EMPIRICAL ANALYSIS OF THE DYNAMICS OF THE SOUTH AFRICAN RAND (POST-1994)

by

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Declaration

> "I hereby declare that this is my own unaided work, the substance of or any part of which has not been submitted in the past nor will be submitted in the future for a degree to any university, and that the information contained herein has not been obtained during my employment or working under the aegis of any other person or organisation other than this university.

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Signed this _______ day of _______________ 2015 at Johannesburg"

Dedication

This work is dedicated to my family, school teachers and university lecturers, and Almighty God.

In particular, thank you to my great grandmother, for raising me shortly after birth and for grooming my character in early childhood and youth, so that I could live a life that matters. I would also like to express my sincere gratitude to my grandparents for making it possible for me to complete the last three years of secondary school. To my parents, aunts and uncles, your contributions to my development are also appreciated.

Teachers have the power to inspire, through their attitudes, actions, and even through the lessons or activities they engage students in. So I am naturally indebted to my Grade Eight and Nine Mathematics and Sciences teacher, Ms. Natalie Daniels, for being such a great source of inspiration and laying a solid foundation in mathematics; allowing me to excel in my later years of education. You have opened up so many possible career paths for me – it is breathtaking. Whilst most scholars were anxious about their very limited career choices, I was preoccupied with making a choice from a wide and lucrative set of opportunities. And so 'I have a genuine good story to tell'.

And last but not least, I give thanks to the Good Lord – I can do all things through Him who strengthens me. Perhaps the greatest lesson I've learnt throughout this research is

'Knowledge is valuable, but Godly wisdom is priceless'.

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The statements made and views expressed are, however, solely the responsibility of the author and should not be interpreted as reflecting the views of the referee, reviewer, data and programming code providers, and sponsors.

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Acronyms and Abbreviations

AC	Autocorrelation
ACF	Autocorrelation function
ADF	Augmented Dickey-Fuller
A-FIAPARCH	Adaptive fractionally integrated asymmetry power autoregressive conditional heteroskedasticity
A-FIEGARCH	Adaptive fractionally integrated exponential generalised autoregressive conditional heteroskedasticity
A-FIGARCH	Adaptive fractionally integrated generalised autoregressive conditional heteroskedasticity
A-GARCH	Adaptive generalised autoregressive conditional heteroskedasticity
AIC	Akaike information criterion
ANC	African National Congress
AO	Additive outlier
APARCH	Asymmetric power generalised autoregressive conditional heteroskedasticity
AR	Autoregressive
ARCH	Autoregressive conditional heteroskedasticity
ARCH-M	Autoregressive conditional heteroskedasticity in mean
ARFIMA	Autoregressive fractionally integrated moving average
ARMA	Autoregressive moving average
ASGISA	Accelerated and Shared Growth Initiative of South Africa
BFGS	Broyden, Fletcher, Goldfarb and Shanno
BIC	Bayesian information criterion
BIS	Bank for International Settlements
BRICS	Brazil, Russia, India, China and South Africa
CHF	Swiss franc
CLS	Continuous linked settlement
CMR	Clemente, Montanes and Reyes
COSATU	Congress of South African Trade Unions
CPI	Consumer price index
CPIX	Consumer price index excluding mortgage costs
CSFI	Centre for the Study of Financial Innovation
CSID	Corporate Strategy and Industrial Development (Research Programme)
CUSUM	Cumulative sum of squares
DF	Dickey-Fuller
DF-GLS	Dickey-Fuller generalised least squares
DGP	Data generating process
DEM	Deutsche mark
ECB	European Central Bank
ECU	European currency unit
EGARCH	Exponential generalised autoregressive conditional heteroskedasticity
EGDPU	Employment, Growth and Development Policy Unit
EMH	Efficient markets hypothesis
EMU	European Monetary Union
ERS	Elliot, Rothenberg and Stock
ERSPO	Elliot, Rothenberg and Stock point optimal
EU	European Union
EUR	Euro
FDI	Foreign direct investment
Fed	United States Federal Reserve Bank

FIAPARCH	Fractionally integrated asymmetry power autoregressive conditional heteroskedasticity
FIGARCH	Fractionally integrated generalised autoregressive conditional heteroskedasticity
FRA	Forward rate agreement
FRC	Faculty Research Committee
G4 currencies	United States dollar, euro, Japanese yen, and British pound
G7	Seven advanced economies
GARCH	Generalised autoregressive conditional heteroskedasticity
GATT	General Agreement on Tariffs and Trade
GBP	British pound (sterling)
GC	Governing Council
GDP	Gross domestic product
GED	Generalised error distribution
GIPS	Greece, Italy, Portugal and Spain
GIIPS	Greece, Italy, Ireland, Portugal and Spain
GJR-GARCH	Glosten, Jagannathan and Runkle generalised autoregressive conditional heteroskedasticity
GLS	Generalised least squares
GNP	Gross national product
HQC	Hannon-Quinn criterion
ICSS	Iterative cumulative sum of squares
IGARCH	Integrated generalised autoregressive conditional heteroskedasticity
IMF	International Monetary Fund
IO	Innovative outlier
IT	Inclan and Tiao
JB	Jarque-Bera
JPY	Japanese yen
JSE-ALSI	Johannesburg Securities Exchange All Share Index
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
LB	Ljung-Box
LF	Loss function
LL	Log-likelihood
LM	Lagrange multiplier
LR	Likelihood ratio
LUB	Least upper bound
MA	Moving average
MAIC	Modified Akaike information criterion
MLE	Maximum likelihood estimator (or estimation)
MPC	Monetary Policy Committee
MS	Markov-switching
MSIC	Modified Schwarz information criterion
NBER	Nominal bilateral exchange rate
NEER	Nominal effective exchange rate
NH	Nyblom-Hansen
NIC	News impact curve
NOFP	Net oversold (or open) forward position
OLS	Ordinary least squares
PAC	Partial autocorrelation
PhD	Doctor of Philosophy
PP	Phillips-Perron
PPP	Purchasing power parity

QA	Quandt-Andrews
QGLS	Quasi-generalised least squares
QMLE	Quasi-maximum likelihood estimator
RLS	Recursive least squares
RSS	Residual sum of squares
SA	South Africa
SACP	South African Communist Party
SADC	Southern African Development Community
SADCC	Southern African Development Coordinating Conference
SARB	South African Reserve Bank
SC	Structural change
SC-GARCH	Structural change generalised autoregressive conditional heteroskedasticity
SIC	Schwarz information criterion
SSC-GARCH	Sudden structural change generalised autoregressive conditional heteroskedasticity
UIP	Uncovered interest parity
UK	United Kingdom
US	United States
USD	United States dollar
WTO	World Trade Organisation
ZAR	South African rand

Symbols

£	British pound (sterling)
€	Euro
DM	Deutsche mark
¥	Japanese yen
R	South African rand
SFr	Swiss franc
$	United States dollar

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Abstract

The objective of this thesis is to investigate the recent historical dynamics of the four major nominal bilateral spot foreign exchange rates and the fifteen currency-basket nominal effective exchange rate of the South African rand (hereafter referred to as the rand). The thesis has been organised as three separate studies that add to the advancement of the knowledge of the characteristics and behaviour (causal effects) of the rand. The common thread that holds the individual chapters together is the study of the dynamics of the rand. In particular, the study establishes whether the apparent nonstationarity of the exchange rate is a product of unit root test misspecification (a failure to account for structural change), considers the connexions between the timing of the identified structural shifts and important economic and noneconomic events, and analyses rand volatility and the temporal effect of monetary policy surprises on both the spot foreign exchange market returns and volatility of the rand. In order to do this, low- and high-frequency data are employed. With regard to exchange rate modelling, the theoretical economic-exchange rate frameworks are approached both from the traditional macro-based view of exchange rate determination and a micro-based perspective. The various methodologies applied here tackle different aspects of the exchange rate dynamics.

To preview the results, we find that adjusting for structural shifts in the unit root tests does not render any of the exchange rates stationary. However, the results show a remarkable fall in the estimates of volatility persistence when structural breaks are integrated into the autoregressive conditional heteroskedasticity (ARCH) framework. The empirical results also shed light on the impact of modelling exchange rates as long memory processes, the extent of asymmetric responses to 'good news' and 'bad news', the consistencies and contrasts in the five exchange rate series' volatility dynamics, and the timing and likely triggers of volatility regime switching. Additionally, there are convincing links between the timing of structural changes and important economic (and noneconomic) events, and commonality in the structural breaks detected in the levels and volatility of the rand. We also find statistically and economically significant high-frequency exchange rate returns and volatility responses to domestic interest rate surprises. Furthermore, the rapid response of the rand to monetary policy surprises suggests a relatively high degree of market efficiency (from a mechanical perspective) in processing this information.

Keywords: Exchange rate, expectations, long memory, monetary policy surprises, repo rate, structural breaks, volatility; unit root.

JEL Code: C22, E52, E58, F31, F41, G14 and G15

CHAPTER 1

General introduction

1.1 Preface

1.1.1 Research objectives

Understanding exchange rate dynamics is a longstanding research challenge. The dynamics of exchange rates can differ across currency pairs and also evolve for a single exchange rate. Thus, currency value fluctuations remain one of the most topical economic issues. The overarching aim of this study is to advance our knowledge of the data generation process (DGP) and pertinent characteristics of the key nominal exchange rates of the rand, the nature, extent and significance of varying rand volatility over extended periods, and the level and volatility responses of the rand in short window periods around the time of repo rate announcements. In order to advance this objective, this thesis consists of three distinct essays – chapters 2 to 4. Chapters 1 and 5 are the introduction and conclusion, respectively.

- The introductory chapter provides a synopsis of the South African rand foreign exchange market and its evolving environment.
- Chapter 2 examines the unit root properties of the key nominal exchange rates of the rand. In particular, this chapter establishes whether the apparent exchange rate level nonstationarity is a product of unit root test misspecification (a failure to account for structural change). Additionally, the links between the timing of the structural shifts and important economic and noneconomic events are explored.
- In Chapter 3, rand volatility is analysed. This chapter presents a broad empirical investigation of the volatility dynamics of the rand from the time of the demise of the dual exchange rate mechanism on 10 March 1995. The starting point is an assessment of the basic characteristics of the currency returns; namely, the first, second, third and fourth moments of the returns distribution. The principle analysis explores the impact of integrating smooth and sudden structural changes into the volatility measurement frameworks, to find the 'best-fit' models, and attempts to shed light on the degree of long memory in the volatility process following a shock, the extent of asymmetric responses of the rand to 'good news' and bad news', the consistencies and dissimilarities in the volatility dynamics of the individual key exchange rates of the rand, and the timing and likely causes of exchange rate volatility regime switching.
- Chapter 4 examines the temporal effect of domestic monetary policy surprises, repo rate shocks, in particular, on both the levels and volatility of currency returns – how quickly the rand reacts to the surprises, the magnitude of the responses and how long the impacts on the currency take to die off. The relative extent of the rand foreign exchange market efficiency, that is, whether the rand reacts or not to anticipated changes in the repo rate, is also investigated.
- The final chapter summarises the key findings of the research, notes limitations of the three studies, and discusses potential directions for future research.

1.1.2 Research methodology

In order to realise the research objectives outlined above, time series econometric methodologies are applied to high- and ultra-high-frequency data. The models, estimation techniques, sample periods and data frequencies are chapter specific.

- In Chapter 2 on unit roots and structural change testing, the sample period covers 13 March 1995 to 31 August 2010. The time horizon of this sample is motivated by the South African authorities' reversion to a single exchange rate mechanism on March 13, 1995. This empirical analysis uses daily data of the major nominal bilateral and effective exchange rate levels of the rand. Both traditional unit root test and structural break adapted unit root test models are applied. The ordinary least squares (OLS) and the quasi-generalised least squares (QGLS) methods are used to test for stationarity and nonstationarity, and structural beak points. Potential events that may have caused the detected structural breaks are obtained from economic reports.
- The sample period for the returns in Chapter 3 (exchange rate volatility) is identical to that in Chapter 2. Volatility is estimated using the ARCH-type modelling framework and the maximum likelihood estimation (MLE) methodology. Again, the likely events that may have caused the identified volatility shifts are extracted from economic reports.
- In Chapter 4 on the rand's reaction to repo rate surprises, the shorter sample period, 14 August 2003 to 24 January, is dictated by South African monetary policy and exchange rate regimes, the availability of intra-day high-frequency exchange rate data and historical market consensus forecasts for the repo rate, and information regarding the South African Reserve Bank (SARB) Monetary Policy Committee (MPC) repo rate decision. The quantitative analysis proceeds using intra-day high-frequency minute-by-minute exchange rate data, repo rate data from the SARB's scheduled monetary policy announcements and Bloomberg, an 'event study' approach and the OLS estimation methodology.

1.1.3 Summary of key findings

For each of the three distinct essays, it is useful to start with a brief note on the emerging literature in this sphere of economics and econometrics, followed by a summary of the key findings.

Chapter 2: Testing for structural breaks in economic time series and time series relationships, and accounting for such change in economic models can avert spurious inference. Perron (1990) empirically showed that the existence of a structural shift in a stationary series may result in nonrejection of a unit root null, with more evidence for misconstrued unit roots tests being provided by Zivots and Andrews (1992) and Lee and Strazicich (2001). The endogenisation of breakpoints has been an important milestone in unit root testing. Motivated by these findings and breakthroughs in unit root testing, this chapter evaluates some of the time series properties of the levels of the four major nominal bilateral exchange rates of the rand and an index of its trade-weighted nominal exchange rates. There are several key findings in this study:

- we find that several statistically significant structural breaks are evident in the data (at the 95% and 99% confidence levels);
- there is convincing evidence that the exchange rate levels are nonstationary and *I(1)*, even in the presence of structural breaks at the 1% level of significance, although the evidence for the pound/rand exchange rate is not as clear-cut as for the other rates;
- the unit root test *t*-statistics and *LM*-statistics for all five exchange rates lie much closer to their corresponding asymptotic 5% level critical values when structural shift is accommodated, with a greater convergence observed in the yen/rand – consistent with Perron's (1990) results which showed that the power to reject a unit root decreases when the stationarity alternative is true and a structural break is ignored; and,
- the rand is susceptible to a wide range and diverse set of economic and non-economic structural change triggers;

Chapter 3: This chapter responds to empirical work already executed by Farrell (2001), Duncan and Liu (2009), and Thupayagale and Jefferis (2011); extending it in a number of directions. The study poses the question of non-stationarity in unconditional variance as a misspecification issue. Currently, the ARCH and generalised autoregressive conditional heteroskedasticity (GARCH) models developed by Engle (1982) and Bollerslev (1986), respectively, appear to be the most popular measures of volatility as they are able to replicate salient features of the dynamics of asset returns in general. But newer models promise more robust results in the sense that structural shift is not misconstrued as volatility persistence. Our main findings are:

- the descriptive statistics in the preliminary analysis of this chapter confirm some of the stylized facts about nominal financial time series such as leptokurtic distributions, ARCH effects – autocorrelation and heteroskedasticity – and volatility clustering of risky assets returns, indicating that the data are candidates for ARCH-type modelling;
- the Nyblom parameter stability and iterative cumulative sum of squares (ICSS) test results indicate strong and widespread instability in conditional volatility (between 20 and 44 breakpoints are detected) – we detect more than double the amount of statistically significant structural breaks in the conditional variance than those uncovered in a recent study on the US dollar/rand exchange rate returns, for a similar period, by Duncan and Liu (2009);
- volatility persistence falls markedly when fractional integration and a larger set of structural shifts are accounted for;
- the top three approximating models across the board reflect the importance of long memory, asymmetry and structural change, both abrupt and smooth, in exchange rate volatility modelling;

- a consequence of accounting for the latter phenomena is that the unconditional variance is stationary in stark contrast to the simpler models which produce a unit root, thus nullifying the spurious results that suggest that the volatility process is not mean reverting;
- although the sudden structural shift ARCH-type models better fit the data than the smooth transitional competing models, the latter modelling framework does not perform considerably worse and is a notable improvement on the basic models; and,
- the timing of changes in volatility regimes, and thus their likely causes, are more or less consistent with those in chapter 2.

Chapter 4: Over the past 15 years or so, many 'event studies' have had success in identifying the level and volatility responses of foreign exchange rates to monetary policy surprises, and macroeconomic shocks in general, in advanced economies. Contrary to the results of developed economies, empirical evidence on some emerging markets fail to provide evidence of statistically significant currency reactions to domestic monetary policy surprises. For South Africa (SA), this is the first such study on South African interest rate announcement effects using intra-day high-frequency (minute-by-minute) exchange rate data; Fedderke and Flamand (2005) employ daily exchange rate data.[1] The main results of this chapter can be summarised as follows:

- we find both statistically and economically significant responses of the level and volatility of the rand returns to repo rate shocks but anticipated changes have no bearing on the rand;
- our estimation results suggest that monetary policy news is an important determinant of the exchange rate for approximately 20 minutes after the estimated time of the pronouncement; and,
- the relatively rapid rate of exchange rate response to a 100-basis-point hike 5-minutes post-event – elevated returns peak within 30 minutes post-announcement and volatility subsides about 40 minutes following the event – suggest a relatively high degree of market 'efficiency' in its mechanical sense and not 'efficient' market in the deeper economic-informational sense.

1.2 South African rand foreign exchange market: A historical synopsis

Explaining historical exchange rate behaviour and forecasting the future path of currency prices remains 'a hard nut to crack' for both technical and fundamental currency analysts. Instances of exchange rate movements that appear to be in conflict with theory are common; for example, rand weakness immediately after the SARB MPC announced a 25 basis point hike in the repo rate on 17 July 2014. As background to this study, we first set out some basic recent historical characteristics of the rand and its environment. Table 1.1 below provides an overview of the evolution of SA's exchange rate regimes and complementary policies in recent decades.

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[1] Farrell *et al.* (2012) also use high-frequency data but look at South African inflation and not interest rate surprises.

Table 1.1: Exchange rate regimes and capital controls: The South African experience (1983-2012)

1983 – 1985	(Premature) reintroduction of a unitary exchange rate system: exchange controls on non-residents were lifted, abolishing the multiple exchange rate system, and further development of the forward exchange market aimed at establishing an independent private forward market. This major shift in exchange rate policy was not sustainable based on SA's economic fundamentals.
1985 – 1994	Reversion to dual exchange rate regime and tightening of exchange controls as part of the response to the South African 1985 debt crisis sparked by international sanctions and disinvestment.
1994 – 1995	Advent of democratisation of South African political institutions, normalisation of international relations, liberalisation of foreign exchange market, further development of forward market with less SARB participation and gradual relaxation of exchange controls, but the multiple exchange rate system remained in place.
1995 - 1999	SA reverts to a unified managed exchange rate regime, a step towards a market determined exchange rate system – from 1960 onwards, multiple exchange rates are usually transitional in nature, and are primarily used to alleviate direct pressures on financial markets and indirect effects on the real economy. The actions of the SARB were mainly aimed at smoothing out severe fluctuations in the exchange rate, bolster its foreign currency reserves to accommodate balance of payment transactions and to reduce its net oversold (or open) forward position (NOFP).
2000 - 2012	Concurrent adoption of inflation targeting monetary policy and a more flexible exchange rate system where the central bank made no attempts to influence the market exchange rate (Van der Merwe, 2004). At face value, the SARB's net purchases of foreign currency over most or the entire period is consistent with its stated goal of buying foreign currency but the SARB intervenes in relatively small amounts to gradually build-up its foreign reserves, *albeit* not aggressively and when market conditions are conducive.

Source: May, C. (2014). Exchange Rate Regimes in *"Blanchard and Johnson"*, *Macroeconomics: Global and Southern African Perspectives, 2014*.

1.2.1 South Africa in the global foreign exchange market

Triennial central bank surveys conducted by the Bank for International Settlements (BIS) indicate that activity in the global foreign exchange market has more than quadrupled in just under 20 years. The size of the daily global foreign exchange market turnover averaged 5.3 trillion United States (US) dollars in April 2013, approximately 340 per cent higher than in April 1995. SA's global share remains largely unchanged in terms of turnover at around 0.3% implying that its daily turnover grew at roughly the same rate as that of the global market average. Based on the most recent 2013 survey, the rand is the 18th most traded currency in the world, surpassed by only two of its BRICS partners' currencies;[2] namely, the Chinese yuan (or renminbi) and the Russian rouble. By currency pair, rand/US dollar average daily turnover is currently ranked number 16.

[2] BRICS is the acronym for a recently founded association of five major emerging national economies – Brazil, Russia, India, China and SA – which are all deemed to be advanced emerging economies (in some respects) and have the potential of being a powerful economic bloc.

The question that flows from these statistics is 'What makes such a small economy's currency an attractive emerging market currency in 'normal' times?' Increased transparency and liquidity, and reduced risk, are some of the contributing factors. But emerging market currency liquidity also has drawbacks. Using data from a cross-section of emerging markets, Eichengreen and Gupta (2014) point out a few emerging market snags emanating from the recent mid-2013 US Federal Reserve's (Fed) unexpected talk of the possibility of tapering its securities purchases. Emerging markets' economies responded disproportionately to this shock: the ones severely affected were those with larger financial markets, and those who experienced spectacular currency appreciation and remarkable current account deficit deterioration during the Fed's earlier monetary easing phase. Stronger macroeconomic fundamentals appeared to play little role on the uneven impact of this shock on individual countries in the sample. With greater emphasis on the size of their financial markets and currency liquidity, Eichengreen and Gupta (2014) find that:

> "Investors seeking to rebalance their portfolios concentrated on emerging markets with relatively large and liquid financial systems. These were the markets where they could most easily sell without incurring losses, and where there was the most scope for portfolio rebalancing. The obvious contrast is with so-called frontier markets with smaller and less liquid financial systems. This is a reminder that success at growing the financial sector can be a mixed blessing. Among other things, it can accentuate the impact on an economy of financial shocks emanating from outside."

Thus, the implication for SA, a small open-economy with a very low national savings rate by emerging markets standards, is that its highly liquid currency, *ceteris paribus*, is desirable for attracting currency capital inflows to fund the shortfall between its national savings and investment during 'normal' times but potentially devastating when shocks or crises alter market sentiment resulting in massive and rapid capital outflows. Pressures on the exchange rate, foreign currency reserves and stock market are evidently far more substantive for liquid emerging currencies than less liquid ones (Eichengreen and Gupta, 2014).

We address a few other developments in the rand foreign exchange market and its changing environment in the following sub-section.

1.2.2 South African international trade and financial markets liberalisation

Globalisation is inevitable. The size of a country's foreign exchange market and trade of its currency in the global foreign exchange market move in tandem with the growing volume and value of transactions on its balance of payments. Rapidly increasing international trade in goods, services, factors of production and financial assets expands trade in the foreign exchange market. Technological advances such as the internet and other global electronic media enable an easier and quicker flow of both money and information across borders. And as SA becomes more integrated into the world economy, the country and its major trading partners become more interdependent.

Like many other countries, liberalisation of trade in goods (and services) by South African authorities has preceded financial market reforms. Following the lifting of trade sanctions on SA in the early 1990s, it becoming signatory to the GATT/WTO agreement at the end of 1993,[3] a trade agreement with the European Union (EU) effective from the year 2000, and most-favoured-nation agreements with several other countries, tariff liberalisation has led to substantial reductions in nominal tariffs and export markets have become more accessible, raising international trade in goods considerably. However, the controversy about the extent to which the effective rates of protection have fallen stems from the conflicting methodologies and data sources. Fedderke and Vaze (2001) find a higher rate of effective protection on most of SA's output in 1998 compared with 1988 whilst Rangasamy and Harmes (2003) hold a converse view. Edwards (2005) attributes the lack of consensus to the nonavailablity of detailed data for each year in the 1990s. Edwards' (2005) study, using actual disaggregated data that became available in later years only, shows that nominal protection fell from 22.9% in 1994 to 8.2% in 2004 while the effective rate of protection fell from 48% to 12.7% over the same period.

SA's adoption of a more flexible exchange rate system in 2000, preceded by a dismantling of essentially all capital restrictions on nonresidents, and a gradual relaxation of capital controls on residents further encouraged cross-border financial flows. As already noted in Table 1.1 above, capital account liberalisation after SA's first democratic elections in 1994 eventually culminated in an outright dismantling of restrictions on non-residents in 1995, accompanied by a more cautious gradual relaxation of controls on residents (Aron and Muellbauer, 2000; Farrell and Todani, 2006; Leape and Thomas, 2009).

Labour market structural deficiencies – a shortage of high skilled labour, in particular – naturally increases inward highly skilled labour mobility, and together with greater capital flow flexibility, leads to swelling factor payment and income transfers. Expanded trade in consumer and capital goods, factors of production and financial capital also induce an upsurge in flows on the services sub-account of the current account; for example, trade in goods leads to transport payments and receipts, inward and outward banking service fees arise from financial flows, and so forth. All in all, the demand for and supply of foreign exchange and rands also rises.

1.2.3 Performance of the South African rand

According to England and Blackden (2015), the rand has become one of the most liquid and traded emerging market currencies, following the substantial reforms in SA since the early 1990s, and its reintegration into global markets – but not without some of the undesirable side-effects of free markets. Bouts of sizeable and rapid rand depreciation have been followed by episodes of significant corrections, *albeit* around a long-term declining trend in its external value against the currencies of developed economies.[4]

[3] GATT: General Agreement on Tariffs and Trade. WTO: World Trade Organisation.
[4]See panel diagram A1 in appendix A.

Freefalls in the rand and heightened volatility are a reflection of many factors – ranging from policy shifts such as exchange rate regime changes, macroeconomic news shocks and microstructural factors in the foreign exchange market; to mention a few. This makes forecasting the future path of the rand very difficult. Persistent current account deficits after the lifting of trade sanctions on SA required substantial net inflows on the financial account. With these flows predominantly comprised of carry-trade and speculative short-term inflows, sudden rises in uncertainty and negative sentiment under a free float regime tend to result in rapid outflows and consequently often extreme short-run rand currency plunges. Hassan and Smith (2011) conjecture that a significant portion of foreign exchange turnover and fixed income speculative flows to SA are driven by carry trade as the returns to targeting, for example, the yen-funded carry trade implemented through the derivatives forward market, remain highly profitable after adjusting for high volatility. Pooler (2014) estimates that many investors are investing in South African rand, Brazilian real and Turkish lira denominated bonds by borrowing cheaply in dollars and other hard currencies and reinvesting in local currency instruments with higher returns where the 'carry' is the differential between the two interest rates. Galati *et al.* (2007) envisage that, for example, the considerable reporting bank's net claims on residents of SA in 2004 – more than US$ 15 billion – could in principle reflect investments linked to on-balance-sheet carry trade activity at that time.

Given the local currency's high liquidity, the rand tends to respond rapidly when risk appetite is reversed. For example, when emerging markets started experiencing the effects immediately after the Fed Chairperson's tapering talk in May 2013 – from a group of seven leading emerging markets, SA recorded both the third highest depreciation in its currency against the US dollar and percentage fall in external reserves between April and July 2013 (Eichengreen and Gupta, 2014).[5]

Increasing rand liquidity since democracy in 1994 has been underpinned by factors including the gradual relaxation of exchange controls, well-developed spot and derivative financial markets (by emerging markets standards) and SA's utilisation of the global foreign exchange market continuous linked settlement (CLS) trade settlements system (which mitigates credit risk at the settlement of a transaction). As controlling the exchange rate and inflation concurrently is a difficult task to accomplish, the adoption of inflation targeting in 2000 was accompanied by the SARB assuming a more flexible exchange rate, with the central bank interventions being restricted to foreign currency purchases to build its foreign currency reserves but only when market conditions were conducive during a large influx of foreign currency liquidity in the market. The SA National Treasury is responsible for formulating exchange rate policy and the implementation of the policy such as a managed float in pre-2000 is delegated to the SARB. Any losses or profits incurred by the central bank through its interventions in the spot and forward market, and gold and foreign exchange valuation adjustments are, however, for the account of government. "In 1996 and 1998, for example, the

[5] The seven emerging markets in the study were comprised of the BRICS countries, and Indonesia and Turkey.

SARB intervened heavily in the foreign exchange market (with net losses of around US$14 billion and US$10 billion, respectively; that is, 10 percent and 8 percent of SA gross domestic product (GDP), respectively). As a consequence, there was a large build-up in the SARB's NOFP." (Bhundia and Ricci, 2005). The SARB's decision to discontinue its active participation in the foreign exchange market – exchange rate management attempts – and close its NOFP was in part prompted by the consequent huge losses incurred by National Treasury, and resulting pressures on the fiscus.

This background knowledge on the rand foreign exchange market and its environment sets the stage for the detailed analyses in the following chapters of some important features of the levels and volatility of the rand, and its reaction to domestic monetary policy announcements. In summary, the analysis of the dynamics of the rand exchange rate is the common thread that runs through and holds the individual chapters together.

CHAPTER 2

Structural shifts in exchange rates of the South African rand (post-1994): Do they matter (for unit root testing)? What are the most likely triggers?

2.1 Introduction

An increasing number of recent studies establish that structural breaks can severely affect the results of models that study the dynamics of macroeconomic and financial variables. Structural break or parameter stability tests are crucial for at least two reasons. First, the presence of structural breaks may reduce the power of unit root tests – a stationary time-series may appear to be nonstationary when there are structural breaks in the intercept or trend, or both the intercept and trend, leading to bias towards accepting the null hypothesis of a unit root. Second, the presence or absence of structural breaks in a sample period influences the choice of time series model used to predict or improve understanding of the dynamic properties of the data – some parametric models assume a constant linear dynamic structure over time whilst models that incorporate structural breaks are appropriate where the dynamics change permanently in a way that cannot be predicted by the history of the data.

The South African rand, one of the most volatile emerging market currencies, is an interesting candidate for study. The aim of this chapter can best be represented by the question: Do the unit root test results change when endogenously identified structural change is accounted for? Perron (1990) showed that the existence of a structural shift in a stationary series may result in nonrejection of a unit root null, with more evidence for misconstrued unit roots tests being provided by Zivots and Andrews (1992) and Lee and Strazicich (2001). Motivated by these findings, this chapter evaluates some of the time series properties of several key nominal exchange rates of the rand – the DGP may differ not only across different bilateral exchange rates but the characteristics of an index of its trade-weighted exchange rate may also be at variance with that of its component bilateral exchange rates.

This chapter examines the unit root properties of the key nominal exchange rates of the rand. In particular, this chapter contributes to the literature by establishing whether the apparent exchange rate level nonstationarity is a product of unit root test misspecification (a failure to account for structural change). Additionally, the links between the timing of the structural shifts and important economic and noneconomic events are explored. We first examine the unit root properties of the four most traded currencies against the rand, as well as the 15-currency basket nominal effective exchange rate of the rand, using the conventional unit root tests. Because reliance on a single test by some previous studies can be misleading, a confirmatory unit root testing approach – applying unit root tests in conjunction with tests that have stationarity as a null hypothesis – is pursued here. Next, the Quandt-Andrews (QA) test is used to capture unknown breaks and also to verify suspected breaks in the exchange rate time series. The third set of tests are the crucial ones – structural shift adapted unit root tests on the exchange rates. To this end, we use the single structural break unit root procedure developed by Zivot and Andrew (1992), Perron and Volgesang's (1992) unit root methodology that tests for both instantaneous and gradual structural change, and Clemente, Montanes, and Reyes' (1998) double abrupt and gradual shifts unit root procedures. We then compare these results with the conventional unit root tests that do not account for any breaks in the data. The concluding analysis is descriptive – an exploration of some of the events that may have triggered the structural shifts is identified.

Briefly foreshadowing our main detailed results, we find that several statistically significant structural breaks are evident in the data (at the 95% and 99% confidence levels). There is convincing evidence that the exchange rate levels are nonstationary and *I(1)*, even in the presence of structural breaks at the 1% level of significance, although the evidence for the pound/rand exchange rate is not as clear-cut as for the other rates. The final important result is that when structural shift is accommodated, the new unit root test *t*-statistics and *LM*-statistics for all five exchange rates lie much closer to their corresponding asymptotic 5% level critical values with a greater convergence observed in the yen/rand – consistent with Perron's (1990) results which showed that the probability of rejecting a unit root is higher when structural break is accounted for. An adjunct to these findings – the wide-range and diverse set of structural change triggers in the rand – is also a vital contribution to empirical work on the rand.

The structure of the chapter is as follows. Section 2.2 reviews the literature on the standard and structural break-adapted unit root tests, followed by a presentation of the methodology in section 2.3. The latter includes the econometric strategies of the confirmatory analysis approach to testing stationarity – the joint use of tests with stationarity and unit root nulls – and unit root tests in the absence and presence of structural breaks. In section 2.4, we describe and conduct the tests on the data, present, interpret and critically evaluate the results, and also identify important events that might have caused the structural shifts in the various exchange rate series. Section 2.5 offers some conclusions and provides directions for future research.

2.2 Literature review

Stationarity is a rather intuitive concept which means that the statistical properties of the process do not change over time. There are two important forms of stationarity: strong stationarity and weak stationarity. A process (X_t) is strongly stationery if its finite dimensional probability distribution is invariant under a shift in time. On the other hand, a process is weakly stationary if its mean, variance and covariance are finite and invariant under a shift in time. Since the definition of strong stationarity is generally too strict for the real world, the weaker definition is usually used. Non-stationary series suffer permanent effects from random shocks and thus the series follows a random walk.

Many international studies have investigated nonstationarity of financial time series data – either as a preliminary analysis or the core of a study. In recent years, endogenous structural shifts in univariate time series in both theoretical and applied research have received a great amount of attention. Literature on unit root tests can be classified into two categories. The first group of studies, referred to here as the 'traditional unit root tests' (Augmented Dickey-Fuller, 1979; Said and Dickey, 1984; Phillips and Perron, 1988; Kwiatkowski *et al*, 1992; Elliott *et al*, 1996) comprises those that do not account for structural change in a series. Advanced tests principally modify the traditional tests either to increase the power of the test or/and test the opposite null hypothesis. In general, in finite samples, it has been difficult to reject the null hypothesis of a unit root or accept the null of stationarity in bilateral nominal exchange rates in the absence of structural change dummy regressors – a difficulty more pronounced under the post-Bretton Woods 'floating' exchange rate system in more modern economies. Unit root tests by Meese and Singleton (1982) on weekly data for the Swiss, Canadian, and deutschemark exchange rates against the US dollar for the period January 1976 to July 1981 uncover that the processes generating these exchange rates are well documented by random walks. This supports Cornell (1977) and Mussa's (1979) conjecture that the major nominal exchange rates post-Bretton Woods are nonstationary. Formal procedures for estimating lag length (Geweke and Mees, 1981) also suggest that exchange rates follow first-order autoregressive (AR) processes. And more recently, Lu and Guegan (2011) find that almost all of 23 daily nominal bilateral foreign exchange rates examined exhibit unit roots (see discussion below) – so do many other studies for the intermediate sample period 1983 to 2010. The second group of studies (Perron, 1989 and 1990; Zivot and Andrews, 1992; Perron and Volgesang, 1992; Clemente *et al*, 1998) apply unit root tests in the presence of structural shifts in the parameters. Recent tests introduce two structural breaks in the specifications of the models – an innovation to the single structural shift tests. However, utilising unit root tests with the actual number of structural breaks, at best, ensures that the results are not spurious. Glynn *et al* (2007) and Byrne and Perman (2007) review the recent developments in testing of the unit root in the presence of structural change.

Diverting momentarily from the core analysis of this paper – unit roots and structural breaks in nominal exchange rates – there is a theoretical case for real exchange rates to be stationary. The absolute purchasing power parity (PPP) theory states that the price of a basket of goods & services consumed by a typical household should be identical in both countries when denominated in the same currency (contingent on some assumptions). Thus, PPP predicts that a rise (fall) in the domestic price level, *ceteris paribus*, will be associated with a equiproportionate depreciation (appreciation) of the nominal value of domestic currency in terms of the foreign currency. A testable implication is that real exchange rates should be mean reverting, at least in the long run (Cheung and Lai, 1994). The alternative *ex ante* PPP theory suggests a martingale process with no mean reversion for real exchange rates.[6] Cheung and Lai's (1994) results – using the Dickey-Fuller Generalised Least Squares (DF-GLS) test – are shown to be more favourable to the hypothesis of mean reversion in real exchange rates than the standard Dickey-Fuller (DF) test results. The results obtained by Perron and Volgesang (1992) strongly suggest that both the United States (U.S.)/Finland real exchange rate based on the consumer price index (CPI) and U.S./United Kingdom (U.K.) real exchange rate based on the gross national product (GNP) deflator are stationary series in the presence of a one-time shift in the mean of the series; the unit root can be rejected at the 5% significance level. However, the real exchange rate is

[6] A basic definition of a discrete-time *martingale* is a discrete-time stochastic process (i.e., a sequence of random variables) $X_1, X_2, X_3, \ldots$ that satisfies for any time n, $(X_n)_{n\geq 0}$: i) $E|X_n| < \infty$, and ii) $E(X_{n+1}|X_0, \ldots, X_n) = X_n$; that is, the conditional expected value of the next observation, given all the past observations, is equal to the current observation.

nonstationary if the break is not allowed for. Akinboade and Makina (2006) test for mean reversion and structural breaks in the key real exchange rates of the rand (1978 to 2002). Traditional ADF, PP and KPSS tests – without allowing for structural changes – fail to reject the null of a unit root in the real exchange rates of the rand at the 5% significance level (Akinboade and Makina, 2006). However, their structural break unit root tests results, including sharp double breaks, support stationarity of the rand's bilateral real exchange rates, although the comparative tests incorporating gradual shifts do not support mean reversion. The latter findings thus highlight that evidence of (non)stationarity also depends on how the breaks are modelled – abrupt versus slow changes in a series in this case

It is well known that conventional augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) stationarity tests on the US dollar/rand exchange rates form part of the preliminary analysis of several papers where the foreign exchange rate is an explanatory and/or dependent variable in the empirical analysis. In a recent comparative study, Lu and Guegan (2011) examine unit roots and the long range dependence of 23 daily nominal bilateral foreign exchange rates, including the rand.[7] Several sample sizes T from 100 to 3000 are considered. Consistent with the findings of most empirical studies, the unit root null (at the 95% confidence level) cannot be rejected for most of the nominal exchange rate series, including the South African rand, when structural breaks are not included in the specifications of the unit root test models. There are several innovations in our study of the rand: i) a much broader set of unit root tests in the non-structural break and structural shift frameworks is applied; ii) these tests are applied to the nominal bilateral and effective exchange rates of the rand; and, iii) a more recent sample period of financial market history (1995 to 2010) is investigated, compared with earlier studies.

2.3 Methodology

2.3.1 Traditional stationarity tests

Four different unit root tests are applied to test the null hypothesis of a unit root or the null hypothesis of stationarity: the augmented Dickey-Fuller (ADF) test (Said and Dickey, 1984), the Phillips-Perron (PP) test (Phillips and Perron, 1988), Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test (Kwiatkowski *et al*, 1992) and the Dickey-Fuller Generalised Least Squares (DF-GLS) test proposed by Elliott, Rothenberg and Stock (ERS) (Elliot *et al*, 1996).

[7] The studies include the Brazilian real, Canadian dollar, Chinese yuan, Danish kroner, Hong Kong dollar, Indian rupee, Japanese yen, Malaysian ringgit, Mexican new peso, Norwegian kroner, Singapore dollar, South African rand, South Korean won, Sri Lankan rupee, Swedish kroner, Swiss franc, New Taiwan dollar, Thai baht and Venezuelan bolivares, all to one U.S. dollar, along with the rates of U.S. dollar to one Australian dollar, to one euro, to one New Zealand dollar and to one British pound.

2.3.2 Unit root tests in the presence of structural breaks

Because of events like the great depression (1930s), oil price shocks (1970s), abrupt policy changes (such as the switch in exchange rate system and monetary policy regime in South Africa in 2000), and so on, models with constant parameters or coefficients have been found to perform poorly in explaining and forecasting univariate (and multivariate) relationships and analysing the effect of policy changes (Maddala and Kim, 1998). A well-known problem in the unit root literature is the potential for a series which exhibits structural shifts to fail to reject the unit root null; that is, a stationary time series may appear nonstationary when there are structural breaks in the intercept or trend or both the intercept and trend. Put differently, the presence of structural breaks reduces the power of the unit root tests set out in 2.3.1. A number of approaches are available to detect the presence of exogenous structural changes in the univariate DGP, for example, Chow's breakpoint test (Chow, 1960) for a known or exogenous structural break(s) can be evaluated for the *AR(1)* process:

$$Y_t = \rho Y_{t-1} + u_t \quad -1 \le \rho \le 1. \tag{2.1}$$

To test for a structural break(s) or parameter stability, the breakpoint Chow test runs the specified regression for the entire sample period and for each sub-sample. The null hypothesis is no break; that is, the parallel parameters (corresponding intercept and slope coefficients) in the subsample regressions are equal. For an *a priori* single structural break, the Chow test statistic is:

$$F = \frac{(RSS_R - RSS_{UR})/k}{(RSS_{UR})/(n_1 + n_2 - 2k)} \;\sim\; F_{[k,(n_1+n_2-2k)]} \tag{2.2}$$

where $RSS_{UR} = RSS_1 + RSS_2$, RSS is the residual sum of squares and the subscripts 'R' and 'UR' denote 'restricted' and 'unrestricted' respectively. Equation (2.2) can be adapted for more than one known structural breaks. We do not reject the null hypothesis of parameter stability (i.e., no structural change) if the computed *F*-value does not exceed the critical *F*-value at the chosen level of significance (or the *p*-value), and *vice versa*. Where there is no *a priori* reason to expect a structural break, the Quandt-Andrews (QA) breakpoint test for one or more unknown structural breakpoints in the sample period is applied to equation (2.1) with drift. This test is basically a rolling Chow breakpoint test; that is, a single Chow breakpoint test is performed at every observation between the two dates, or observations, τ_1 to τ_2 (Andrews, 1993, and Andrews and Ploberger, 1994). The basic test statistics are the likelihood ratio (LR) *F*-statistic (based on the difference between the restricted and unrestricted sum of squared residuals) and the Wald *F*-statistic (computed from a standard Wald test with the restriction that the coefficients in the equation are the same in all samples).[8] The null

[8] The Wald test is documented in Efron and Hinkley (1978).

hypothesis of a nonstationary (or integrated) series can be evaluated by first applying the Chow or/and QA parameter stability (structural break) tests to equation (2.1) and then testing whether the value of the estimated coefficient for ρ , $\hat{\rho}$, is unity in the presence of a structural break(s).

