crises in the rand is due to the fact that whilst our volatility intervals are detected using daily data, KS identify crises on the basis of monthly observations. In order to refine KS's crisis identifications, we consider daily volatility as a high frequency indicator of crises.

[INSERT TABLE 4]

In the sample period considered by KS, we identify three structural changes in variance that each result in an extreme spike in market volatility. During this period, the average ratio of unconditional variance following a structural change is 3.8. In comparison, the respective ratios associated with structural changes sc_7 , sc_9 , and sc_{14} are equal to 12.12, 13.26, and 16.56. The latter structural changes are hence distinguishable by their extraordinary magnitudes from other significant shifts in variance. Accordingly, we select a crisis threshold ratio of 10, and thus, obtain SC-GARCH identifications of crisis periods in the South African rand.¹⁵

Each of the SC-GARCH identified crises coincides with part of a crisis period identified by KS. The first SC-GARCH crisis, denoted by structural change sc_7 , captures the increase in volatility observed during the latter stages of the 1996 crisis. In this instance, the crisis is modelled as having lasted for a considerable period – 203 trading days, beginning on 16/5/1996 and ending on 13/3/1997. In comparison, the second crisis identified by the SC-GARCH model, beginning with structural change point sc_9 , is more closely centred on the crisis period identified by KS. The duration of the volatility spike associated with the 1998 crisis is 26 trading days between 10/6/1998 and 19/7/1998. Results of the SC-GARCH estimation indicate that, from the perspective of observed volatility, the rand crisis during 1998 was relatively short-lived in comparison to the 1996 crisis. Interestingly, with starting-date 12/12/2001 and ending-date 22/1/2002, the 2001 crisis is estimated as having identical duration to the 1998 crisis.

Although our findings are broadly consistent with those of KS, there are some notable differences between the SC-GARCH- and MS crisis identifications. For instance, the SC-GARCH model fails to detect a crisis in June 2006. This reflects the fact that, although the rand lost 25 percent of its value in the first half of 2006, the depreciation was not characterised by the extent of market turmoil observed during previous crisis periods. A further cause for concern is the lack of accuracy with which the model identifies the 1996 crisis. Analysis of the data suggests that the rand was most

¹⁴By measuring average variance prior to points of structural change we ensure that calculation of the threshold is not biased by future levels of market volatility (or, by implication, crisis periods that have yet to be observed).

¹⁵Although it is chosen to be consistent with the South African data, we acknowledge the arbitrariness of our crisis threshold. In this respect, our approach suffers from a common weakness in models of crisis identification (see, for example, Abiad (2003) for a discussion of crisis thresholds). The suggested threshold may not be appropriate in the case of currency pairings other than the rand / dollar exchange rate.

volatile during February to May of 1996 (refer to Figure 2 in Section 4). In this case, the SC-GARCH model is late in its identification of the crisis. A possible reason for this may be the fact that foreign exchange market intervention played an important role in subduing market volatility during 1996. These findings suggest that the SC-GARCH model is not equally well suited to modelling all types of currency crises. The model is most informative when studying crises that are characterised by a high degree of short-term volatility. For instance, the SC-GARCH indicates that the high volatility associated with the 2001 crisis extended well into January 2002. From this perspective, the model's crisis identification may be regarded as more precise than that of KS's MS model.

In addition to studying previously identified crises, our sample period includes the latter stages of 2008, a period of very high volatility in the rand. The ratio of unconditional variance preceding and following structural change sc_{19} is 24.6. This ratio easily exceeds the chosen threshold of 10 and is significantly greater than the ratios calculated for the 1996, 1998 and 2001 crises. Consequently, the SC-GARCH model indicates starting-date 26/9/2008 and ending-date 5/11/2008 as the most volatile crisis period in the South African foreign exchange market to date. The estimated duration of the 2008 crisis is 29 trading days.

6 CONCLUSION

This study tests the theory that currency crises are associated with sudden large changes in the structure of foreign exchange market volatility. Due to increases in market uncertainty, crisis periods exhibit abnormally high levels of volatility. By studying short-term changes in volatility dynamics, it is possible to identify the start- and end-dates of crisis periods with a high degree of precision.

The crisis periods identified by the SC-GARCH model (16/5/1996 – 13/3/1997; 10/6/1998 – 19/7/1998; 12/12/2001 – 22/1/2002; 26/9/2008 – 5/11/2008) are broadly consistent with those provided by Knedlik and Scheufele (2008). Notable differences between the two studies include: 1) SC-GARCH identified crises have shorter durations, and more precise start- and end-dates than MS identified crises; 2) the SC-GARCH does not detect a crisis in the rand during 1996; and 3) the sample period is extended to detect a crisis period in the rand during 2008.