A more efficient unit root test that allows for structural instability in an otherwise deterministic model is the Zivot-Andrews or "Zandrews" test devised by Zivot and Andrews (1992); a variation of Perron's (1989) test for a unit root with a structural break in which the unknown breakpoint is estimated (the breakpoint is endogenised) rather than fixed (breakpoint is known or exogenous). This procedure allows for a single structural break in the intercept or trend or both the intercept and trend of the series, as determined by a systematic search over possible breakpoints, and then conducts a DF-style unit root test allowing for the estimated optimal break. To detect the optimal lag, a sequential *t*-test is employed where the degree of augmentation with additional lags of the dependent variable ensures that the residuals are sufficiently whitened. To test for a unit root against the alternative of a one-time structural break, the Zandrews test uses the following three models,

(Model A) : $$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \gamma DU_t + \sum_{i=1}^{k} \alpha_i \Delta Y_{t-i} + \varepsilon_t \qquad (2.3)$$

(Model B) : $$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \theta DT_t + \sum_{i=1}^{k} \alpha_i \Delta Y_{t-i} + \varepsilon_t \qquad (2.4)$$

(Model C) : $$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \gamma DU_t + \theta DT_t + \sum_{i=1}^{k} \alpha_i \Delta Y_{t-i} + \varepsilon_t \qquad (2.5)$$

where DU_t is an indicator dummy variable for a mean shift occurring at each possible break-date (T_b) while DT_t is the corresponding trend shift variable where

$$DU_t = \begin{Bmatrix} 1 \ldots\ldots.if \quad t > T_b \\ 0 \ldots\ldots.otherwise \end{Bmatrix}$$ and

$$DT_t = \begin{Bmatrix} t - T_b \ldots if \quad t > T_b \\ 0 \ldots\ldots\ldots.otherwise \end{Bmatrix}.$$

Model A permits a one-time change in the level of the series, model B allows for a one-time change in the slope of the trend function, and model C combines one-time changes in the level and the slope of the trend function of the series. The null hypothesis in all three models is $\delta = 0$, which implies that the series $\{Y_t\}$ contains a unit root with a drift that excludes any structural break, while the alternative hypothesis $\delta < 0$

implies that the series is a trend-stationary process with a one-time break occurring at an unknown point in time.

To test for the unit root hypothesis allowing for a possible change in the level of the series occurring at an unknown point, Perron (1990) considered an *additive outlier* (AO) *model* for a discrete change in mean and an *innovative outlier* (IO) *model* appropriate for a gradual change in the series mean. Perron and Volgesang (1992) proposed similar tests for single breaks. Under the single break additive outlier (AO1) model, for a fixed value of the breakpoint T_b, the following two-step procedure is used. First, the deterministic part of the series is removed using the estimates of the regression

$$Y_t = \mu + \delta DU_t + \tilde{Y}_t \qquad t = 1,\ldots,T \tag{2.6}$$

where $\tilde{Y}_t$ denotes the residuals and

$$DU_t = \begin{cases} 1.......if \quad t > T_b \\ 0.......otherwise \end{cases}$$

under the null hypothesis of a unit root. The residuals $(\tilde{Y}_t)$ are then regressed on their lagged values and lagged differences

$$\tilde{Y}_t = \sum_{i=0}^{k} \omega_i DT_{t-i} + \alpha \tilde{Y}_{t-1} + \sum_{i=1}^{k} c_i \Delta \tilde{Y}_{t-i} + e_t \qquad t = k+2,\ldots,T. \tag{2.7}$$

In the AO1 model, equation (2.7), the change is assumed to take effect instantaneously. In particular, the effect of the change on the level of the series $\{\tilde{Y}_t\}$ does not depend on the dynamics exhibited by the correlation of the structure of $\{\tilde{Y}_t\}$ (Perron and Volgesang, 1992). The IO1 model is estimated using the finite-order autoregressive model

$$Y_t = \mu + \delta DU_t + \theta DT_t + \alpha Y_{t-1} + \sum_{i=1}^{k} c_i \Delta Y_{t-i} + e_t \qquad t = k+2,\ldots,T. \tag{2.8}$$

under the null hypothesis of a unit root, $\alpha = 1$ (which also implies $\delta = 0$). The IO1 model allows for a change in the intercept term that is supposed to affect the level of the series $\{\tilde{Y}_t\}$ gradually – there is a transition period.

An obvious weakness of the Zandrews, and the above AO and IO strategies, is their inability to deal with more than one break in a time series. To address this problem, Clemente, Montanes, and Reyes (CMR) (1998) proposed tests that would allow for two events within the observed history of a time series, either an

AO2 model or an IO2 model. The former captures two abrupt changes in the series (i.e., two discrete changes in the coefficients of a function) while the latter allows for two gradual shifts in the mean of the series (i.e., two gradual changes in the coefficients of a function). This taxonomy of structural breaks follows from Perron and Vogelsang's work (1992). The CMR double-break counterparts for equations (2.6), (2.7) and (2.8) above are:

$$Y_t = \mu + \delta_1 DU_{1t} + \delta_2 DU_{2t} + \widetilde{Y}_t , \tag{2.9}$$

$$\widetilde{Y}_t = \sum_{i=0}^{k} \omega_{1i} DT_{1t-i} + \sum_{i=0}^{k} \omega_{2i} DT_{2t-i} + \alpha \widetilde{Y}_{t-1} + \sum_{i=1}^{k} c_i \Delta \widetilde{Y}_{t-i} + e_t , \tag{2.10}$$

$$Y_t = \mu + \delta_1 DU_{1t} + \delta_2 DU_{2t} + \theta_1 DT_{1t} + \theta_2 DT_{2t} + \alpha Y_{t-1} + \sum_{i=1}^{k} c_i \Delta Y_{t-i} + e_t , \tag{2.11}$$

respectively. The appropriate procedure, the modelling approach adopted here, is to implement the AO and IO models for two structural breaks, respectively. If their estimates show that there is no evidence of a second break in the series, then the single structural break tests, AO1 and IO1, should be used.

2.4 Data and empirical estimates

2.4.1 Data

The sample period covers 13 March 1995 to 31 August 2010. The time horizon of the sample is motivated by the South Africa Reserve Bank's (SARB's) reversion to a single exchange rate mechanism on March 13, 1995.[9] This empirical analysis uses the levels of the indirect nominal foreign exchange rates of the rand;[10] these rates are spot quotes rather than the actual spot transaction prices. Quote data are indicative rather than firm, and actual foreign exchange market trade data for the sample period are virtually nonexistent; indicative means that the bank or dealer posting such prices is not committed to trade at them, but generally will.

Four daily nominal bilateral exchange rates (NBERs) of the rand with the highest transactions volumes are examined: US dollar/rand (USD/ZAR); the euro/rand (EUR/ZAR);[11] the British pound (sterling)/rand

[9] The dual exchange rate system, introduced in response to internal and external socio-economic and political pressures in the mid-1980s, consisted of the commercial rand for current account transactions and the financial rand which applied to investment and disinvestment by nonresidents. South Africa's oppressive political system led the United States to join the global community by imposing economic sanctions on South Africa. The debt crisis in 1985 emerged as a result of the financial sanctions, in particular, prompting the South African authorities to introduce the dual exchange rate system.
[10] The indirect foreign exchange rates of the rand (foreign currency per unit of rands) are used to ensure that the nominal bilateral exchange rate (NBER) quotations are consistent with the nominal effective exchange rate (NEER) – the SARB calculates the indirect NEER of the rand. Depreciation of the rand is indicated by a fall in a nominal bilateral exchange rate or exchange rate index in the case of the nominal effective exchange rate.
[11] The euro was introduced to world financial markets as an accounting currency in 1999 and launched as physical coins and banknotes in 2002. It replaced the former European Currency Unit (ECU) at a ratio of 1:1. To extrapolate the

(GBP/ZAR); and the Japanese yen/rand (JPY/ZAR). The daily NBERs are the 10h30 weighted average midpoint rates of the major South African banks; each bank's exchange rate weighting is based on the relative size of its transactions in the foreign exchange market.

To consider aggregated information, the levels of the nominal effective exchange rate (NEER) of the rand – a 15-currency basket of South Africa's major trading partners – is also examined.[12] The currencies in the basket and their weights, expressed as percentages in descending order of importance, are: Euro (34.82), US dollar (14.88), Chinese yuan (12.49), British pound (10.71), Japanese yen (10.12), Swiss franc (2.83), Australian dollar (2.04), Indian rupee (2.01), Swedish krona (1.99), South Korean won (1.96), Hong Kong dollar (1.48), Singapore dollar (1.40), Brazilian real (1.37), Israeli shekel (1.11), and Zambian kwacha (0.80). The individual NBERs in this basket are calculated along the same lines as those for the four major currencies discussed above and the base year of the NEER index is the year 2000.

Daily exchange rate data was provided by the South African central bank – SARB. Due to the well-known fact that activity in the foreign exchange market slows down decidedly over the weekend and certain holiday periods, we explicitly exclude weekends and South African public holidays so as not to confound the distributional characteristics of the various volatility measures by these largely deterministic calendar effects. Although our cuts do not capture all the holiday market slowdowns such as holidays of the developed G4 economies, they do succeed in eliminating at least one of the most important such daily calendar effects; the rand is a highly liquid currency traded even when the South African markets are closed, but with lower volumes.[13] After filtering the data for calendar effects – weekends and local public holidays – the full daily frequency sample consists of 3865 observations.

2.4.2 Preliminary stationarity and structural breaks test results

For an intuitive feel for stationarity, we plot the levels of each of the five exchange rates series. Panel diagram A1 in the Appendix A suggests that all of the daily series are nonstationary; stochastic random processes with negative drift.[14] All the autocorrelation coefficients generated by a random walk series without drift in Table 2.1 indicate nonstationarity.[15] The autocorrelation coefficients for the daily series decline very slowly as the lag lengthens and remain high at approximately 0.7 even up to 200 lags. The dramatic decline in the partial

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euro/rand exchange rate for the period pre-1999, we use the ECU/rand exchange rate, a common practice in most empirical studies surveyed.

[12] Weights are based on total trade in merchandise and by taking into account the currency denomination of commodities traded on international markets. See Walters (1999) for note on the introduction of the euro and the revised weighting structure of the NEER of the rand, and Walters and de Beer (1999) for a presentation of the methodology used to calculate the SARB's measure of external price competitiveness in the pre-euro and euro periods.

[13] The extent of calendar effects in the rand exchange rates, and other domestic financial asset prices, is an empirical question that needs to be addressed on its own in future research.

[14] A deterministic trend is a form of variation that is predictable. Observed economic processes rarely follow a deterministic trend. In a stochastic trend, the observed series can directly affect all remaining values, introducing some form of autocorrelation in the series, where the size of this effect is not decaying.

[15] Random walk without drift: $Y_t = Y_{t-1} + u_t$.

autocorrelation coefficients indicates that a large proportion of correlation between nonadjacent observations is due to the correlations they have with intermediate observations (Table 2.1). Also, the *LB*-statistics and their corresponding *p*-values – tests for the joint hypothesis that all ρ_k up to certain lags are simultaneously equal to zero – also reinforces our prior results in Panel diagram A1 (in Appendix A) of nonstationarity.

Table 2.1: Autocorrelation coefficients

USD/ZAR				
Lag	*AC*	*PAC*	*LB-Stat*	*Prob*
1	0.999	0.999	3857	0.0000
50	0.927	-0.006	180675	0.0000
100	0.853	-0.011	336953	0.0000
200	0.696	0.000	579522	0.0000

JPY/ZAR				
Lag	*AC*	*PAC*	*LB-Stat*	*Prob*
1	0.999	0.999	3858	0.0000
50	0.942	0.013	183139	0.0000
100	0.885	-0.008	347486	0.0000
200	0.762	0.002	620079	0.0000

EUR/ZAR				
Lag	*AC*	*PAC*	*LB-Stat*	*Prob*
1	0.999	0.999	3859	0.0000
50	0.941	0.035	183149	0.0000
100	0.879	0.000	346304	0.0000
200	0.747	0.006	612778	0.0000

NEER				
Lag	*AC*	*PAC*	*LB-Stat*	*Prob*
1	0.999	0.999	3859	0.0000
50	0.943	0.026	183557	0.0000
100	0.884	-0.004	348205	0.0000
200	0.752	-0.002	617730	0.0000

GBP/ZAR				
Lag	*AC*	*PAC*	*LB-Stat*	*Prob*
1	0.999	0.999	3858	0.0000
50	0.934	0.026	181744	0.0000
100	0.867	0.001	341674	0.0000
200	0.714	0.004	595281	0.0000

Graphically, a structural break appears when we see a sudden or gradual shift in a time series. Conspicuous and subtle infrequent large fluctuations evident in the empirical process of each time series in Panel diagram 1 (Appendix A) suggest that each data series might have one or more structural breaks.

2.4.3 Unit root tests without structural breaks: Estimates

In the presence of uncertainty as to whether or not a (linear or non-linear) deterministic trend is present in the data, the objective of a unit root testing strategy should be to identify the class of unit root test model; that is, whether to use a specification with a constant only or a constant and trend, or test the residuals of a demeaned/detrended series. Elder and Kennedy (2001) recommend the following strategy for choosing between unit root test specifications – a random walk with drift and no trend and the random walk with drift and a trend: Conduct an *F*-test to test the joint null hypotheses that $\delta = 0$ and $\beta_2 = 0$. If this null is not rejected, we conclude that Y_t has a unit root with drift. If this null is rejected, there are three possibilities: (i) $\delta \neq 0$ and $\beta_2 = 0$; (ii) $\delta \neq 0$ and $\beta_2 \neq 0$; or (iii) $\delta = 0$ and $\beta_2 \neq 0$. Ayat and Burridge (2000) reject on the grounds

Table 2.2: ADF *tau* unit root tests for exchange rate levels and 1st-differences

	Trend *t*-statistics				ADF test *t*-statistic			
	Level		1st-Difference		Level		1st-Difference	
Exchange Rate	*t*-statistic	*p*-value	*t*-statistic	*p*-value	*t*-statistic	*p*-value	*t*-statistic	*p*-value
USD/ZAR	-0.1061	0.9155	1.7407	0.0818	-2.7727	0.0623	-11.1962	0.0000
EUR/ZAR	-1.2980	0.1944	1.0149	0.3103	-1.9640	0.3031	-14.8964	0.0000
GBP/ZAR	0.1589	0.8738	2.0761	0.0379	-2.7881	0.0605	-13.4504	0.0000
JPY/ZAR	-1.3633	0.1729	0.0486	0.9612	-1.3681	0.5995	-15.5804	0.0000
NEER	-0.8018	0.4227	1.0919	0.2749	-1.9765	0.2975	-13.5346	0.0000

Notes: Trend test hypotheses are: H_0: No trend, H_1: Trend. ADF test hypotheses are H_0: unit root (nonstationary), H_1: no unit root (stationary). Lag orders in the ADF equations are determined by the significance of the coefficient for the lagged terms. The 1% and 5% levels of significance, commonly used in empirical analysis, mean 99% and 95% levels or degrees of confidence, respectively. A 99% confidence level, for example, means that we are prepared to accept at most a one percent probability of committing a type I error. The *p*-value (probability value), that is, the exact significance level of the *t*-statistic, is the lowest significance level at which the null hypothesis can be rejected. The *p*-values are MacKinnon (1996) one-sided *p*-values. In all instances, for each ADF specification, the asymptotic critical values are identical after rounding off to four decimal places. The test statistic is the familiar *t*-statistic, calculated using the conventional *t*-ratio for δ, $t_\delta = \hat{\delta}/se(\hat{\delta})$, but with special critical values employed to reflect its nonnormal distribution under the null of a unit root; the ADF test of $\delta = 0$, that is, $\rho = 1$, is one-sided because the alternative $\rho > 1$ is ruled out as implying unreasonable explosive behaviour. The 1%, 5% and 10% asymptotic critical values for the random walk with drift and no trend unit root statistic are -.34319, -2.8621 and -2.5671, respectively.

Table 2.3: PP unit root tests for exchange rate levels and 1st-differences

	Trend *t*-statistics				ADF test *t*-statistic			
	Level		1st-Difference		Level		1st-Difference	
Exchange Rate	*Adjusted* *t*-statistic	*p*-value	*Adjusted* *t*-statistic	*p*-value	*Adjusted* *t*-statistic	*p*-value	*Adjusted* *t*-statistic	*p*-value
USD/ZAR	-.0413	0.9671	1.8422	0.0655	-2.6073	0.0915	-64.0788	0.0001
EUR/ZAR	-1.4640	0.1433	1.1300	0.2586	-1.9233	0.3217	-63.8619	0.0001
GBP/ZAR	0.0822	0.9345	2.2214	0.0264	-2.8032	0.0579	-63.3203	0.0001
JPY/ZAR	-1.4680	0.1422	0.1853	0.8530	-1.3660	0.6005	-63.7702	0.0001
NEER	-0.9546	0.3398	1.2478	0.2122	-1.9710	0.2999	-64.5307	0.0001

Notes: PP test hypotheses are H_0: unit root (nonstationary), H_1: no unit root (stationary). Lag orders in the PP equations are determined by the significance of the coefficient for the lagged terms. The hypotheses are tested at the 1% and 5% levels of significance. The *p*-value (probability value), that is, the exact significance level of the *t*-statistic, is the lowest significance level at which the null hypothesis can be rejected. The *p*-values are MacKinnon (1996) one-sided *p*-values. In all instances, for each PP specification, the asymptotic critical values are identical after rounding off to four decimal places. The PP test *t*-statistic is calculated as follows: $\bar{t}_\delta = t_\delta(\gamma_0/f_0)^{1/2} - T(f_0 - \gamma_0)(se(\hat{\delta}))/(2f_0^{1/2}s)$ where $\hat{\delta}$ is the estimate, and t_δ the t-ratio of δ, $se(\hat{\delta})$ is the coefficient standard error, and s is the standard error of the test regression. In addition, γ_0 is a consistent estimate of the error variance calculated as $(T-k)s^2/T$ where k is the number of regressors and T is the sample size. The remaining term, f_0, is an estimator of the residual spectrum at frequency zero. We apply the Bartlett kernel spectral estimation method and the Newey-West (1994) bandwidth. The asymptotic critical values and asymptotic distribution of the PP modified t-ratio are the same as those for the ADF *t*-test.

of redundancy the use of joint F-type tests for unit roots and trend. Instead, the relatively less robust unit root tests – ADF and PP tests – are implemented using a simple strategy, similar to that proposed by Volgesang (1998) for testing for the presence of a linear trend. This test involves the following procedure. First estimate the general model with a constant and trend. If no trend is detected, perform a unit root test invariant to the mean under the null; if a trend is detected; perform a unit root test invariant to linear trend under the null. The ADF and PP test (or Phillips Z-test) results in Tables 2.2 and 2.3 do not reject the null hypothesis of no linear trend in the levels (consistent with graphical evidence suggesting stochastic trend). (Note, though, that this does not imply that a nonlinear trend does not exist.) Applying the unit root test with drift but no linear trend, the results suggest that all the exchange rate levels are not stationary at the 1% and 5% levels of significance. A trend is also not present in the 1st-differences of all the series at the 95% and 99% confidence levels (except for the pound/rand at the 5% level of significance). Nevertheless, the null hypothesis of nonstationarity of the 1st-differences for the unit root tests are rejected at the 0.01 and 0.05 levels of significance indicating stationarity; that is, the exchange rate levels are $I(1)$ (integrated of order 1) and their 1st-differences are $I(0)$ based on asymptotic and finite-sample evidence. Harvey *et al* (2009) recommend a simple union of rejections-based decision rule where the unit root null hypothesis is rejected whenever either of the detrended or demeaned unit root tests yields a rejection; this approach generally outperforms more sophisticated strategies based on auxiliary methods of trend detection. Results from the DF-GLS test – a test applied to a series that has been detrended using pseudo-GLS estimates - are presented in Table 2.4: the DF-GLS *tau*-test *t*-statistics suggest that all the levels are $I(1)$ and almost all the first-differences are $I(0)$ – there is convincing evidence that the exchange rate levels are nonstationary and $I(1)$, even in the presence of structural breaks at the 1% level of significance, although the evidence for the pound/rand exchange rate is not as clear-cut as for the other rates.

For the KPSS test, the null hypothesis of stationarity is tested against the alternative of a unit root. All the results in Table 2.5 are congruent with those of the DF-GLS test.

Therefore, on the basis of graphical analysis, the autocorrelation coefficients, and the formal unit root tests without structural breaks, the evidence suggests that all the key four nominal bilateral exchange rates of the rand and the 15-currency basket nominal effective exchange rate of the rand are nonstationary.

2.4.4 Structural breaks estimation results

We first apply the Quandt-Andrews (QA) test – an $AR(1)$ process with drift to capture the unknown breaks and also to verify suspected breaks – for each exchange rate. In the 'pure structural change' model, all the parameters (constant and $AR(1)$ coefficient in this case) are subject to shift – the QA test will tell us only if the regressions in two or more sub-samples are different without telling us whether the difference is on account of the intercepts or the slopes, or both. The 'partial structural change' model tests for structural change in a subset of the parameters. The QA unknown breakpoint test statistics are given in Table 2.6. All

Table 2.4: DF-GLS *tau* unit root tests for exchange rate levels and 1st-differences

Exchange Rate	Level	1st-Difference
	t-statistic	t-statistic
USD/ZAR	0.5441	-5.2871
EUR/ZAR	0.3698	-4.3251
GBP/ZAR	0.4782	-2.0795
JPY/ZAR	0.1375	-2.6581
NEER	0.5286	-4.2489

DF-GLS test hypotheses are H_0: unit root (nonstationary), H_1: no unit root (stationary). In the constant only case, the DF-GLS t-ratio follows a DF distribution. And like the ADF and PP tests, the p-values are MacKinnon (1996) one-sided *p*-values. In all instances, for each specification, the DF-GLS asymptotic critical values for the daily series are either identical or not statistically different from zero after rounding off to four decimal places. The 1% and 5% asymptotic critical values are -2.5657 and -1.9409, respectively.

Table 2.5: KPSS *LM* unit root tests for exchange rate levels and 1st-differences

Exchange Rate	Level	1st-Difference
	LM-statistic	*LM*-statistic
USD/ZAR	4.0778	0.4361
EUR/ZAR	6.2416	0.1551
GBP/ZAR	5.0102	0.5631
JPY/ZAR	4.7385	0.0671
NEER	5.7222	0.2070

Notes: KPSS test hypotheses are H_0: no unit root (stationary), H_1: unit root (nonstationary). The KPSS statistic is based on the residuals from the OLS regression of Y_t on the exogenous variables $X_t : Y_t = X_t^{'}\delta + \mu_t$. The *LM*-statistic is defined as: $LM = \sum_t S(t)^2 / \left(T^2 f_0\right)$ where f_0, is an estimator of the residual spectrum at frequency zero and where $S(t)$a cumulative residual function is: $S(t) = \sum_{r=1}^{t} \hat{u}_r$ based on the residuals $\hat{u}_t = Y_t - X_t^{'}\hat{\delta}(0)$. The estimator of δ used in this calculation differs from the estimator for δ used by DF-GLS detrending since it is based on a regression involving the original data and not on the quasi-differenced data. We apply the Bartlett kernel spectral estimation method and the Newey-West bandwidth. Critical values are based upon the asymptotic results presented in KPSS (1992, Table 1.1). The 1% and 5% asymptotic critical values for the random walk with drift and a linear trend are 0.7390 and 0.4630, respectively.

the summary statistics from the 'pure structural change' model estimations fail to reject the null hypothesis of no structural breaks. In stark contrast, the partial structural change model detects shifts in all the individual parameters – means and *AR(1)* coefficients – at the 95% confidence interval. (The frequency of the data may impact on the number of structural breaks found. Future work will explore this possibility in more detail.) Perron (2006) notes that using the partial structural change models where only some of the parameters are allowed to change can be beneficial in terms of obtaining more precise estimates; the main advantage of imposing restrictions on the number of coefficients to be tested is that much more powerful tests are possible. What does the presence of structural breaks imply for the test results reported in section 2.4.3? Since the tests do not allow for structural breaks, the results may be spurious. Conventional unit root tests generally find nonstationarity in most economic data expressed in nominal terms; exchange rates in particular. Perron (1989) questioned the latter interpretation on the basis that the presence of a unit root may be a manifestation of not allowing for structural change – a finding reaffirmed later by Zivot and Andrews (1992) and Clemente *et al* (1998) when single and double abrupt and gradual endogenous breakpoints are accounted for in unit root tests. (The likely causes of the breaks in Tables 2.6 and 2.7 are explored in section 2.4.5). The results for the unit root tests in the presence of structural breaks are presented in Table 2.7. In all instances, we reject the null that structural shifts do not exist – all *p*-values for the dummy variables coefficients are equal to or less than 0.02. (We do not report the individual statistics here but they may be requested from the author.) However, despite the structural breaks, we fail to reject the null hypothesis of a unit root when taking into account the existence of different types of structural breaks through the Zandrews, AO1, AO2, IO1 and IO2 tests. These results are consistent with the results obtained from the unit root test without structural breaks. Perron (1989) showed that the power to reject a unit root decreases when the stationarity alternative is true and a structural break is ignored. This is indeed the case here, for example, the Zandrews break in intercept, Clemio1 and Clemio2 structural break unit root test *t*- statistics in Table 2.7, the yen/rand, in particular, now lie much closer to their corresponding asymptotic 5% level critical values when structural shift is accommodated.

What can one infer from the unit root results with breaks and without breaks? When there are several structural breaks, the standard unit root tests are biased toward the nonrejection of the unit root null. The results here indicate that this bias is not sufficiently significant to produce conflicting results. In Tables 2.6 and 2.7, a large number of potential breaks are identified suggesting construction (and coding) of unit root tests with multiple structural breaks that capture more than two shifts, and new *t*-statistic asymptotic critical values simultaneously.

2.4.5 Structural breakpoints and potential causes

In this section, we tabulate the structural breakpoints identified in section 2.4.4 and pinpoint important – economic and noneconomic – events that may have triggered the structural shifts in the means and/or coefficients of the regressions of the univariate DGP models. Table 2.8 presents the months encompassing the various structural breakpoints detected in Tables 2.6 and 2.7, the sign of each shock (negative or positive) and the potential events that may have caused these shifts that are identifiable using various and diverse prominent historical business and economic reports; mainly the SARB quarterly bulletins and occasional papers.[16] We first explicate the likely sources of the structural breakpoints in chronological order of each shift before categorising the numerous likely sources of structural shift. To uncover structural breaks, the data was trimmed to exclude at least 10% and at most 15% of the observations in the sample – depending on the statistical technique used – so that breaks cannot be detected closer to the two ends of the sample. Therefore, the results do not imply that there are no breaks in 1995 and 2009/2010.

January 1996 and February 1996

Two key events in early 1996 around the time of the two breaks identified in the US dollar/rand and pound/rand are the speculative attack on the rand and the SARB's foreign exchange market intervention policy shift. Several factors have been cited as the causes of the speculative sell-off of the rand in early 1996, namely:

i) the rumour or expectation of an imminent relaxation of exchange controls around the time of the Budget;
ii) investor uncertainty about economic policy – perceived conflicting policy targets within South African government and between the South African ANC-led government and its alliance partners (COSATU and SACP);[17]
iii) investor concerns about domestic fundamentals – rising inflation, the size of public debt and its ratio to gross domestic product, rand overvaluation, and the widening current account deficit and the resulting weak overall balance of payments;[18] and,
iv) one-sided expectations of rand depreciation.

In response to the speculative sales of the rand, and rand depreciation, the SARB became an active seller of US dollars in the forward market to smooth rand depreciation – reversing both its foreign reserves accumulation and the rapid reduction in its active participation in the foreign exchange market in 1995 and the first six weeks of 1996.

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[16] Aron and Elbadawi (1999) also documents some of these factors that may have triggered the 1996 and 1997 crises periods.

[17] ANC – African National Congress; COSATU - Congress of South African Trade Unions; SACP - South African Communist Party.

[18] The South African government and central bank policies (including the dual exchange rate mechanism – financial and commercial rand exchange rates – exchange and capital controls, amongst others) ensured current account surpluses since the debt standstill in 1985 up to 1994. These surpluses served to finance the outflows on the financial account – repayment of international loans. Although the financial account surplus more than comfortably funded the current account deficits in 1995 and 1996, these inflows consisted predominantly of "hot money" – the ebb and flow of short-term financial capital is highly unpredictable. However, the persistence of equity flows in SA tend to be more stable than the interest-bearing security flows.

Table 2.6: Quandt-Andrews breakpoint test for an *AR(1)* with drift (exchange rate levels)

	Pure structural change model			Partial structural change model					
				intercept			ρ		
	Maximum *F*-statistic value	Breakpoint	*p*-value	Maximum *F*-statistic value	Breakpoint	*p*-value	Maximum *F*-statistic value	Breakpoint	*p*-value
USD/ZAR	8.1210	06 Jul 1998	0.1961	15.2247	06 Jul 1998	0.0022	12.4326	06 Jul 1998	0.0084
EUR/ZAR	9.6504	06 Jul 1998	0.1088	14.6380	20 Dec 2001	0.0030	12.1221	20 Dec 2001	0.0098
GBP/ZAR	8.7791	06 Jul 1998	0.1529	17.0274	06 Jul 1998	0.0009	13.8456	06 Jul 1998	0.0043
JPY/ZAR	9.6390	15 Jan 1999	0.1093	11.1781	15 Jan 1999	0.0152	8.6440	19 May 2000	0.0492
NEER	9.6761	06 Jul 1998	0.1077	13.7839	20 Dec 2001	0.0045	12.5065	20 Dec 2001	0.0082

Notes: H_0: No breakpoints within the "trimmed" data. H_1: One breakpoint within the "trimmed" data. The maximum *F*-statistic is the maximum of the individual Chow *F*-statistics. Since the original equation was linear, the LR and Wald *F*-statistics are identical. The distribution of these test statistics is non-standard and becomes degenerate as τ_1 approaches the beginning of the sample, or τ_2 approaches the end of the sample. Andrews (1993) developed their true distribution and Hansen (1997) provided approximate asymptotic *p*-values. To compensate for this behaviour, it is generally suggested that the ends of the equation sample be excluded in the testing procedure. We use the standard 15% level for "trimming" - we exclude the first and last 7.5% of the observations.

Table 2.7: Unit root tests with structural breaks results (exchange rate levels)

	USD/ZAR		EUR/ZAR		GBP/ZAR		JPY/ZAR		NEER		Asymptotic critical values	
Test	*t*-statistic	Break point	*t*-statistic	Break point	*t*-statistic	Break point	*t*-statistic	Break point	*t*-statistic	Break point	1%	5%
Zandrews: break in intercept	-3.157 (3)	22 Oct 2002	-2.981 (6)	06 Apr 1998	-2.593 (6)	15 Aug 1997	-4.138 (6)	15 Jun 1998	-3.126 (6)	07 Apr 1998	-5.43	-4.80
Zandrews: break in trend	-2.636 (3)	29 Jun 1998	-2.805 (6)	04 Oct 2001	-2.954 (6)	29 Jun 1998	-3.051 (6)	30 Nov 1999	-2.825 (6)	15 Dec 2000	-4.93	-4.42
Zandrews: break in intercept and trend	-4.191 (3)	16 Oct 2002	-3.282 (6)	30 May 2003	-3.446 (6)	26 Sep 2002	-4.163 (6)	15 Jun 1998	-3.993 (6)	13 Nov 2002	-5.57	-5.08
Clemao1	-2.725 (11)	07 Jul 1998	-2.946 (11)	28 Jun 2001	-2.745 (8)	07 Jun 1998	-2.814 (12)	21 Sep 1998	-2.473 (11)	07 Jul 1998	-4.29	-3.56
Clemao2	-2.944 (0)	08 Mar 2000	-2.860 (8)	07 Jul 1998	-2.789 (11)	07 Jul 1998	-3.363 (12)	21 Sep 1998	-2.767 (11)	07 Jul 1998	5.96	-5.49
		14 May 2003		04 Sep 2001		06 Jun 2001		14 Jan 2004		15 Jan 2001		
Clemio1	-3.719 (12)	13 Feb 1996	-3.021 (3)	11 Sep 2000	-4.508 (6)	30 Jan 1996	-4.235 (3)	11 Jun 1998	-3.310 (3)	3 Apr 1998	-4.97	-4.27
Clemio2	-2.771 (12)	13 Jan 2000	-3.365 (5)	02 Apr 1998	-4.632 (6)	30 Jan 1996	-5.017 (5)	11 Jun 1998	-3.072 (5)	03 Jun 1998	-5.96	-5.49
		11 Nov 2002		03 Jul 2001		05 Apr 2006		15 Jan 2004		12 Sep 2000		

Notes:

The unit toot test hypotheses are H_0: unit root (nonstationary), H_1: no unit root (stationary). Lags are specified in parentheses. Dummy or structural shift variable hypotheses are: H_0: no breakpoint(s) within data; H_1: one or two breakpoints within data.

For the Zandrews statistics, lags are selected via the *t*-test similar to the method implemented in DF-GLS in that you are looking to reject the null of a unit root in the process. We use the standard 15% level for "trimming" where we exclude the first and last 7.5% of the observations.

In the AO-IO tests, the appropriate lag order is determined by a set of sequential *F*-tests and the minimal *t*-ratio is compared with critical values provided by Perron and Vogelsang (1992) and Clemente *et al* (1998), as they do not follow the standard DF distribution. For the AO-IO tests, we use the suggested 5% level for "trimming" from each end of the sample; that is 10% of the observations are excluded.

Lags are reported in the parentheses, alongside each *t*-test statistic.

Table 2.8: Structural shifts in foreign exchange rates of the rand

Period	*Shock*	*Potential causes*
January 1996 - February 1996	(-)	# Rand suffered a speculative currency attack, triggered in February
	(-)	# Shift in SARB's intervention policy in foreign exchange market
August 1997	(-)	# Southeast Asian financial markets contagion erupted in July 1997 in Thailand
April 1998 - September 1998	(-)	# Southeast Asian financial markets contagion spreads to other emerging markets in April and May
	(-)	# Russian debt default in August
	(-)	# Build-up in SA's net open forward position (NOFP)
January 1999	(-)	# Brazilian real crisis
November 1999	(-)	# Millennium changeover raises emerging market risk
	(-)	# Oil price shock
January 2000 - December 2000	(-)	# Monetary policy and exchange rate regime shifts in South Africa – adoption of inflation targeting and more flexible exchange rate system in February
	(-)	# Dot com bubble burst, US dollar strength, coupled with concerns about worsening SA's balance of payments and regional economic and political stability
	(+)	(March - May)
	(-)	# International rating agency upgrades SA's long-term foreign-currency debt in June
		# Rise in emerging market risk in Q4
January 2001 - December 2001	(+)	# Expectation of sizable inward FDI flows (De Beers) and Standard and Poors' reaffirms SA's investment grade foreign-currency rating (January - February)
	(-)	# Rand crisis on the back of concerns about domestic fundamentals, anticipated policy shifts, rumours and declining commodity prices (July - December)
	(-)	# Global financial market turmoil due to terrorist attacks on the U.S.A. in September
September 2002 - November 2002	(+)	# Sharp rand appreciation due to decline in perceived risks associated with SA
May 2003	(+)	# Strong domestic macroeconomic fundamentals bolster rand
	(+)	# Prudent macroeconomic policy commitments by policymakers
	(+)	# Upgrading of SA's foreign and local sovereign debt ratings and stable economic outlook
	(+)	# Continued dollar weakness against international currencies in general
January 2004	(-)	# Profit taking, fall in financial asset prices & concerns about SA's widening current account deficit
April 2006	(+)	# Positive international rating agency and central bank announcements, euro strength and renewed appetite for emerging market financial assets

August 1997

The Southeast Asian financial markets contagion erupted in July 1997 in Thailand as investors flagged concerns about Southeast Asian countries' key macroeconomic fundamentals, namely:

i) rapid and excessive credit and money supply growth;
ii) unsustainable current account deficits;
iii) considerable net open forward positions (NOFPs) in foreign exchange;[19]
iv) nominal exchange rates pegged against the US dollar; and,
v) inappropriate real exchange rate appreciations.

International rating agencies' generally revised the credit risk associated with emerging economies by some international portfolio investors downwards leading to a sharp decline in the net inflow of long-term capital and a fairly substantial increase in the outflow of short-term capital in the third quarter of 1997 – and consequently, rand depreciation.

April 1998 - September 1998

The financial turbulence that hit many East Asian countries in 1997 then spread to other parts of the world in 1998. The contagion arising from this crisis hit all emerging markets in May 1998 and the rand was materially affected, as were currencies of many other developing countries. Greater reluctance to invest in emerging markets in general and speculative attacks on emerging market currencies in 1998 was a clear signal of the spread of Southeast Asian financial markets contagion. In August 1998, Russia devalued the rouble, defaulted on its domestic debt and declared a moratorium on payment to foreign creditors as confidence in global financial markets weakened, causing further declines in short-term capital inflows into and capital withdrawals from emerging markets. The unprecedented build-up in SA's NOFP, an attempt to alleviate pressures on the rand, further fuelled expectations of future rand depreciation, triggering a speculative sell-off of domestic currency and further rand weakness.

January 1999

With a widening current account/gross domestic product (GDP) ratio, depleting foreign currency reserves, and an escalating unemployment rate, combined with the Southeast Asian and Russian crises, investors believed that Brazil could no longer maintain its crawling peg foreign exchange rate regime. An expectation of a devaluation of the Brazilian real prompted a speculative sell-off of the currency and a currency crisis, forcing the Brazilian central bank to float the real against the US dollar, and the real to plunge in January 1999. Although the crisis in Brazil sparked a sell-off of other emerging market currencies, including the rand,

[19] Net open forward position is the difference between the forward book and the net official reserves. The forward position is the full foreign currency (or US dollar) commitment held by the central bank to deliver foreign currency (US dollars) on maturing forward currency contracts. To defend a currency, a central bank may either intervene in the spot market by selling dollars and thus running down its foreign reserves and reducing its international liquidity and/or buying dollars in the forward market increasing its oversold book.

the relatively muted response of the rand to the Brazilian incident could probably be attributed to the comprehensive restructuring of portfolio investments in 1998.

November 1999

Unease in global financial markets in the last two months of 1999 – triggered by markets' uncertainty about potential problems associated with the changeover to the new millennium – stirred foreign investors to reposition their asset portfolios ahead of the millennium changeover in order to curb their exposure to the potential volatility of emerging-market asset prices. Also, in November 1999, turbulence in financial markets and emerging market risk were heightened by Iraq's unexpected suspension of exports, forcing crude oil prices to surge to their highest levels since the end of the Gulf War.

2000

Events on the domestic front and southern African sub-continent underpinned exchange rate structural shifts over the first five months of 2000 whilst external shocks were the dominant forces in the last four months of that year. The year kicked off with South African authorities announcing the adoption of a formal inflation-targeting strategy, repurchase (repo) interest rate and a 'free' float exchange rate system in February 2000.[20] The strength of the dollar in the global currency markets, coupled with the net outflow of capital from the local economy, and investor concerns about economic and political stability in parts of sub-Saharan Africa caused further rand depreciation from end of March to end of May 2000. A temporary turnaround in the rand's fortunes in June and most of the third quarter of 2000 may be attributed to international rating agency Fitch's announcement of its revised improved rating of South Africa's long-term foreign-currency debt to investment grade. International investor concerns about emerging market prospects once again led to some selling off of rand assets in the fourth quarter of 2000.

2001

In the latter half of January, and in February, news that the restructuring of the De Beers diamond corporation could lead to a substantial inflow of foreign capital into South Africa and Standard and Poors' reaffirmation of SA's investment grade foreign-currency rating both boosted the nominal effective exchange rate of the rand.[21] A wide range of diverse factors cited as the triggers of renewed downward pressure on the rand between July and December 2001:

[20] The adoption of inflation-targeting monetary policy was aimed at enhancing policy transparency, accountability and predictability. The repo rate is determined in daily tenders of liquidity through repurchase transactions. Together, the introduction of the repo rate and 'free' float exchange rate was a further step towards market determined financial asset prices. The SARB's definition of a 'free' float exchange rate regime is one where the exchange rate floats independently, but the SARB intervenes in relatively small amounts to gradually build-up its foreign reserves, *albeit* not aggressively and when market conditions are conducive.

[21] De Beers is a 'near monopoly' in the diamond industry and a significant source of foreign exchange in SA.

i) regional instability, particularly in Zimbabwe, and the threat that expropriation of assets may spread to other parts of the Southern African Development Community (SADC) region;[22]
ii) concern about a debt default by Argentina worsened market sentiment towards emerging markets;
iii) rumours about the probable deferment of the restructuring of shareholdings in Telkom;[23]
iv) the lingering strike in the local car manufacturing industry;
v) the large net oversold position in foreign currency of the SARB;
vi) the decline in international commodity prices that took place in 2000 and 2001;
vii) introduction of capital gains tax;
viii) other concerns about domestic fundamentals and socio-economic policies;
ix) dot-com bubble burst triggers a crisis;
x) terrorist attacks on the United States in September 2001 sparked global financial market turmoil;
xi) expectations of further relaxations of exchange controls early in 2002; and,
xii) SA President Mbeki's appointment of a commission of inquiry into the rapid depreciation of the rand by allegedly dubious transactions in the foreign-exchange market and by speculative activity that was in breach of the existing exchange control which may have been interpreted as a potential tightening in exchange controls.

With the exception of controls on emigrants' blocked rands and borrowing by nonresidents in the Common Monetary Area, all exchange controls on nonresidents – including funds that were caught up in the debt standstill – were dismantled on 13 March 1995, the same time the unified managed float exchange rate was introduced.[24] Controls – put in place by governments, and enforced and administered by the central bank – impose a ban or restrict the amount of foreign currency or local currency that is allowed to be traded or purchased. Typically, countries that employ exchange controls are those with weaker economies. These controls allow countries a greater degree of economic stability by limiting the amount of exchange rate volatility due to currency inflows/outflows and to an extent, buffer the domestic financial and real sectors from the effects of international transactions on the balance of payments. The International Monetary Fund

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[22] SADC was established in 1992 as a successor to the Southern African Development Coordinating Conference (SADCC) in 1980. It is an inter-governmental organisation whose goal is to promote sustainable and equitable economic growth and socio-economic development through efficient productive systems, deeper co-operation and integration, good governance and durable peace and security among fifteen Southern African member states, namely, Angola, Botswana, Democratic Republic of Congo, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, United Republic of Tanzania, Zambia and Zimbabwe.

[23] Telkom is a partially state-owned 'near monopoly' in the local telecommunications industry.

[24] In terms of the Exchange Control Regulations introduced in 1961, the proceeds of sales of South African securities by non-residents were blocked within the country, and deposited in blocked rand accounts with commercial banks. The balances could only be repatriated under certain circumstances. And although these funds were not freely transferable from one resident to another in terms of exchange control regulations, a parallel legal market for "blocked rands" did nevertheless develop, but without official Reserve Bank recognition. See Farrell and Todani (2006) for general conditions for repatriation of blocked rands extracted from the relevant Government Notices issued in terms of the Currency and Exchange Act No 9 of 1933. South Africa, Lesotho, Namibia and Swaziland as a group are known as the Common Monetary Area – the South African rand is the common currency.

(IMF) has a provision article 14, which only allows countries with transitional economies to employ foreign exchange controls. A free float (accompanied by the inflation targeting monetary policy framework) superseded the dirty float in January 2000 followed by a removal of all exchange controls on nonresidents and a gradual relaxation of controls on residents – individuals and business. This array of market liberalisations rendered the rand more susceptible to shocks, structural shifts and volatility that are empirically evident in the foreign exchange rates of the rand.

<u>September 2002 - November 2002</u>

From the end of September through to October 2002, the rand unwound its losses – the rand appreciated sharply due to decline in perceived risks associated with SA. The likely influences were:

i) an improvement in the SA's international liquidity position;
ii) sound macroeconomic – monetary and fiscal – policies;
iii) IMF and international rating agencies' positive credit outlook for SA;
iv) favourable interest rate differentials;
v) a general reduction in risk aversion towards emerging-market asset classes;
vi) uncertainty about the health of the US economy and the associated weaker trend in the value of the US dollar;
vii) an improvement in South Africa's terms of trade;
viii) speculation against currency risk probably abetted the strength of the rand - for example, importers might have been induced not to cover forward their expected foreign exchange purchases and/or to sell back existing forward cover; and
ix) an improvement in perceptions regarding South Africa's status as a safe haven during 2002 following increased geopolitical tensions.

<u>May 2003</u>

Further rand strength in May was underpinned by an improvement in local economic fundamentals. Firstly, Standard & Poor's and Fitch ratings agencies upgraded South Africa's foreign and local currency sovereign debt ratings and assigned a stable outlook to the country. Added to this was the sustained attractive SA interest rate differential, continued commitment by SA policymakers to prudent fiscal and monetary policies and rising foreign-currency prices of South Africa's export commodities. Also, the SARB closed its NOFP. Continued dollar weakness against international currencies in general also fuelled rand appreciation.

<u>January 2004</u>

In early 2004, profit taking on speculation that the rand's two-year rally was over, exacerbated by a fall in the euro (against the US dollar) and the US dollar gold price, and concerns about SA's widening current account deficit resulted in a significant fall in the rand. The European Monetary Union (EMU) is SA's major trading partner, so generally and unsurprisingly, the rand tracks the euro – that is, movements in the rand/US dollar exchange rate tend to mirror those of the euro/US dollar exchange rate. Also, gold is a significant component of SA exports and thus a source of foreign currency.

April 2006

Rand strength in April 2006 may be ascribed to Moody's hint that it may upgrade SA's foreign currency debt rating due to the comfortable external liquidity position, renewed appetite for emerging markets financial assets, dramatic gains in the euro and SARB Governor's announcement of a "tightening bias" to monetary policy.

Exchange rates are susceptible to a wide range of shocks and the double-breaks evident from the results of the AO2 and IO2 models are not surprising. And although the nominal exchange rate series may not be adequately characterised by single shifts (QA, Zandrews, AO1 and IO1 models), the single break unit root tests do identify breaks which coincide with important events – these may well be detected as breaks when a multiple structural break test that allows for more than two structural shifts is applied. There are many and diverse contributing factors to the ongoing shifts in the key nominal bilateral and effective foreign exchange rates of the rand. These include, *inter alia*:

- economic and noneconomic shocks, including geo-political uncertainty and instability;
- macro- and microeconomic shocks;
- real and financial sector shocks;
- shocks in real and nominal variables, including oil price shocks;
- demand- and supply-side shocks;
- internal and external shocks;
- positive and negative shocks;
- economic fundamentals and government policy/regulation shifts and credibility shocks;
- actual and expected events;
- rumours and facts; and
- risk and safety.

Parameter instability stemming from both domestic and international developments is unsurprising for a small open emerging economy with generally increasing exchange rate flexibility, and pervasive financial market reforms, over the sample period. The rand is highly sensitive to global risk appetite – changes in risk sentiment underpin much of the short-run movements in the rand. Risk is captured directly and indirectly in the influences listed above. A common source of structural shift across exchange rates is conspicuous during the 1998 East-Asian contagion. The world remains vulnerable to repeated oil price shocks. None of the tests capture the 1995 exchange rate mechanism change and exchange control relaxation, the U.S. subprime market or credit crunch woes beginning in 2007 and the fears of sovereign debt crisis around the world from late 2009 which intensified in early 2010 amid concerns of looming GIPS countries debt defaults;[25] especially Greece, at least initially. This may be explained by the lagged transmission effect on the foreign exchange market – rand exchange rates in particular – combined with the trimming of a significant percentage of the data at both ends of the 13 March 1995 to 31 August 2010 sample spectrum, and the dominance of events preceding 2007 on the rand. Also worth noting is the timing of the breakpoints in the US dollar/rand exchange rates – more often than less, the structural shifts in this series either precede or coincide with those in the other series. Finally, negative shocks dominate – 65% of the shocks identified are negative shocks. The results of this analysis raise several questions. Should we be prepared for and concerned about a new era of more frequent shocks to floating exchange rates? What are the implications for other financial asset prices, economic growth, income distribution, the forecasting ability of economic models and economic policymakers?

2.5 Concluding remarks and discussion

A growing empirical literature has emerged in recent years in search of structural breaks in univariate time series data. The endogenisation of breakpoints has been an important milestone in unit root testing. Eyeballing the South African rand exchange rate time series, copious structural breaks are apparent in the data, the principal motivation for the research presented here. These several shifts are not surprising given the extensive financial market liberalisation that has been implemented in a small open economy such as South Africa since 1995. Why is the presence of structural shifts critical? When there are structural breaks, the various standard unit root test statistics are biased toward nonrejection of the unit root null or nonacceptance of the stationarity null. The implications for practitioners and policymakers are perhaps best summarised by the following excerpt from Hansen (2001): *"Structural change is pervasive in economic time series relationships, and it can be quite perilous to ignore. Inferences about economic relationships can go astray, forecasts can be inaccurate, and policy recommendations can be misleading or worse."* Testing for structural breaks in economic time series and time series relationships, and accounting for such change in the economic models can avert this source of spurious inference.

In this chapter, we endogenously identified structural breaks in the four key nominal bilateral exchange rates of the rand and the 15-basket currency nominal effective exchange rate of the rand, tested for structural shifts, applied the traditional and modern advanced unit root tests that account for structural change, compared and contrasted the latter set of results, and then linked the timing of the structural shifts to important economic and noneconomic events. The key finding of this study is that the results show overwhelming support for both structural shifts in the DGP and nonstationarity. The single or double structural break tests are statistically significant and the unit root test statistics suggest that the levels are *I(1)*

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[25] The acronym GIPS refers to the economies of Greece, Italy, Portugal and Spain – often in regard to matters relating to sovereign debt markets. Its extension, GIIPS, encompasses Ireland.

both in the absence and presence of structural breaks. So in this case, accounting for structural breaks does not change the results – but might in other cases as stationarity is also a sample phenomenon. There are also some unanswered questions about the stationarity of the differenced series of the pound/rand exchange rate, which need to be explored in future research.

However, the models used flag some important concerns. The linear unit root test models and accounting for a maximum of two structural changes in each series prompts future research in applying nonlinear unit root tests with multiple structural breakpoint tests – it is more reasonable to think that breaks occur over several periods, a notion corroborated by eyeballing the series. Also, in some instances, the power of nonlinear models can be considerably higher than that of linear versions. So including nonlinear parameters together with multiple structural changes further diminishes the problem of model misspecification and thus spurious results. Expanding unit root tests to encompass more than two breaks, deriving the new asymptotic distributions, writing the programmes or code to run both nonlinear stationarity tests and multiple structural break tests is a challenging task, a further direction for research on the dynamics of the foreign exchange rates of the rand. (Standard econometric software packages do not include nonlinear unit root tests.) However, Lee and Strazicich (2001) argue that the computational burden of the tests with more than two breaks (for example via a grid search) would increase significantly – evident when running the tests for two breaks as opposed to one break in the above analysis. So, the analysis in this paper is limited by the current state of knowledge in this area (as are all other applied papers).[26] Byrne and Perman (2007) also raise the following important issue that requires investigation in future research: *"the possible superiority of testing for structural breaks within a multivariate or cointegration framework, rather than the univariate frameworks"*. Johansen and Juselius (1990) have a preference for this and have argued along these lines for a while. Glynn *et al* (2007) note that the development in this area is very limited making it a strong candidate for future research. Glyn *et al*'s (2007) survey also concludes that there is no consensus on the most appropriate methodology to perform unit root tests, but addressing the aforementioned issues will advance the power of unit root testing.

The deliberate <u>univariate</u> analyses carried out in this paper – an introductory element of a broader study of the dynamics of the foreign exchange rates of the South African rand being undertaken in this thesis – helped us understand some of the <u>basic</u> characteristics of South African foreign exchange rate data. In summary, in order to obtain a richer understanding of the dynamics of the foreign exchange rates of the South African rand and increase the size and power of unit root tests, as already noted above, nonlinear unit root tests in a multivariate and multiple structural break (more than two breaks) set-up is prescribed for future research.

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[26] Quote from Smyth and Inder (2004): "Once econometric time series testing becomes sufficiently advanced to consider more than two structural breaks, tests will also need to be developed to determine the optimal number of structural breaks. When these advances occur in unit root testing, the impact of events such as the Great Leap Forward and market reforms on real output and other variables can be tested within a more comprehensive framework."

Notwithstanding the aforementioned shortcomings of the econometric tools, the approach in this paper is a significant contribution towards a more rigorous study of the DGP of the nominal bilateral and effective exchange rates of the rand by applying a broader set of confirmatory stationarity tests together with a better specification of the unit root tests – by incorporating structural shifts – a notable difference from *extant*, published literature on the univariate analysis of the nominal exchange rates of the rand time series.

2.6 Software

All of the results reported in this paper were generated using R/GAUSS codes, Eviews7 and StataSE12.1; including StataSE12.1 user written commands to implement the Zandrews, IO and AO structural break unit root tests.

CHAPTER 3

Modelling exchange rate volatility: A study of the South African rand (post-1994)

3.1 Introduction

In the post-Bretton Woods international monetary system, a conspicuous attribute of nominal exchange rates is their inherent instability. Bouts of volatility in the international prices of the rand are a recurring issue in this period, and recent events have sparked widespread interest and debates amongst academics, practitioners, policymakers and other interest groups. Intuitively, exchange rate stability or instability is at least directly linked to the exchange rate regime. Floating exchange rates, particularly 'pure' floats, are inherently erratic, varying with the demand and supply conditions in the foreign exchange market. Relatively higher nominal exchange rate volatility under a float is confirmed by a number of studies; for example, Gagnon and Hinterschweiger (2011), Flood and Rose (1999) and Obstfeld (1985), to mention a few. With the demise of the dual exchange rate on 10 March 1995, the ensuing gradual relaxation of exchange controls and the current 'noninterventionist' policy of the South African authorities, rand volatility is perhaps not surprising.[27,28] However, the frequent and often persistent gyrations of the rand in the short-term (and the medium- to long-term swings in the currency) are of concern and require rigorous investigation.[29]

Heightened exchange rate instability can have serious adverse and pervasive ramifications. In the absence of well-developed derivatives markets, unpredictable variations of exchange rates could mean huge losses or profits.[30] And although South Africa has a relatively sound and sophisticated financial sector by international standards, hedging gives rise to both direct costs (cost of hedge) and indirect costs (instability in other financial markets and real economic variables). Greater volatility also raises the exchange rate spread and currency derivative prices, and the limited amount of long-term hedging instruments compared with their short-term counterparts has further cost implications for importers, exporters and international investors. Furthermore, volatile foreign exchange markets make it difficult or undesirable for companies to raise capital in international capital markets. Price instability also impacts on the real sector of the economy: it affects fixed investment, economic growth and employment. In South Africa, currency volatility is an important element of exchange rate, monetary and macroeconomic policy decisions and there is thus a strong need for

[27] Noninterventionist policy in this context means that the central bank does not intervene in the foreign exchange market to influence the rand, but instead occasionally accumulates foreign currency reserves, *albeit* nonaggressively and when market conditions are conducive (during spells of rand strength), to diminish exchange rate risk arising from external liquidity. The latter economic rationale for central bank intervention is a contentious issue though.

[28] Although the impact of structural features of the foreign exchange market such as exchange controls is a contentious issue, a cross-section study by Canales-Kriljenko and Habermeier (2004) uncovers lower nominal effective exchange rate (NEER) volatility in countries where trade in domestic currency by nonresidents is restricted; the limitation of banks' foreign exchange positions also tends to dampen NEER instability.

[29] Even though exchange rate volatility – a short-run phenomenon – can have undesirable effects, its impact is lessened substantially by the availability of foreign exchange derivatives in the well-developed global foreign exchange market. However, persistent medium- and long-run exchange rate misalignments <u>can</u> have depressing effects on the volume of trade; mainly exports.

[30] National Treasury formulates exchange rate policy, although the central bank is mandated to implement the policy. So profits and losses incurred by the central bank related to its operations in the foreign exchange market are largely absorbed by National Treasury as expenditure in its budget.

modelling and forecasting volatility. Understanding the sources of currency volatility can also go a long way in trying to contain this (largely but not entirely undesirable) phenomenon in turn curtailing its effects.[31]

The two main contributions of this chapter are: i) establishing whether the modern conditional volatility models that integrate asymmetry, long memory and structural shifts, in particular, better fit the historical nominal exchange rate returns data than standard conditional volatility models; and, ii) an investigation of the extent to which persistence in exchange rate conditional variance may be overstated because of the existence of, and failure to take account of, (a larger number of) deterministic structural shifts and long memory in the volatility models. Disregarding structural breaks in the GARCH parameters has implications not only for the choice of optimal GARCH model but also affects the forecasting ability of GARCH models in general.

This chapter poses the question of non-stationarity in unconditional variance as a misspecification issue. We begin with a preliminary analysis of some salient characteristics of the five exchange rate returns series and present the descriptive summary statistics; namely, statistics that show evidence of (non)normality, and then test for unit root and ARCH effects (autocorrelation and heteroskedasticity). The main analysis then: i) uses the non(normality) test results to select an apposite error distribution to fit to the data; ii) estimates and presents the standard volatility model results; iii) estimates and presents the long memory and competing structural change model results; iv) based on the latter two sets of results, ranks the models in terms of 'best-fit' for each exchange rate returns series employing information criteria and loss functions; and, v) provides a descriptive analysis of the volatility structural breakpoints.

All the returns show evidence of non-normality with negative skewness and leptokurtosis. Nonnormality in the returns prescribes fitting the skewed Student-*t* distribution to the returns. Consistent with most conditional volatility model studies surveyed, the returns are stationary. The presence of ARCH-effects is confirmed, and conditional volatility estimation thus proceeds by first applying the standard ARCH- and GARCH-type models

Given that this chapter undertakes a broad study in terms of both the models employed and exchange rates analysed, we provide an unusually extensive list of important discoveries. In summary, our key findings are: i) exchange rate returns are non-normally distributed; ii) unit root results on the returns suggest stationarity; iii) Nyblom parameter stability and ICSS test results indicate strong and widespread instability in conditional volatility – between 20 and 44 breakpoints are detected, more than double the amount of statistically significant structural breaks in the conditional variance than those uncovered in a recent study on the US dollar/rand exchange rate returns, for a similar period, by Duncan and Liu (2009); iv) volatility persistence falls markedly when fractional integration and a larger set of structural shifts are accounted for; v) the top three approximating models reflect the importance of long memory, asymmetry and structural

[31] Exchange rate volatility may be desirable though for speculators and currency derivative sellers. Currency volatility also acts as a signal of uncertainty to market participants and policymakers.

change, both abrupt and smooth, in exchange rate volatility modelling; vi) a consequence of accounting for the latter phenomena is that unconditional variance (or the long-run variance), ${}_{u}\hat{\sigma}^{2}$, is stationary in contrast to the results produced by most of the simpler models estimated here, thus supporting the view that findings of non-mean reverting volatility are spurious; vii) although the sudden structural shift GARCH models better fit the data than the smooth transitional competing models, the latter modelling framework does not perform considerably worse and is a notable improvement on the basic models; and, viii) the timing of changes in volatility regimes, and thus their likely causes, are more or less consistent with the exchange rate level shifts detected in chapter 2.

The chapter unfolds as follows. Section 3.2 reviews the literature followed by a theoretical background on the methodology of standard and sophisticated GARCH-type volatility models, and motivation for this modelling approach in section 3.3. The focus is on structural break and long memory models – a detailed presentation of the standard models is deferred to the addendum (Appendix D). Section 3.4 describes the data and presents preliminary tests on the returns series. Estimation results for the basic GARCH models and those incorporating structural breaks and long memory are presented and interpreted in section 3.5 – preceded by a detection of the break points. Section 3.6 provides a descriptive analysis of the abrupt structural change points identified in the preceding section. Concluding remarks and some directions for future research are proposed in the epilogue.

3.2 Literature review: ARCH-type models and empirical evidence

Literature on univariate ARCH-type models is voluminous. Measuring the extent of exchange rate volatility is useful, and perhaps a necessary precursor for prognosis of plausible sources of exchange rate instability and establishing the (direct and indirect) effects of such volatility, which can have economy-wide repercussions. The extensive research on exchange rate volatility undertaken over the past two decades or so, time-varying volatility in particular, reflects its importance in a host of financial issues such as investment, portfolio diversification, security valuation, risk management and derivative pricing (Maheu, 2005; Poon and Granger, 2003). Incorporating developments, extensions and applications of the ARCH model to exchange rate time series and other economic and financial phenomena is executed in a number of articles and handbooks over the past three decades or so; for example, Bollerslev (2008), Bauwens *et al.* (2006), Singleton (2006), Poon (2005), Diebold (2004), Engle (2004, 2001), Christoffersen (2003), Chan (2002), Engle and Patton (2001), Franses and van Dijk (2000), Andersen and Bollerslev (1998[a]), Campbell *et al.* (1997), Palm (1996), Diebold and Lopez (1995), Bollerslev *et al.* (1994), Mills (1993), and Bollerslev *et al.* (1992).

In a subset of these studies, the univariate ARCH models, and its various expansions, have been applied to international currency prices of developed countries and some emerging markets to explore the significance and nature of structural shift, and its impact on the estimation results. For example, Frommel and

Menkhoff (2003), investigate whether the major floating exchange rates showed any change in volatility during the float period (1973 to 1998) – this is one of the earliest prominent studies on structural shift in exchange rate variance. The results uncover volatility increases due to both structural shifts and continuous changes which implies that the overall volatility increase may also be influenced by macroeconomically-caused shifts and not only by permanent microstructural shifts.

Empirical work published in internationally reputable journals that provides insight on which ARCH-type model – selected from a wide-range of basic and innovative models – best captures the historical volatility and predicts the future variance of the South African rand is remarkably minuscule. Farrell (2001), Duncan and Liu (2009), and Thupayagale and Jefferis (2011) are perhaps three conspicuous and rigorous studies on the measurement of the historical conditional volatility of the South African rand (excluding exogenous variables); with somewhat divergent themes though. Farrell (2001), one of the earliest studies on the dynamics of the conditional volatility of the rand using the simple GARCH and exponential GARCH (EGARCH) models, investigates fluctuations in the key nominal (and real) bilateral and effective exchange rates of the rand during the dual exchange rate system (2 September 1985 to 10 March 1995) and the contiguous periods when rand exchange rates were unified (7 February 1983 to 28 August 1985 and 13 March 1995 to 20 October 1998). His results reveal that: a) the proxies for the volatility of various nominal commercial rand exchange rates, the mean conditional variances obtained from ARCH-type models, were lower in all but one case in the period when the controls were in place than in periods when the rate was unified; b) volatility in the financial rand exchange rate was on average higher than that in the commercial rand market; c) volatility 'spillovers' from the commercial rand exchange rate to the financial rand exchange rate were prevalent but volatility was not found to 'spill over' in the opposite direction; and, d) no evidence was found of a common volatility process in the dual exchange rates. Conforming to Wilson *et al.* (1996), Duncan and Liu (2009), Malik *et al.* (2005), Malik (2003) and Aggarwal *et al.* (1999) integrate structural changes (SCs) into the standard GARCH volatility model – structural changes are endogenously detected using the iterative cumulative sum of squares (ICSS) technique proposed by Inclan and Tiao (1994). Their empirical results on the rand/US dollar exchange rate returns conditional volatility, covering the sample period 3 January 1994 to 31 March 2009, suggest: a) the SC-GARCH model is capable of discovering currency crisis using daily frequency time series data; b) the SC-GARCH model is more accurate than Knedlik and Scheufele's (2008) Markov-switching (MS) model in locating crisis periods in the rand; and, c) consistent with the empirical literature, the GARCH(1,1) model overestimates the extent of volatility persistence in financial time series when structural breaks are present. Thupayagale and Jefferis (2011) also corroborate Duncan and Liu's (2009) findings of volatility overestimation when structural breaks are not considered but both studies are less comprehensive than the ones employed here in the sense that substantially more structural shifts are accounted for here – explaining the lower volatility persistence detected in this study.

3.3 Theoretical background, methodology and motivation

The concept 'volatility' has received extensive treatment in the finance, financial economics and international finance literatures. In some financial market analysis, the concepts 'volatility' and 'risk' are often used interchangeably. A classical definition of volatility is the variability or degree to which the price of a security, commodity, or market rises or falls within a short period. In addition to short-term fluctuations in asset prices, and more specifically, variations in exchange rates, economists are also interested in long-term variations as well which may be influenced by factors different from those affecting exchange rates in the short-run. And although various long-run models can produce somewhat divergent equilibrium exchange rates, they remain useful for gauging the degree of exchange rate misalignment. Short-run asset price variability can be disaggregated into two components, predictable changes and unpredictable changes. Predictable changes are incorporated in decision-making and thus do not expose market participants to any form of risk. Risk is that part of variability that cannot be predicted.[32] Risk and volatility are thus not necessarily equivalent unless total volatility is unpredictable.

In the extensive empirical studies on the volatility of financial asset prices, attention is drawn to a wide range of quantitative tools for gauging variations in these prices. Using any measure of volatility has both its advantages and disadvantages. In this section, a brief overview of a broad set of historical conditional volatility measures is presented – categorised into standard volatility models and more sophisticated models. GARCH models, classified under the latter group, are probably the most extensively applied volatility models in finance, financial economics and international finance. The GARCH approach, employed in this study, is popular not only for its simplicity in specification and its parsimonious nature in capturing the time series properties of volatilities, but also because of its generalisation of other measures of volatilities. Performance of individual GARCH models depends on many factors, including whether the model is fitted to historical data or employed as a forecasting tool. In their analysis of exchange rates, Hansen and Lunde (2004) find no evidence that the GARCH(1,1) model is outperformed by more sophisticated models but this does not necessarily apply to explaining the past behaviour of exchange rates – a key finding in this investigation. In fact, the aptness of individual GARCH models here is exchange rate series specific.

3.3.1 Standard volatility models

Historically, variance, σ^2, and standard deviation, σ, are the most popular numerical measures of dispersion and volatility in economics and finance. However, both measures can and have been shown to produce inaccurate measures of volatility in financial data mainly because they are inappropriate for non-symmetrical distributions and sensitivities to outliers – infrequent jumps and collapses in exchange rates, in particular. Parkinson (1980) and Garman and Klass (1980) propose the high-low variation or extreme value variance to

[32] In some literature, risk is associated with small and negative returns.

reduce the influence of outliers or extremes. Some empirical studies show that the latter volatility measure provides more accurate estimates – about $2\frac{1}{2}-8$ times better than the traditional standard deviation method and at least 5 times more efficient than the close-close estimator when an outlier screen is applied to the data (Garman and Klass, 1980; Parkinson, 1980; Wiggins, 1991).[33] An alternative procedure to exploit or moderate the impact of extremes is the maximum likelihood estimation (MLE) procedure. The method of maximum likelihood, as the name indicates, involves estimating the unknown parameters in such a manner that the probability of observing the given *r*'s is as high as possible.[34] Controlled simulation studies have established that, for reasonable sample sizes, this procedure yields essentially unbiased estimates with the highest degree of efficiency (Ball and Torous, 1984). Ball and Torous (1984), however, raise a number of caveats regarding the practical limitations of this and all other proposed high-low estimators of security price volatility. Firstly, their usefulness depends critically on the actual security price dynamics being governed by the posited diffusion process.[35] Secondly, questions exist whether observed security price highs and lows correspond to actual security price highs and lows. Finally, security price volatility estimation procedures must more fully integrate the closed market effect.[36] Additional historical statistical measures of volatility that are resilient to outliers include the mean absolute deviation or average deviation and the interquartile range, amongst others. Appendix D (section D.1) provides a more detailed presentation of these standard volatility measures.

3.3.2 Motivation for and theoretical background of ARCH class conditional volatility models

Historically, least squares estimation has been the great workhorse of applied econometrics. Traditional econometric measures such as variance and standard deviation assume a normal probability distribution of the data – mesokurtic and symmetrical distributions – and homoskedasticity – constant variance or volatility. Time series financial data are generally inconsistent with the normal distribution making the variance and standard deviation measures less appropriate for exchange rate analysis. Stylised facts about volatility note several salient characteristics about financial time series, such as stock prices, exchange rates, inflation rates, *etcetera*. These include fat tail (leptokurtic) distributions of risky asset returns, asymmetry, time-varying volatility and volatility clustering, pronounced persistence, mean reversion, and comovements of volatilities across assets and financial markets. More recent research finds correlation among asset return volatility is stronger than among the level of returns and both tend to increase during bear markets and financial crises.

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[33] An outlier screen involves applying a screen for errors in high and low prices because without direct observation of actual transactions, it is impossible to know whether these high- and low-price data represent actual trades or recording errors. Close-to-close are the comparative closing prices of a financial asset.

[34] The $r's$ are rates of return: $r_t = \ln\left(\frac{e_t}{e_{t-1}}\right)*100$. In the case of a normal distribution, the maximum is unique whereas the MLE need not exist nor be unique.

[35] In the context of this paper, a diffusion process is the past evolution of exchange rate volatility following a shock, or how market participants actually form expectations about the future volatility of the exchange rate after a shock.

[36] Weekend effect (or closed market effect) is when financial asset prices display significantly lower or negative returns over the period between Friday's close and Monday's close.

It is well established that the (conditional and unconditional) distribution of asset returns exhibit excess kurtosis relative to the normal distribution.[37] Typical kurtosis coefficient estimates range from 4 to 50 indicating very extreme non-normality (Engle and Patton, 2001). Fat tails imply larger probability of outliers relative to the normal distribution, so using conditional variances from a normal distribution would understate the true variance or volatility.

An additional property of the normal distribution function is symmetry around its mean. Financial data, however, can and have been shown to exhibit a skew or asymmetric probability distribution. For some financial time-series data, returns are skewed to the left, that is, there are more negative than positive outlying observations. Skewness risk arises when a quantitative model relies on symmetric distribution when the actual distribution is skewed. Ignoring skewness risk will also cause any model to understate the volatility – a distribution that is skewed to the left typically has a mean smaller than its median and thus a higher variance than a a normal distribution. As Xiong and Idzorek (2011) point out "Investors are particularly concerned about significant losses – that is, downside risk, which is a function of skewness and kurtosis."

Comovements of volatilities across assets and financial markets are evidence that asset prices do not evolve independently of the markets around them. The direction of causality is an empirical one – intuitively, causality could be unidirectional or multidirectional. For example, a sell-off of domestic financial assets by foreigners, *ceteris paribus*, that reduces the market prices of these assets, will lead to a fall in the value of the domestic currency in terms of foreign currency. Conversely, a fall in the external value (or depreciation) of the domestic currency, all things equal, reduces foreign investors' rate of return on domestic assets which in turn triggers offshore sales of domestic financial assets and a decline in these asset prices.

Volatility clustering refers to periods in which prices show wide swings for an extended time period (high values of volatility followed by high values) trailed by periods in which there is relative calm (low values of volatility followed by low values). As Franses (1998, 155) notes:

> "Financial time series data reflect the result of trading among buyers and sellers, for example, stock markets. Various sources of news and other exogenous economic events may have an impact on the time series pattern of asset prices. Given that news can lead to various interpretations, and also given that specific economic events like an oil crisis can last for some time, we often observe that large positive and large negative observations in financial time series tend to appear in clusters."

And although volatility can also be quite persistent in asset returns, implying that returns have quite a long memory, it still tends to be mean reverting, that is, there is a normal level of volatility to which volatility

[37] In probability theory and statistics, kurtosis is a measure of the 'peakedness' of the probability distribution of a random variable. Higher kurtosis means more of the variance is due to infrequent extreme variations, as opposed to frequent modestly-sized deviations. In a normal distribution, about 68% of the values drawn from a normal distribution are within one standard deviation away from the mean, about 95% of the values are within 2 standard deviations and about 99.7% lie within three standard deviations ("68-95-99.7 rule" or "empirical rule"). See endnote '*d*' for statistical measurement of kurtosis.

will eventually return.[38] The normal level – for any asset price or asset price return – and whether it is constant or time-varying is, however, controversial and an empirical question.

A 'leverage effect' – when stock prices change, in response to news shocks, induces an inverse change in its volatility – is an additional property of financial time series. (Black, 1976).

The ARCH and GARCH class of conditional volatility models – probably the most extensively applied family of volatility models in finance, financial economics and international finance – are designed to deal with just this set of issues; that is, they attempt to account for the above stylised facts associated with time series of asset prices and associated returns. ARCH processes, a class of stochastic processes first introduced by Engle (1982), model time series, such as stock prices, exchange rates and inflation rates, that exhibit the phenomenon of volatility clustering, distinguish between the unconditional variance, ${}_u\hat{\sigma}^2$, and the conditional variance, h_t^2.[39] Simpler ARCH and GARCH models then allow the conditional variance to change over time leaving the unconditional variance constant.[40] The conditional variance of returns is estimated using the maximum likelihood procedure. For all the <u>standard</u> (G)ARCH models presented below returns, r_t, have the following process defined as conditionally normally distributed with time-depending variance:

$$r_t = \gamma + \chi + \phi + \tau + \varepsilon_t \tag{3.1}$$

$$\varepsilon_t = h_t z_t \tag{3.2}$$

$$z_t \sim N(0,1) \tag{3.3}$$

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[38] For example, if the changes in the exchange rate levels follow a particular discrete time stochastic process $e_t - e_{t-1} = \alpha_0 - \alpha_1 e_{t-1} + \varepsilon_t$ implying $e_t - e_{t-1} = -\alpha_1\left(e_{t-1} - \dfrac{\alpha_0}{\alpha_1}\right) + \varepsilon_t$ where $\alpha_0 > 0$ and $\alpha_1 > 0$, then from the latter equation, when the exchange rate at time $t-1$ is above (below) its average, we expect a decrease (increase) in the exchange rate at t. The speed of mean reversion depends on the magnitude of α_1. See Lee and Yin (1997) for a detailed discussion of mean reversion.

[39] A stochastic or random process is a collection of random variables ordered in time. It differs from a deterministic process in that there is some indeterminacy in its evolution described by probability distributions. This means that if an initial value of a time series is known, there are many possible paths for the process, but some paths are more probable than others.

[40] The standard (non-GARCH) volatility models assume homoscedasticity, that is, equal spread or constant variance, $\hat{\sigma}^2$, in the random disturbance or error term, $\varepsilon_i = r_i - \bar{r}$. Just as the disturbances, ε_i's, can be correlated, there can also be autocorrelation in the variance, $\hat{\sigma}^2$. Such autocorrelation has been observed in financial time series data. If data exhibit this pattern, then heteroscedastic (or non-constant or time-varying) conditional volatility, denoted by h_t^2, is present.

where the parameter γ is the mean return, χ is the 1-lag autoregressive (AR(1)) parameter, ϕ is the 1-lag moving average (MA(1)) parameter, τ is the ARCH-in-mean (ARCH-M) parameter,[41] ε_t is the disturbance term and z_t is purely random or white noise.[42] By assumption, ε_t is serially uncorrelated with a mean equal to zero but its conditional variance is time varying. The conditional variance denoted by h_t^2 follows one of the ARCH class models in equations (3.4) to (3.10) below. Thus, the error terms (return residuals, with respect to a mean process) are split into a stochastic piece z_t and a time-dependent standard deviation, h_t.[43] The standardised residuals, $z_t = \frac{\varepsilon_t}{h_t}$, are simply the quotient of the mean equation residuals divided by the conditional standard deviation.[44] The standard GARCH class models estimated in this study are presented below in sub-sections 3.3.2.1 and 3.3.2.2. A detailed discussion of each model is presented in section D.2 of Appendix D. The models used in this study are a selection and there are many others.

3.3.2.1 Symmetrical nonlinear ARCH and GARCH models[45]

This group of models assumes that positive and negative shocks have a symmetric impact on conditional volatility:

ARCH (p) model:
$$h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 \tag{3.4}$$

GARCH(p,q) model:
$$h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 \tag{3.5}$$

IGARCH(p,q)model:
$$h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 ; \quad \left(\sum_{k=1}^{p} \alpha_k + \sum_{j=1}^{q} \beta_j \right) = 1 \tag{3.6}$$

---

[41] Engle *et al.* (1987) extend Engle's (1982) ARCH model to allow the conditional variance to be a determinant of the mean and is called ARCH-M. The ARCH-M parameter captures the latter in this paper.

[42] Some alternative ways of specifying the returns or mean equation are $r_t = \gamma_0 + \gamma_1 \varepsilon_{t-1} + \varepsilon_t$ or $r_t = \gamma_0 + \gamma_1 \varepsilon_{t-1} + \gamma_2 h_t^2 + \varepsilon_t$ or $r_t = \gamma_0 + \gamma_1 \varepsilon_{t-1} + \gamma_2 h_t + \varepsilon_t$. Exogenous factors can also be added as regressors in the mean equation.

[43] A stochastic process is termed a purely random or white nose process if it has zero mean, constant variance and is serially uncorrelated. If it is also independent, such a process is called strictly white noise.

[44] The estimated residuals, $\hat{\varepsilon}_t$, and estimated conditional standard deviation, $\hat{h}_t$, are measured in the units in which the regressand is measured. The values of the standardised estimated residuals, $\hat{z}_t$, will therefore be pure numbers (devoid of units of measurement) and can be compared to the standardised residuals of other regressions.

[45] See endnote '*e*' for a brief discussion on the distinction between linear and nonlinear models.

where p refers to the lag on the disturbance term, ε_t^2, and q to the lag on the conditional variance, h_t^2.[46] In the vast empirical findings, GARCH(1,1) is the most commonly used model for many financial times series and it is difficult to beat a GARCH(1,1) in a forecasting contest for exchange rates – Hansen and Lunde (2004) find this for exchange rates but that the GARCH(1,1) is clearly inferior to models that can accommodate a leverage effect in their analysis of IBM returns. An integrated GARCH model (IGARCH) has been shown to be powerful for prediction over a short horizon, as it is not conditioned on a mean level volatility, and as a result it adjusts to changes in unconditional volatility quickly (Poon and Granger, 2003). The GARCH model is popular not only for its simplicity in specification and its parsimonious nature in capturing time series properties of volatilities, but also because it is a generalisation of other measures of volatility presented below.

3.3.2.2 Asymmetrical nonlinear GARCH models

A number of empirical studies provide evidence that positive and negative shocks have an asymmetric impact on conditional volatility. As the conditional variance in the GARCH models discussed above depends on the squared shock, positive and negative shocks of the same magnitude have the same effect on conditional volatility and these models cannot capture such asymmetric effects of positive and negative shocks. The nonlinear extensions of the GARCH model presented below were designed to allow for different effects of ‘good news’ (positive shocks) and ‘bad news’ (negative shocks) or other types of asymmetries:

EGARCH (p,q) model:

$$\ln h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k g(z_{t-k}) + \sum_{j=1}^{q} \beta_j \ln h_{t-j}^2 \tag{3.7}$$

$$g(z_t) \equiv \theta_1 z_t + \theta_2 \left(|z_t| - E|z_t| \right) \tag{3.8}$$

GJR-GARCH(p,q) model:

$$h_t^2 = \omega + \sum_{k=1}^{P} \left(\alpha_k \varepsilon_{t-k}^2 + \alpha_k^* S_{t-k}^- \varepsilon_{t-k}^2 \right) + \sum_{j=1}^{q} \beta_j h_{t-j}^2 \tag{3.9}$$

APARCH model:

$$h_t^\delta = \omega + \sum_{k=1}^{p} \alpha_k \left(|\varepsilon_{t-k}| - \alpha_k^* \varepsilon_{t-k} \right)^\delta + \sum_{j=1}^{q} \beta_j h_{t-j}^\delta . \tag{3.10}$$

---

[46] Note that for h_t^2 to be interpreted as a (conditional) variance, it must always be nonnegative; sufficient conditions are that the constant term and coefficients satisfy $\omega > 0$, $\alpha_k \geq 0$ and $\beta_j \geq 0$. Stationarity of the unconditional variance imposes the condition $\left(\sum_{k=1}^{p} \alpha_k + \sum_{j=1}^{q} \beta_j \right) < 1$. The latter result is due to Bollerslev (1986) theorem 1.

In the exponential GARCH (EGARCH) model of equation (3.7), proposed by Nelson (1991), the asymmetry effect is introduced by the nonlinear function in equation (3.8). The GJR-GARCH model (equation (3.9)), proposed by Glosten, Jagannathan, and Runkle (GJR) (1993), is an alternative device to the nonlinear EGARCH model where S_{t-k}^{-} is a dummy variable that takes the value unity when α_k^{*} is negative and zero when it is positive. In addition, because the dependent variable in the GJR model is the same as that of the other models presented above – excluding the EGARCH model – ranking based on information criteria is apt. In the asymmetric power ARCH, APARCH(*p,q*), model (specification (3.10)), introduced by Ding, Granger, and Engle (1993), the parameter δ plays the role of a Box-Cox power transformation of the conditional standard deviation process and the asymmetric absolute residuals,[47] while α_k^{*} reflects the so-called 'leverage effect'. A benefit of this model is that it combines the flexibility of a varying exponent with the asymmetry coefficient to account for the 'leverage effect'.

3.3.2.3 Modelling short and long memory: Fractionally-integrated GARCH (FIGARCH) models

A data generation process – be it a returns series, volatility series or any other time series – can be stationary, nonstationary (or unit root) or explosive; the latter is generally unreasonable for economic and financial time series and a model that generates such a series is probably misspecified. Focusing on the former two popular processes in the conventional econometrics literature, the distinction between stationary and nonstationary is narrower than a razor's edge, and thus not always very helpful. The analysis of fractionally integrated processes allows for more subtle mean reverting behaviour in time series. The knife-edge distinction between the integer *I(0)* and *I(1)* processes, which restricts mean reverting dynamics to *I(0)* processes alone is generalised to allow non-integer orders of integration *I(d)*. More specifically, an *I(d)* process with $0 < d < 1$ is also mean reverting, although sometimes rather persistent. Empirical work in this area is generally based on the autoregressive fractionally integrated moving average (ARFIMA) model introduced by Granger and Joyeux (1980) in economics. In some financial time series, volatility tends to die off quite slowly thus making the distinction between stationary and unit root processes too restrictive. An ARFIMA process is proposed to fill the gap between short and complete persistence so that the autoregressive moving average (ARMA) parameters capture the short-run behaviour of the time series while the fractional parameter allows for modelling the long-run dependence. Muller *et al.* (1997) provide economic justifications for the long memory empirical behaviour of financial series in a heterogeneous market with diverse agents. Movements or volatility of exchange rates and currency returns can be disaggregated into two components, a permanent and a transitory component, in the same way that foreign exchange traders and investors can be divided into two

[47] The Box-Cox method, developed by statisticians Box and Cox (1964) is one particular way of parameterising a power transform; this method is used to automatically identify a suitable power transformation for the data which can make big improvements in model fit.

categories, namely short-term dealers and investors and long-term dealers and investors based on their trading and investment horizons. "Short-term traders evaluate the market at a higher frequency and have a shorter memory than long-term traders" while "long-term traders may look at the market only once a day or less frequently" (Muller *et* al, 1997). Long-term traders thus monitor the market, market prices and price volatility with a 'coarse time grid' and short-term traders on the other hand judge the market with a 'fine time grid'. "For short-term traders, the level of coarse volatility matters because it determines the expected size of trends and thus the scope of trading opportunities. Short-term traders react to clusters of coarse volatility by changing their trading behaviour and so causing clusters of fine volatility. On the other hand, the level of fine volatility does not affect the trading strategies of long-term traders (who are often considering the 'fundamentals' of the market)" (Muller *et* al, 1997).