Our analysis relies on the ICCS technique proposed by Inclan and Tiao (1994) to endogenously detect structural changes in the volatility of financial time series. Following Wilson, et al. (1996), Aggarwal, et al. (1999), Malik (2003), and Malik, et al. (2005), the detected structural changes are incorporated into the GARCH volatility modelling framework. Our results suggest that, using high frequency financial time series, the SC-GARCH model is able to identify currency crises. Moreover, the SC-GARCH model is more precise than Knedlik and Scheufele's MS model in identifying crisis periods in the rand. Finally, our finding that the GARCH(1,1) overestimates the degree of volatility persistence in financial time series is consistent with the empirical literature.

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Figure 1. The rand / dollar exchange rate and crisis periods identified by KS (2008).

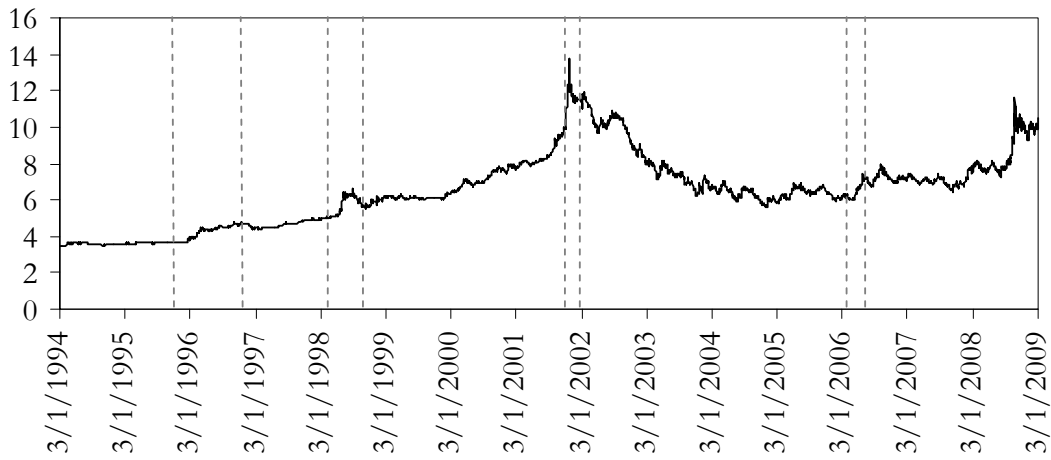


Figure 2. Squared rand/ dollar returns and crisis periods identified by KS (2008).

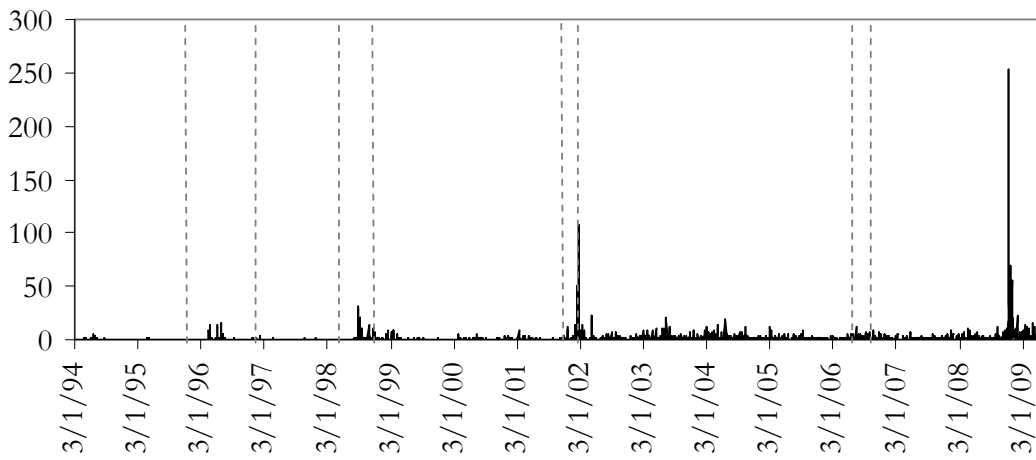


Table 1. Locations of possible structural changes in variance of rand / dollar returns

Structural Change	Location (k)	Date
SC_1	64	31/3/1994
SC_2	88	11/5/1994
SC_3	282	20/2/1995
SC_4	349	2/6/1995
SC_5	523	15/2/1996
SC_6	585	16/5/1996
SC_7	788	14/3/1997
SC_8	1086	10/6/1998
SC_9	1112	20/7/1998
SC_{10}	1234	21/1/1999
SC_{11}	1483	27/1/2000
SC_{12}	1889	20/9/2001
SC_{13}	1946	12/12/2001
SC_{14}	1972	23/1/2002
SC_{15}	2622	23/8/2004
SC_{16}	3183	17/11/2006
SC_{17}	3421	22/10/2007
SC_{18}	3662	26/9/2008
SC_{19}	3691	6/11/2008

Table 2. GARCH models of daily rand / dollar volatility

(A) GARCH(1,1)

μ	ω	α	β	$\omega/(1-\alpha-\beta)$	$\alpha + \beta$	TR^2
0.0112 (0.0075)	0.0034 (0.0023)	0.1486 (0.0298)	0.8684 (0.0252)	0.0040	1.0170	0.7985 (3.1139)

(B) SC-GARCH(1,1)

0.0101 (0.0065)	0.0547 (0.0109)	0.1134 (0.0236)	0.5769 (0.0593)	0.1767	0.6903	1.0479 (1.8631)
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Notes: Robust standard errors (Bollerslev and Wooldridge, 1992) relating to estimated coefficients are reported in brackets. The TR^2 statistic is an ARCH LM test for remaining heteroscedasticity in the estimated error term at a lag interval of 15.