Baillie *et al.* (1996) proposed the FIGARCH model which captures a finite persistence of volatility shocks; that is, long memory behaviour and a hyperbolic or slow rate of decay for the influence of lagged squared innovations. Bollerslev and Mikkelson (1996) extend the fractional integration idea to the EGARCH model. In the literature surveyed, the GJR-GARCH model does not appear to have been extended to the long-memory framework – it is, however, nested in Tse's (1998) asymmetric power ARCH (APARCH) class of models. Each of these fractionally integrated GARCH(p,d,q) models is obtained by adding an exponent d to the first difference operator $(1-L)$ in the IGARCH model. An elaboration of each of these three models is presented in Appendix D, section D.2.3.

3.3.2.4 Modelling structural change

Structural shift means that parameters of a model do not remain the same throughout the entire sample period. Empirical evidence and economic theoretical justifications have been provided for the presence of structural breaks in the volatility of financial and economic time series, in addition to long memory. In some instances, there may be obvious points at which a break in structure might have taken place – a war, geopolitical tensions, a piece of legislation, an oil shock, a policy framework shift, financial market liberalisation, a change in investors' behaviour, *etcetera*. Traditional GARCH estimation techniques assume a constant unconditional variance. The degree to which conditional variance is persistent in exchange rate return data is an important economic issue. Ignoring structural changes in estimations may result in sub-optimal GARCH models being selected. For example, the observed IGARCH or $\left(\sum_{k=1}^{p}\alpha_k+\sum_{j=1}^{q}\beta_j\right)\geq 1$ behaviour may result from misspecification of the conditional variance function; that is, ignoring structural breaks can result in our estimates suggesting IGARCH or unconditional volatility persistence behaviour, $\left(\sum_{k=1}^{p}\alpha_k+\sum_{j=1}^{q}\beta_j\right)\geq 1$. A second consequence is that forecasting may be undermined.

Sudden Structural Change GARCH (SSC-GARCH) Class Models

The simplest way to account for structural breaks involves the use of dummy variables – SSC-GARCH models account for known and unknown breaks in the data using dummy variables. To detect or nullify the presence of abrupt structural changes in the univariate data generating process (DGP), Chow's breakpoint test may be performed for a known structural break(s) (Chow, 1960). As already discussed in chapter 2, to test for a structural break(s) or parameter stability, the breakpoint Chow test runs the specified regression for the entire sample period and for each subsample.

Where there is no reason *a priori* to expect a structural break or breaks, informal preliminary visual inspections of data or eyeballing the data and/or formal tests for the presence of change points should be applied. One such formal test is the Quandt-Andrews breakpoint test for one unknown structural breakpoint in the sample period. As already explained in chapter 2, this test is basically a rolling Chow breakpoint test; that is, a single Chow breakpoint test is performed at every observation between the two dates, or observations, τ_1 to τ_2, recursively over an expanded sample (Andrews, 1993, and Andrews and Ploberger, 1994). The k test statistics from the Chow tests are then summarised into one test statistic for a test against the null hypothesis of no breakpoints in the parameters between τ_1 to τ_2. The test can also be used to test for structural change in a subset of parameters. The basic statistics are the likelihood ratio (LR) *F*-statistic (based on the difference between the restricted and unrestricted sum of squared residuals) and the Wald *F*-statistic (computed from a standard Wald test with the restriction that the coefficients in the equation are the same in all samples). The maximum statistic is simply the maximum of the individual Chow *F*-statistics:

$$MaxF = \max_{\tau_1 \le \tau \le \tau_2} \left[F(\tau) \right]. \tag{3.11}$$

The Quandt-Andrews test to capture the unknown breaks can also be used to verify suspected breaks, from a visual inspection of the data series.

An alternative diagnostic tool approach to identifying parameter instability is the recursive least squares (RLS) procedure. Suppose that there are k parameters to be estimated in the regression model:

$$Y_t = \alpha_1 + \alpha_2 X_{1t} + ... + \alpha_k X_{(k-1)t} + u_t . \tag{3.12}$$

The first t observations of the data are used to form the first estimate of vector $b = \alpha_1, \alpha_2, ...\alpha_k$. The next observation is then added to the data set and $t+1$ observations are used to compute the second estimate of vector b. This process is repeated until the entire T sample points have been used, yielding $T-k+1$ estimates of the b vector. Thus each regression will produce a new set of estimates for the parameters. Plots of the estimated values of $\alpha_1, \alpha_2, .. \alpha_k$ against each iteration shows how the estimated values change. Small and random changes in the values of $\alpha_1, \alpha_2, .. \alpha_k$ suggest that the model parameters are unstable. Otherwise, a structural break(s) is present when the estimated values of $\alpha_1, \alpha_2, .. \alpha_k$ change significantly. Equivalently, if the maintained model is valid, the recursive residuals – the scaled difference between the observed Y_t and the predicted value of Y_t – will be independently and normally distributed with zero mean and constant variance, σ^2. The recursive residuals are plotted about the zero mean line, and plus and minus two standard errors are also shown at each point. Residuals outside the standard error bands suggest instability in the parameters of the equation. Here, a GARCH variance equation would be estimated repeatedly, using ever larger subsets of the sample data.

Yet another approach, used historically, is the cumulative sum (CUSUM) of squares test (Brown *et al.*, 1975). This is based on the cumulative sum of the recursive residuals:

$$W_t = \sum_{r=k+1}^{t} w_r / s \tag{3.13}$$

for $t = k+1, \ldots, T$, where w is the recursive residual defined above and s is the standard deviation of the recursive residuals w_t. If vector $b = \alpha_1, \alpha_2, .. \alpha_k$ remains constant from period to period, $E(W_t) = 0$, but if vector b changes, W_t will tend to diverge from the zero mean line. The significance of any departure from the zero line is assessed by reference to a pair of 5% significance lines, the distance between which increases with t. The 5% significance lines are provided by:

$$\left[k, \quad \pm -0.948(T-k)^{\frac{1}{2}}\right] \qquad \text{and} \qquad \left[T, \quad \pm 3 \times 0.948(T-k)^{\frac{1}{2}}\right].$$

As in the RLS procedure above, movement outside the significance lines is suggestive of parameter or variance instability, structural shift in particular.

Inclan and Tiao (IT) (1994) propose a procedure based on an iterated cumulative sum of squares (ICSS) to detect multiple change points in the unconditional variance of a sequence of independent observations or stochastic process. IT's approach is based on a centered version of the CUSUM presented by Brown *et al.* (1975). The search for change points in the volatility series is done systematically, following an algorithm to identify multiple shift points iteratively. Following IT (1994), let $\varepsilon_t \sim iidN(0, \sigma^2)$ where $t = 1, 2, \ldots, T$ and T is the number of observations. Denote the cumulative sum of squares as:

$$C_0 = 0 \tag{3.14}$$

and

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 \ , \ t = 1,2,...,T \ . \tag{3.15}$$

Then the IT test statistic, to test the null hypothesis of constant unconditional variance, is:

$$IT_{stat} = \sup_k \left| \sqrt{T/2} D_k \right| \tag{3.16}$$

where

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \qquad , \ k = 1,2,...,T \tag{3.17}$$

and $\sqrt{T/2}$ is the normalising factor and T is the sample size.[48, 49] D_k, a sequential statistic, is computed to find the point where variance exhibits structural shifts or breaks. Graphically, D_k will oscillate around 0 for a series with homogeneous variance when D_k is plotted against k. A sudden change in variance occurs when the plot D_k moves outside of some specified boundaries with high probability. IT (1994) obtain these boundaries from an asymptotic distribution of D_k assuming constant variance. Smith and Bracker (2003) present a step-by-step process for first identifying the 'potential' breakpoints and verifying them.

Sanso *et al.* (2004) note drawbacks in the IT test. The IT test assumes that the disturbances are independent and Gaussian distributed. In section 3.4.2 of this paper, in contrast, preliminary tests show that the distributions are leptokurtic and asymmetric conditional volatility is persistent. Thus the IT test is strictly appropriate only when the stochastic process is mesokurtic and the conditional variance is constant. The test has big size distortions for leptokurtic and platykurtic innovations, possibly (but not certainly) invalidating its use in the time series of floating exchange rates, and financial time series in general. If the distribution is leptokurtic or heavy tailed, one can expect many rejections of the constant variance null hypothesis, implying

[48] In mathematics, given a subset *S* of a totally or partially ordered set *T*, the supremum (sup) of *S*, if it exists, is the least element of *T* that is greater than or equal to every element of *S*. Consequently, the supremum is also referred to as the least upper bound (lub or LUB). If the supremum exists, it is unique. If *S* contains a greatest element, then that element is the supremum; otherwise, the supremum does not belong to *S* (or does not exist).

[49] The asymptotic distribution of the IT test is given by $IT \Rightarrow \sup_k \left| W^*(r) \right|$ where $W^*(r) \equiv W(r) - rW(1)$ is a Brownian Bridge, $W(r)$ is a standard Brownian motion and '$\Rightarrow$' stands for a weak convergence of the associated probability measures. The null hypothesis of constant unconditional variance is rejected if the critical value is less than the *IT*-statistic, for the given sample.

that <u>some</u> (<u>but not necessarily all</u>) of the structural breaks detected by IT tests <u>may</u> be spurious. To overcome the aforementioned problems, Sanso *et al.* (2004) propose new tests that take the fourth order moment properties of disturbances and conditional heteroskedasticity into explicit account. First, using the same algorithm as IT, to free the IT test of nuisance parameters for identical and independent zero-mean random variables, the following correction is suggested to the IT test:

$$ICSS(\kappa_1) = \sup_k \left| T^{-\frac{1}{2}} B_k \right| \tag{3.18}$$

where

$$B_k = \frac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}^4}}, \tag{3.19}$$

and $\hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon^4$, $\hat{\sigma}^2 = T^{-1} C_T$ for $k \in \{1,2,...,T\}$.[50] Thus, the $ICSS(\kappa_1)$ statistic controls for kurtosis of the series. To control for fourth order moment properties of the process (kurtosis) and conditional heteroskedasticity, Sanso *et al* (2004) propose the following statistic:

$$\kappa_2 = \sup_k \left| T^{-\frac{1}{2}} G_k \right| \tag{3.20}$$

where

$$G_k = \hat{\omega}_4^{-1/2} \left(C_k - \frac{k}{T} C_T \right), \tag{3.21}$$

$\hat{\omega}_4$ is a consistent estimator of ω_4,[51] and the asymptotic distribution is

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[50] The asymptotic distribution is $\kappa_1 \Rightarrow \sup_k \left| W^*(r) \right|$.

[51] One possibility is to use a non-parametric estimator of ω_4: $\hat{\omega}_4 = \frac{1}{T} \sum_{t=1}^{T} \left(\varepsilon_t^2 - \hat{\sigma}^2 \right)^2 + \frac{2}{T} \sum_{l=1}^{m} w(l,m) \sum_{t=l+1}^{T} \left(\varepsilon_t^2 - \hat{\sigma}^2 \right)$ where $w(l,m)$ is a Bartlet *t* lag window, given by $w(l,m) = 1 - l/(m+1)$ and the lag length is calculated according to Newey and West (1994) as $l = \left[4(T/100)^{1/5} \right]$. Another possibility is to use a parametric estimation of the long-run variance of the zero-

$$\kappa_2 \Rightarrow \sup_k p\left|W^*(r)\right| \quad . \tag{3.22}$$

An important distinction between B_k and G_k resides in the fact that the former corrects the CUSUMs for the (square root of the) "short-run" variance of $\xi_t \equiv \varepsilon_t^2 - \sigma^2$, $E(\xi^2) = \eta_4 - \sigma_4$ (see footnote 53), whereas the latter corrects for the (square root of the) "long-run" variance of ξ_t, given by ω_4 (Sanso, *et* al, 2004). The square root of the short-run residual variance, t_{sr}, suffers from size distortions when there are autocorrelated disturbances while the square root of the long-run variance, t_{lr}, is robust in this case. Following Vyrost *et al.* (2011), the structural breaks that are detected are used to partition the observations into groups corresponding to regimes, during which the variance is considered to be constant. Let t_{sr} $\{t_{(1)}, t_{(2)}, \ldots, t_{(N_T)}\}$ be the set of indices corresponding to the breakpoint where $1 \le t_{(1)} < t_{(2)} < \ldots < t_{(N_T)} \le T$; setting $t_{(0)} = 1$ and $t_{(N_T+1)} = N+1$. The indicator function is defined as

$$D_i(t) = \begin{cases} 1; & 1 \le i \le N_T \wedge t_{(i)} \le t \le t_{(t+1)} \\ 0; & otherwise \end{cases} . \tag{3.23}$$

Using the indicator function as a dummy variable, the various GARCH models with breaks are formulated as the original models (sections 3.3.2.1 and 3.3.2.2) with additional explanatory variables, $\sum_{i=0}^{N_T} \gamma_i D_i(t)$, in the variance equations. For example, the simple GARCH(1,1) model with breaks is expressed as:

$$h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 + \sum_{i=0}^{N_T} \gamma_i D_i(t) \tag{3.24}$$

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mean variable $\xi_t \equiv \varepsilon_t^2 - \sigma^2$: $\tilde{\omega}_4 = \left(1 - \sum_{j=1}^{p} \lambda_j\right)^{-2} T^{-1} \sum_{t=1}^{T} e_t^2$ where λ_j and e_t are obtained from the regression $\xi_t = \hat{\delta} + \sum_{j=1}^{p} \hat{\lambda} \xi_{t-j} + e_t$ where p is chosen using Akaike's information criterion (AIC). In this paper, the ICSS, κ_1 and κ_2 procedures for detecting breaks are conducted using R software; source code was requested from and provided by Vyrost *et al.* (2011). Vyrost *et al.*'s critical values for each statistic were obtained from a response-surface provided by Sanso *et al.* (2004).

where persistence of volatility is still given by $(\alpha+\beta)$. An advantage of all the above breakpoint tests – IT tests and modifications of IT tests, κ_1 and κ_2 tests – is that once the 'potential' breakpoints have been identified and verified, one can further explore the possible and likely causes of each of the structural shifts.

The focus thus far has been on sudden or abrupt structural changes as volatility moves from one regime to another. In the next section, a simpler, time efficient approach to accounting for structural breaks in the unconditional variance, without identifying the actual breakpoints, is presented where changeovers are modelled as smooth or gradual transitions – an alternative and competing approach to abrupt changes.

Adaptive-GARCH (A-GARCH) Class Models

To account for the persistence of the conditional variance process, Ding and Granger (1996) and Baillie *et al.* (1996), amongst others, proposed the adaptive-GARCH (A-GARCH) class models, an alternative to the SSC-GARCH approach. Simpler ARCH and GARCH models allow the conditional variance to change over time leaving the unconditional variance constant. A-GARCH models allow for time variance in both the conditional and unconditional variance. Morana and Beltratti (2004) tested for the existence of long memory and structural change in the realised Deutschemark/US dollar exchange rate variance process. Using various semi-parametric models, structural shifts are evident, and once the structural breaks have been accounted for, long memory is weaker but long memory remains an important property of the data generating volatility process. Importantly, Baillie and Morana (2009) introduced the long memory volatility adaptive-FIGARCH (A-FIGARCH) model to account for both long memory and structural change in the unconditional variance. From the Baillie *et al.* (1996) FIGARCH specification (D31) in Appendix D (section D.2.3), the long memory FIGARCH process can be rewritten as:

$$[1-\beta(L)]h_t^2 = \omega + \left[1-\beta(L)-\phi(L)(1-L)^d\right]\varepsilon_t^2 . \tag{3.25}$$

Allowing for the intercept ω in the conditional variance equation to be time-varying according to Andersen and Bollerslev's (1997 and 1998[b]) flexible functional form, Baillie and Morana's (2009) A-FIGARCH conditional variance equation may be written in a form analogous to the FIGARCH model as:

$$[1-\beta(L)](h_t^2-\omega_t) = \left[1-\beta(L)-\phi(L)(1-L)^d\right]\varepsilon_t^2 \tag{3.26}$$

where

$$\omega_t = \omega_0 + \sum_{j=1}^{k}\left[\psi_j \sin(2\pi jt/T) + \rho_j \cos(2\pi jt/T)\right]. \tag{3.27}$$

By setting $\omega_t = \omega[1-\beta(1)]^{-1}$ reduces the above A-FIGARCH model to a FIGARCH model. Rearranging equation (3.26), produces the alternative form of the A-FIGARCH(*p,d,q,k*) model as

$$h_t^2 = \omega_t + \left[1-\phi(L)(1-L)^d\,[1-\beta(L)]^{-1}\right]\varepsilon_t^2 . \tag{3.28}$$

In order for the conditional variance to be positive almost certainly at each point in time requires $\omega_t > 0$ and $\left[1-\phi(L)(1-L)^d\,[1-\beta(L)]^{-1}\right]\varepsilon_t^2 \geq 0$.

In this chapter, the flexible functional form or time-varying unconditional variance is extended to the other GARCH models; A-FIEGARCH and A-FIAPARCH models are two innovations in this empirical research. A great advantage of the A-GARCH type models approach over the ICSS procedure is that structural shifts can be incorporated in the variance equation without identifying the breaks, a more efficient approach. An obvious drawback of A-GARCH type models is that one cannot identify structural breakpoints, inhibiting an investigation of their likely causes, an advantage of the ICSS procedure. Here, we estimate both types of models, a valuable exercise – the regression results allow one to compare and contrast the effectiveness of each model in capturing time-varying unconditional variance.

3.4 Data and preliminary tests

3.4.1 Data issues

The sample covers 13 March 1995 to 31 August 2010**.** The continuously compounded or logarithmic return is defined as $r_t = \ln(e_t/e_{t-1})*100$ where e_t is the spot rate on day t,[52] for the daily series. Daily logarithmic returns, r_t, squared returns, r_t^2, and the absolute returns, $|r_t|$, are generated from the levels of the four key indirect nominal bilateral exchange rates (NBERs). To receive aggregated information, the returns of the 15-currency NEER of the rand are also examined.[53] The four daily NBERs of the South African rand with the highest transactions volumes are: US dollar/rand (USD/ZAR); euro/rand (EUR/ZAR); British pound (sterling)/rand (GBP/ZAR); and Japanese yen/rand (JPY/ZAR).[54] Daily NBERs are the 10h30 weighted average midpoint rates of the major banks and each bank's exchange rate weighting is based on the relative size of its transactions in the foreign exchange market. These rates are spot quotes rather than the actual spot

[52] Continuous compounding can be thought of as making the compounding period infinitesimally small which applies to very high-frequency exchange rate data; here, compounding is daily.

[53] The indirect foreign exchange rates of the rand (foreign currency per unit of rands) are used to ensure that the NBER quotations are consistent with the NEER quotation – the SARB calculates the indirect NEER of the rand.

[54] The euro was introduced to world financial markets as an accounting currency in 1999 and launched as physical coins and banknotes in 2002. It replaced the former European Currency Unit (ECU) at a ratio of 1:1. To extrapolate the euro/rand exchange rate for the period pre-1999, we use the ECU/rand exchange rate, a common practice in empirical studies.

transaction prices. Quote data are indicative rather than firm, and actual trade data for the sample period is virtually nonexistent;[55] indicative means that the bank or dealer posting such prices is not committed to trade at them, but generally will.

Table 3.1: Old and revised NEER weights based on international trade in manufactured goods

Country/region (currency)	Old weight (%)	New weight (%)	Change
Euro area (euro)	36.38	34.82	↓
United States of America (US dollar)	15.47	14.88	↓
China (Chinese yuan or renminbi)	3.14	12.49	↑
United Kingdom (British pound or sterling)	15.37	10.71	↓
Japan (Japanese yen)	10.43	10.12	↓
Switzerland (Swiss franc)	5.54	2.83	↓
Australia (Australian dollar)	1.68	2.04	↑
Sweden (Swedish krona)	1.81	1.99	↑
India (Indian rupee)	-	2.01	↑
Republic of Korea (South Korean won)	2.64	1.96	↓
China - Hong Kong (Hong Kong dollar)	2.70	1.48	↓
Singapore (Singapore dollar)	1.66	1.40	↓
Brazil (Brazilian real)	-	1.37	↑
Israel (Israeli shekel)	1.22	1.11	↓
Zambia (Zambian kwacha)	-	0.80	↑
Canada (Canadian dollar)	1.96	-	↓
Total	100.00	100.00	-

The currencies in the NEER basket and their weights – old and new weights – expressed as percentages in descending order of importance, are shown in Table 3.1. The original calculated NEER index was based on bilateral trade – exports and imports between South Africa and her major trading partners – and the SARB's comprehensive revised weighting scheme was introduced on 1 January 1999, primarily due to the introduction of the euro, with a minor amendment in 2003.[56] In the revised NEER index, the weights account for third-market competition,[57] in addition to bilateral trade, and the basket of currencies is expanded from thirteen to fifteen currencies, accounting for changes in trade patterns (Motsumi *et al.* , 2008). However, in the new NEER series, the revised set of weights are applied in the calculation of the nominal exchange rates as from 1 January 2005 only, and the new series is statistically linked to the old pre-2005 series.

[55] The extent of bias inherent in both spot quotes and actual transaction prices is a matter for further investigation.

[56] Weights are based on total trade in merchandise and by taking into account the currency denomination of commodities traded on international markets. See Walters (1999) for a note on the introduction of the euro and the revised weighting structure of the NEER of the rand, and Walters and de Beer (1999) for a presentation of the methodology used to calculate the SARB's measure of external price competitiveness in the pre-euro and euro periods.

[57] Third-market weights measure the intensity of competition between two countries (domestic and foreign) outside their respective local markets by multiplying the foreign country's share of total supply in each third market by the relative importance of the third markets' destinations for the domestic country's exports. For details on how the weights are computed by the SARB, see Motsumi *et al.* (2008). Also, Bayoumi *et al.* (2006) describe the framework of updating nominal and effective real exchange rate weights on the basis of trade.

Figure 3.1: Nominal effective exchange rate of the rand

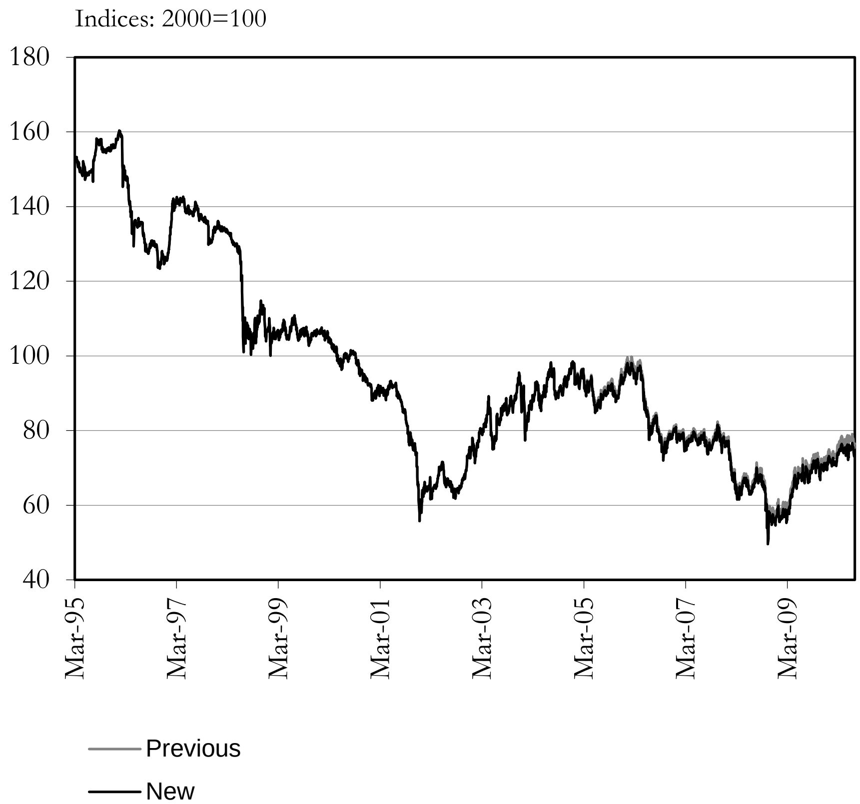

Figure 3.1 illustrates that, post-2004, the difference between the two indices is small suggesting that global patterns change only gradually and the effect of third-market exports adjustments in the weights on the level of the NEER is negligible; the old series marginally over-evaluates the rand. This paper examines the new series for the NEER. To remove (at best) or reduce (at worst) serial correlation observed in the US dollar/rand and pound/rand returns and thus improve the mean equation specification, the following exogenous variables are considered: the US dollar gold price, rand gold price, US 90-day Treasury bills rate, South African 91-day Treasury bills tender rate, South Africa-United States Treasury bills rates differentials and the return on the Johannesburg Securities Exchange All Share Index (JSE-ALSI).

Daily exchange rate data were kindly provided by the SARB. Due to the well-known fact that activity in the foreign exchange market slows down over the weekend and certain holiday periods, weekend and South African public holiday data are excluded so as not to confound the distributional characteristics of the various volatility measures by these largely deterministic calendar effects. Although the cuts do not capture all the holiday market slowdowns such as holidays of the US, UK, Germany and Japan (G4 economies), they do succeed in eliminating the most important such daily calendar effects. (The extent of calendar effects in the rand exchange rates, and other domestic financial asset prices, is an empirical question that needs to be addressed on its own, perhaps in future research.) After filtering the data for calendar effects – weekends and local public holidays – the full daily sample of returns consists of 3864 observations for each exchange rate.

3.4.2 Descriptive statistics

Table 3.2 reports the summary statistics along with the Jarque-Bera (*JB*) (Jarque and Bera, 1987) test statistic for normality. The *JB* test statistic, a measure of the difference of the skewness and kurtosis of the series with those from the normal distribution, is computed as

$$JB = \frac{n}{6}\left(\hat{S}^2 + \frac{\left(\hat{K}-3\right)^2}{4}\right) \qquad JB_{asy} \sim \chi^2_{(2)} \tag{3.29}$$

where n is the number of observations, $\hat{S}$ and $\hat{K}$ denote the sample skewness and kurtosis respectively, and the *JB* statistic given in the *JB* test equation follows the chi-square distribution with 2 degrees of freedom (in large samples). The reported probability in Table 3.2 is the probability that a *JB* statistic exceeds (in absolute value) the observed value under the null – a small probability value leads to the rejection of the null hypothesis of a normal distribution. For a normal distribution, the statistic equals zero and larger statistics show greater non-normality. Under the null that the data are *iid*, the null hypothesis is rejected if the *p*-value of the computed chi-square value is zero. The *JB* statistics clearly reject the normality assumption for the unconditional distribution of the five returns series – all the returns show evidence of non-normality with negative skewness, which means that the left tail is particularly extreme (Skew = 0 for a normal distribution), and the kurtosis statistics suggest that probability distribution functions are peaked or leptokurtic (Kurt = 3

Table 3.2: Summary statistics of daily currency returns (r_t)[d]

Exchange rate	Minimum	Mean	Maximum	Standard Deviation	Skewness (*prob*)	Kurtosis (*prob*)	JB (*prob*)
USD/ZAR	-10.5520	-0.0183	7.4025	1.0771	-0.6568 (0.0000)	6.6762 (0.0000)	7453.8 (0.0000)
EUR/ZAR	-9.5842	-0.0177	5.8904	1.0367	-0.6211 (0.0000)	5.7051 (0.0000)	5488.6 (0.0000)
GBP/ZAR	-9.3494	-0.0177	5.7313	1.0390	-0.5821 (0.0000)	5.6051 (0.0000)	5276.4 (0.0000)
JPY/ZAR	-11.4090	-0.0202	8.6905	1.3071	-0.5190 (0.0000)	5.6569 (0.0000)	5325.5 (0.0000)
NEER	-9.6650	-0.0181	5.5155	0.9985	-0.6932 (0.0000)	6.8784 (0.0000)	7926.8 (0.0000)

Note: The first six descriptive statistics reported in the table above are defined in endnote '*d*'. The *JB*-statistic test is described above.

for a normal distribution) (Table 3.2, and Figure C10 in Appendix C). Because shocks to the US dollar are typically transmitted to other bilateral (floating) exchange rates, the rand crosses show relatively weaker non-normality; asymmetry in the yen/rand exchange rates, in particular, due to greater foreign exchange market interventions by the Bank of Japan (Bank of Japan, 2000). Pronounced non-normality in the NEER is perhaps not surprising as its level is determined by continuous random changes in all its components; responding to changes in the US dollar/rand, the exchange rate with the second highest weighting in the NEER.

3.4.3 Unit root tests

It is customary to formally verify stationarity of all the variables that appear in any time series regression. The behaviour of stationary series is characterised by the observation that over a time period, one can find a clear tendency to return to a fixed value or a linear trend. The plots of the returns in figure C1 (in Appendix C) indicate that the returns appear to be mean reverting. The presence of unit roots in the returns series is formally tested by applying the augmented Dickey-Fuller (ADF) (1979), the Phillips-Perron (PP) test (1988), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (1992) and the Dickey-Fuller Generalised Least Squares (DF-GLS) test proposed by Elliott, Rothenberg and Stock (ERS) (1996).[58] The random walk with drift and random walk with drift around a trend models are used to test for stationarity. Tables B1 to B4 (in Appendix B) report the various unit root test results for the returns of the four NBERs and NEER of the rand. All the returns series variables appear stationary – at the 1% level of significance – indicating that the series are likely to be *I(0)*; a finding apparent in many empirical financial time series studies, exchange rates in particular. In stark contrast, unit root tests performed in chapter 2 on the exchange rate levels, even in the presence of structural shift, failed to reject the null hypothesis of nonstationarity or accept the stationary null for all the exchange rate series.

3.4.4 Some stylised facts of asset returns: A motivation for (G)ARCH modelling

Figures C1 to C3 (in Appendix C) plot the sample period daily returns, r_t, the absolute values of the returns, $|r_t|$, and the squared returns, r_t^2, respectively. All the graphs indicate that the foreign currency returns exhibit volatility clustering as the amplitudes of the returns vary over time – periods of low volatility tend to follow periods of high volatility. Epochs of high volatility are concentrated in the vicinity of global crises and domestic financial markets upheavals. Striking periods of clusters of heightened volatility are the mid-February 1996 to mid-May 1996 speculative attack on the rand (observations 233-290), the 1998-1999 emerging markets crisis (observations 821-961), September 2001 to March 2002 global and domestic market turmoil on the back of terrorist attacks on the US and uncertainty about domestic policy shifts (observations

[58] A comprehensive discussion of unit toot tests can be found in chapter 2.

1678-1747), profit taking, fall in financial asset prices & concerns about SA's widening current account deficit in early 2004 (observations 2206-2229), heightened global risk aversion towards emerging-market countries and a reduction in export commodity prices during April to September 2006 (observations 2788-2880),[59] and the 2008-2009 sub-period of the US financial market crisis (observations 3391-3490). This is a clear sign of presence of ARCH effects in the series. Although no clear discernible pattern of volatility is evident from all three measures, persistence is indicated in all the graphs. The autocorrelation coefficients (ACs) and partial autocorrelation coefficients (PACs), and the corresponding 95% confidence bands from lag 0 to lag 36 (0 to 36 business days) were estimated for the r_t, returns, $|r_t|$ and r_t^2 series (Figures C4-C9 in Appendix C). No trend is observable in the sample autocorrelation plot for the daily returns, r_t. The latter appear random with a rather very low degree of autocorrelation between adjacent and near-adjacent observations (Figure C4 in Appendix C), suggesting some form of 'short memory' or stationarity; in all cases, the partial autocorrelation functions (PACFs) (Figures C7-C9 in Appendix C) are similar to the corresponding autocorrelation functions (ACFs) (Figures C4 to C6 in Appendix C). Volatility persistence and ARCH effects are further confirmed in the absolute value of returns and squared returns ACF correlograms (Figures C5 and C6 in Appendix C) – the gradual decaying pattern of the autocorrelation suggests the presence of a dominant autoregressive process. Autocorrelation is significant up to 26 to 36 lags (26 to 36 business days) in a very few cases – 36 and more lags (36 or more business days) in most exchange rates return series (Figures C5 and C6 in Appendix C). A faster decaying pattern of the PACFs for absolute value of daily returns and squared daily returns confirms the dominance of the autoregressive process, relative to the moving average process (Figures C8 and C9 in Appendix C). The above analyses of auto- and partial-correlation coefficients motivate GARCH modelling of currency returns volatility.

Formally testing for ARCH effects – autocorrelation and heteroskedasticity – in financial asset returns has become a routine diagnostic ever since the development of the ARCH model by Engle (1982). Volatility clustering in returns manifests itself as autocorrelation in the raw, absolute and squared returns, or in the residuals and squared residuals from the estimated conditional mean equation. Instead of testing the statistical significance of any individual autocorrelation coefficient, we can test the joint hypothesis that all the sample autocorrelation coefficients up to a certain lag are simultaneously equal to zero. The significance of the raw, absolute or squared returns autocorrelations may be tested using the *Ljung Box* or modified *Q*-statistic. In this chapter, $\hat{\rho}_k^2$ is the *k*-lag sample autocorrelation of the raw or absolute or squared returns, and *n* is the number

[59] The rand is a commodity currency; that is, a currency of a country whose income depends heavily on the export of certain raw materials.

of observations. Both statistics test for white noise. The null hypothesis is that there is no serial correlation. A significant value for $Q_{LB}(p)$ provides evidence of time-varying conditional variance.[60]

A popular test for heteroskedasticity is the Lagrange multiplier (*LM*) ARCH test. Engle (1982) showed that a simple *LM* test for ARCH effects can be constructed based on the auxiliary regression

$$\varepsilon_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + \ldots + a_p\varepsilon_{t-p}^2 + u_t = a_0 + \left(\sum_{p=1}^{q} a_p\varepsilon_{t-p}^2\right) + u_t \tag{3.30}$$

since an ARCH model implies an autoregressive (AR) model for the squared residuals, ε_t^2. Under the null hypothesis, H_0, there are no ARCH effects, $a_1 = a_2 = \ldots = a_p = 0$. The alternative hypothesis, H_1, is that, in the presence of ARCH components, at least one of the estimated a_p coefficients must be significant. Engle's *LM* test statistic is computed as

$$LM = TR^2 \tag{3.31}$$

where T is the sample size and R^2 is computed from equation (3.30) using estimated residuals. The *LM* test statistic has an asymptotic chi-square distribution with q degrees of freedom.[61]

Looking at the Q_{LB}-statistics of the residuals, ε_t, and the squared residuals, ε_t^2, of the return series, there is strong evidence of autocorrelation in all the series except for the euro currency and lower lags of the pound/rand residuals series (Tables 3.3 and 3.4).

Positive correlation in the US dollar/rand returns, at even extremely high lags, might be due to noise traders with positive feedback strategies (De Long *et al.*, 1990) or to the use of stop-loss strategies (Krugman and Miller, 1993). Also, one cannot rule out the influence of other exogenous variables. The euro currency raw returns exhibit no serial dependencies up to 50 business days. However, serial correlation is evident after

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[60] To test for autocorrelation in the raw returns when it is suspected that there are GARCH effects present, Diebold and Lopez (1995) suggested using the following heteroskedasticity robust version: $Q_{LB}{}^{HC}(p) = n(n+2)\sum_{j=1}^{p}\frac{\hat{\rho}_j^2}{n-j}\left(\frac{\hat{\sigma}^4}{\hat{\sigma}^4+\hat{\gamma}_j}\right)\hat{\rho}_j^2$ where $\hat{\sigma}^4$ is a consistent estimate of the squared unconditional variance of returns, and $\hat{\gamma}_j$ is the sample autocovariance of squared returns. In both the above tests, the null is that there is no serial correlation.

[61] Lumsdaine and Ng (1999), however, caution that a misspecified mean equation due to omitted variables, structural parameter instability and other factors, may lead to overrejection of the null hypothesis of conditional homoskedasticity.

Table 3.3: Ljung-Box *Q*-statistics for residuals, $\varepsilon_t\,(prob)$

Series	*p*	1	2	5	10	20	50
USD/ZAR		4.5456	4.7198	9.6049	14.5238	33.3228	67.3864
		(0.0330)	(0.0944)	(0.0872)	(0.1504)	(0.0311)	(0.0510)
EUR/ZAR		1.1675	1.7788	7.8071	15.3191	23.5334	57.4906
		(0.2799)	(0.4109)	(0.1672)	(0.1209)	(0.2634)	(0.2175)
GBP/ZAR		1.9417	2.5991	7.0708	19.8412	34.3985	71.8247
		(0.1635)	(0.2727)	(0.2154)	(0.0308)	(0.0236)	(0.0232)
JPY/ZAR		5.0685	5.1839	17.5796	22.3470	30.7712	70.9338
		(0.0244)	(0.0749)	(0.0035)	(0.0134)	(0.0583)	(0.0273)
NEER		4.1821	4.3618	10.4528	16.6294	28.8598	65.8788
		(0.0409)	(0.1129)	(0.0634)	(0.0830)	(0.0906)	(0.0655)

Note: The Q_{LB}-statistic at lag *p* is a test statistic for the null hypothesis that there is no autocorrelation up to order *p*. H_0: No serial correlation and H_1: presence of serial correlation. Accept H_0 when probability, in parentheses, is high [Q < Chi-square (lag)].

Table 3.4: Ljung-Box *Q*-statistics for squared residuals, $\varepsilon_t^2\,(prob)$

Series	*p*	1	2	5	10	20	50
USD/ZAR		256.33	398.83	985.07	1727.0	2226.9	2573.7
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EUR/ZAR		137.67	222.24	473.18	867.20	1110.6	1245.5
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GBP/ZAR		173.35	245.94	541.24	1056.3	1442.1	1726.4
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	[0.0000)
JPY/ZAR		434.99	737.79	1662.4	2812.1	3772.5	4471.3
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NEER		194.98	306.08	712.79	1250.0	1602.7	1797.3
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: The Q_{LB}-statistic at lag *p* is a test statistic for the null hypothesis that there is no autocorrelation up to order *p*. H_0: No serial correlation and H_1: Presence of serial correlation. Accept H_0 when probability, in parentheses, is high [Q < Chi-square (lag)]. *P*-values are adjusted by 2 degrees of freedom.

Table 3.5: ARCH *LM* test statistics for squared returns, $r_t^2\,(prob)$

Series	*p*	1-1	1-2	1-5	1-10	1-20	1-50
USD/ZAR		274.11	175.08	124.21	76.761	39.795	17.171
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EUR/ZAR		142.53	98.703	63.945	43.551	22.394	9.7234
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GBP/ZAR		181.21	109.53	79.004	58.037	29.980	12.861
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
JPY/ZAR		489.37	324.65	200.93	117.12	60.497	26.358
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NEER		205.02	134.90	92.337	58.428	30.050	12.674
		(0.0000)	(0.0000)	(0.0000)	(0.00000	(0.0000)	(0.0000)

Note: The ARCH *LM* statistic at lag *p* is a test statistic for the null hypothesis that there are ARCH effects up to order *p*. H_0: No ARCH effects and H_1: Presence of ARCH effects. Accept H_0 when probability is high [TR^2 < Chi-square (lag)].

approximately 120 lags,[62] suggesting that market participants may not be able to systematically profit from market inefficiencies within six months – 120 days excluding weekends and public holidays is more or less six months – because the movement in the returns are determined (almost) entirely by information not contained in the returns series. The absence of serial correlation in low lags of the sterling/rand – lags one, two and five – is not surprising because in many cases, if there is serial correlation in the error structure, it may manifest itself in a more complex relationship, involving higher-order autocorrelations. The input lags, therefore, affects the power of the test. If the lag is too small, the test will not detect high-order autocorrelations; if it is too large, the test will lose power when significant correlation at one lag is washed out or diluted by insignificant correlations at other lags. Tsay (2005) cites simulation evidence that a lag value (*m*) approximating *log(T)* provides better power performance, where *T* is the sample size. For a sample size of 3864 observations, $\ln(3864) \approx 8$. Notably, serial correlation is much stronger in the squared returns than in the raw returns (Tables 3.3 and 3.4). From Tables 3.3 and 3.4, one thus concludes that, with the exception of the euro/rand returns, the raw and squared returns are generally autocorrelated and an autoregressive moving-average- (ARMA) type model seems justified.

Table 3.5 reports the values of the *LM*-statistics, computed from the squared returns. The ARCH *LM* test results suggest strong evidence of ARCH in the squared residuals. Therefore, the estimation results in Tables 3.4 and 3.5 confirm the presence of that ARCH-type effects, an indication that the data are candidates for GARCH-type modelling.

3.5 Empirical analysis: GARCH models

Model selection for a time series data set is a non-trivial task. An important practical problem is the determination of the appropriate autoregressive lag for a particular time series; ARCH order p, GARCH order q and asymmetry order r. Choosing the first order GARCH models is motivated by the fact that they are most widely applied and it is hard to beat the simple GARCH(1,1) models, more so in forecasting. Considering higher order models is more tedious, especially in this case where five exchange rate series are analysed. So this analysis is restricted to $p \leq 9$ in the basic ARCH model and $p,q,r = 1$ in the symmetric and asymmetric GARCH models. (Higher order models for each time series can be considered as a separate exercise in future research.)