Table 3. Significant Structural Change Coefficients.

SC-GARCH(1,1)

ν_1	ν_2	ν_4	ν_5	ν_7	ν_8	ν_9	ν_{11}
0.2582 (0.1343)	-0.0339 (0.0097)	-0.0484 (0.0102)	0.5152 (0.2529)	-0.0353 (0.0091)	1.7661 (0.6601)	0.3457 (0.1039)	0.0684 (0.0188)
ν_{12}	ν_{13}	ν_{14}	ν_{15}	ν_{16}	ν_{17}	ν_{18}	ν_{19}
0.4634 (0.1791)	3.1997 (1.5565)	0.4083 (0.0758)	0.2614 (0.0513)	0.1476 (0.0372)	0.3884 (0.0808)	7.3386 (4.3864)	0.9324 (0.2328)

Notes: Robust standard errors (Bollerslev and Wooldridge, 1992) relating to estimated coefficients are reported in brackets.

Table 4. Comparison of Markov-switching and SC-GARCH identified crisis periods

Volatility Interval	Beginning	End	σ_x^2	$\bar{\sigma}_{x-1}^2$	ρ_x	Crisis Identifications	
						KS's (2008) MS model	SC-GARCH(1,1) model
I_0	3 / 1 / 1994	30 / 3 / 1994	0.1767				
I_1	31 / 3 / 1994	10 / 5 / 1994	1.0104	0.1767	5.7166		
I_2	11 / 5 / 1994	19 / 2 / 1995	0.1767	0.4067	0.4346		
I_3	20 / 2 / 1995	1 / 6 / 1995	0.0672	0.2479	0.2711		
I_4	2 / 6 / 1995	14 / 2 / 1996	0.0204	0.2132	0.0955	CRISIS (12 / 1995 - 12 / 1996)	
I_5	15 / 2 / 1996	15 / 5 / 1996	0.1767	0.1489	1.1871	CRISIS (12 / 1995 - 12 / 1996)	
I_6	16 / 5 / 1996	13 / 3 / 1997	1.8401	0.1518	12.1181	CRISIS (12 / 1995 - 12 / 1996)	CRISIS (16 / 5 / 1996 - 13 / 3 / 1997)
I_7	14 / 3 / 1997	9 / 6 / 1998	0.0628	0.5873	0.1069	CRISIS (12 / 1995 - 12 / 1996)	
I_8	10 / 6 / 1998	19 / 7 / 1998	5.8786	0.4433	13.2622	CRISIS (5 / 1998 - 10 / 1998)	CRISIS (10 / 6 / 1998 - 19 / 7 / 1998)
I_9	20 / 7 / 1998	20 / 1 / 1999	0.1767	0.5705	0.3098	CRISIS (5 / 1998 - 10 / 1998)	
I_{10}	21 / 1 / 1999	26 / 1 / 2000	1.2930	0.5315	2.4327		
I_{11}	27 / 1 / 2000	19 / 9 / 2001	0.3975	0.6594	0.6028		
I_{12}	20 / 9 / 2001	11 / 12 / 2001	1.6729	0.6031	2.7738	CRISIS (12 / 2001)	
I_{13}	12 / 12 / 2001	22 / 1 / 2002	10.5070	0.6345	16.5603	CRISIS (12 / 2001)	CRISIS (12 / 12 / 2001 - 22 / 1 / 2002)
I_{14}	23 / 1 / 2002	22 / 8 / 2004	1.4950	0.7647	1.9551		
I_{15}	23 / 8 / 2004	16 / 11 / 2006	1.0206	0.9458	1.0790	CRISIS (4 / 2006 - 6 / 2006)	
I_{16}	17 / 11 / 2006	21 / 10 / 2007	0.6532	0.9590	0.6812		
I_{17}	22 / 10 / 2007	25 / 9 / 2008	1.4307	0.9377	1.5257		
I_{18}	26 / 9 / 2008	5 / 11 / 2008	23.8694	0.9702	24.6033		CRISIS (26 / 9 / 2008 - 5 / 11 / 2008)
I_{19}	6 / 11 / 2008	31 / 3 / 2009	3.1870	1.1501	2.7710		