3.5.1 Implementation of GARCH models

A challenge in ARCH and GARCH modelling is the selection of an apposite error distribution. Amongst the most common fat-tailed error distributions for fitting ARCH and GARCH models are the Student's *t*-distribution, proposed by Bollerslev (1987), and the generalised error distribution (GED), proposed by

[62] These statistics are not reported here but may be requested from the author.

Nelson (1991). A particularly appropriate non-Gaussian (or non-normal) error distribution for financial time series is the asymmetric Student's *t*-distribution to capture both skewness and excess kurtosis in the standardised residuals (Fernandez and Steel, 1998). The log-likelihood (LL) of a standardised (zero mean and unit variance) skewed-Student's *t*-distribution is:

$$L_{SkSt} = \sum_{t=1}^{T} l_t = T\left\{\log\Gamma\left(\frac{\upsilon+1}{2}\right) - \log\Gamma\left(\frac{\upsilon}{2}\right) - 0.5\log[\pi(\upsilon-2)] + \log\left(\frac{2}{\xi+\frac{1}{\xi}}\right) + \log(s)\right\} \tag{3.32}$$
$$-0.5\sum_{t=1}^{T}\left\{\log\sigma_t^2 + (1+\upsilon)\log\left[1+\frac{(sz_t+m)^2}{\upsilon-2}\xi^{-2I_t}\right]\right\},$$

where

$$I_t = \begin{cases} 1 & if \quad z_t \geq -\frac{m}{s} \\ -1 & if \quad z_t < -\frac{m}{s} \end{cases},$$

ξ is the asymmetry parameter, υ is the degree of freedom of the distribution,

$$m = \frac{\Gamma\left(\frac{\upsilon+1}{2}\right)\sqrt{\upsilon-2}}{\sqrt{\pi}\,\Gamma\left(\frac{\upsilon}{2}\right)}\left(\xi - \frac{1}{\xi}\right),$$

and

$$s = \sqrt{\left(\xi^2 + \frac{1}{\xi^2} - 1\right) - m^2}\ .$$

Here, the mean return and variance are estimated by the maximum likelihood method under the assumption that the errors have a conditional skewed-Student's *t*-distribution; the skewed-Student's *t*-distribution is motivated by the presence of excess kurtosis and asymmetry in the skewness, kurtosis and *JB* statistics. Estimation results in an earlier draft of this chapter report the lowest Schwarz information criterion (SIC) statistic for the skewed Student's *t*-distribution, rating the latter distribution for the disturbances as the best distribution. (Information criterion and model selection are discussed at length under sub-section 3.5.4).

The problem faced in nonlinear estimation is to find the values of parameters $\theta = f\left(\varepsilon_t^2, \sigma_t^2\right)$ that optimise (maximise or minimise) an objective function $F(\theta)$. ARCH and GARCH estimation uses maximum likelihood to jointly estimate the parameters of the mean and the variance equations. Iterative optimisation algorithms work by taking an initial set of values for the parameters, $\theta_{(0)}$, then performing calculations based on these values to obtain a better set of parameter values, θ_1. This process is repeated for $\theta_{(2)}$, $\theta_{(3)}$ and so on until the objective function F no longer improves between iterations. There are three main parts to the optimisation process: a) obtaining the initial parameter values (or variance initialisation); b) updating the candidate parameter vector θ at each iteration; and, c) determining when we have reached the optimum. If the objective function is globally concave so that there is a single optimum, any algorithm which improves the parameter vector at each iteration will eventually find this optimum (assuming that the size of the steps taken does not become negligible). If the objective function is not globally concave, different algorithms may find different local optima, but all iterative algorithms will suffer from the same problem of being unable to tell apart a local and a global optimum. Therefore, practical issues considered in implementing the maximum likelihood estimator (MLE) include choosing the starting values for the model parameters and the initialising of ε_t^2 and σ_t^2 must be supplied. Fortunately, econometric programming languages such as OX, GAUSS, MATLAB, RATS AND EVIEWS usually provide reliable default settings for the user-supplied information required by a optimisation routine (Christensen *et al.*, 2008); GARCH models are estimated using OX in our study.[63] Once the log-likelihood (*LL*) is initialised, it can be optimised using numerical optimisation techniques.[64] The gradient vector and the Hessian matrix can be obtained numerically or by evaluating their analytical expression.[65] Due to the high number of possible models and distributions available, the OX-G@RCH statistical programme uses numerical techniques to approximate the derivatives of the *LL* function with respect to the parameter vector. Here, the standard MLE approach is applied; maximum likelihood methods may outperform quasi-maximum likelihood estimation in terms of efficiency if the parametric distribution is non-normal.[66] Unless otherwise stated, the standard MLE method employed in this study uses

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[63] Christensen *et al.* (2008) explicates some of the devil in the detail lurking behind successful practical optimisation and sheds some light on the nuts and bolts of practical optimisation.

[64] The log-likelihood function is the basis for deriving the parameter estimates for the sample period and the *p*-value that corresponds to the optimum point, $\hat{p}$, is the MLE.

[65] The Hessian matrix is the square matrix of second-order partial derivatives of a function; that is, it describes the local curvature of a function of many variables.

[66] If the distribution of the standardised residuals, z_t, in the mean equation is symmetric, then the quasi-maximum likelihood estimator (QMLE) is often close to the MLE. However, if z_t has a skewed distribution, an inherent property in all the data employed in this study, then the QMLE can be quite different from MLE. See Bollerslev and Wooldridge (1992), Weiss (1986) and Zivot (2009) for discussion of MLE and QMLE.

the quasi-Newton method of Broyden, Fletcher, Goldfarb and Shanno (BFGS),[67] and the sample mean of the squared residuals is used to start recursion.

3.5.2 Standard ARCH and GARCH models: Estimations and results

Selected ARCH model statistics reported in Tables 3.6 and 3.7 are used to authenticate a satisfactory and improved specification of the mean equation which is implied by the presence or absence of serial correlation at higher levels of confidence in the residuals of the mean equation. These statistics establish the presence of ARCH effects or long memory, and further substantiate fitting a skewed Student's *t*-distribution for the errors – the preliminary summary statistics in sections 3.4.2 and 3.4.4 uncover non-normality (excess kurtosis and skewness), ARCH effects and serial correlation in all the raw returns series and autocorrelation in most of the squared residuals. Other ARCH model estimation results are deliberately omitted. In the (G)ARCH variance equations, conditional volatility is modelled as a function of the disturbances (or shocks), ε_t, obtained from the mean equation, or some variant of the mean equation residuals. From equations (3.2) and (3.3), $\varepsilon_t = h_t z_t$ and $z_t \sim N(0,1)$, respectively. So a necessary condition is that the standardised residuals, $z_t = \varepsilon_t / h_t$, should be normally distributed with zero mean and unit variance. There are many ways of modelling the mean equation. Following the approach in numerous empirical studies, the simplest specification for the augmented mean equation (3.1) is estimated first – currency returns are regressed on a constant or the mean return; that is, $r_t = \gamma$. An examination of the probabilities for significance of the ARCH coefficients instead of the levels of the coefficient estimates show that most of the ARCH or shock coefficients, α_k, in the ARCH model are statistically significant (statistically different from zero) at the 1% level up to seven business days, and all parameters are statistically significant at the 10% level up to 9 business days (Table 3.6). These results further confirm the presence of ARCH effects, and suggest they are persistent; that is, shocks decay at a slow rate. Long memory is protracted in US dollar/rand returns (and consequently in the NEER) while ARCH effects tend to die 1 lag earlier in the yen/rand daily series (a marginal result); possibly due to the Bank of Japan's interventions in the foreign exchange market. The Bank of Japan as the agent of the Minister of Finance intervenes in the foreign exchange market in order to stabilise the yen's value which may weaken ARCH effects. The asymmetry and tail statistics indeed confirm non-normality in the mean equation residuals, a justification for a skewed Student's *t*-distribution. Finally, the null hypothesis of no serial correlation in the

[67] This is a method used to solve an unconstrained nonlinear optimisation problem. The BFGS method is derived from the Newton's method in optimisation, a class of hill-climbing optimisation techniques that seeks the stationary point of a function, where the gradient is 0. Newton's method assumes that the function can be locally approximated as a quadratic in the region around the optimum, and uses the first and second derivatives to find the stationary point. In Quasi-Newton methods the Hessian matrix of second derivatives of the function to be minimised does not need to be computed at any stage. The Hessian is updated by analysing successive gradient vectors instead. See the Ox package (OxMetrics 6.1) documentation for details (https://www.oxmetrics.net).

Table 3.6: ARCH model estimates

Parameter	USD	EUR	GBP	JPY	NEER
			Mean equation		
γ	-0.0225	-0.0025	-0.0168	0.0066	-0.0078
p-value	(0.0011)	(0.8482)	(0.1632)	(0.6812)	(0.4307)
			Variance equation		
α_1	0.1908	0.1457	0.1757	0.1420	0.1727
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2	0.1710	0.1252	0.1350	0.0966	0.1356
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)
α_3	0.1747	0.0946	0.0886	0.0722	0.1375
p-value	(0.0000)	(0.0003)	(0.0004)	(0.0016)	(0.0000)
α_4	0.1538	0.0758	0.0791	0.0985	0.1001
p-value	(0.0000)	(0.0014)	(0.0011)	(0.0001)	(0.0001)
α_5	0.1400	0.0915	0.1081	0.0898	0.138313
p-value	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0000)
α_6	0.1593	0.0884	0.0958	0.0856	0.1406
p-value	(0.0000)	(0.0020)	(0.0001)	(0.0026)	(0.0000)
α_7	0.1226	0.0614	0.1222	0.0974	0.1091
p-value	(0.0000)	(0.0032)	(0.0000)	(0.0000)	(0.0000)
α_8	0.1386	0.0677	0.0663	0.0608	0.0834
p-value	(0.0000)	(0.0020)	(0.0039)	(0.0111)	(0.0000)
α_9	0.0816	0.0538	0.0379	0.0334	0.0584
p-value	(0.0042)	(0.0102)	(0.0867)	(0.0555)	(0.0000)
			Asymmetry and Kurtosis		
Asymmetry	-0.1070	-0.1208	-0.0928	-0.1236	-0.1124
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tail	4.6393	5.4058	5.9662	6.6872	5.0046
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
			Standardised residuals serial correlation statistic, $Q_{LB(z_t)}$		
lag=10	12.3494	5.9776	7.3454	3.7885	4.6873
p-value	(0.2625)	(0.8171)	(0.6925)	(0.9564)	(0.9111)
lag=20	21.6675	11.3759	23.8424	13.8247	14.1070
p-value	(0.3588)	(0.9359)	(0.2494)	(0.8393)	(0.8250)
lag=50	44.6932	34.1164	53.6151	34.8499	38.0247
p-value	(0.6856)	(0.9580)	(0.3374)	(0.9483)	(0.8927)
			Squared standardised residuals serial correlation statistic, $Q_{LB(z_t^2)}$		
lag=10	143.475	8.2968	14.8886	10.7420	14.9799
p-value	(0.0000)	(0.0040)	(0.0001)	(0.0011)	(0.0001)
lag=20	149.182	11.6131	17.9724	15.9130	16.9892
p-value	(0.0000)	(0.3934)	(0.0822)	(0.1440)	(0.1082)
lag=50	174.823	35.0616	55.5186	53.2749	40.8431
p-value	(0.0000)	(0.7310)	(0.0650)	(0.0950)	(0.4775)

Note: The $Q_{LB(z_t)}$ -statistic at lag *p* is a test statistic for the null hypothesis that there is no autocorrelation up to order *p*. H_0: No serial correlation and H_1: Presence of serial correlation. Accept H_0 when probability is high [Q < Chi-square (lag)]. *P*-values are adjusted by 2 degrees of freedom.

standardised residuals from the simple mean equation is not rejected even at the 1% level of significance across series – implying that the simple mean equation is an adequate specification in the basic ARCH model structure to remove serial correlation in the raw standardised residuals (but not so in some of the models estimated later). However, autocorrelation persists in the standardised squared residuals at lower lags throughout all series and at higher lags in the USD/ZAR returns series. (Estimates from the optimal GARCH models may prove otherwise - this problem is revisited later in the discussion.)

Table 3.7: Basic GARCH model estimates – endogenously determined returns

Parameter	USD	EUR	GBP	JPY	NEER
		Mean equation			
γ	-0.0275	-0.0096	-0.0715	-0.0010	-0.0317
p-value	(0.0000)	(0.5771)	(0.0113)	(0.9678)	(0.0902)
χ	0.5103	0.6146	0.5843	0.5514	0.5389
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
ϕ	-0.5646	-0.6604	-0.6279	-0.5985	-0.5999
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	0.0114	0.0062	0.0703	0.0039	0.0279
p-value	(0.2580)*	(0.7331)*	0.0487)**	(0.8268)*	(0.3052)*
	Mean equation standardised residuals serial correlation statistic, $Q_{LB(z_t)}$				
lag=10	28.8378	14.5719	17.8068	10.0794	18.4000
p-value	(0.0003)	(0.0680)	(0.0227)	(0.2550)	(0.0184)
lag=20	41.9499	20.1944	33.0761	19.9804	28.6515
p-value	(0.0011)	(0.3220)	(0.0163)	(0.3339)	(0.0528)
lag=50	68.5361	44.7168	67.2312	41.6971	56.5992
p-value	(0.0274)	(0.6082)	(0.0348)	(0.7274)	(0.1848)
	Mean equation squared standardised residuals serial correlation statistic, $Q_{LB(z_t^2)}$				
lag=10	73.1570	3.1239	11.3050	4.5774	14.8487
p-value	(0.0000)	(0.9263)	(0.1850)	(0.8016)	(0.0622)
lag=20	84.2949	8.8865	19.1799	15.0415	22.2696
p-value	(0.0000)	(0.9623)	(0.3808)	(0.6591)	(0.2202)
lag=50	139.942	26.6821	41.8000	38.1899	42.6847
p-value	(0.0000)	(0.9946)	(0.7236)	(0.8437)	((0.6898)

Note: *The* Q_{LB}-statistic at lag *p* is a test statistic for the null hypothesis that there is no autocorrelation up to order *p*. H_0: No serial correlation and H_1: presence of serial correlation. Accept H_0 when probability is high [Q < Chi-square (lag)]. *P*-values are adjusted by 2 degrees of freedom.

* Conditional variance

** Conditional standard deviation (instead of conditional variance to remove serial correlation in the mean equation residuals).

Five specifications of conventional GARCH – symmetric and asymmetric – models are tested; namely, unrestricted GARCH(1,1), IGARCH(1,1), GJR(1,1,1) EGARCH (1,1,1) and APARCH(1,1). To explore some additional basic attributes of the currency returns, the simple GARCH(1,1) equation is initially estimated for each series (Table 3.7). The mean returns for EUR/ZAR, JPY/ZAR and NEER, measured by the constant parameter, γ, are statistically insignificant at the 1% and 5% levels meaning that the zero coefficient null hypothesis cannot be rejected. However, for USD/ZAR and GBP/ZAR, the opposite conclusion is reached, an indication of time-varying mean return. The AR(1) and MA(1) coefficients, χ and ϕ respectively, are statistically significant at the 1% and 5% levels across all exchange rate returns series. A positive mean reversion parameter, χ, suggests that there is a tendency for a high (low) currency return in one period to be followed by a higher (lower) return in the next period; that is, the presence of volatility clustering, highly persistent returns and a short memory process in the level of the returns with a tendency to revert to their long-run average or time-varying mean after an extended period. Ubiquitous negatively signed MA(1) parameters, ϕ, imply that the effect of the shock in period $t-1$ on the return in period t dissipates weakening the combined effect of the current and immediate past shocks on the current return. Separate tests are undertaken for ARCH-M in currency returns variance and ARCH-M in currency returns standard deviation and the results for the mean equation parameter, τ, with the lowest *t*-probability or statistically significant are reported. The ARCH-M model is often used in financial applications where the expected return on an asset, rand holdings by foreigners in this instance, is related to the expected asset risk – the estimated coefficient on the expected risk is a measure of the risk-return tradeoff. Only the GBP/ZAR ARCH-M parameter, τ, is (marginally) statistically significant and at the same time correctly signed (+) at the 5% level, suggesting that the increased risk of converting pound denominated assets into rand holdings is associated with an excess return. However, the latter improved specification is still inadequate to remove autocorrelation in the raw standardised residuals for the USD/ZAR and GBP/ZAR returns – persistence of autocorrelation in these series implies that currency returns are (additionally) being driven by exogenous factors.

Domestic and U.S. interest rates, the interest rate differential, the gold price and the EUR/ZAR are the initial exogenous explanatory candidates used to try to complete the dynamic structure of the USD/ZAR and GBP/ZAR mean equations. In Table 3.8, only the results for the statistically significant parameters of the exogenous form mean equations are reported. The specifications of the mean equation for both the USD/ZAR and GBP/ZAR returns are undoubtedly improved by adding two exogenous explanatory variables – percentage change in the USD gold price (with parameter κ) and percentage change in EUR/USD exchange rate (with parameter ν) – and omitting the AR, MA and ARCH-in-mean explanatory variables. (The exploratory results for the latter variant of the mean equation are not reported here.) For the USD/ZAR returns, both the κ and ν parameter estimates are statistically different from zero and correctly signed – an increase in the US dollar gold price causes rand appreciation against the US dollar,[68] and euro appreciation

[68]However, the relative importance of gold in SA exports declined to around 10% in 2010 from 22% some-odd in 1995.

Table 3.8: Basic GARCH model estimates – <u>exogenously</u> determined returns

Parameter	USD	EUR	GBP	JPY	NEER
Mean equation					
γ	-0.0149	-	-0.0243	-	-
p-value	(0.0213)		(0.0342)		
κ	0.1028	-	0.1072	-	-
p-value	(0.0000)		(0.0000)		
ν	-0.2253	-	0.1850	-	-
p-value	(0.0000)		(0.0000)		
Standardised residuals serial correlation statistic, $Q_{LB(z_t)}$					
lag=10	9.3942	-	9.9273	-	-
p-value	(0.4951)		(0.4468)		
lag=20	23.1197	-	23.6798	-	-
p-value	(0.2830)		(0.2567)		
lag=50	50.4177	-	53.2208	-	-
p-value	(0.4569)		(0.3513)		
Squared standardised residuals serial correlation statistic, $Q_{LB(z_t^2)}$					
lag=10	18.2052	-	12.7700	-	-
p-value	(0.0197)		(0.1200)		
lag=20	25.4075	-	21.0484	-	-
p-value	(0.1141)		(0.2770)		
lag=50	54.3065	-	49.0003	-	-
p-value	(0.2467)		(0.4328)		

Note: *The* Q_{LB}-statistic at lag p is a test statistic for the null hypothesis that there is no autocorrelation up to order p. H_0: No serial correlation and H_1: presence of serial correlation. Accept H_0 when probability is high [Q < Chi-square (lag)]. *P*-values are adjusted by 2 degrees of freedom.

against the US dollar translates into a higher dollar price of rands (the rand generally tracks the euro due to strong economic ties, trade and finance, in particular, between the euro zone and South Africa.[69] The US dollar gold price effect on the pound price of rands emulates that of the euro price of rands. Euro weakness against the rand also produces pound depreciation against the rand – suggesting that the ties between European countries are much stronger than that between South Africa and the European Union. A better specification of the mean equation also reverses (at best) or weakens (at worst) serial correlation. All the above results for the mean equations and standardised residuals mean that the competing GARCH models can now be implemented with greater confidence, mitigating spurious regression results in the sense that the residuals introduced as shocks in the conditional variance equation are obtained from a better specification of the mean equation.

In the remainder of this section, GARCH-type models with more attractive attributes than the basic ARCH model are fitted to the data with a view to investigating the dynamics of each exchange rate returns series. Tables B5 to B9 in Appendix B report the comprehensive estimation results for the competing <u>basic</u>

[69]Gold appears to be (one of) the world's most preferred commodity to store excess liquidity, an inflation hedge and measure of protection against currency debasement.

GARCH-type models: GARCH, IGARCH, GJR-GARCH, EGARCH and APARCH. Mean equation results (top panels of Tables A5-A9) are more or less in line with those in Table 3.7 (for the EUR/ZAR, JPY/ZAR and the NEER) and Table 3.8 (for the USD/ZAR and GBP/ZAR). The autocorrelation in the standardised residuals is remedied by the two different specifications of the mean equation (bottom panels of Tables B5-B9).

The middle panels of Tables B5-B9 report the conditional variance results from the GARCH-type models designed to describe the volatility process of currency returns. With the exception of the EGARCH model, all the estimated ARCH(α_1) and GARCH(β_1) coefficients are significant at the 95% level of confidence. This provides evidence of volatility clustering where positive currency returns tend to be followed by positive currency return changes, and *vice versa*, which reflects the time-varying nature of volatility of currency returns, in particular, and financial asset returns, in general. Also, all θ_2 (magnitude effect parameter) and θ_1 (sign effect coefficient) in EGARCH are significant at the 5% level of significance.

The signs and magnitudes of the symmetric GARCH and IGARCH point estimates – $\alpha_1 = \pm 0.11$ and $\beta_1 = \pm 0.88$ – are generally consistent with their respective values reported in the empirical finance and financial economics literature reviewed (Tables B5 to B9). EGARCH and GJR-GARCH models also capture the asymmetric response of positive shocks and negative shocks to volatility. And, whereas volatility in the standard GARCH(1,1) and IGARCH(1,1) models responds to 'bad news' and 'good news' equally, asymmetric models allow 'good' and 'bad' news surprises to have different impacts on future volatility. In terms of the GJR-GARCH model, asymmetry or the leverage effect enters the conditional variance equation via the indicator or dummy variable, α_1^* (or S_{t-k}^-), that takes the value unity when $\left(\varepsilon_{t-1}^2 < 0\right)$ and zero otherwise. The positive signed α_1^* for all currency returns series when the GJR-GARCH model is implemented makes sense because the impact of negative shocks on volatility is measured by the size of $\alpha_1 + \alpha_1^*$, and α_1 captures the effect of positive shocks; $\alpha_1 > 0$, evident in all GJR model estimation results ensures that $\alpha_1 + \alpha_1^* > \alpha_1$ so that negative shocks have a greater impact on volatility than positive ones. Significant point estimates (at the 1% level) for α_1^* in the GJR-GARCH model confirms the existence of the leverage effect; *albeit* relatively weaker leverage in the USD/ZAR. The weaker asymmetry in the USD/ZAR – measured by the difference between positive and negative shocks – suggests that its news impact curve (NICs) is much closer to a symmetric news impact curve than that of its counterparts. NICs, introduced by Pagan and Schwert (1990) and popularised by Engle and Ng (1993), measure how new information is incorporated into volatility estimates. If information in the pre-$t-1$ periods is held constant, the news impact curve is a metric for analysing the relation between ε_{t-1} (innovations or shocks) and h_t^2 (conditional heteroskedasticity). EGARCH results are derived from the Nelson (1991) specification in equations (3.7) and

(3.8). These results are in line with expectations since positive shocks tend to have smaller impacts. For the EGARCH model, a statistically significant $\theta_1 < 0$ is evidence of a leverage effect. A negative signed θ_1, across all data sets using EGARCH, is in line with expectations since positive shocks tend to have smaller impacts. The absolute value of the parameters $\theta_1 + \theta_2$ in the EGARCH model reflects the magnitude of the positive shocks $\left(\varepsilon_{t-1}^2 > 0\right)$ and the absolute value of the parameters $\theta_1 - \theta_2$ reflects the magnitude of the negative shocks $\left(\varepsilon_{t-1}^2 < 0\right)$. Indeed, $|\theta_1 - \theta_2| > |\theta_1 + \theta_2|$ for all estimated coefficients.

If $\alpha_1 + \beta_1 < 1$, the process ε_t^2 is second order stationary, and a shock to the conditional variance, h_t^2 (or its variants) has a decaying impact on h_{t+k}^2 and is asymptotically negligible. A closer look at the variance equation parameters reveals that $\alpha_1 + \beta_1 \approx 1$ for the GARCH(1,1) and GJR-GARCH(1,1) model results for almost all currency return volatilities; that is the conditional variance of currency returns are approximately nonstationary indicating that volatility shocks are highly persistent. This result is often observed in high frequency data when structural breaks are not accounted for. However, $\varepsilon^+ : \alpha_1 + \beta_1 = 0.9282$ for positive shocks to JPY/ZAR returns in the GJR model suggests its variance is mean reverting but the rate of decay of shocks is very slow (Tables B5-B9). When structural shift is ignored, overall, the results are consistent with some of the empirical work; that is, currency return volatility is also highly persistent when the symmetric GARCH(1,1) model and the (simpler) asymmetric GJR-GARCH(1,1) models are applied to financial asset and currency returns data. Also, the much higher EGARCH values for $\alpha_1 + \beta_1$, significantly above unity, corroborates Engle and Ng (1993) findings that the EGARCH model is found to lead to a conditional variance that is too high and more volatile than the GJR-GARCH, although it captures most of the asymmetry – the EGARCH model is more appropriate for capturing heightened short-term volatility during a crisis. The respective APARCH model estimates lie between the latter two sets of estimates – the statistically significant power transformation parameter, δ, in APARCH suggests that the power transformation identified by APARCH is suitable for all the data;[70] but not necessarily the best. 'Best fit' model ranking is explored in sub-section 3.5.4 only after taking into account structural shift.

Fat tails and asymmetry are evident in the error distributions regardless of the model applied or time series estimated (Tables B5-B9 in Appendix B). The extremely low R^2 and adjusted-R^2 statistics are not meaningful if there are no exogenous regressors in the variance equation which is the case here, and are thus not reported.[71]

[70]One limitation of GARCH-type modelling is that its techniques do not easily capture wild, spurious swings in a return series. In Appendix B (Figures C1 to C3), an extreme spike on 16 October 2008 (observation 3396), evident in all the returns series led to non-convergence in one of the exploratory estimations for JPY/ZAR.

[71] Low R^2 are consistent with standard volatility time series models using highly volatile and stationary series; the primary reason for the low r-squared is the noise in the volatility measure. Negative r-squared (though small in absolute terms) is

3.5.3 Long memory and structural change: GARCH model estimations and results

High volatility persistence suggests alternative approaches can be explored – long memory or structural breaks. The motivations for each of these methodologies have already been presented in subsections 3.3.2.3 and 3.3.2.4 above. Beine and Laurent (2000) integrate these approaches and show that both features are necessary in a single model to capture the short term dynamics of exchange rate volatility. Their empirical results provide evidence of a strong interaction between long memory and structural change but find that these two salient features in time series exchange rate data are imperfect substitutes in the sense that both characteristics are necessitated to capture all of the observed persistence in volatility.

Although the DGP may not be exactly identical across financial time series, Ding *et al.'s* (1993) finding of positive autocorrelations over fairly long periods in the S&P500 Index is also evident in the exchange rate data in panel diagrams C5 and C6 (in Appendix B). The slow rate at which volatility tends to change over time and the considerable time it takes for shocks to decay means that distinguishing between an *I(0)* process (the transmission of shocks occurs at an exponential rate of decay) and an *I(1)* process (propagation of shocks is infinite) is too restrictive. Baillie *et al.* (1996) introduced the FIGARCH-type model to bridge this gap and thus better capture the observed volatility – long memory behaviour with finite persistence of volatility shocks and a hyperbolic or slow rate decay. Here, the GARCH, EGARCH and APARCH fractional integration models are estimated for exchange rate returns. The GJR does not appear to have been extended to the long-memory framework but is nested in the FIAPARCH class of models. A statistically significant long-memory parameter, *d*, as is shown below, indeed improves the modelling of exchange rate volatility.

One purpose of estimating the mean, ω, in the variance equation is to calculate the constant unconditional variance or volatility, ${}_u\sigma^2$. In tables B5 to B9 (in Appendix B), the null hypothesis that the unconditional variance is constant is rejected in all instances, a justification for modelling volatility with structural shift parameters. As a precursor to, and an additional motivation for estimating GARCH model variants that account for structural change, Nyblom's parameter stability test (Nyblom, 1989) and adapted by Hansen (1990) to test for parameter instability or time invariance of parameters in nonlinear models is examined. The Nyblom test can be used to verify the constancy of the mean and variance equation parameters, and the error distributions. The test is a test of the null hypothesis that all the parameters Φ_i in the conditional mean and variance equations for currency returns *i* are constant against the alternative that the

common in ARCH and GARCH modelling. In other words, low *r*-squareds are not an anomaly, but rather a direct implication of standard volatility models (Anderson and Bollerslev, 1998[b]). R-squared can also be negative for a number of other reasons, including, for example, if the regression does not have an intercept or constant, if the regression contains coefficient restrictions, or if the estimation method is two-stage least squares.

parameters Φ_i follow a martingale process.[72] Using a variant of Kang's (1999) notation, and explanation for the Nyblom-Hansen (NH) test, the test statistic NH_i is represented by the following specification:

$$NH_i = \frac{1}{T}\sum_{j=1}^{T} S_j \Omega^{-1} S_j \,, \qquad i = 1,\ldots,8, \tag{3.33}$$

where

$$S_j = \sum_{i=1}^{j} \frac{\partial l_t(\Phi_i)}{\partial \Phi_i}, \tag{3.34}$$

$$\Omega = \sum_{t=1}^{T} \frac{\partial t_t(\Phi_i)}{\partial \Phi_i} \frac{\partial l_t(\Phi_i)'}{\partial \Phi_i}, \tag{3.35}$$

and

$$l_t(\Phi_i) = -\frac{1}{2}\ln h_t^2 - \frac{\kappa_i + 1}{2}\ln\left(1 + \frac{\varepsilon_t^2}{(\kappa_i - 2)h_t^2}\right) + \ln\left(\frac{\Gamma(\kappa_i + 1/2)}{\Gamma(\kappa_i/2)\sqrt{\pi(\kappa_i - 2)}}\right). \tag{3.36}$$

Nyblom (1989) and Hansen (1990) tabulate the asymptotic distribution of the NH_i statistic, which is a function of the parameters Φ_i only; Table 1 in Hansen (1990) tabulates the asymptotic values for the joint parameter test statistic. The *k^th^* individual parameter in the mean and conditional variance equations and error distribution parameters (tail and asymmetry) can be tested with the statistic

$$NH_{ik} = \frac{1}{T}\sum_{j=1}^{T} S_{kj}^2 / \Omega_{kk} \,, \qquad i = 1,\ldots,8, \tag{3.37}$$

where S_{kj} is the k^{th} element of S_j and Ω_{kk} is the k^{th} diagonal element of S_{kj}. We do not reject the null of parameter stability if the Nyblom statistic for a parameter is less than the critical value; the asymptotic 1% and 5% critical values are reported in the bottom of Tables B5 to B9 (in Appendix B). The null is the parameter is stable or constant, that is, there is no structural change. All the Nyblom test statistics obtained from the basic

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[72] A simple yet rigorous definition of a martingale process is one that, in the mean, does shift up or down with time. So, the Y_t, in terms of mean-square values, is the best predictor of Y_{t+1}.

symmetric and asymmetric GARCH model in Tables B5 to B9 (in Appendix B) unambiguously indicate joint instability in all the model parameters and justify extending the basic models to incorporate structural shift.

The strong and widespread evidence of instability in the variance equation parameters motivates fitting A-GARCH- and SSC-GARCH-type models to the currency returns series. Tables B10 to B14 (in Appendix B) report the estimation results for the A-FIGARCH-type model – accounting for both long memory and smooth transitional structural change. The mean equation estimation results are uniform to those produced by the simple GARCH models in tables B5 to B9 (in Appendix B) – the signs of the parameters remain the same whilst the sizes of the coefficients, standard errors and *p*-values are only marginally different. The long memory parameter (*d-FIGARCH*) is statistically significant at the 99% level of confidence across the board – confirming long-run dependence behaviour evident in financial asset nominal prices. The most appropriate flexible functional form (trigonometric function) used to capture smooth structural changes varies across both currency returns and models. Here, only the results for the significant ones are reported. Perhaps the most crucial findings are that the unconditional variance (or long-run variance), ${}_u\hat{\sigma}^2$, is no longer nonstationary when long memory and smooth structural change are accounted for in the simple GARCH framework; the unconditional variance of positive shocks now also appears stationary when the less extreme asymmetric APARCH is applied but unconditional variance remains nonstationary for negative shocks in the APARCH model and in the extreme EGARCH model, regardless of the shock sign (except for yen/rand series); *albeit* lower. The stationarity or nonstationarity of the unconditional variance (or long-run variance) is also captured by the volatility persistence statistics, $(\alpha_1 + \beta_1)$ in the symmetric models, and $\alpha_1 + \alpha_1^* + \beta_1$, $|\theta_1 + \theta_2| + \beta_1$ and $|\theta_1 - \theta_2| + \beta_1$ in the asymmetric models (Tables B5-B16 in Appendix B). The conditional variances for each of the above models (which describe the short-run dynamics) still follow a GARCH process; that is, are heteroskedastic even in the presence of long memory and structural change. The flexible functional form has not yet been extended to the GJR-GARCH framework.

Next, we present and analyse the SSC-GARCH estimation results. Although the Nyblom test can be informative about the type of structural change (detect whether the structural change is in the mean and/or variance equations parameters), and the A-GARCH-type models flexible functional form captures smooth structural change, neither one identify the actual break points as required by the SSC-GARCH models. Estimation of the SSC-GARCH models is a four-step procedure. First, the breakpoints of the different volatility regimes are identified in the residuals of the mean equations using the ICSS, κ_1, and κ_2 tests (discussed in sub-section 3.3.2.4). The variance equations are then extended with dummy variables regressors to capture the latter breakpoints. The SSC-GARCH model is then estimated with all the breaks identified in the latter set of tests, and then re-estimated with only the statistically significant breaks that influence conditional variance. Table 3.9 reports the number of change points identified by the ICSS procedure. Although the κ_1 and κ_2 structural break point tests detect a substantially lower number of breaks (not reported here), the number of statistically significant breaks that influence variance uncovered by the ICSS exceed those from the latter two more rigorous tests. To begin from a more general situation, estimation thus progresses employing the significant ICSS shifts in the conditional variance equation. The largest number of breaks, in absolute terms, are identified in the US dollar/rand series with the yen/rand returns detecting the least – less than 50% of those in the US dollar/rand data. Relatively speaking, for each data series, statistically significant variance equation breakpoints range between 73% to 83% of the total change points identified - the euro/rand and US dollar/rand are the extrema – suggesting that the ICSS tests are still quite robust in the presence of non-normality in the disturbances.

Table 3.9: ICSS test breakpoints

Structural breaks	USD/ZAR	EUR/ZAR	GBP/ZAR	JPY/ZAR	NEER
Identified	44	37	38	20	37
Statistically significant*	36	27	29	16	28

* At 90% or more levels of confidence (in GARCH variance equations).

Tables B10 to B14 (in Appendix B) report the adaptive-GARCH models regression estimates. The SSC-GARCH models results are presented in tables B15 to B16. When attempting to estimate the SSC-GARCH models incorporating fractional integration, no convergence is achieved using numerical derivatives. Algorithms often encounter problems in locating the maximum likelihood estimates which is unsurprising in this instance given the large number of structural shifts – 16 to 44 breaks. The problem of no convergence also arises in the more complex and demanding asymmetric EGARCH and APARCH models. An extreme difficulty in convergence may be an indication that the model chosen is too complex and does not describe the data well and hence the most effective way of avoiding convergence problems is to select a simpler model that adequately describes the data. Silva and Tenreyro (2011) argue that although in some cases it is not possible to bypass this problem using some sort of data transformation, using different optimisation methods or specifications can address the problem. Even when estimating the SSC-GARCH and SSC-GJR-GACH models without fractional integration, in some cases, the inclusion of endogenous and exogenous variables in the mean equation also lead to nonconvergence. Using both comparative frameworks, $\alpha_1 + \beta_1$ for positive shocks and $\alpha_1 + \alpha_1^* + \beta_1$ in the case of negative shocks are much lower for the SSC-GARCH models than those produced by the adaptive-GARCH models (in Tables B10 to B14, Appendix B) suggesting that models with the shifts observed in the data are better approximated by abrupt structural change as opposed to smooth structural change.

3.5.4 Information criteria and 'best-fit' model selection

Although no universally agreed methodology exists for selecting a 'best-fit' model amongst a set of standard and sophisticated GARCH models, there are numerous sets of tools and methods that can be applied. A simple approach is to enumerate a number of different models and to compare the regression results. The 'best' model from the set estimated is one that is best capable of reproducing the actual volatility. A longstanding common practice is to select the model with the biggest log likelihood and smallest information criterion values. In the voluminous literature on ARCH and GARCH modelling, the information criteria include the Akaike's information criterion (AIC) proposed by Akaike (1974, 1976), the Schwarz's information criterion (SIC) proposed by Schwarz (1978), and the Hannan-Quinn criterion (HQC) proposed by Hannan and Quinn (1979), among others; since the Schwarz information criterion is derived using Bayesian arguments, this criterion is also known as the Bayesian Information Criterion (BIC). The basic information criteria are defined by the following equations:

$$AIC : -2(l/n) + 2(k/n) \tag{3.38}$$

$$BIC : -2(l/n) + 2\log(n)/n \tag{3.39}$$

$$HQC : -2(l/n) + 2k(\log(n))/n \tag{3.40}$$

where l is the value of the log of the LL function with the k parameters estimated using n observations. The various information criteria are all based on -2 times the average log likelihood function, adjusted by a penalty function. Selecting the optimal model for a time series data set is obviously a crucial one, as selecting a suboptimal model could incorrectly classify the data set, consequently rendering any forecasts unreliable, and even invalid. The Kullback-Leibler (1951) quantity of information contained in a model is the distance from the 'true' model and is measured by the *LL* function. The notion of an information criterion is to provide a measure of information that strikes a balance between this measure of goodness-of-fit and parsimonious specification of the model. The various information criteria differ in how to strike this balance. When estimating model parameters using MLE, it is possible to increase the likelihood by adding more parameters, which may result in overfitting. The SIC (or BIC) resolves this problem by introducing a harsher penalty term for the number of parameters in the model. This penalty for additional parameters is stronger than that of the AIC; the AIC may asymptotically overshoot the correct number of parameters (Shibata, 1976). The Hannan-Quinn criterion (HQC) differs from BIC with respect to the penalty term; the HQC penalty is less severe than that of the BIC. In this paper, the information criterion to be minimised is the BIC since it benefits parsimony (simpler models), which is desirable in econometrics.

Longmore and Robinson (2005), however, contend that since the statistical properties and hence reliability of the above information criteria, which focus on the estimation of loss functions, are unknown in the context of time varying volatility, such loss functions (LF) depend on the squared residuals and the variance when applied to models with time varying volatility. One such measure proposed by Longmore and Robinson (2005) is:

$$LF = \sum_{t=1}^{T} \left[\ln\left(\varepsilon_t^2 \sigma_t^{-2} \right) \right]^2 . \tag{3.41}$$

Tables B17 to B21 (in Appendix B) report the comprehensive model selection criterion results and rankings, and their unconditional variance or volatility persistence statistics, $(\alpha_1 + \beta_1)$. Across all five exchange rates, the BIC and log-likelihood statistics rankings are more or less congruent. However, the loss function (LL) ranking statistics are inconsistent with the BIC and log-likelihood statistics for the USD/ZAR and consequently, the NEER as well. Table 3.10 extracts the key statistics from the loss function (LF) based on the squared residuals and variance – an apposite model selection criterion for time-varying volatility. The top

Table 3.10: Loss function statistic model rankings*

Model	USD/ZAR	EUR/ZAR	GBP/ZAR	JPY/ZAR	NEER
GARCH	10	8	10	7	9
IGARCH	4	10	9	10	4
GJR-GARCH	9	9	8	9	10
EGARCH	7	6	7	4	6
APARCH	8	7	5	8	7
A-FIGARCH	3	4	3	3	3
A-FIEGARCH	6	5	4	6	8
A-FIAPARCH	5	2	6	5	5
SC-GARCH	1	3	2	2	1
$\alpha_1 + \beta_1$: +/- shocks	(0.4835)				(0.6099)
SC-GJR-GARCH	2	1	1	1	2
$\alpha_1 + \beta_1$: + shocks		(0.5929)	(0.6009)	(0.6868)	
- shocks		(0.7095)	(0.7275)	(0.8511)	

* '1' is best, '2' is the second best, and so forth.

three approximating models – across the board – reflect the importance of long memory, asymmetry and structural change – both abrupt and smooth – in exchange rate volatility modelling (the SC-GJR-GARCH model ranks highest for the EUR/ZAR, GBP/ZAR and JPY/ZAR exchange rates, and the SC-GARCH model ranks highest for the USD/ZAR exchange rate and the NEER). A consequence of accounting for this phenomena is that unconditional variance, $(\alpha_1 + \beta_1)$, is stationary in stark contrast to the simpler models which produce a unit root, thus nullifying the spurious results that suggest that the volatility process is not mean reverting.

Plots of the conditional volatility estimates for the highest ranked model for each of the five exchange rates over the sample period are given in Figure C11 (in Appendix C). To a large degree, the conditional volatilities mirror the squared returns, r_t^2, in Figure C1 (in Appendix C). Common conditional volatility processes seem to be present across all five exchange rates with heightened volatility around the 1998 emerging market crisis, the global market turmoil on the back of terrorist attacks on the US in September 2001, concerns about SA's widening current account deficit in 2004, and most notably during the 2008 US sub-prime mortgage crisis.

One of the crucial findings in this study are drawn from a comparison of this chapter's US dollar/rand results applying the SSC-GARCH model with those of Duncan and Liu (2009) for the same model and frequency, and a fairly similar sample period 3 January 1994 to 31 March 2009 (3794 observations) – the sample period in this study covers the period 14 March 1995 to 31 August 2010 (3864 observations). Duncan and Liu (2009) detect 19 significant shifts in the volatility of the rand with 16 of these having a statistically significant effect on the variance in contrast to 44 breaks and 36 significant ones identified in this study. Consequently, and in line with expectations, the volatility persistence value $(\alpha_1 + \beta_1) = 0.4835$ in this paper is substantially lower than the comparative value of 0.6903 estimated by Duncan and Liu (2009). The differences in the volatility persistence outcomes can be linked to a number of factors. The main suspect is the divergence in the level of statistical significance and consequently the critical *t*-statistic values yardsticks used in the ICSS tests of the two comparative studies – we apply an asymptotic critical value of $D_{0.05}^* = 1.358$ (a confidence level of 95%) compared with $D_{0.01}^* = 1.628$ (99% confidence level) in Duncan and Liu (2009). Other possible minor influences are the slightly different sample periods, different specifications of the mean equations resulting in different sized regressor shocks (ε_t^2) in the variance equation and an application of the skewed Student-*t* distribution in our analysis which may differ from the one employed by Duncan and Liu (2009). Additionally, their data was sourced from the I-net Bridge databank – here, the data was obtained from the SARB database. Also, this paper analyses the US dollars per rand returns whilst Duncan and Liu (2009) investigate the rands per US dollar returns. A number of other differences cannot be ruled out. In a recent study, Thupayagale and Jefferis' (2011) surprisingly uncover only four to six volatility regime shifts in the nominal exchange rates of the rand against the G4 currencies for a much larger sample period (January 1990 to November 2010) that encompasses both Duncan and Liu's (2009) and our sample. Both the latter studies employ the methodology of Bai and Perron (1998, 2003[a,b]).

Very briefly, Bai and Perron (2003[a]) use an efficient algorithm to obtain global minimisers of the sum of squared residuals based on the principle of dynamic programming which requires at most least-squares operations of order $O(T^2)$ for any number of breaks. They, however, caution that care must be taken when using particular specifications; for example, the tests can miss the true break values too often which perhaps explains the massive structural change detection gap in their study and Duncan and Liu (2009) and our empirical analysis.

In the remaining section of the empirical results (section 3.6), the timing and potential causes of structural shift are explored and compared with those in the unit root AR processes of the raw returns in chapter 2.

3.6 Descriptive analysis of structural breakpoints

From Table 3.9 in the preceding section, volatility regime switching is less frequent in the yen/rand but more frequent in the US dollar/rand. Table B22 in Appendix B presents the timing of each change point identified by the ICSS test that has a significant bearing on variance at the 90% level of confidence. To explore the number of breaks that coincide across series, a maximum interval lag of 5 business days is allowed for. Initially focusing on the four bilateral rates only, there is not a single common breakpoint across the four bilateral exchange rates, 10 common change points in three bilateral rates, and 14 in two bilateral rates. Twenty shifts in the weighted exchange rate coincide with one or more breaks in the bilateral rates. Overlapping breakpoints are more prominent in the US dollar and the two European currencies' bilateral exchange rates of the rand.

The duration of the volatility regimes ranges between 3 and 777 business days, and not surprisingly, the US dollar/rand records the shortest regime and the yen/rand the longest – the latter may be explained by the Bank of Japan's interventions aimed, in part, at dampening the effects of shocks on yen volatility. Trailing the yen/rand, there is also relatively greater tranquillity in the euro/rand – the currency of South Africa's major trading partner in both goods and financial assets.

Reverting to the 10 change points which are pervasive – occur across three bilateral exchange rates – Table 3.11 below ties up these break points with important economic and non-economic events. The timing of these particular changes in volatility regimes are more or less consistent with the structural shifts detected in the changes in the levels of the exchange rates in in chapter 2. The number of change points discovered in the levels is significantly less due to the limitations of the estimation models applied in chapter 2 as opposed to the ICSS tests applied in this chapter – individual structural break adapted unit root tests in chapter 2 detect a maximum of two break points. The coincidence of structural shifts in both the levels and volatility of returns implies that a sharp movement in the exchange rate is usually or often accompanied by volatility as

Table 3.11: Common structural shifts in rand volatility – timing and potential triggers

Dates	*Shocks*
12-14 Feb 1996	# Rand suffered a speculative currency attack – followed by a shift in SARB's intervention policy in foreign exchange market
13-14 May 1996	# Moderation in volatility as relative market stability returns following currency crisis in February 1996
23 Oct 1996	# Rumours of an imminent relaxation of exchange controls triggers another speculative attack on the rand following a brief interlude of relative stability
22-27 Oct 1997	# Adverse effects of Southeast-Asian financial markets contagion which erupted in July 1997 in Thailand
10-11 Jun 1998	# Nervousness about prospects for emerging markets –Southeast-Asian financial markets contagion continued to spread to other emerging markets in April and May 1998
21-22 Jul 1998	# Rand instability elevated further as concerns about financial troubles in Russia surface – exacerbated by a build-up in SA's net open forward position (NOFP)
04-09 Feb 1999	# Markets settle somewhat after Brazilian real crisis in January 1999
24-28 Jan 2002	# Tranquillity in foreign exchange market following a string of events that unnerved the currency in 2001 – concerns about domestic fundamentals, anticipated policy shifts, rumours, declining commodity prices, and global financial market turmoil due to terrorist attacks on the U.S. in September
12-13 Jul 2005	# Positive international credit rating agencies' upgrades and outlooks for South Africa reduce rand volatility
02-03 Oct 2008	# 2007-2008 US financial market crisis spillover effects on rand

well – that is, large movements in exchange rates when their exact timing is unanticipated causes uncertainty and thus nervousness in the market. Bidirectional causality is not only plausible but likely as investors and speculators offload foreign assets whose prices suddenly become erratic leading to a plunge in the foreign currency's international price. The next chapter addresses one dimension of this financial market phenomenon - the impact of macroeconomic news (shocks) on exchange rate volatility around the timing of the announcement.

3.7 Concluding remarks and discussion

Exchange rate volatility – a manifestation of uncertainty – and its causes and effects is arguably the most topical issue in international finance in the post-Bretton Woods era. The analysis undertaken in this chapter motivates the use of ARCH-type volatility models for the rand exchange rates, estimates the standard models for these rates and replicates common findings in the literature that volatility is 'persistent'. It investigates whether this 'persistence' is due to structural breaks or long memory, and identifies the 'best fit' volatility model for each of the five nominal exchange rates of the rand examined.

The data sample spans a more flexible exchange rate regime in South Africa. The descriptive statistics in the preliminary analysis of this chapter confirm some of the stylized facts about nominal financial time series such as leptokurtic distributions, ARCH effects – autocorrelation and heteroskedasticity – and volatility clustering of risky assets returns, indicating that the data are candidates for GARCH-type modelling. Furthermore: i) Nyblom parameter stability and ICSS test results indicate strong and widespread instability in conditional volatility – between 20 and 44 breakpoints are detected, more than double the amount of statistically significant structural breaks in the conditional variance than those uncovered in a recent study on the US dollar/rand exchange rate returns, for a similar period, by Duncan and Liu (2009); ii) volatility persistence falls markedly when fractional integration and a larger set of structural shifts are accounted for; iii) the top three approximating models across the board reflect the importance of long memory, asymmetry and structural change, both abrupt and smooth, in exchange rate volatility modelling; iv) a consequence of accounting for the latter phenomena is that unconditional variance, $(\alpha_1 + \beta_1)$, is stationary in contrast to the most of the simpler models estimated which suggest a unit root, supporting the view that results that find that the volatility process is not mean reverting are spurious; v) although the sudden structural shift GARCH models better fit the data than the smooth transitional competing models, the latter modelling framework does not perform considerably worse and is a notable improvement on the basic models; and, vi) the timing of changes in volatility regimes, and thus their likely causes, are more or less consistent with the exchange rate level shifts detected in chapter 2.

Therefore, accounting for long memory, asymmetric responses to shocks, and in particular, structural change, in the variance of the currency returns of the rand has produced some novel and striking evidence that advances work undertaken over the past decade or so on the nominal exchange rates of the rand. This study will hopefully serve as a catalyst in fostering research on further improving the parametric modelling of historical volatility and the volatility predictive power of ARCH-type models. Then, the question of whether rand volatility is excessive remains a perennial issue that also requires rigorous investigation. The rand's asymmetric response to news – negative shocks raise volatility more than positive ones of equal magnitude – also prompts an inspection of the effect of macroeconomic announcements on the foreign exchange rates of the rand around the time of the announcement. In the next chapter, the response of the rand to monetary policy pronouncements, under different monetary policy frameworks and exchange rate regimes, is explored using high-frequency minute-by-minute exchange rate data.

3.8 Software

EVIEWS 6 for summary statistics and unit root tests

OxMetrics 6.1 for GARCH model estimations

R 2.14.1 for detecting structural breaks

CHAPTER 4

Do monetary policy announcements affect foreign exchange returns and volatility? Some evidence from intra-day high-frequency South African data

4.1 Introduction

Analysing the response of nominal exchange rates – in terms of their level and volatility – to economic and noneconomic news, in developed and emerging markets, has become a very active research area in international finance over the past decade or so. This chapter examines the behaviour of the rand/US dollar exchange rate in reaction to domestic monetary policy announcements. The study uses high-frequency intra-day (one-minute-slice) exchange rate data from 2003 to 2013. In particular, the chapter examines how the rand/dollar exchange rate digests information contained in the surprise component of scheduled repo rate announcements – how soon the exchange rate responds to this news, to what extent the exchange rate reacts and how long the news effect lasts. The "surprise" or unexpected component of the repo rate announcement is defined here as the difference between the actual rate announcement and the market consensus median rate forecast.

Virtually everyone that is interested in financial markets seems to agree that rapid movements and heightened volatility cause many problems.[73] Concerns about the undesirability of elevated volatility in the external value of the domestic currency are highlighted in a number of recent studies and government policy documents, for example: the Accelerated and Shared Growth Initiative of South Africa (ASGISA) policy framework (The Presidency, 2006) which incorporates some of the final recommendations to the South African government and the SARB by the International Growth Advisory Panel (the so-called Harvard University-led group) (Hausmann, 2008); firm surveys by the Employment, Growth and Development Policy Unit (EGDPU) of the Human Sciences Research Council (Altman, 2007); the Corporate Strategy and Industrial Development (CSID) Research Programme at the University of the Witwatersrand (CSID, 2005); the Banking Banana Skins Survey conducted by the Centre for the Study of Financial Innovation (CSFI) (CSFI, 2008); and the Myburgh Commission's investigation into the collapse of the rand in 2001 (Myburg, 2002). Market participants attentively monitor macroeconomic announcements; and so do economics and financial journalists.[74]

An 'event study' methodology is used here to investigate the reaction of the rand/US dollar exchange rate – the returns and their volatility – to unexpected changes in the policy variable (the repo rate) around the time of the monetary policy announcement. In some respects, this study follows that of Fedderke and Flamand (2005) which tests the significance of macroeconomic news surprise effects, including monetary policy shocks on the rand exchange rates between 2001 and 2004, using daily data. This chapter contributes

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[73] Exchange rate volatility and exchange rate misalignment are not equivalent. Misalignment occurs when the exchange rate deviates from its (long run) equilibrium level predicted by macroeconomic fundamentals, resulting in substantial external and internal imbalances. By contrast, exchange rate volatility, one dimension of this study, is a short-term phenomenon. In the context of a 70-minute or shorter window period, exchange rate volatility emanating from news shocks has little relevance in terms of economic effects if it does not alter exchange rate future expectations and thus result in a revision of other economic fundamentals forecasts.

[74] The importance of monetary policy news on exchange rates is manifest in the following news headline excerpts: "Rand weakens on rates hike" (Business Day, 2014) and "Rand steady, awaits rates decision" (Business Day, 2014).

to the South African literature on exchange rate responses to monetary policy repo rate announcements in three ways. This is the first such study on South African interest rate announcement effects using intra-day high-frequency (minute-by-minute) exchange rate data; Fedderke and Flamand (2005) employ daily exchange rate data.[75] Second, in addition to estimating the currency returns reaction function, volatility responses are also considered. And thirdly, this study covers a much longer period of the inflation targeting regime – 2003 to 2013 – allowing more time for the SARB's inflation targeting framework to become entrenched.

Three key empirical questions that this analysis attempts to answer are: a) How do the returns of the rand/dollar exchange rate respond to shocks in scheduled domestic MPC repo rate announcements? b) Do these repo rate surprise announcements also elevate rand/dollar volatility? and, c) How much of the fluctuations in returns and volatility in the rand do monetary policy 'surprises' account for (or explain)? Our findings are as follows. We find both statistically and economically significant responses of the level and volatility of the rand returns to repo rate shocks but anticipated changes have no bearing on the rand. Our estimation results suggest that monetary policy news is an important determinant of the exchange rate in the immediate 20 minutes after the estimated time of the pronouncement. The relatively rapid rate of exchange rate response to a 100-basis-point hike 5-minutes post-event – elevated returns peak within 30 minutes post-announcement and volatility subsides about 40 minutes following the event – suggest a relatively high degree of market efficiency in this event study context. Here we mean the word "efficient" only in a mechanical sense – communications are speedy and exchange rates adjust rapidly to new unanticipated announcements – and not "efficient" market in the deeper economic-informational sense. The non-instantaneous response based on the 5-minute window may be attributed to inconsistent event times or an initially less swift price adjustment as market participants absorb the information and revise expectations.

The structure of the paper is as follows. Section 4.2 provides an overview of exchange rate models – a basis for the event study. A literature review on the empirical relationship between monetary policy and exchange rates is discussed in section 4.3. An overview of the inflation targeting framework, workings of the repo rate system in South Africa and changes that were made over time is presented in section 4.4 followed by a description of the proposed methodology – an event study – and the justifications for this approach. Section 4.6 discusses data issues and the preliminary data analysis results. Next, the empirical findings – regression and graphical results on the responsiveness of the rand to monetary policy surprises – are analysed and compared with those in recent studies on the exchange rates of the rand and other major currencies. The relative extent of market efficiency in its mechanical sense is also inferred from the data and econometrics results. Section 4.8 concludes.

[75] Farrell *et al.* (2012) also use high-frequency data but look at South African inflation and not interest rate surprises.

4.2 The economics of exchange rates: A synopsis

Theoretically, changes in the levels and second moments (variance or volatility) of exchange rates are driven by a broad set of factors – both microstructural and macroeconomically-caused shifts. Here, we explore broad theoretical economic-exchange rate levels frameworks – with a supplementary and more focused discussion on interest rate-exchange rate modelling, followed by a narrative of hypothesised exchange rate volatility responses to monetary policy surprises (and macroeconomic shocks in general). As a brief final point, some light is shed on advances in exchange rate modelling.

Taylor (1995) argues that macroeconomic fundamentals are clearly important in setting the parameters within which the exchange rate moves in the short term, but they do not appear to tell the whole story. While short-horizon changes tend to be dominated by noise, this noise is apparently averaged out over time, thus revealing systematic exchange-rate movements that are determined by economic fundamentals in the long run. Whilst a substantial amount of historical econometric exchange rate modelling focused on long run relationships, much progress has been made in recent years on macro fundamentals explanations of short-term exchange rate movements. In particular, macroeconomic announcements, be it local or foreign government statistical agencies' news releases, are the source of some of the fluctuations in exchange rates around the time of the data or information broadcast.

Evans (2011) examines the total spot exchange rate responses to macro news releases from two perspectives – the traditional macro-based view of exchange rate determination and a micro-based perspective. Macro exchange rate models predict that macro announcements can potentially affect spot rates though three channels. First, the domestic currency will depreciate if the data release causes an unanticipated rise in the current risk-adjusted real interest rate differential.[76] An immediate depreciation of the local currency if the expected differentials are revised upwards is the second channel through which the macro information announcement affects the exchange rate. The third channel is the changing long-term real exchange rate expectations in response to the data release.[77] In summary, data releases that contain new information on current and future macro variables will affect the exchange rate provided that the information communicated in the release does not have offsetting effects on the risk-adjusted interest rate differentials through the three channels.

The micro-based models show how macro announcements affect both high intra-day and low daily and weekly frequency spot exchange rates by changing the structure of information about the macroeconomy available to traders and other market participants. Here, three channels are also identified through which data releases might affect the dynamics of the spot exchange rate and order flows.[78] As long as the data release

[76] The current risk-adjusted real interest rate differential is the foreign real interest rate *minus* the domestic real interest rate *plus* foreign exchange risk premium. See Evans (2011) for the detailed model and explanations.
[77] This channel is shut down if purchasing power parity (PPP) holds in the long run.
[78] Order flow or transaction flow occurs when someone believes the price of a security will move and then decides to execute an order (transaction) in the market.

contains financial asset price-relevant information, but the information is not clear-cut, dealers undertake risk-return analysis of providing liquidity to the market and adjust their spot quotes accordingly to reflect the new information. Consequently, order flows – long and short currency positions – ensue causing traders to adjust their quotes yet again. At length, three channels through which the releases affect spot rate quotes and order flows are identified. First, spot rates respond immediately to the shock if the release contains common knowledge information;[79] a channel that is operable only if everyone agrees on the price implications of the news. The second channel is through the quotes and order flow responses to dispersed information shocks.[80] Finally, the process through which the dispersed information is impounded into prices is the third channel. Evans and Lyons (2008) find that approximately one-third of the effect of a macro announcement is transmitted directly into the US dollar/Deutschemark spot rate and two-thirds is transmitted indirectly through order flows.

With particular emphasis on exchange rate reactions to monetary policy surprises, the main focus of this study, Kearns and Manners (2006) provide two reasons why an understanding of the interest rate impact on exchange rates is important: i) to test the validity of the uncovered interest parity (UIP) condition; and, ii) the vital monetary transmission channel role of exchange rates in small open economies. The basic UIP condition, a key economic theory governing exchange rate predictions, is represented by the equation

$$i_t - i_t^* = \frac{\Delta s_{t+1}^e}{s_t}. \tag{4.1}$$

where i_t and i_t^* denote the domestic and foreign interest rates, respectively, s_t is the direct spot exchange rate of the domestic currency (amount of units of domestic currency required to purchase a unit of foreign currency), and $\Delta s_{t+1}^e (= s_{t+1}^e - s_t)$ is the expected change in the spot exchange rate between periods t and $t+1$. Equation (4.1) is interpreted as the interest rate differential equals the expected appreciation or depreciation of the foreign currency when UIP holds. The prediction of UIP, *ceteris paribus*, is that if domestic interest rates, i_t, are higher than foreign interest rates, i_t^*, the domestic currency should appreciate, relative to the foreign currency, in order to equalise returns. Macroeconomic models that incorporate rational expectations, such as Dornbusch (1976), typically predict an immediate sharp appreciation in the domestic currency in response to a surprise domestic monetary tightening in order for the domestic currency to subsequently depreciate in line with UIP in the long-run.

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[79] Evans (2011) defines the 'common knowledge' component of a shock as that part of the surprise that represents unambiguous (or precise) price-relevant information that is simultaneously observed by everyone and impounded fully and instantaneously into dealers' spot rate quotes. This shock affects spot rates instantaneously and directly.

[80] A dispersed information shock is one which is viewed by different agents as having different price implications.

Monetary policy surprises (and macroeconomic shocks in general) have also been theoretically and empirically identified as one of the sources of exchange rate volatility. The volatility effects of announcements can be explained using theories on the microstructure of the foreign exchange market. On the basis of a simple descriptive theoretical model, Moosa and Shamsuddin (2003) argued that exchange rate volatility can be explained in terms of the heterogeneity of traders with respect to their currency trading – buying and selling – strategies. The broad strategy categories are based on expectation mechanisms, trading rules and fundamentals. Within these broad categories, traders can be classified into 19 different types.

> "The model is based on the idea that observed exchange rate volatility can only result from erratic shifts in the market's excess money demand function that is made up of the excess demand functions of heterogenous traders. The heterogeneity of traders means that they have different sentiments and different expectations at any point in time. Hence, they are likely to react differently to new developments: some want to buy (thus raising excess demand) and some want to sell (thus reducing excess demand). The net effect of their actions is to shift the aggregate excess demand function by a certain amount in a certain direction." (Moosa, 2002).

Therefore, fundamentals have relevance for exchange rate determination in the short run because unexpected changes in the macro-fundamentals affect volatility indirectly through their impact on various trading strategies. Hashimoto and Ito's (2009) theoretical predictions of the impact of surprise components of the news on foreign exchange returns volatility is approached from a statistical rather than a microstructural perspective. They assert that if a shock has a significant impact on the return, it should significantly affect volatility as well, since volatility is the sum of the accumulated absolute changes. The magnitude of volatility will depend on whether the exchange rate moves from one level to another in several miniature changes or by one big jump, and whether the changes to the new level are monotonous or include some reversals.

The performance of macroeconomic models in explaining exchange rates during most of the period after the collapse of the Bretton Woods system has been poor.

> "In the last few decades exchange rate economics has seen a number of developments, with substantial contributions to both the theory and empirics of exchange rate determination. Important developments in econometrics and the increasingly large availability of high-quality data have also been responsible for stimulating the large amount of empirical work on exchange rates in this period. Nonetheless, while our understanding of exchange rates has significantly improved, a number of challenges and open questions remain in the exchange rate debate, enhanced by events including the launch of the euro and the large number of recent currency crises...Overall, the conclusion emerges that, although the theory of exchange rate determination has produced a number of plausible models, empirical work on exchange rates still has not produced models that are sufficiently satisfactory to be considered reliable and robust...In particular, although empirical exchange rate models occasionally generate apparently satisfactory explanatory power in-sample, they generally fail badly in out-sample forecasting tests in the sense that they fail to outperform a random walk. " (Sarno and Taylor, 2002).

Rogoff (2008) and Engel *et al.* (2008) portray a slightly more positive interpretation of developments in exchange rate modelling, presenting evidence that exchange rate models are not as bad as is commonly thought. Rogoff (2008), a comment to Engle *et al's* (2008) conclusion that exchange rate models are not as bad as one would think, asserts that the successes of empirical exchange rate models at very long and very short forecast horizons is noncontroversial. Canonical monetary models explain a significant fraction of long-run nominal exchange rate movements, seemingly outperforming the random walk model in forecasting horizons over two years. Relevant to this investigation, more concrete evidence of success is apparent for very high-frequency exchange rate models – increasing recent evidence on the exchange rates of the dollar against other major currencies uniformly shows that the dollar exchange rate reactions are in line with the Taylor-rule model predictions; with mixed results for some emerging economies and some non-dollar developed countries' exchange rates. But despite the theoretical and empirical exchange rate modelling improvements, and accompanying methodological accomplishments, Rogoff (2008) believes that exchange rates remain a very hard nut to crack. Successful modelling of exchange rates in the intermediate period – a month to one year – still appears the most challenging.

4.3 Literature review: Monetary policy and exchange rates

This section first looks at some of the recent literature on exchange rate movements or responses to scheduled monetary policy announcements, followed by a review of empirical evidence on the effects of these shocks on exchange rate volatility.

4.3.1 Monetary policy surprises and foreign exchange returns: Some empirical evidence

Some important empirical results on the effects of monetary policy surprises on the exchange rates of the currencies of developed economies is presented first, followed by evidence on developed countries-emerging markets exchange rates, including the rand/US dollar exchange rate reaction to SARB repo rate shocks. This section concludes with a summary of evidence on exchange rate responses to broader macro-fundamentals; an important exercise for comparison purposes.

Using seven calendar years (January 1992 to December 1998) real-time (5-minute) exchange rate quotations, macroeconomic expectations (forecasts) and macroeconomic realisations (actual announcements), Andersen *et al.* (2003) find that U.S. target Federal funds rates surprises (amongst other macroeconomic shocks) produce statistically significant mean returns jumps for the pound/dollar, yen/dollar, Deutsche mark/dollar, and Swiss franc/dollar at the 5% level of significance; but not for the euro/dollar. The returns responses for the former four spot rates are not only statistically significant but also large with signs consistent with economic theory; for example within 5 minutes from the Fed rate pronouncement, the dollar appreciates by between 0.032% and 0.072% against four major European currencies (pound, euro, Deutschemark and Swiss franc) and yen rates for a one percentage point positive standardised shock to the

Fed rate. The *r*-squareds (ranging between 0.14 and 0.26) are also striking. Also, given that intra-day high-frequency 5-minute data was employed in the study, the responses suggest that exchange rates adjust almost instantaneously following monetary policy surprise announcements.

Faust et al. (2007) cover a longer span (January 1987 to December 2002) of data than was usually used in the literature pre-2007. In a 20-minute window (5-minutes before the data release and 15-minutes after the data release), they uncover a stronger than expected U.S. Fed rate announcement also appreciates the dollar against the Deutsche mark (euro) and pound; for a 100 basis point surprise rise in the Fed rate, the Deutsche mark (euro) and pound depreciate by 1.23% and 0.66%, respectively, against the dollar. (This translates into a 1.25% and 0.664% appreciation in the dollar against the Deutsche mark and pound respectively.)[81] Conrad and Lamla's (2010) model predicts that a European Central Bank (ECB) surprise monetary policy tightening of 50 basis points appreciates the euro by 0.43% against the US dollar in the subsequent 5 minutes, employing irregularly spaced tick-by-tick quotes from the period of January 1999 to October 2006. Generally, bad news is found to have a greater impact than good news. Conrad and Lamla (2010) also find that the ECB central bank introductory statement provides forward-looking information for expectation formation – there is compelling evidence that statements that indicate increasing risks to price stability induce an appreciation of the euro. Therefore, the dollar/euro exchange rate tends to adjust in a theoretically consistent direction even before the actual interest rate change is announced as long as the monetary policy statement information that precedes the announcement of the actual decision suggests such a change.

Contrary to the results that were obtained for a number of developed economies, empirical evidence on some emerging markets – Brazil Chile and Mexico – fail to provide evidence of currency appreciation when their central banks raise interest rates (Kohlscheen, 2014). Like the developed economies' studies, the central bank's MPC meetings (between January 2003 and May 2011) were pre-scheduled in this case. However, daily data and market interest rates, instead of central bank policy rates, are employed. To address Zettelymeyer's (2004) concern of low-frequency data contamination, observations that may have been influenced by other events, or due to reverse causality resulting from central bank foreign exchange market interventions, are dropped from the sample (Kohlscheen, 2011). Kohlscheen (2011) concludes that this elusive link between interest rates and exchange rates has implications for monetary policy effectiveness and resolving this puzzle should indeed be a research priority.

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[81] Let $e_{DC/FC}$ denote the direct exchange rate of the domestic currency; that is, the amount of units of domestic currency required to purchase one unit of foreign currency. A positive (negative) percentage change in this exchange rate measures percentage appreciation (depreciation) of the foreign currency. Let this percentage change equal x (<u>expressed as a decimal instead of percent</u>). Then the magnitude of depreciation (appreciation) of the domestic currency (based on the indirect exchange rates of the domestic currency, namely, $e_{FC/DC}$) equals $\frac{1}{1+x} - 1 = -\frac{x}{x+1}$. When the percentage change in any given exchange rate is small, then the differences between that currency's percentage appreciation and the other currency's contemporaneous percentage depreciation are negligible but the deviation between the two measures rises with an increase in the percentage change in the given exchange rate.

Turning to the South African literature on this topic, Fedderke and Flamand (2005) test the impact of macroeconomic news surprises on the rand/dollar exchange rate between June 2001 and June 2004. Similar to the emerging economies studies above, daily data is analysed. However, the monetary policy shock is the actual repo rate surprise, consistent with the major economies' investigations presented above. Although the sign of the surprise coefficient is consistent with the UIP prediction, it is nevertheless statistically insignificant in explaining the exchange rate. In one respect, the investigation of exchange returns data in this chapter is an extension of Fedderke and Flamand's (2005) analysis – the focus is on repo rate shock reactions but using high-frequency data as opposed to daily data. Not only are the economic channels through which monetary policy affects the economy important, but so is the mass media that conveys the central bank's verbal and nonverbal monetary policy utterances. Reid and du Plessis (2011) find a relative lack of critical assessment of monetary policy by the media – although the media increases the extent of coverage when inflation breaks through its target range, inter-meeting communication by both the media and central bank can be made more effective. For Africa in general, Plenderleith (2003) stresses that both the clarity of an inflation target and its effective communication are important for delivering consistency and transparency in inflation targeting. Moreover, the inscrutable relationship between interest rates and exchange rates of African countries (but not necessarily South Africa) poses a challenge for the role the currency plays as an additional transmission channel of monetary policy (Plenderleith, 2003).

A number of other papers have also found significant evidence of macroeconomic news effects upon exchange rates. Hashimoto and Ito (2009) examine the dollar/yen exchange rate behaviour using high-frequency (one-second-slice) data from 2001 to 2005. Macro surprises are non-standardised and the investigation excludes central bank interest rate surprise announcements. Key economic variables such as Japanese GDP and CPI were found to have significant but small impacts – in fact, smaller than the exchange rate bid-ask spread. Returns responses were found to be immediate (mostly in 1-minute) and persistent. The yen appreciated when the announcements were stronger than anticipated. They failed to detect statistically significant trade balance data releases effects on foreign exchange returns. The inflation coefficient sign in Fedderke and Flamand (2005) is counterintuitive. Evidence that only US-based news drives the rand/dollar exchange rate is also an important research finding in the latter study. Following the growing developed countries literature, Farrell *et al.* (2012) follow the high-frequency approach of Clarida and Waldman (2008) and extend Fedderke and Flamand's (2005) event study on inflation shocks effects on the rand/dollar exchange rate during 10-minute interval frequencies (five minutes before and five minutes after the inflation statistics release). The data set runs from the beginning of 1997 to the end of August 2010. During the pre-inflation targeting period, immediate rand depreciation followed higher than anticipated inflation releases but the effect was statistically insignificant. The statistically significant and positive coefficient for the inflation surprise for the inflation targeting period shows that bad (good) inflation news appreciates (depreciates) the rand because poor (good) inflation data leads to an expectation of monetary policy tightening (loosening) in the form of higher (lower) interest rates. Interpreted jointly, these two sets of results signal credible central bank monetary policy under inflation targeting. Asymmetric news responses are also evident based on the sign of the shock and whether the inflation target is breached or not. Farrell *et al*'s (2012) main results are consistent with those of Clarida and Waldman (2008) for US consumer inflation and the dollar performance against the currencies of nine developed economies; the sample period is 1993 to 2000.

Many more recent studies – over the past 15 years or so – have also had success in identifying the level responses of exchange rates to monetary policy changes: Eichenbaum and Evans (1995), Engel (1996), Kuttner (2001), Bernanke and Kuttner (2005), and Piazzesi and Swanson (2008), to mention a few. Neely and Dey (2010) review the huge literature on macroeconomic news effects on foreign exchange returns.

4.3.2 Monetary policy surprises and exchange rate volatility: Some empirical evidence

Studies on exchange rate volatility responses to central bank rates are discussed first, followed by a survey of some of the important broad macroeconomic fundamentals studies that excluded policy rates, and a reference to some other relevant work. Sager and Taylor (2004) test the volatility reaction of 5-minute euro/dollar exchange rate data on the days the ECB Governing Council (GC) announced its interest rate decisions in 2002 and 2003 compared with other days. Their Markov switching model is based on two volatility regimes; a high-volatility state associated with informed trading and a low-volatility state associated with liquidity trading. Two important findings are reported. First, on GC meeting days when interest rate decisions are announced, the probability of switching into a high-volatility state rose significantly with a significant concurrent fall in the probability of remaining in a low volatility state. The full impact of the announcement on volatility took 15 minutes to be felt and dissipated in approximately one hour. Significant evidence of an increase in the probability of being in an informed state commencing one hour before the announcement (an interest change or no change) suggests that dealers were closing their positions to minimise risk exposure rather than a response to policy rate information leakages.

In a similar study, Melvin *et al.* (2010) find that the volatility state transition probabilities switch systematically and significantly to a high-volatility state on Bank of England MPC meeting days when interest rates were changed by an amount different from the *ex ante* median consensus forecast or rates were unchanged when a change was expected by the market. And similar to Sager and Taylor's (2004) regression results, there is evidence of pre-positioning during the morning of the meeting. The data sample spanned more than a decade – June 1997 to October 2007 – of dollar/pound exchange rates tick data.

Conrad and Lamla's (2010) investigation of ECB monetary policy shocks on the high-frequency euro/dollar exchange rates provides evidence of an initial instantaneous jump in volatility on impact, followed by a gradual decline. Also, positive surprises tend to trigger stronger volatility reactions than negative ones.

Andersen *et al.* (2003) present exchange rate conditional volatility estimates for several macroeconomic shocks for some major dollar exchange rates; unfortunately, excluding the Fed rate. They report that exchange rate volatilities adjust only gradually, with complete adjustment occurring only after one hour or so, in stark contrast to the more immediate response of foreign exchange returns. Another variation is the smaller statistically significant contemporaneous volatility response coefficients for the surprise in the GARCH variance equation relative to the surprise coefficients in the returns mean equation, but the complete volatility response tends to be larger than both the latter two reactions. Also, announcement effects are asymmetric: forecast dispersions are higher following bad news releases than at other times.

Hashimoto and Ito's (2009) broad study on macroeconomic news effects on the dollar/yen returns mentioned above also tests for price volatility impacts; regrettably, this also excludes the central bank rate impact. Whilst some standardised macroeconomic shocks have no foreign currency return impacts, they do impact the number of deals and realised volatility. Unemployment, CPI and GDP surprises are found to significantly increase exchange rate volatility.

Other empirical work on monetary policy shocks and exchange rate volatility includes, amongst others: Jansen and Haan (2005), and Hayo and Neuenkirch (2012). Neely (2011) reviews research that studies the reaction of foreign exchange volatility to macroeconomic news.

4.4 Monetary policy frameworks and repo rate system in South Africa: An overview

Between 1960 and 1998, South Africa followed a number of monetary policy and complementary exchange rate frameworks. These included exchange-rate targeting, discretionary monetary policy, monetary-aggregate targeting and an eclectic approach. Ultimately, South Africa officially adopted inflation targeting in February 2000 after announcing its intentions to introduce the framework in August 1999; at the same time, a floating exchange rate mechanism with no SARB interventions intended to influence the exchange rate was also adopted where the central bank no longer targeted the exchange rate (Van der Merwe, 2004).[82] The primary objective of monetary policy in South Africa is to achieve and maintain price stability in the interest of sustainable and balanced economic development and growth. Under South Africa's inflation targeting regime, the Bank focuses on ensuring that inflation is in line with the government-set explicit year-on-year consumer price inflation target range of 3% to 6%; a relatively more flexible inflation targeting framework than a point target.[83] The SARB then adjusts the repo rate in an attempt to keep forecast inflation within this band; 'no

[82]South Africa had a floating exchange rate with central bank intervention applied during periods of rapid rand movement and escalated volatility; for example, during the 1998 Asian crisis. After 1998 when the SARB's fingers were burnt, it had less appetite and resources to intervene in the foreign exchange spot and forward markets. The NOFP was eliminated during Governor Tito Mboweni's reign and the more flexible exchange rate adopted in 2000 entailed no central bank intervention in the foreign exchange market to influence the rand but to gradually accumulate foreign currency reserves, *albeit*, only when market conditions were conducive.

[83]Since the introduction of the more flexible inflation-targeting framework in February 2000, the specification of the target has been reviewed on a number of occasions. From an initial target of the CPIX (consumer price index excluding interest costs on mortgage bonds) in metropolitan and other urban areas, headline CPI was targeted thereafter (commencing February 2009) after a change in the treatment of housing in the CPI when mortgage interest costs no longer had to be removed from the CPI when evaluating monetary policy.

changes' are made should the central bank be satisfied with its current policy stance. Since the adoption and subsequent introduction of inflation targeting and a fixed repo rate system, South Africa's repo rate is reviewed and set at MPC meetings. An MPC was constituted shortly before South Africa adopted the inflation-targeting framework, in line with the global trend, so that rate decisions are based on diverse view points from constituent members. The timetable for meetings is finalised and publicised before the beginning

Table 4.1: South African Reserve Bank Monetary Policy Committee meetings

Years	Scheduled Meetings (per year)	Unscheduled Meetings (per year)
2000-2002	7-8	3
2003	5	1
2004-2008	2-3	0
2009	9	0
2010-2012	6	0

Source: South African Reserve Bank and Bloomberg

of each year, alleviating uncertainty regarding the timing of possible rate changes. The Bank experimented with varying the number of scheduled yearly meetings since 2000, eventually settling at 6 scheduled MPC yearly meetings, commencing on a Tuesday followed by the MPC press conference at 15h00 two days later (Thursday), in recent years. An infrequent number of unscheduled meetings were held during the early phase of inflation targeting – a total of four such incidences between the years 2000 and 2003. For example, the unscheduled announcement and unexpected tightening on 15 January 2002 was prompted by significant upward inflationary expectations elicited by a plunge in the rand during the last quarter of 2001 following the terrorist attacks on the U.S. on 9 September 2001.

Monetary policy repo rate decisions are publicly announced shortly after the end of the SARB MPC's meeting. Although the overwhelming majority of repo rate decisions in South Africa since the adoption of inflation targeting framework have been on scheduled dates, there is no guarantee that each statement is released exactly at the pre-announced time; that is, it is not necessarily released on the stipulated embargo time. The Governor takes between 15 to 25 minutes to announce the MPC's rate decision after the commencement of the press conference – the timing of the announcement of each decision would depend on the actual commencement time of the written press statement, the pace of the reading of each statement and the length of each statement.[84] This has been confirmed by viewing the last 22 available webcasts of the press conference on the Bank's website. However, for the most recent 31 webcasts, the announcement of the monetary policy stance on the repo rate takes places as early as around 8 minutes 32 seconds after the

[84] Note that the Governor usually briefly greets the guests and invites them to ask questions – but the questions may only be posed after she/he has delivered the prepared MPC statement. Also, note the commencement of the delivery of each formal MPC statement may start a bit later (or possibly a tad earlier) than scheduled for additional reasons to the one just mentioned. So a mismatching in the time of release of the MPC statements (relative to the scheduled time) leads to a mismatch in the actual repo rate pronouncement compared with the information in appendix F.

commencement of the conference to as late as 21 minutes 16 seconds after the beginning of statement delivery (appendix F). So the difficulty here, unlike other macroeconomic releases, is that the actual time of the rate announcement is not invariant – posing a challenge for accurately identifying the initial response time of exchange rates to the surprise using the information at hand when high-frequency analysis is undertaken.

All in all, the data suggests progressively greater certainty about the timing of policy announcements and potential repo rate moves. Additionally, the South Africa's simultaneous adoption of a more flexible exchange rate mechanism together with an inflation targeting framework and scheduled MPC meetings averts the endogeneity problem because adjustments in the exchange rate to repo rate shocks do not trigger immediate central bank alterations to the rate again to support the exchange rate.

Since the focus of this investigation is the exchange rate impact of repo rate shocks, a brief history of how the mechanics of the South Africa's repo system evolved is valuable in understanding how the SARB arrived at its present scheduled repo rate practice. The repo system was introduced in March 1998 before the formal adoption of inflation targeting in 2000. The repo rate – established under the repurchase tender system of the central bank – is the rate at which the SARB lends money to the banking sector to meet daily liquidity shortages. Liquidity here means commercial banks' credit balances with the central bank that are available to settle interbank transactions over and above the minimum statutory level of reserves that they are required to hold. To force commercial banks to borrow substantial amounts from the central bank and thus make the repo rate system effective, the Bank creates the required liquidity shortage (or drains excess liquidity) through open-market transactions using various instruments at its disposal. The Bank then refinances the liquidity shortage it created through repurchase agreement auctions – it purchases selected liquid bonds and other money market instruments from commercial banks in return for cash paying the central bank borrowing rate (repo rate) for the cash they receive. On maturity, commercial banks return the cash to the Bank in exchange for the securities they sold to the Bank at the auction thus reversing the initial transaction.[85] In its early stages, daily liquidity was provided through repurchase agreements at a variable repo rate which was market determined – the objective was for the market to provide signals to the Bank about underlying liquidity conditions and an adjustment in the repo rate to reflect the changes in market liquidity. However, inefficiencies in mainly the interbank market caused a sub-optimal functioning of the system. The oligopoly-type structure of the banking sector caused less flexibility in the rate and markets not clearing effectively. Therefore, the initial repo rate system did not accurately reflect market conditions, occasionally resulting in unclear monetary policy signals. To improve the functioning of the system, the central bank made some modifications, including, amongst others, fixing the repo rate to eliminate ambiguity in the Bank's monetary policy signals and replacing the daily repo auctions with weekly ones with a seven-day maturity. By

[85]See "The South African Reserve Bank's system of accommodation" (2011) paper compiled by the Financial Markets Division of the SARB for a detailed discussion on the Bank's refinancing repo rate system.

the time inflation-targeting was officially adopted, the Bank had already shifted from a variable to a fixed repo rate set by the Bank instead of the market.

4.5 Methodology

Whereas the common 'purely statistical approach' applies regression analysis to estimate the relationship between time series variables – based on their contemporaneous values – the 'event study approach' or 'narrative approach' employed in this analysis assesses the impact of an event(s) on the price of a financial asset around the time of the event(s) – shortly before and/or after the event(s). The 'event study approach' focuses on the identification of 'shocks' through non-statistical procedures and then estimating the impact of these shocks on other economic variables.[86] Although this methodology was popularised by Romer and Romer (1989) and Cook and Hahn (1989), it can be traced to as far back as the early 1960s – Romer and Romer (1989) credit Friedman and Schwartz (1963) for pioneering this procedure. Schwartz and Friedman (1989) contest Romer and Romer's (1989) latter assertion arguing that this methodology goes further back to the "Digression concerning the variations in the value of silver during the course of the last four centuries" in Adam Smith's *Wealth of Nations* (1776).

More specifically, this study applies the 'event study' methodology to investigate the reaction of the rand/US dollar exchange rate – percentage changes in levels and shifts in their variance – to unexpected changes in the policy variable (repurchase agreement or repo rate) around the time of the monetary policy announcement using intra-day high-frequency minute-by-minute data in narrow event windows. Shocks or surprises are identified as unexpected or unpredictable monetary policy repo rate announcements, measured as the realised (or actual) repo rate *minus* the expected repo rate. To ensure that the policy change is exogenous, Kearns and Manners (2006) advise that the sample periods should be carefully selected. Kearns and Manners (2006) and Zettelmeyer (2004) recommend that observations when the exchange rate may have reacted to other news that became public on the same day (or around same time) of monetary policy announcements and those periods where the central bank intervenes in the foreign exchange market to offset or mitigate the policy shock effect should be excluded to deal with the potential endogeneity and misspecification problems. Endogeneity arising from bank interventions in the foreign exchange market is not a problem in our sample period as the Bank pursued a 'free' float. To minimise the number of observations that would have to be discarded due to the endogeneity problem, and compare and contrast with other empirical studies, the principal regressions in this study experiment with a 5-minute window (5 minutes after the rate decision announcement) and a 20-minute window (5 minutes before the rate decision announcement and 15 minutes after the event); a 70-minute window is used in the preliminary regressions to examine market activity some time before the lifting of the MPC statement embargo and later after the

[86] One definition of the word 'narrative' is an account of connected events, and thus the terms 'narrative study' and 'event study' are equivalent.

Governor has completed the delivery of her/his press statement. A general reason for conducting the study over these varying window sizes is the trade-off between minimising contamination and allowing some time for the market to fully digest the shock. Contamination includes the endogeniety problem – simultaneous relationship between exchange rates and interest rates – and the additional exchange rate effect of variables other than the interest rate. This contamination is reduced when the window is narrowed. However, too narrow a window may not allow enough time for market participants to digest the policy news shock (Rigobon and Sack, 2004). To gauge how rapid the exchange rate responds to the shock, we first estimate the cumulative minute-by-minute exchange rate responses (over 1-minute periods from 10 minutes before the pronouncement up to the announcement time and 1-minute after the announcement up to 60 minutes after the policy declaration) to a 100-basis point surprise repo rate shock using the OLS estimation method, and then plot the regression surprise coefficients from the latter set of regressions graphically. This will demonstrate whether exchange rate changes take place immediately after the announcement or whether markets need a substantial amount of time to digest the information. And given that the actual rate pronouncement does not occur at a specific time, the 70-minute window period also allows us to estimate the approximate average time of the announcement from the start of the press release statement.

In many cases, monetary policy decisions are widely anticipated by the market, and so their impact should already be incorporated into interest rates and exchange rates – in line with the efficient market hypothesis (EMH). The EMH implies that financial asset prices should respond instantaneously to the surprise component of announcements that have direct or indirect bearings on asset prices. To test the validity of the efficiency of the foreign exchange market – 'efficiency' from a mechanical perspective (that is, how soon the shock is absorbed into the exchange rate and how long it takes to die-off), currency returns and their variance responses to repo rate surprises are estimated over different window sizes. Finally, we test whether the market reacts to the component of the repo rate change that is anticipated by the market.

4.5.1 Econometric models

Our measure of the repo rate surprise component (S_{kt}) of the announcement k, is defined as the difference between the actual announced value of the repo rate (A_{kt}) and the median expected repo rate of the Bloomberg market consensus survey (F_{kt}) :

$$S_{kt} = A_{kt} - F_{kt}. \tag{4.2}$$

To estimate the effect of the repo rate news shock on the exchange rate, we first regress foreign exchange returns on the surprise in the repo rate

(*Model A*): $$r_{k,t+k} = \theta_0 + \theta_1 S_{kt} + \varepsilon_t \tag{4.3}$$

where, $r_{k,t+k}$ is the percentage change in the rand bilateral exchange rate between time periods *k* and *t+k* (around the time of the event),[87] and θ_1 is the sensitivity of the exchange rate to the news shock.[88]

To estimate the impact of shocks on volatility, our second model is specified as follows:

(*Model B*):
$$r_{k,t+k} = \theta_0 + \theta_1 S_{kt} + \varepsilon_t \tag{4.4}$$

$$h^2_{k,t+k} = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon^2_{t-k} + \sum_{j=1}^{q} \beta_j h^2_{t-j} + \delta_1 S_{it} \tag{4.5}$$

where equations (4.4) and (4.5) are the GARCH model mean and variance (conditional volatility) equations. The policy shock enters both equations – θ_1 measures the foreign currency returns sensitivity to the repo rate surprise, δ_1 captures the exchange rate returns conditional volatility reaction to this policy shock – and β and α are the lagged conditional volatility coefficient (up to $t-q$) and the lagged disturbance term parameter which measures the conditional volatility response to shocks in previous periods (up to $t-p$) other than the repo rate surprise, respectively. By assumption, $\varepsilon_t (= h_t z_t)$ is serially uncorrelated with a mean equal to zero, $(z_t \sim N(0,1))$, but its conditional standard deviation, h_t, is time varying, $z_t (= \varepsilon_t / h_t)$ is the standardised residuals. A test to detect the absence or presence of serial correlation is carried out in the next section.

4.6 Data

4.6.1 Data issues

The sample period, 14 August 2003 to 24 January 2013, is dictated by the availability of historical market consensus forecasts for the repo rate, information regarding the MPC repo rate decision and the intra-day high-frequency exchange rate data. This time horizon falls within the period during which the SARB adopted a single floating exchange rate mechanism, accompanied by gradual exchange control relaxations and adoption of a formal inflation targeting framework. The four raw data series are the minute-by-minute bid and ask quotes of the US dollar in terms of the rand (direct exchange rates of the rand) obtained from Olsen Financial Technologies,[89] the actual repo rate announced by the SARB on the day of the release of its MPC

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[87] For reasons already stated, and further explicated in section 4.7, we experiment with various values for *k* and *t+k;* the exact values will be specified before running each of the regressions.

[88] To compare the magnitudes of regression coefficients on announcement surprise series with different units of measurement, for example, exchange rate response to repo rate surprise *versus* the exchange rate reaction to trade balance shock, researchers typically follow Balduzzi *et al.* (2001) by dividing the surprises by their standard deviation across all observations to facilitate interpretation. The standardised shock measure is $SS_{kt} = S_{kt} / \sigma_k$ and the regression coefficient is interpreted as the change in the return for a one standard deviation change in the surprise.

[89] A rise in the exchange rate is interpreted as rand depreciation.

statement and the Bloomberg median repo rate market consensus forecasts. On average, approximately 20 economists were surveyed regarding expectations for each announcement over the sample interval. The secondary data generated before running the regressions are the mid-point currency quotes (average of the bid and ask quotes), the currency returns (percentage change in the mid-point currency quotes) and the surprise component of the repo rate announcement (arithmetic difference between the actual repo rate and median repo rate forecast measured in percentage points). Use of median shocks (as opposed to mean shocks) is consistent with a substantial amount of the empirical research reviewed thus allowing comparison of results in this study with those surveyed. A first statistical advantage of the median over the mean is that extreme values (outliers) do not affect the median as strongly as they do the mean. And congruent with Conrad and Lamla's (2010) repo rate shocks data generated using the median rate, median surprises occur less frequently than mean surprises but the magnitudes of the former are significantly larger than the latter, thus allowing for a 'strong' separation in surprise and no-surprise days.

Here only scheduled monetary policy announcement decisions are considered; that is, those that the market knew beforehand would take place. There are no events when the policy was known to have reacted to contemporaneous exchange rate movements. Also, there does not appear to be any day(s) where the policy announcement coincided with other important economic and noneconomic news that might have affected the exchange rate as well. After taking all these factors into account, the full sample is 43 observations compared with, Zettlemeyer's (2004) sample range of between 23 and 60 observations for three developed economies, and Kearn and Manners' (2006) sample ranges of between 33 and 82 observations for four industrialised economies.

4.6.2 Policy surprise data: A descriptive analysis

In Table 4.2, there is a trend lower in the frequency of policy surprises – both the number and magnitude of shocks decline, accompanied by a fall in the incidence of uncertainty amongst economists on central bank repo rate decisions. Of the total 43 monetary policy decisions incorporated in this study, more than 80% of the actual repo rate changes were fully anticipated and their sizes were also in line with the market consensus median forecast. One should err on the side of caution though before generalising given the relatively small sample size, but this finding is broadly consistent with those of Swanson (2006) for the US and the a number of South African studies that we return to. There were no instances where the market expected a change in the policy rate in the opposite direction to the change actually announced. On 6 occasions, the MPC changed the repo rate with no adjustment anticipated by the market. This is a tentative but non-scientific indication that market participants have gained improved (though not perfect) understanding of which macroeconomic variables condition the Bank's monetary policy reaction function and that the South African Reserve Bank's more effective (verbal and nonverbal) communication of its policy stance since late 1999, to make its conduct of monetary policy more transparent to the public, have been highly fruitful. We hypothesise that the

Table 4.2: Monetary policy meetings and Bloomberg repo rate surprise measures

Date	Shock (act-med)*	Shock (act-mean)*	Uncertainty (high-low)*	Rate change	Expected direction
2003/06/12	Yes	-0.40	1.00	Yes	Yes
2003/08/14	No	0.09	0.50	Yes	Yes
2003/12/11	Yes	0.55	0.50	Yes	Yes
2004/02/26	No	0.11	0.50	No	-
2004/06/10	No	0.00	0.00	No	-
2004/12/09	No	0.10	0.50	Yes	-
2005/02/10	No	0.20	0.50	No	-
2005/04/14	Yes	-0.50	0.00	Yes	-
2005/08/11	No	0.04	0.50	No	-
2006/06/08	Yes	0.48	0.25	Yes	-
2006/10/12	No	-0.08	0.50	Yes	Yes
2007/02/15	No	-0.17	0.50	No	-
2007/06/07	No	0.10	0.50	Yes	Yes
2008/01/31	No	-0.07	0.50	No	-
2008/12/11	No	-0.16	0.50	Yes	Yes
2009/02/05	No	-0.18	0.50	Yes	Yes
2009/03/24	No	0.00	0.00	Yes	Yes
2009/04/30	No	-0.02	0.50	Yes	Yes
2009/05/28	No	-0.17	0.50	Yes	Yes
2009/06/25	Yes	0.44	0.50	No	-
2009/08/13	Yes	-0.44	0.50	Yes	-
2009/09/22	No	0.06	0.50	No	-
2009/10/22	No	0.05	0.50	No	-
2009/11/17	No	0.04	0.50	No	-
2010/01/26	No	0.05	0.50	No	-
2010/03/25	Yes	-0.46	0.50	Yes	-
2010/05/13	No	0.02	0.50	No	-
2010/07/22	No	0.15	0.50	No	-
2010/09/09	No	-0.06	0.50	Yes	Yes
2010/11/18	No	-0.11	0.50	Yes	Yes
2011/01/20	No	0.02	0.50	No	-
2011/03/24	No	0.00	0.00	No	-
2011/05/12	No	0.00	0.00	No	-
2011/07/21	No	0.00	0.00	No	-
2011/09/22	No	0.03	0.50	No	-
2011/11/10	No	0.09	0.50	No	-
2012/01/19	No	0.00	0.00	No	-
2012/03/29	No	0.00	0.00	No	-
2012/05/24	No	0.00	0.00	No	-
2012/07/19	Yes	-0.44	0.50	Yes	-
2012/09/20	Yes	0.03	0.50	No	-
2012/11/22	No	0.00	0.00	No	-
2013/01/24	No	0.00	0.00	No	-

*Act – actual repo rate announced
Med – market survey consensus median forecast
Mean – market survey consensus mean forecast
High – market survey highest forecast;
Low – market survey lowest forecast.

introduction of scheduled monetary policy announcement dates and central bank policy signals between MPC meetings since the implementation of the inflation targeting framework in 2000 have contributed to the ability of market participants to better understand the monetary policy reaction function. The descriptive information in Table 4.2 tentatively suggests that the SARB has made progress in achieving its goal of improving monetary policy transparency. (Melvin *et al*, (2010) use a similar crude approach to infer monetary policy transparency). This evidence on monetary policy transparency reinforces earlier findings, using divergent approaches and for different sample periods, such as Ballim and Moolman (2005), Aron and Muellbauer (2008), Arora (2008), and Reid and du Plessis (2011).[90]

4.6.3 Preliminary data analysis

Table 4.3: Statistical properties of exchange rate returns and repo rate surprises*

*5-minute returns (16 minutes to 21 minutes after lifting of scheduled embargo)***												
	Min.	Max.	Mean	Med	Std. Dev.	Skew.	Kurt.	JB (*prob*)	Q_{LB} (20)	ADF stat.	PP stat.	KPSS stat.
Returns	-0.79	0.27	-0.10	-0.05	0.23	-0.87	3.45	5.81 (0.06)	-	-6.00	-6.00	0.17
Surprises	-0.50	0.50	-.02	0.000	0.22	-0.26	5.32	10.1 (0.01)	-	-7.70	-8.52	0.24
Residuals***	-2.84	1.540	-.01	0.24	1.01	-0.82	3.02	4.85 (0.09)	19.47 (0.49)	-	-	-
*20-minute returns (16 minutes to 36 minutes after lifting of scheduled embargo)***												
Returns	-1.98	1.02	-0.11	-0.10	0.53	-0.81	5.49	15.80 (0.00)	-	-7.29	-7.29	0.13
Surprises	-0.50	0.50	-.02	0.000	0.22	-0.26	5.32	10.1 (0.01)	-	-7.70	-8.52	0.24
Residuals**	-2.09	2.28	-0.02	0.05	0.97	0.02	3.02	0.00 (0.99)	11.97 (0.92)	-	-	-

* Returns are the approximate percentage changes calculated by the differences in the logarithms of the foreign exchange mid-rates. Interest rate shocks are measured in percentage points.

** This window period opens around the average time that the repo rate announcement is made; explained in section 4.7.

*** GARCH mean equation standardised residuals.

The 1%, 5% and 10% asymptotic critical values for both the augmented Dickey-Fuller (DF) (based on the modified Akaike information criterion with a maximum lag of 13) and Phillips-Perron (PP) nonstationarity tests with drift and no trend are: -3.59, -2.93 and -2.61,respectively. Both test hypotheses are H_0: unit root (nonstationary), H_1: no unit root (stationary).

The 1%, 5% and 10% asymptotic critical values for the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test with drift and no trend are 0.739, 0.463 and 0.347, respectively. The KPSS test hypotheses are the converse; that is, H_0: no unit root (stationary), H_1: unit root (nonstationary).

[90] But our descriptive analysis does not constitute empirical proof that there has indeed been learning and that communication has definitely improved over time. Elliott and Muller (2006) and Muller and Petalas (2010) developed a methodology to formally and empirically test monetary policy transparency; that is, the stability of the asset price returns response to surprises, and the paths of these effects, which has also been applied by Goldberg and Grisse (2013). Applying this test to South Africa entails an entire new study which can be explored in later research.

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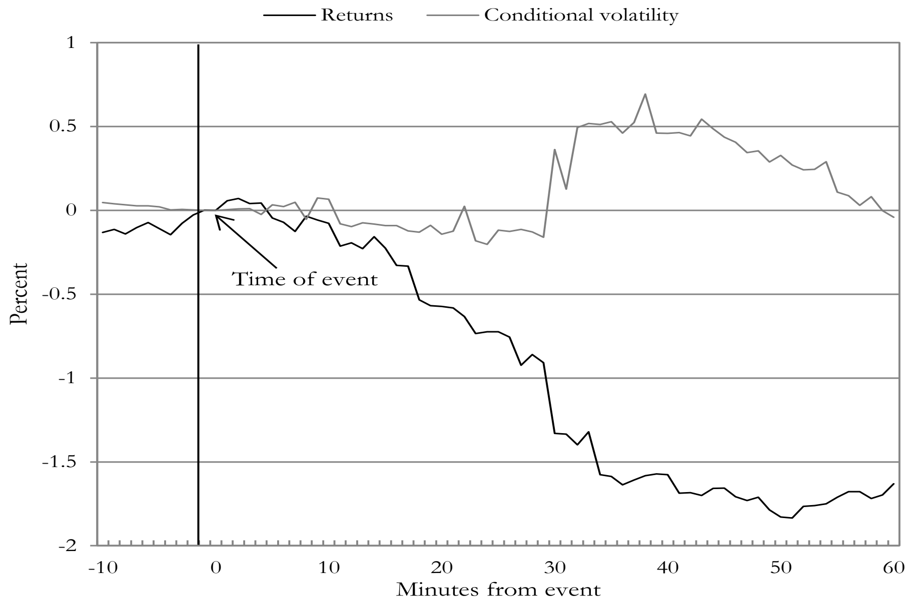
Table 4.3 displays the statistical properties of the currency returns, surprise components of the changes in the repo rate and the raw and squared residuals generated from the GARCH mean equation. Significant skewness and excessive kurtosis are detected in both the returns and repo rate surprises. Excessive kurtosis present in the surprise data is due to a significant number of shocks being equal to zero and the remaining almost evenly spread at 50 and -50 basis-points; there is one more unexpected monetary tightening than policy loosening. However, the standardised residuals of the 20-minute returns are close to a normal distribution with a low level of non-normality in the corresponding 5-minute returns standardised residuals. Both the augmented Dickey-Fuller and Phillips-Perron unit root tests suggest that both the returns and policy surprise series do not have a unit root. Congruently, the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) stationarity test does not refute the null of stationarity. Looking at the Q_{LB}-statistics (Ljung-Box *Q*-statistics for the standardised residuals, $z_t = \varepsilon_t / h_t$), the null hypothesis that there is no serial or autocorrelation in the standardised residuals cannot be rejected; suggesting that estimation of the returns equation may proceed using the OLS technique.

4.7 Empirical analysis

4.7.1 Shock response plots (speed of impact): 70-minute window period analysis

Following Kearns and Manners (2006), the timing of the impact of the repo rate surprise on the exchange rate here is determined by estimating equations (4.3), (4.4) and (4.5) and recording θ_1 and δ_1 for *k* ranging from 10 minutes before the scheduled embargo is lifted to 60 minutes after the scheduled commencement time of the MPC statement release – at one-minute intervals – with the actual scheduled embargo lift time as the reference point in each case. For example, $r_t = ln\left(\frac{e_0}{e_{-8}}\right)$ is the approximate cumulative percentage change in the exchange rate from 8 minutes before the scheduled time of the commencement of the MPC release statement to the actual time that the embargo is lifted, and $r_t = ln\left(\frac{e_{20}}{e_0}\right)$ is the approximate cumulative percentage change in the exchange rate from the actual time that the embargo is lifted to 20 minutes after the Governor starts delivering the MPC statement. A benefit of this approach is that it allows us to evaluate whether there is an immediate response or whether the response builds up over time and positioning or possible new repo rate leakages before the official pronouncement on the MPC's decision. The 70 regression estimates are summarised in Table 4.4 while Appendix E presents the same results in the form of diagrammatic reactions of exchange returns (θ_k) and volatility (δ_k) to a one percentage point unanticipated hike in the repo rate, in two separate diagrams, with their respective standard error bands. The combined effects excluding their standard error bands are shown in Figure 4.1. Time zero, denoted as '0' in the graphs represents the time that the SARB is scheduled to lift the embargo on its MPC statement – this is not the time the final decision on whether to change the repo rate or not is announced. The concluding remark in the

Figure 4.1: Rand response to a 100-basis-point repo rate surprise



press statement that contains the actual interest rate decision is made publicly available only immediately after the Governor announces the actual decision; and not before.

We first interpret the results in Table 4.4. We find significant (θ_k) and (δ_k) coefficients (at the 5% level) from around $k = 18$; both coefficients are simultaneously and uninterruptedly statistically significant at the 10% or lower levels of significance from $k = 18$ up to $k = 60$ for the returns and from $k = 18$ up to $k = 54$ for volatility. The negative θ_1 coefficient signs mean that a positive repo rate surprise is correlated with rand appreciation. Returns from positive (negative) surprises are maximised (minimised) after 51 minutes from the time of the start of the MPC report press statement (about 30 minutes after the rate announcement) while the impact on volatility starts to die off much earlier at around 39 minutes into the MPC report release (approximately 10 minutes after the repo rate decision is released.) Conditional volatility due to the surprise only becomes statistically insignificant after 54 minutes from the commencement of the Governor's press statement or in the region of 35 minutes after the rate pronouncement. The significance of the shocks from 18 minutes after the scheduled time is more or less consistent with the average time of most recent 22 MPC statement deliveries in appendix F.

Table 4.4: Returns and conditional volatility regression estimates (70-minute window period)

k	θ_1	δ_1	k	θ_1	δ_1	k	θ_1	δ_1	k	θ_1	δ_1	k	θ_1	δ_1
	-0.1314	0.0464		-0.0461	0.0326		-0.5682	-0.0892		-1.3207	0.5185		-1.7300	0.3444
-10	(0.1210)	(0.0284)	5	(0.1022)	(0.0050)	19	(0.2341)	(0.0531)	33	(0.3496)	(0.2231)	47	(0.3967)	(0.1511)
	[0.2841]	[0.1029]		[0.6544]	[0.0000]		[0.0198]	[0.0930]		[0.0005]	[0.0201]		[0.0001]	[0.0226]
	-0.1134	0.0386		-0.0708	0.0229		-0.5728	-0.1415		-1.5768	0.5122		-1.7105	0.3557
-9	(0.1142)	(0.0370)	6	(0.1152)	(0.0369)	20	(0.2529)	(0.0322)	34	(0.3406)	(0.1380)	48	(0.3850)	(0.1361)
	[0.3267]	[0.2976]		[0.5423]	(0.5348)		[0.0290]	[0.0000]		[0.0000]	[0.0002]		[0.0001]	[0.0089]
	-0.1401	0.0331		-0.1253	0.0499		-0.5826	-0.1244		-1.5866	0.5289		-1.7871	0.2887
-8	(0.1035)	(0.0237)	7	(0.1304)	(0.0154)	21	(0.2602)	(0.0678)	35	(0.3560)	(0.1598)	49	(0.3884)	(0.1578)
	[0.1835]	[0.1625]		[0.3424]	[0.0012]		[0.0308]	[0.0663]		[0.0001]	[0.0009]		[0.0000]	[0.0674]
	-0.1026	0.0272		-0.0343	-0.0532		-0.6340	-0.6439		-1.6368	0.4602		-1.8292	0.3281
-7	(0.1100)	(0.0311)	8	(0.1434)	(0.0388)	22	(0.2737)	(0.3626)	36	(0.3846)	(0.2331)	50	(0.3867)	(0.1375)
	[0.3205]	[0.3811]		[0.8123]	[0.1707]		[0.0257]	[0.0757]		[0.0001]	[0.0483]		[0.0000]	[0.0170]
	-.0726	0.0270		-0.0581	0.0742		-0.7349	-0.1811		-1.6082	0.5236		-1.8353	0.2703
-6	(0.0924)	(0.0104)	9	(0.1499)	(0.0208)	23	(0.2783)	(0.1142)	37	(0.3966)	(0.1940)	51	(0.3774)	(0.1516)
	[0.4367]	[0.0090]		[0.7004]	[0.0004]		[0.0118]	[0.1128]		[0.0002]	[0.0070]		[0.0000]	[0.0744]
	-0.1096	0.0209		-0.0768	0.0660		-0.7238	-0.2031		-1.5828	0.6932		-1.7654	0.2422
-5	(0.0909)	(0.0052)	10	(0.1452)	(0.0315)	24	(0.2840)	(0.1554)	38	(0.4016)	(0.2448)	52	(0.3616)	(0.2900)
	[0.2347]	[0.0001]		[0.6000]	[0.0363]		[0.0148]	[0.1911]		[0.0003]	[0.0046]		[0.0000]	[0.4033]
	-0.1452	0.0027		-0.2132	-0.0802		-0.7243	-0.01181		-1.5719	0.4614		-1.7611	0.2452
-4	(0.0696)	(0.0064)	11	(0.1633)	(0.0476)	25	(0.2890)	(0.0507)	39	(0.3990)	(0.1266)	53	(0.3626)	(0.2407)
	[0.0433]	[0.6686]		[0.1991]	[0.0919]		[0.0164]	[0.0198]		[0.0003]	[0.0003]		[0.0000]	[0.3084]
	-0.0768	-0.0054		-0.1937)	-0.0961		-0.7551	-0.1258		-1.5757	0.4600		-1.7494	0.2900
-3	(0.0741)	(0.0059)	12	(0.1763)	(0.0821)	26	(0.2896)	(0.0655)	40	(0.4007)	(0.2251)	54	(0.3649)	(0.1576)
	[0.3060]	(0.3643)		[0.2785]	[0.2416]		[0.0128]	[0.0548]		[0.0003]	[0.0410]		[0.0000]	[0.0657]
	-0.0268	0.0026		-0.2289	-0.0742		-0.9240	-0.1129		-1.6864	0.4638		-1.7111	0.1094
-2	(0.0530)	(0.0066)	13	(0.1722)	(0.0686)	27	(0.3014)	(0.0703)	41	(0.4161)	(0.2718)	55	(0.3833)	(0.4203)
	[0.6158]	[0.6941]		[0.1914]	[0.2791]		[0.0039]	[0.1084]		[0.0002]	[0.0879]		[0.0001[	[0.7947]
	0.0007	0.0006		-0.1579	-0.0814		-0.8602	-0.1288		-1.6835	0.4440		-1.6775	0.0871
-1	(0.0511)	(0.0031)	14	(0.1665)	(0.0234)	28	(0.3175)	(0.0658)	42	(0.4230)	(0.3404)	56	(0.3757)	(0.3363)
	(0.9885)	[0.8377]		[0.3486]	[0.0005]		[0.0099]	[0.0502]		[0.0003]	[0.1921]		[0.0001]	[0.7955]
	0.0570	0.0045		-0.2248	-0.0913		-0.9084)	-0.1610		1.7000	0.5446		-1.6768	0.0297
1	(0.0470)	(0.0041)	15	(0.1755)	(0.0550)	29	(0.3276)	(0.0772)	43	(0.4335)	(0.1677)	57	(0.3799)	(0.4209)
	(0.2319)	[0.2737]		[0.2076]	[0.0967]		[0.0084]	[0.0370]		[0.0003]	[0.0012]		[0.0001]	[0.9437]
	0.0709	0.0095		-0.3274	-0.0905		-1.3294	0.3624		-1.6578	0.4860		-1.7180	0.0822
2	(0.0723)	(0.0056)	16	(0.1918)	(0.0951)	30	(0.3363)	(0.2598)	44	(0.4271)	(0.3030)	58	(0.3913)	(0.4574)
	(0.3326)	[0.0905]		[0.0956]	[0.3415]		[0.0003]	[0.1631]		[0.0004]	[0.1087]		[0.0001]	[0.8574]
	0.0402	0.0104		-0.3323	-0.1223		-1.3338	0.1265		-1.6560	0.4371		-1.6973	-0.0009
3	(0.0941)	(0.0124)	17	(0.2063)	(0.1019)	31	(0.3345)	(0.4143)	45	(0.4145)	(0.1583)	59	(0.3849)	(0.4476)
	(0.6717)	[0.3992]		[0.1151]	[0.2302]		(0.0003)	(0.7602)		[0.0003]	[0.0058]		[0.0001]	[0.9984]
	0.0431	-0.0241		-0.5334	-0.1308		-1.3984	0.4939		-1.7082	0.4057		-1.6311	-0.0416
4	(0.0988)	(0.0107)	18	(0.2098)	(0.0557)	32	(0.3486)	(0.1221)	46	(0.4018)	(0.1789)	60	(0.3864)	(0.4267)
	(0.6646)	[0.0248]		[0.0150]	[0.0190]		(0.0003)	(0.0001)		[0.0001]	[0.0234]		[0.0001]	[0.9223]

The information in round parentheses is the standard errors.

The probability statistics are inserted in square parentheses.

Note that statistically significant and correctly signed regression θ_1 estimates before the (general) expected or estimated time of the actual rate change (or 'no change') announcement would be indicative of a leakage of the MPC's decision. An interesting observation is the 10 or so statistically significant δ_1 coefficients (with positive and negative signs) during the $-10 < k < 18$ interval. This is probably evidence of dealers' positioning before the repo rate announcement where some traders expect a positive shock, others expect no shock and yet another group anticipate a negative shock. Sager and Taylor (2004) argue that one would expect greater positioning when the probability of movement to a high volatility state is due to information leakage. Thus, systematic exchange rate behaviour tends to be observed on the MPC (or other macroeconomic data) announcement days – news effects after the announcement preceded by some positioning before the announcement.

4.7.2 Principal regression estimates

Interval returns, window periods and the measure of the surprise – actual or standardised shock – vary across empirical studies. To minimise data contamination while simultaneously allowing for adequate time for the market to absorb the data, and to compare the results with a similar and recent study in our literature review by Faust *et al* (2007), we initially estimate the coefficients in a regression of 20-minute exchange rate returns on announcement surprise. In Faust *et al* (2007) the 20-minute window period runs from 5 minutes before the surprise to 15 minutes afterwards. Since the SARB's monetary policy stance announcement takes place anywhere from 8 to 22 minutes after the start of the press conference, as shown in appendix F, we run seven regressions based on 20-minute windows to incorporate the earliest and latest announcement times in Appendix F: 8–28 minutes, 10–30 minutes, 15–35 minutes, 16–36 minutes, 18–38 minutes, 20–40 minutes and 22–42 minutes. To compare our results with very recent empirical work by Conrad and Lamla (2010), we follow the same procedure based on shorter 5-minute windows: 8–13 minutes, 10–15 minutes, 15–20 minutes, 16–21 minutes, 18–23 minutes, 20–25 minutes and 22–27 minutes.[91]

The statistically insignificant results for the 5-minute returns in Table 4.5 may be an indication of a somewhat slower market initial response to the unexpected policy rate changes than the euros response to an ECB surprise – in the 5 minutes following a 100 basis point surprise monetary policy tightening by the ECB, the euro appreciates by about 0.86% against the dollar (Conrad and Lamla, 2010). Dollar appreciation against the pound, euro, Deutsche mark, Swiss franc and yen in response to a 100 basis point standardised Fed rate shock ranges between a meagre 0.032% and 0.072% (Andersen *et al.*, 2003). However, these Fed rate shocks explain a significant proportion of these small moves – adjusted *r*-squareds range between 0.14 and

[91] Although the results in Table 4.4 (p1410, Comrad and Lamla, 2010) are the 5-minute returns response to standardised shocks, the raw shocks response result is reported in the discussion on p1411 (Comrad and Lamla, 2010).

0.26.[92] The inability of our investigation to find statistically significant exchange rate reactions over shorter 5-minute intervals might be due to the varying times of each event – the gap between the earliest and latest release of around 13 minutes is substantial for an intra-day high-frequency event study.

Table 4.5: Impact of a 100-basis-point monetary policy surprise on returns

5-minute window periods			*20-minute window periods*		
Time interval*	$\boldsymbol{\theta_1}$	$\bar{R}^2$	**Time interval***	$\boldsymbol{\theta_1}$	$\bar{R}^2$
8m–13m	-0.0767 (0.1013) [0.4530]	0.01	8m–28m	-0.6917 (0.2754) [0.0161]	0.11
10m–15m	-0.1392 (0.1166) [0.2397]	0.01	10m–30m	-1.1945 (0.0276) [0.0000]	0.32
15m–20m	0.2219 (0.1834) [0.2331]	0.01	15m–35m	-1.2589 (0.3225) [0.0003]	0.25
16m–21m	-0.1243 (0.1663) [0.4591]	0.01	16m–36m	-1.0613 (0.3438) [0.0036]	0.19
18m–23m	-0.1947 (0.1355) [0.1585]	0.05	18m–38m	-0.8387 (0.3475) [0.0203]	0.12
20m–25m	-0.1077 (0.1005) [0.2903]	0.00	20m–40m	-0.8470 (0.3223) [0.0120]	0.12
22m–27m	-0.1455 (0.1125) [0.2032]	0.02	22m–42m	-0.8175 (0.3414) [0.0213]	0.10

The information in round parentheses is the standard errors.
The probability statistics are inserted in square parentheses.
* 'm' denotes minutes.

By contrast, a significant and theoretically coherent relationship between the monetary policy shocks and exchange rate movements emerges for South Africa for the 20-minute windows. OLS regressions results in Table 4.5 suggest that a 100-basis-point surprise tightening of domestic monetary policy is estimated to lead to rand appreciation against the dollar by as much as 1.28%.[93] This is more than double the pound/dollar reaction to Fed surprises (0.66%) for the same window (Faust *et al.*, 2007). Also, a larger proportion of rand returns movements – up to 32% – are explained by repo rate surprises. So not only is the rand more sensitive to SARB policy rate surprises but the reaction is also far more economically significant. Since Fed rate and ECB rate shocks tend to have pervasive direct and indirect effects, another useful comparison would be one based on the dollar/rand reaction to a Fed rate surprise and the euro/rand reaction to an ECB rate shock.[94]

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[92] Conrad and Lamla (2010) do not report the regression *r*-squareds.
[93] Calculated from the 1.2589% dollar depreciation against the rand in the 15–35 minute window period.
[94] See Tozana and May's (2014), a working paper on the rand/dollar exchange rate returns response to Fed rate surprises.
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Table 4.6: Impact of a 100-basis-point monetary policy surprise on volatility

5-minute window periods					*20-minute window periods*				
Time interval*	$\boldsymbol{\delta_1}$	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	$\boldsymbol{\bar{R}^2}$	**Time interval***	$\boldsymbol{\delta_1}$	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	$\boldsymbol{\bar{R}^2}$
	-0.0361	-0.1170	0.4593			-0.0085	-0.1614	0.4686	
8m–13m	(0.0158)	(0.0773)	(0.4604)	0.00	8m–28m	(0.2976)	(0.0980)	(0.5420)	0.13
	[0.0227]	[0.1301]	[0.3184]			[0.9772]	[0.0988]	[0.3873[	
	-0.0428	0.0260	0.6341			-0.2679	-0.1961	0.9209	
10m–15m	(0.0285)	(0.0620)	(0.2422)	0.00	10m–30m	(0.1141)	(0.1407)	(0.2066)	0.32
	[0.1329]	[0.6745]	[0.0089]			[0.0189]	[0.1636]	[0.0000]	
	0.0483	-0.0915	0.4801			0.0687	-0.1498	1.0405	
15m–20m	(0.1073)	(0.1528)	(1.0012)	0.03	15m–35m	(0.1648)	(0.0463)	(0.0707)	0.27
	[0.6527]	[0.5493]	[0.6316]			[0.6768]	[0.0012]	[0.0000]	
	0.0208	-0.1105	0.4452			0.4169	0.1568	0.4405	
16m–21m	(0.0988)	(0.0001)	(1.0410)	0.01	16m–36m	(0.1382)	(0.2808)	(0.3707)	0.19
	[0.8337]	[0.0000]	[0.6689]			[0.0026]	[0.5766]	[0.2347]	
	-0.0096	-0.1028)	1.1267			-0.1746	0.1051	0.7874	
18m–23m	(0.0438)	(0.0588)	(0.1733)		18m–38m	(0.0979)	(0.1669)	(0.1841)	0.12
	[0.8260]	[0.0805]	[0.0000]			[0.0745]	[0.5291]	[0.0000]	
	-0.0.024	-0.1675	0.9662			-0.0267	0.2088	0.6664	
20m–25m	(0.0120)	(0.0462)	(0.0473)	0.00	20m–40m	(0.1128)	(0.3486)	(0.2858)	0.14
	[0.3063]	[0.0003]	[0.0000]			[0.8131]	[0.5491]	[0.0197]	
	0.0273	0.5937	-0.2636			0.0340	0.1855	0.6795	
22m–27m	(0.0082)	(0.2900)	(0.1700)	0.02	22m–42m	(0.1483)	(0.2292)	(0.2339)	0.12
	[0.0009]	[0.0406]	[0.1210]			[0.8189]	[0.4182]	[0.0037]	

The information in round parentheses is the standard errors.
The probability statistics are inserted in square parentheses.
* 'm' denotes minutes

Some interesting results are produced by the variance equation for both the 5-minute and 20-minute windows (Table 4.6). To start with, the statistically significant and positively (negatively) signed variance equation shock coefficients means that policy rate shocks raise (reduce) returns volatility. At the extreme ends of the 5-minute windows (8m-13m and 22m-27m), the statistically significant $\boldsymbol{\delta_1}$ show a shift from a low volatility regime to a high volatility regime. In the 20-minute windows, the statistically significant $\boldsymbol{\delta_1}$ suggest shifts in volatility regimes in the 10m-30m, 16m-36m and 18m-38m windows. The magnitude of $\boldsymbol{\alpha + \beta}$ significantly lower than unity suggests that the effects of the other minor shocks during the event study interval are not persistent. In the 20-minute windows, the magnitudes of the adjusted r-squareds, $\boldsymbol{\bar{R}^2}$, in Tables 4.5 and 4.6 suggest that the policy surprises explain as much of the conditional volatility as the returns (12% to 32%). Faust *et al* (2007) do not estimate volatility responses so a variance reaction comparison is not possible. Also, our volatility results cannot be directly compared with those of Conrad and Lamla's (2010) filtered returns asymmetric effects because our investigation looks at the raw returns and there is inadequate data to estimate the asymmetric effects. Additionally, Andersen *et al* (2003) do not report the repo rate conditional volatility response coefficients for the central bank rate but only the nonfarm payroll employment, durable goods orders, trade balance and initial unemployment claims surprise effects on volatility coefficients.

In an earlier analysis that covered a broader set of macro announcements and the rand/dollar exchange rate effects, Fedderke and Flamand (2005) find that only US-based important news events have a statistically significant effect on the rand in contrast to the evidence in this study. The differences may be explained by two main factors. First, their sample period covers 37 months compared with the 11-year interval in our research. Second, and probably more importantly, we extend their study by using intra-day high-frequency exchange rate data as opposed to daily data – lower-frequency daily data are noisier indicators which weakens the explanatory power of regressions.

4.7.3 Exchange rate response to anticipated repo rate changes

"A market in which prices always fully reflect available information is called efficient" (Fama, 1970). An expanded definition of an efficient market is a market where there are large numbers of rational, profit 'maximisers' actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. Two implications of the EMH are that: i) market traders will only react to new information in the form of unexpected announcements; and, ii) profit opportunities will be short-lived as traders would respond immediately or very quickly to such news. In this last section of the analysis, we test the first implication of the EMH; that is, whether the market responds to repo rate surprises only. We estimate the 20-minute window returns and variance models with the expected repo rate change as an additional explanatory variable

(*Model C*):
$$r_{k,t+k} = \theta_0 + \theta_1 S_{kt} + \theta_2 E_{kt} + \varepsilon_t \qquad (4.6)$$

(*Model D*):
$$r_{k,t+k} = \theta_0 + \theta_1 S_{kt} + \theta_2 E_{kt} + \varepsilon_t \qquad (4.7)$$

$$h^2_{k,t+k} = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon^2_{t-k} + \sum_{j=1}^{q} \beta_j h^2_{t-j} + \delta_1 S_{it} + \delta_2 E_{it} \qquad (4.8)$$

where E_{kt} is the repo rate change that the market expects the MPC to announce (measured as the market median consensus forecast *minus* the level of the repo rate before the announcement), θ_2 is the sensitivity of the exchange rate to expected changes in the repo rate, and δ_2 is the responsiveness of volatility to expected changes in the repo rate. (The other variables and parameters maintain the same definitions from the methodology section.) Table 4.7 reports the results from regression models C and D. The coefficient for the expected repo rate change is statistically insignificant, and so are all the parameters in the variance equation. The *r*-squareds are marginally bigger than the ones from Models A and B above. The finding that anticipated repo rate changes effect neither the foreign exchange returns nor volatility of the rand/dollar exchange rate in the window period after the policy announcement means that the foreign exchange market response to repo rate shocks conforms with the first implication of the EMH; that is, market traders react to only new information in the form of unexpected announcements.

Table 4.7: Exchange rate response to expected and unexpected repo rate changes

20-minute window period (16m-36m)							
Dependent variable	$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2}$	$\boldsymbol{\delta_1}$	$\boldsymbol{\delta_2}$	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	$\boldsymbol{\bar{R}^2}$
	-1.2639	-0.2003	-	-	-	-	
Returns levels	(0.6088)	(0.4942)	-	-	-	-	0.1919
	[0.0444]	[0.6875]	-	-	-	-	
	-	-	0.4353	0.1538	-0.1714	0.4797	
Returns conditional volatility	-	-	(0.3989)	(0.3269)	(0.2274)	(0.2582)	0.1897
	-	-	[0.2751]	[0.6380]	[0.4510]	[0.0632]	

The information in round parentheses is the standard errors.
The probability statistics are inserted in square parentheses.

4.8 Concluding remarks and discussion

The goal of this analysis– the first on South African interest rate announcements using high-frequency exchange rate data – was to deepen our understanding of the reaction of the intra-day high-frequency rand/dollar exchange rate returns and their volatility to expected and unexpected South African Reserve Bank repo rate changes. To that end, we have documented important news effects. The main overall conclusion of this chapter is that domestic repo rate surprises have a significant effect on the rand/dollar exchange rate. In particular, we find a significant and theoretically-coherent response to domestic repo rate shocks emerges only after 5 minutes following the repo rate announcement; that is in the 20-minute windows. A 100-basis point surprise tightening of domestic monetary policy is estimated to lead to a 1.28% rand appreciation against the dollar, more than double the pound/dollar 0.66% reaction to Fed surprises for the same window. The statistically significant and positively signed variance equation shock coefficients means that policy rate shocks raise returns volatility – in the 20-minute windows, the statistically significant conditional volatility response parameter suggests shifts in volatility regimes in the 10m-30m, 16m-36m and 18m-38m windows. The magnitude of $\alpha + \beta$ in the GARCH specifications is significantly lower than unity, indicating that the effects of the shocks during the event study interval are not persistent. Not only is the rand sensitive to SARB policy rate surprises but the adjusted *r*-squareds of up to 32% for both the returns and conditional volatility suggest economic significance in the responses as well.

The relatively rapid exchange rate response to a 100-basis-point hike – elevated returns peak within 30 minutes post-announcement and volatility subsides about 40 minutes following the event – suggest a relatively high degree of market 'mechanical efficiency' in this event study context. The non-instantaneous returns response based on the 5-minute window may be attributed to inconsistent event times or an initially less swift price adjustment as market participants absorb the information and revise expectations. The finding that anticipated repo rate changes effect neither the foreign exchange returns nor volatility of the rand/dollar exchange rate after the event indicates that the foreign exchange market response to repo rate shocks conforms to the first implication of the EMH; that is, market traders react to only new information in the form of unexpected announcements.

Evidence of declining magnitudes and incidences of repo rate shocks in the most recent years in our analysis tentatively suggest that the South African monetary authorities have reinforced the gains from policy transparency uncovered in earlier work between 2005 and 2007. This is consistent with the Bank's (verbal and nonverbal) articulation of monetary policy aiding the modelling of repo rate decisions leading to greater precision in financial market forecasts.

Where to from here? Like all empirical studies, there are a number of limitations in our inquiry which have future research implications. The use of intra-day ultra-high-frequency tick-by-tick data has been shown to produce more robust results – substantially larger sample size and smaller standard errors – than 1-minute or lower frequency data. Shocks can also be extracted from the future rate agreement (FRA) rates but this approach will also be limited by the availability of an adequately long sample of high-frequency interest rate data. Our models can also be extended in a number of ways to capture exchange rate responses to future exchange rate expectations implied in the MPC release statements and immediate 3-month and say 12-month FRA rate movements. The relatively small sample size (although not small when compared to other similar studies) has inhibited an investigation of different sample responses; for example, exchange rate responses during times of turbulence and normal times, recessions and booms, and asymmetric responses to good and bad news. It is generally found that bad news has a greater impact than good news. Andersen *et al* (2003) contend that these asymmetric responses may be driven by different degrees of uncertainty with respect to the underlying economy, related to theoretical work on information processing and price discovery.[95] When the sample size for South Africa becomes sufficiently large, the interest rate surprise measure can be split into positive and negative surprises in order to control for potential asymmetries. The impact of a wide-range of other (local and foreign) macroeconomic news announcements also requires investigation; and so does a formal econometric approach to empirically test monetary policy transparency along the lines of Elliot and Muller (2006) and Muller and Petalas (2010).

[95] See also Veronesi (1999). Veronesi (1999) shows that in equilibrium, investors have a higher sensitivity to bad news during good times and underreact to good news in bad times.

4.9 Software

All of the results reported in this paper were generated using Eviews7.

CHAPTER 5

General conclusion

The thesis has presented a series of empirical studies on the dynamics of the foreign exchange rates of the South African rand. Each of the three substantive chapters considers specific aspects of the rand's dynamics, using time series econometrics techniques. The models, estimation techniques, sample periods and data frequencies (high and low) are chapter specific.

The thesis adds to the empirical literature by asking three broad questions. (i) Do unit root test results change when endogenously identified structural change is accounted for? (ii) Does misspecification of conditional volatility result in the choice of sub-optimal models and thus spurious regressions? (iii) How does the rand respond to scheduled domestic repo rate announcements – surprises and expected changes? The empirical evidence does not only provide clear-cut answers to these general questions but also sheds light on a multitude of other related issues. In this concluding chapter, the major findings from the three core analytical studies are highlighted and discussed chapter by chapter. Some limitations of the studies are then pointed out. And finally, the implications for future research are deliberated.

5.1 Discussion of the main findings

Chapter 2 addresses the issue of unit root testing and structural shifts in the levels of the key nominal exchange rates of the rand. Testing for structural breaks in economic time series and time series relationships, and accounting for such change in economic models can avert spurious inference. Perron (1990) empirically showed that the existence of a structural shift in a stationary series may result in nonrejection of a unit root null, with more evidence for misconstrued unit roots tests being provided by Zivots and Andrews (1992) and Lee and Strazicich (2001). The endogenisation of breakpoints has been an important milestone in unit root testing. There are several key findings in this study. We find that several statistically significant structural breaks are evident in the data (at the 95% or 99% confidence levels). There is convincing evidence that the exchange rates of the rand are nonstationary and *I(1)*, even in the presence of structural breaks at the 1% level of significance, although the evidence for the pound/rand exchange rate is not as clear-cut as for the other rates. Another important result is that the unit root test *t*-statistics and *LM*-statistics for all five exchange rates lie much closer to their corresponding asymptotic 5% level critical values when structural shift is accommodated, with a greater convergence observed in the yen/rand – consistent with Perron's (1990) results which showed that the power to reject a unit root decreases when the stationarity alternative is true and a structural break is ignored. An adjunct to these findings – the wide-ranging and diverse set of structural change triggers in the rand – is also a vital contribution to empirical work on the rand. These breakpoints coincide with important global and domestic economic and noneconomic events and factors. A common source of structural shift across exchange rates is conspicuous during the 1998 east-Asian contagion. Also worth noting is the timing of the breakpoints in the US dollar/rand exchange rates – more often than not, the structural shifts in this series either precede or coincide with those in the other series. Finally, negative shocks dominate – comprising 65% of all shocks.

Chapter 3 investigates the nature and extent of volatility in the rand exchange rates, whether structural change is evident in the volatility processes and its implications for volatility persistence. Spells of volatility in the international prices of the rand are a recurring issue in the sample period, and recent events have sparked widespread interest and debates amongst academics, practitioners, policymakers and other interest groups because heightened exchange rate instability can have serious adverse and pervasive ramifications. The results reported in the chapter provide abundant information on the properties of currency returns and their variance. Consistent with most conditional volatility model studies surveyed, standard unit root test results confirm stationarity of the returns. Statistical tests detect kurtosis, asymmetry and volatility clustering in the nominal foreign exchange rate returns of the rand, a motivation for using ARCH class conditional volatility models, which are designed to account for the stylised facts associated with financial asset price returns, and fitting a skewed Student-*t* distribution to the returns. The Nyblom parameter stability and ICSS tests results indicate strong and widespread instability in conditional volatility (between 20 and 44 breakpoints are detected). We detect more than double the number of statistically significant structural breaks in the conditional variance than those uncovered in a recent study on the US dollar/rand exchange rate returns, for a similar period, by Duncan and Liu (2009). A striking and important finding of this investigation is the fall in volatility persistence when fractional integration and structural changes are integrated into the GARCH framework. Long memory is evident in US dollar/rand returns (and consequently in the NEER) while ARCH effects tend to die off earlier in the yen/rand daily series; possibly due to the Bank of Japan's interventions in the foreign exchange market. The top three approximating models reflect the importance of long memory, asymmetry and structural change, both abrupt and smooth, in exchange rate volatility modelling. A consequence of accounting for the latter phenomena is that unconditional variance are found to be stationary in contrast to the estimates from simpler models. Although the sudden structural shift GARCH models better fit the data than the smooth transitional competing models, the latter modelling framework does not perform considerably worse and is a notable improvement on the basic models. The timing of changes in volatility regimes, and thus their likely causes, are more or less consistent with the exchange rate level shifts detected in Chapter 2. Evidently, the pricing of risk varies across exchange rates – only the GBP/ZAR ARCH-M parameter, τ, is statistically significant and at the same time correctly signed (+) at the 5% level, suggesting that the increased risk of converting pound denominated assets into rand holdings is associated with an excess return. Lastly, the extent of asymmetric responses of the rand to 'good news' and bad news' are considerable – negative shocks have a greater effect on volatility than their positive counterparts.

The third main empirical section (Chapter 4) deals with the reaction of the rand/US dollar exchange rate to scheduled monetary policy (repo rate) announcements. Pronouncements by the South African Reserve Bank on the repo rate decision following the MPC's deliberations are made at the end of the Governor's prepared monetary policy statements. As the latter vary from event to event, the estimated timing of each interest rate announcement was obtained by carefully studying the press conference webcasts. On intra-day high-frequency exchange rate responses to monetary policy surprises, we find both statistically and economically significant responses of the level and volatility of the rand returns to repo rate shocks, but that anticipated changes have no bearing on the rand. The main finding is that on impact, a 100-basis-point positive (negative) repo rate shock will appreciate (depreciate) the rand/US dollar exchange rate by approximately 1.3% 30 minutes immediately after the announcement, and that most of the 60-minute exchange rate adjustment (±90%) occurs within the same time interval. The relatively rapid of exchange rate response to a 100-basis-point hike – elevated returns peak within 30 minutes post-announcement and volatility subsides about 40 minutes following the event – suggest a relatively high degree of market "efficiency" in a mechanical sense – communications are speedy and exchange rates adjust rapidly to new unanticipated announcements. The non-instantaneous response based on the 5-minute window may be attributed to inconsistent event times or an initially less swift price adjustment as market participants absorb the information and revise expectations. Furthermore, and in support of earlier studies, increased monetary policy transparency by the SARB is evident in the declining trend in the number and magnitude of repo rate shocks suggesting that market participants have improved their understanding of the bank's monetary policy reaction function. The finding that anticipated repo rate changes effect neither the foreign exchange returns nor volatility of the rand/dollar exchange rate after the announcement indicates that the foreign exchange market response to repo rate shocks conforms to the first implication of the EMH; that is, market traders react to only new information in the form of unexpected announcements.

5.2 Limitations and future research

Apiece, the three main studies have their own limitations, providing areas of potential future research on the foreign exchange rates of the rand. Overall, the drawbacks and future research avenues are data, modelling, methodology and computer software related.

The deliberate univariate analyses carried out in Chapter 2 helped us understand some of the basic characteristics of South African foreign exchange rate data. For structural change-adapted unit root testing of the levels of the exchange rates, the available models are the key constraint. The unit root test models employed here are linear models and account for a maximum of two structural changes – standard econometric software packages do not include nonlinear and multiple structural change unit root tests. It is more reasonable to think that breaks occur over several periods, that is, there are multiple structural shifts. Also, in some instances, the power of nonlinear models can be considerably higher than that of linear versions. So including nonlinear parameters together with multiple structural changes, which could further diminish the problem of model misspecification and thus spurious results, prompts future research in this area. Expanding unit root tests to encompass more than two breaks, deriving the new asymptotic distributions, writing the programmes or code to run both nonlinear stationarity tests and multiple structural break tests is a challenging task, a further direction for research on the dynamics of the foreign exchange rates of the rand. Testing for structural breaks within a multivariate or cointegration framework is another area for future research.

Turning our attention to the analysis volatility dynamics in Chapter 3, in many respects, the ARCH-type modelling frameworks applied here are an improvement on the models employed in earlier studies on the rand. There are, however, a multitude of potential future studies on rand volatility. To mention a few:

- expanding exchange rate volatility measurement beyond conditional volatility to realised volatility and implied volatility (implied in currency options prices);
- in-sample and out-of-sample rand exchange rate forecasting; and
- widening the study to multivariate analysis of aggregated and disaggregated financial asset prices – bonds, equities, money market instruments, currency prices and financial market derivatives.

And finally, regarding the study of shocks and high-frequency exchange rate responses in Chapter 4, a much broader range of macroeconomics shocks – over and above domestic monetary policy surprises – warrants investigation. Results from a similar study by Tozana and May (2014) show that in some respects, U.S. monetary policy surprise announcements affect the rand/US dollar exchange rate more or less in line with the results of chapter 4 of this study. Firstly, U.S. Fed funds futures rates (a proxy for expectations of the Fed funds target rates) shocks have an immediate, and statistically and economically significant effect on the rand/U.S. dollar returns. Secondly, the study finds that returns increase by 128 basis points over a 20-minute period following a 100 basis-point target rate surprise. Thirdly, target rate shocks die away 27 minutes after the announcement time. The findings also show that the market reacts within the first minute of a target rate announcement indicating a very high degree of market efficiency (from a mechanical perspective). Results from another comparable study by van Staden, Farrell and May (2015) also show that GDP surprise announcements significantly affect the exchange rate over both the 5- and 20-minute windows, and the current account surprise announcements significantly affect the exchange rate over the 5-minute window but not the 20-minute window. However, we find no evidence that suggests these surprise announcements impact exchange rate volatility. A third study by Ngadu and May (2014) shows that S.A. repo rate surprise announcements have an immediate, and statistically and economically significant influence on the Johannesburg Securities Exchange All-Share Index (ALSI) returns. Using ultra high-frequency tick-by-tick data would help in more fully and precisely characterising the response of currency returns to shocks. There is convincing evidence of asymmetric high-frequency exchange rate conditional volatility responses to monetary surprises in some advanced economies. For South African monetary policy surprises, and some other macroeconomic shocks, this analysis will be feasible only once a large enough sample size becomes available – only in more recent years have government agencies and online news services such as Bloomberg and Reuters recorded the embargo times of all key scheduled local macroeconomic releases; the dates for each release are generally available though.

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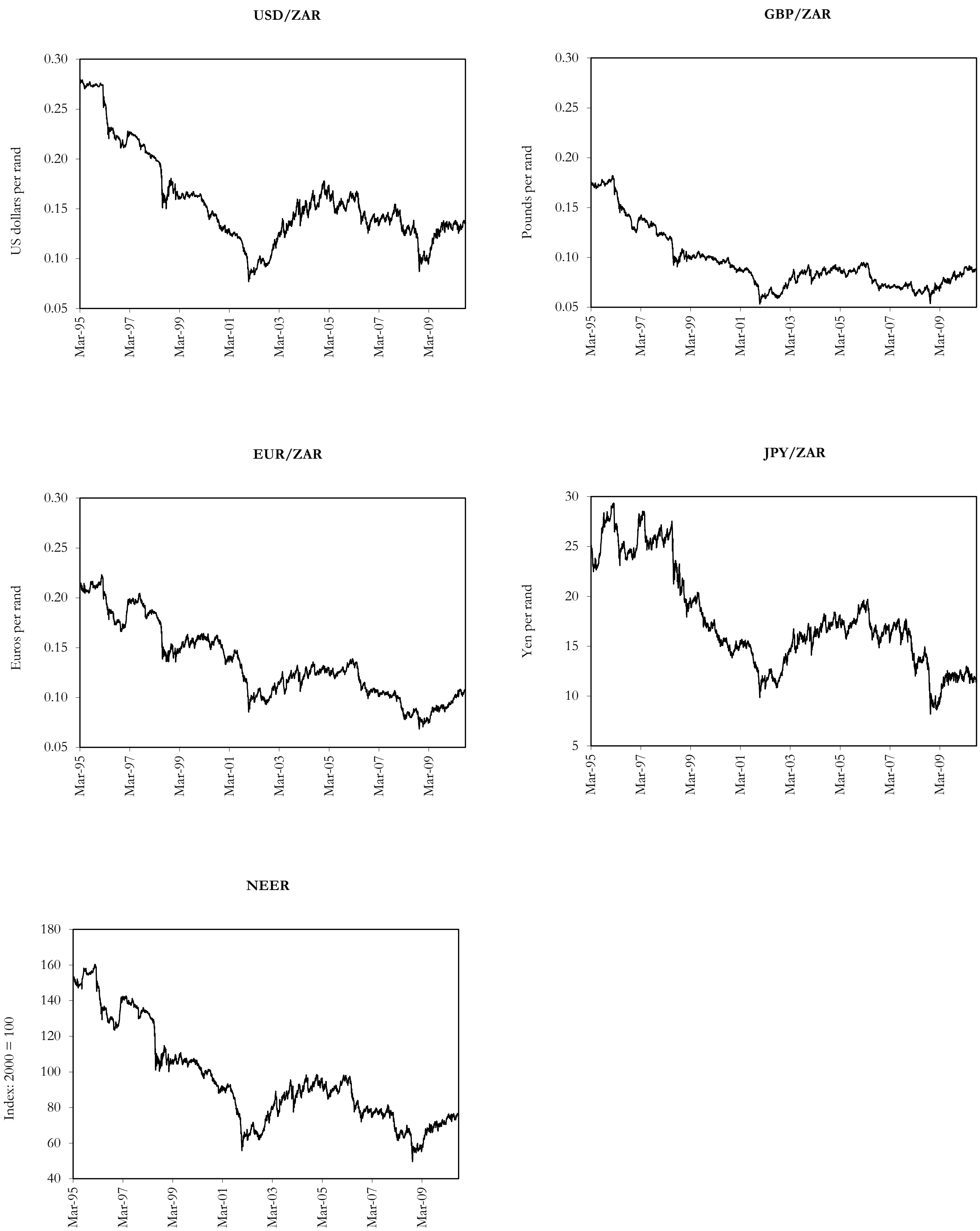
Appendix A

Panel diagram A1: Daily indirect foreign exchange rates of the rand (13 March 1995 - 31 August 2010)



Appendix B

Table B1: ADF *tau* unit root test results for daily returns, r_t

Series	Intercept and no trend *t*-statistic	Intercept and no trend *p*-value	Intercept and trend *t*-statistic	Intercept and trend *p*-value
USD/ZAR	-11.1660	0.0000	-11.2260	0.0000
EUR/ZAR	-11.5955	0.0000	-11.6158	0.0000
GBP/ZAR	-13.8358	0.0000	-13.9253	0.0000
JPY/ZAR	-44.2826	0.0000	-44.2768	0.0000
NEER	-11.4445	0.0000	-11.4685	0.0000

		1%	5%	10%
Asymptotic critical values	*No Trend*	-3.4319	-2.8621	-2.5671
	Trend	-3.9605	-3.4110	-3.1273

Notes: See notes in Table 1.2, chapter 1.

Table B2: PP unit root test results for daily returns, r_t

Series	Intercept and no trend *Adj. t*-statistic	Intercept and no trend *p*-value	Intercept and trend *Adj. t*-statistic	Intercept and trend *p*-value
USD/ZAR	-64.0097	0.0001	-64.0494	0.0000
EUR/ZAR	-62.9527	0.0001	-62.9540	0.0000
GBP/ZAR	-63.2211	0.0001	-63.2631	0.0000
JPY/ZAR	-64.2829	0.0001	-64.2740	0.0000
NEER	-63.9408	0.0000	-63.9441	0.0000

		1%	5%	10%
Asymptotic critical values	*No Trend*	-3.4319	-2.8621	-2.5671
	Trend	-3.9604	-3.4110	-3.1273

Notes: See notes in Table 1.3, chapter 1.

Table B3: DF-GLS *tau* unit root test results for daily returns, r_t

	Intercept and no trend		Intercept and trend	
Series	*t*-statistic	*p*-value	*t*-statistic	*p*-value
USD/ZAR	-7.8895	*	-9.5940	*
EUR/ZAR	-6.3420	*	-8.8453	*
GBP/ZAR	-4.0850	*	-7.4595	*
JPY/ZAR	-3.6235	*	-6.1295	*
NEER	-6.3831	*	-8.8109	*

		1%	5%	10%
Asymptotic critical values	*No Trend*	-2.5656	-1.9409	-1.6166
	Trend	-3.4800	-2.8900	-2.5700

Notes: See notes in Table 1.4, chapter 1.

* EVIEWS 6 does not generate and report these values.

Table B4: KPSS unit root tests for daily returns, r_t

	Intercept and no trend		Intercept and trend	
Series	*LM*-statistic	*p*-value	*LM*-statistic	*p*-value
USD/ZAR	0.2355	*	0.0709	*
EUR/ZAR	0.0927	*	0.0444	*
GBP/ZAR	0.2994	*	0.0357	*
JPY/ZAR	0.06116	*	0.0604	*
NEER	0.11645	*	0.0474	*

		1%	5%	10%
Asymptotic critical values	*No Trend*	0.7390	0.4630	0.3470
	Trend	0.2160	0.1460	0.1190

Notes: See notes in Table 1.5, chapter 1.

* EVIEWS 6 does not generate and report these values.

Table B5: Comparative USD/ZAR Basic GARCH models estimation results

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH	APARCH
			Mean equation results		
γ	-0.0149	-0.0131	-0.0168	-0.0222	-0.0191
S.E.	(0.0065)	(0.0065)	(0.0066)	(0.0036)	(0.0068)
p-value	(0.0213)	(0.0446)	(0.0106)	(0.0000)	(0.0051)
κ	0.1028	0.1046	0.1038	0.1011	0.1023
S.E.	(0.0124)	(0.0130)	(0.0123)	(0.0115)	(0.0122)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ν	-0.2253	-0.2287	-0.2260	-0.2255	-0.2242
S.E.	(0.0173)	(0.0171)	(0.0173)	(0.0097)	(0.0168)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
			Variance equation results		
ω	0.0008	0.0011	0.0008	-7.1558	0.0016
S.E.	(0.0004)	(0.0004)	(0.0004)	(2.3178)	(0.0008)
p-value	(0.0379)	(0.0110)	(0.0324)	(0.0020)	(0.0487)
δ	-	-	-	-	1.4359
S.E.	-	-	-	-	(0.1619)
p-value	-	-	-	-	(0.0000)
α_1	0.1485	0.1122	0.1266	-0.2983	0.1413
S.E.	(0.0186)	(0.0121)	(0.0190)	(0.0983)	(0.0178)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0024)	(0.0000)
α_1^*	-	-	0.0372	-	0.1160
S.E.		-	(0.0197)	-	(0.0459)
p-value	-	-	(0.0585)	-	(0.0116)
$\alpha_1+\alpha_1^*$	-	-	0.1638	-	0.2573
θ_1	-	-	-	-0.0555	-
S.E.	-	-	-	(0.0181)	-
p-value	-	-	-	(0.0022)	-
θ_2	-	-	-	0.3330	
S.E.	-	-	-	(0.0376)	-
p-value	-	-	-	(0.0000)	
$\lvert\theta_1+\theta_2\rvert$	-	-	-	0.2775	-
$\lvert\theta_1-\theta_2\rvert$	-	-	-	0.3885	-
β_1	0.8747	0.8878	0.8765	0.9931	0.8918
S.E.	(0.0131)	-	(0.0134)	(0.0025)	(0.0135)
p-value	(0.0000)	-	(0.0000)	(0.0000)	(0.0000)
$\alpha_1+\beta_1$	1.0232	1.00000	-	-	-
$\varepsilon^+:\alpha_1+\beta_1$	-	-	1.0031	-	1.0331
$\varepsilon^-:\alpha_1+\alpha_1^*+\beta_1$	-	-	1.0403	-	1.1491
$\varepsilon^+:\lvert\theta_1+\theta_2\rvert+\beta_1$	-	-	-	1.2706	-
$\varepsilon^-:\lvert\theta_1-\theta_2\rvert+\beta_1$	-	-	-	1.3816	-
			Skewed Student-*t* distribution statistic for residuals, ε_t		
Asymmetry	-0.1348	-0.1314	-0.1345	-0.1449	-0.1382
S.E.	(0.0223)	(0.0206)	(0.0222)	(0.0220)	(0.0225)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tail	5.4680	6.4863	5.4880	5.5801	5.4781
S.E.	(0.4922)	(0.5025)	(0.4951)	(0.5002)	(0.4921)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH*	APARCH
			Information criteria and log-likelihood statistics		
SIC	2.2613	2.2644	2.2625	2.2612	2.2621
Log likelihood	-4335.70	-4345.95	-4333.92	-4327.28	-4329.04
			Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$		
Lag =10	9.3942	9.4572	9.3933	9.5791	9.5879
p-value	(0.4952)	(0.4893)	(0.4952)	(0.4782)	(0.4774)
Lag =20	23.120	23.585	22.795	24.761	23.599
p-value	(0.2830)	(0.2610)	(0.2990)	(0.2107)	(0.2604)
Lag =50	50.418	50.5885	49.145	49.816	49.292
p-value	(0.4569)	(0.4502)	(0.5076)	(0.4807)	(0.5017)
			Mean equation squared standardised residuals serial correlation statistics, $Q_{LB(z_t^2)}$		
Lag =10	18.205	21.775	15.955	13.793	41.541
p-value	(0.0197)	(0.0054)	(0.0430)	(0.0873)	(0.0000)
Lag =20	25.408	29.2202	24.066	26.286	50.458
p-value	(0.1141)	(0.0458)	(0.1529)	(0.0934)	(0.0001)
Lag =50	54.3065	58.605	51.166	52.121	78.893
p-value	(0.2467)	(0.1404)	(0.3505)	(0.3168)	(0.0033)
			Joint Nyblom stability test statistics		
ω	19.633	19.922	19.950	20.919	20.026

Joint statistic of the Nyblom test of stability - H_0: Parameter is constant and H_1: Parameter is unstable. The asymptotic 1% and 5% critical values for joint Nyblom statistics are 0.75 and 0.47respectively.

Table B6: Comparative EUR/ZAR Basic GARCH models estimation results

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH	APARCH
			Mean equation results		
γ	-0.0053	-0.0071	-0.0094	-0.0247	-0.0505
S.E.	(0.0114)	(0.0113)	(0.0118)	(0.0199)	(0.0117)
p-value	(0.6432)	(0.5289)	(0.4231)	(0.2142)	(0.1968)
χ	0.6187	0.6183	0.5805	0.5219	0.5201
S.E.	(0.1054)	(0.1039)	(0.1270)	(0.1436)	(0.1511)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0006)
ϕ	-0.6647	-0.6642	-0.6208	-0.5660	-0.5640
S.E.	(0.1003)	(0.0990)	(0.1233)	(0.1404)	(0.1478)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
τ				0.0102	
S.E.	*	*	*	(0.0226)	*
p-value				(0.6521)	
			Variance equation results		
ω	0.1870	0.0144	0.0208	-1.7600	0.0222
S.E.	(0.0065)	(0.0050)	(0.0078)	(0.4571)	(0.0080)
p-value	(0.0037)	(0.0037)	(0.0077)	(0.0001)	(0.0038)
δ	-	-	-	-	1.2206
S.E.	-	-	-	-	(0.1429)
p-value	-	-	-	-	(0.0000)
α_1	0.1022	0.1118	0.0733	-0.3897	0.1065
S.E.	(0.0189)	(0.0207)	(0.0178)	(0.1272)	(0.0179)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0022)	(0.0000)
α_1^*	-	-	0.0486	-	0.1160
S.E.		-	(0.0213)	-	(0.0459)
p-value	-	-	(0.0227)	-	(0.0116)
$\alpha_1 + \alpha_1^*$	-	-	0.1219	-	0.2573
θ_1	-	-	-	-0.0725	-
S.E.	-	-	-	(0.0212)	-
p-value	-	-	-	(0.0006)	-
θ_2	-	-	-	0.2731	
S.E.	-	-	-	(0.0343)	-
p-value	-	-	-	(0.0000)	
$\lvert\theta_1 + \theta_2\rvert$	-	-	-	0.2006	-
$\lvert\theta_1 - \theta_2\rvert$	-	-	-	0.3456	-
β_1	0.8855	0.8882	0.8858	0.9800	0.8957
S.E.	(0.0212)	-	(0.0241)	(0.0074)	(0.0200)
p-value	(0.0000)	-	(0.0000)	(0.0000)	(0.0000)
$\alpha_1 + \beta_1$	0.9877	1.00000	-	-	-
$\varepsilon^+ : \alpha_1 + \beta_1$	-	-	0.9591	-	1.0022
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	-	-	1.0077	-	1.1182
$\varepsilon^+ : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	-	-	1.1806	-
$\varepsilon^- : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	-	-	1.3256	-

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH*	APARCH
Skewed Student-*t* distribution statistic for residuals, ε_t					
Asymmetry	-0.1364	-0.1382	-0.1339	-0.1435	-0.1402
S.E.	(0.0227)	(0.0230)	(0.0229)	(0.0232)	(0.0232)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tail	5.5407	5.1803	5.5412	5.6641	5.6033
S.E.	(0.4713)	(0.4123)	(0.4722)	(0.4877)	(0.4805)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Information criteria and log-likelihood statistics					
SIC	2.6169	2.6156	2.6170	2.6146	2.6147
Log likelihood	-5022.83	-5024.51	-5018.86	-5006.02	-5010.30
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$					
Lag =10	14.4300	14.9463	10.629	12.137	11.439
p-value	(0.0712)	(0.0602)	(0.2236)	(0.1452)	(0.1781)
Lag =20	20.0181	20.7213	16.2211	18.632	17.539
p-value	(0.3318)	(0.2937)	(0.5771)	(0.4148)	(0.4864)
Lag =50	45.5731	44.9122	40.2548	42.513	41.575
p-value	(0.6141)	(0.6001)	(0.7789	(0.6964)	(0.7319)
Mean equation squared standardised residuals serial correlation statistics, $Q_{LB(z_t^2)}$					
Lag =10	3.1327	3.3591	2.8249	8.3413	5.8734
p-value	(0.9258)	(0.9098)	(0.9449)	(0.4009)	(0.6614)
Lag =20	8.9338	10.1386	8.8677	14.498	11.971
p-value	(0.9613)	(0.9273)	(0.9627)	(0.6961)	(0.8488)
Lag =50	26.7718	28.0198	28.3591	38.264	33.938
p-value	(0.9944)	(0.9906)	(0.9893)	(0.8415)	(0.9377)
Joint Nyblom stability test statistics					
ω	4.594	3.563	5.123	4.6112	4.949

Joint statistic of the Nyblom test of stability - H_0: Parameter is constant and H_1: Parameter is unstable. The asymptotic 1% and 5% critical values for joint Nyblom statistics are 0.75 and 0.47respectively.

* More or less in line with the ARCH(9) models results, the ARCH-M parameter is statistically insignificant in four of the five GARCH – the latter four GARCH models are estimated without this regressor in turn generating a preferable lower *p*-value for the standardised residuals Q_{LB} test. For the EGARCH model, there is no convergence (no improvement in line search) using numerical derivatives – inclusion of the ARCH-M (standard deviation from variance equation) variable in the mean equation resolves this problem though the parameter is statistically insignificant.

Table B7: Comparative GBP/ZAR GARCH Basic models estimation results

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH	APARCH
			Mean equation results		
γ	-0.0750	-0.0753	-0.0707	-0.0889	-0.0768
S.E.	(0.0278)	(0.0274)	(0.0272)	(0.0292)	(0.0278)
p-value	(0.0069)	(0.0060)	(0.0093)	(0.0024)	(0.0057)
κ	0.1066	0.1066)	0.1086	0.1098	0.1087
S.E.	(0.0153)	(0.0153)	(0.0154)	(0.0149)	(0.0156)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ν	0.1855	0.1854)	0.1858	0.1858	0.1863
S.E.	(0.0243)	(0.0242)	(0.0243)	(0.0238)	(0.0242)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	0.0736	0.0741	0.0584	0.0710	0.0617
S.E.	(0.0371)	(0.0362)	(0.0173)	(0.0391)	(0.0378)
p-value	(0.0470)	(0.0410)	(0.0369)	(0.0695)	(0.1025)
			Variance equation results		
ω	0.0088	0.0089	0.0091	-1.9226	0.0111
S.E.	(0.0034)	(0.0030)	(0.0035)	(0.5512)	(0.0041)
p-value	(0.0086)	(0.0030)	(0.0103)	(0.0005)	(0.0065)
δ	-	-	-	-	1.4942
S.E.	-	-	-	-	(0.1573)
p-value	-	-	-	-	(0.0000)
α_1	0.1125	0.1122	0.0810	-0.4218	0.1103
S.E.	(0.0184)	(0.0175)	(0.0178)	(0.0994)	(0.0180)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1^*	-	-	0.0516	-	0.1733
S.E.		-	(0.0181)	-	(0.0537)
p-value	-	-	(0.0046)	-	(0.0013)
$\alpha_1 + \alpha_1^*$	-	-	0.1326	-	0.2836
θ_1	-	-	-	-0.0780	-
S.E.	-	-	-	(0.0202)	-
p-value	-	-	-	(0.0001)	-
θ_2	-	-	-	0.3054	
S.E.	-	-	-	(0.0338)	-
p-value	-	-	-	(0.0000)	
$\lvert\theta_1 + \theta_2\rvert$	-	-	-	0.2274	-
$\lvert\theta_1 - \theta_2\rvert$	-	-	-	0.3834	-
β_1	0.8879	0.8878	0.8918	0.9857	0.8992
S.E.	(0.0176)	-	(0.0186)	(0.0046)	(0.0171)
p-value	(0.0000)	-	(0.0000)	(0.0000)	(0.0000)
$\alpha_1 + \beta_1$	1.0004	1.0000	-	-	-
$\varepsilon^+ : \alpha_1 + \beta_1$	-	-	0.9728	-	1.0095
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	-	-	1.0244	-	1.1828
$\varepsilon^+ : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	-	-	1.2131	-
$\varepsilon^- : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	-	-	1.3691	-
			Skewed Student-*t* distribution statistic for residuals, ε_t		
Asymmetry	-0.0810	-0.0810	-0.0854	-0.0998	-0.0888
S.E.	(0.0218)	(0.0218)	(0.0220)	(0.0222)	(0.021)
p-value	(0.0002)	(0.0002)	(0.0001)	(0.0000)	(0.0001)
Tail	6.0871	6.1026	6.1415	6.2433	6.1590
S.E.	(0.5834)	(0.5458)	(0.5950)	(0.6144)	(0.5994)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH	APARCH
Information criteria and log-likelihood statistics					
SIC	2.5612	2.5591	2.5610	2.5591	2.5614
Log likelihood	-4911.11	-4911.12	-4906.56	-4898.77	-4903.18
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$					
Lag =10	10.060	10.057	10.621	10.662	11.123
p-value	(0.4353)	(0.4355)	(0.3878)	(0.3083)	(0.3481)
Lag =20	23.948	23.940	24.124	25.674	24.961
p-value	(0.2447)	(0.2450)	(0.2370)	(0.1769)	(0.2029)
Lag =50	53.196	53.172	43.741	54.468	54.124
p-value	(0.3522)	(0.3530)	(0.3331)	(0.3085)	(0.319)
Mean equation squared standardised residuals serial correlation statistics, $Q_{LB(z_t^2)}$					
Lag =10	11.916	11.888	11.375	19.458	14.773
p-value	(0.1550)	(0.1563)	(0.1814)	(0.0126)	(0.0631)
Lag =20	19.946	19.881	20.327	25.784	22.954
p-value	(0.3359)	(0.3400)	(0.3147)	(0.1048)	(0.1924)
Lag =50	57.4205	47.361	47.621	47.087	48.1805
p-value	(0.4965)	(0.4989)	(0.4883)	(0.5102)	(0.4655)
Joint Nyblom stability test statistics					
ω	11.796	11.594	12.400	11.837	12.458

Joint statistic of the Nyblom test of stability - H_0: Parameter is constant and H_1: Parameter is unstable. The asymptotic 1% and 5% critical values for joint Nyblom statistics are 0.75 and 0.47respectively.

Table B8: Comparative JPY/ZAR GARCH Basic models estimation results

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH	APARCH
			Mean equation results		
γ	0.0032	0.0006	-0.0088	-0.0072	-0.0104
S.E.	(0.0148)	(0.0150)	(0.0157)	(0.0153)	(0.0171)
p-value	(0.8274)	(0.9684)	(0.5743)	(0.6370)	(0.5422)
χ	0.5548	0.5453	0.4428	0.4616	0.4201
S.E.	(0.1386)	(0.1378)	(0.1676)	(0.1364)	(0.1645)
p-value	(0.0001)	(0.0001)	(0.0083)	(0.0007)	(0.0107)
ϕ	-0.6020	-0.5924	-0.4797	-0.5034	-0.4579
S.E.	(0.1353)	(0.1348)	(0.1685)	(0.1371)	(0.1659)
p-value	(0.0000)	(0.0000)	(0.0044)	(0.0002)	(0.0058)
			Variance equation results		
ω	0.0365	0.0238	0.0446	-1.0715	0.0423
S.E.	(0.0106)	(0.0074)	(0.0129)	(0.3438)	(0.0118)
p-value	(0.0006)	(0.0012)	(0.0005)	(0.0018)	(0.0003)
δ	-	-	-	-	1.4060
S.E.	-	-	-	-	(0.1665)
p-value	-	-	-	-	(0.0000)
α_1	0.1059	0.1178	0.0588	-0.3335	0.1075
S.E.	(0.0167)	(0.0196)	(0.0138)	(0.1212)	(0.0155)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0060)	(0.0000)
α_1^*	-	-	0.0847	-	0.2899
S.E.		-	(0.0263)	-	(0.0735)
p-value	-	-	(0.0013)	-	(0.0001)
$\alpha_1 + \alpha_1^*$	-	-	0.1435	-	0.3974
θ_1	-	-	-	-0.0813	-
S.E.	-	-	-	(0.0206)	-
p-value	-	-	-	(0.0001)	-
θ_2	-	-	-	0.2602	
S.E.	-	-	-	(0.0325)	-
p-value	-	-	-	(0.0000)	
$\lvert\theta_1 + \theta_2\rvert$	-	-	-	0.1789	-
$\lvert\theta_1 - \theta_2\rvert$	-	-	-	0.3415	-
β_1	0.8735	0.8822	0.8694	0.9750	0.8780
S.E.	(0.0206)	-	(0.0225)	(0.0078)	(0.0203)
p-value	(0.0000)	-	(0.0000)	(0.0000)	(0.0000)
$\alpha_1 + \beta_1$	0.9794	1.00000	-	-	-
$\varepsilon^+ : \alpha_1 + \beta_1$	-	-	0.9282	-	0.9855
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	-	-	1.0129	-	1.2754
$\varepsilon^+ : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	-	-	1.1539	-
$\varepsilon^- : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	-	-	1.3163	-
			Skewed Student-*t* distribution statistic for residuals, ε_t		
Asymmetry	-0.1385	-0.1373	-0.1391	-0.1398	-0.1396
S.E.	(0.0232)	(0.0239)	(0.0230)	(0.0232)	(0.0232)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tail	6.5939	5.8086	6.7230	6.6191	6.7173
S.E.	(0.6526)	(0.5277)	(0.6789)	(0.6551)	(0.6789)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH*	APARCH
		Information criteria and log-likelihood statistics			
SIC	3.0463	3.0464	3.0436	3.0448	3.0436
Log likelihood	-5852.45	-5856.65	-5842.98	-5841.31	-5838.99
		Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$			
Lag =10	10.040	11.232	5.9292	8.3446	6.3009
p-value	(0.2623)	(0.1889)	(0.6552)	(0.4006)	(0.6136)
Lag =20	19.892	21.586	15.9552	17.739	16.140
p-value	(0.3389)	(0.2509)	(0.5957)	(0.4730)	(0.5828)
Lag =50	41.621	43.376	37.9144	38.961	37.6415
p-value	(0.7302)	(0.6625)	(0.8514)	(0.8208)	(0.8589)
		Mean equation squared standardised residuals serial correlation statistics, $Q_{LB(z_t^2)}$			
Lag =10	4.5426	3.848	2.8122	9.2088	4.5234
p-value	(0.8052)	(0.8706)	(0.9456)	(0.3250)	(0.8071)
Lag =20	15.0411	18.861	11.947	17.147	13.772
p-value	(0.6591)	(0.4005)	(0.8500)	(0.5130)	(0.7439)
Lag =50	38.215	42.118	43.1557	44.369	45.852
p-value	(0.8430)	(0.7116)	(0.6713)	(0.6224)	(0.5613)
		Joint Nyblom stability test statistics			
ω	5.194	4.142	5.649	5.121	5.337

Joint statistic of the Nyblom test of stability - H_0: Parameter is constant and H_1: Parameter is unstable. The asymptotic 1% and 5% critical values for joint Nyblom statistics are 0.75 and 0.47respectively.

Table B9: Comparative NEER Basic GARCH models estimation results

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH	APARCH
			Mean equation results		
γ	-0.0171	-0.0155	-0.0211	-0.0258	-0.0238
S.E.	(0.0076)	(0.0077)	(0.0077)	(0.0085)	(0.0081)
p-value	(0.0244)	(0.0442)	(0.0064)	(0.0025)	(0.0032)
κ	0.3396	0.3329	0.3385	0.3403	0.3431
S.E.	(0.0208)	(0.0219)	(0.0209)	(0.0259)	(0.0210)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ν	0.0978	0.1000	0.0993	0.0936	0.0965
S.E.	(0.0132)	(0.0135)	(0.0131)	(0.0097)	(0.0131)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
			Variance equation results		
ω	0.0015	0.0024	0.0015	-6.5851	0.0032
S.E.	(0.0008)	(0.0009)	(0.0008)	(2.5285)	(0.0015)
p-value	(0.0466)	(0.0119)	(0.0424)	(0.0092)	(0.0308)
δ	-	-	-	-	1.2470
S.E.	-	-	-	-	(0.1448)
p-value	-	-	-	-	(0.0000)
α_1	0.1602	0.1212	0.1195	-0.4434	0.1365
S.E.	(0.0208)	(0.0135)	(0.0212)	(0.0731)	(0.0204)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1^*	-	-	0.0663	-	0.1923
S.E.		-	(0.0213)	-	(0.0516)
p-value	-	-	(0.0019)	-	(0.0002)
$\alpha_1 + \alpha_1^*$	-	-	0.1858	-	0.3288
θ_1	-	-	-	-0.0825	-
S.E.	-	-	-	(0.0201)	-
p-value	-	-	-	(0.0000)	-
θ_2	-	-	-	0.3683	
S.E.	-	-	-	(0.0377)	-
p-value	-	-	-	(0.0000)	
$\lvert\theta_1 + \theta_2\rvert$	-	-	-	0.2858	-
$\lvert\theta_1 - \theta_2\rvert$	-	-	-	0.4508	-
β_1	0.8668	0.8788	0.8719	0.9938	0.8974
S.E.	(0.0144)	-	(0.0152)	(0.0028)	(0.0153)
p-value	(0.0000)	-	(0.0000)	(0.0000)	(0.0000)
$\alpha_1 + \beta_1$	1.0270	1.00000	-	-	-
$\varepsilon^+ : \alpha_1 + \beta_1$	-	-	0.9914	-	1.0339
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	-	-	1.0577	-	1.2262
$\varepsilon^+ : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	-	-	1.2796	-
$\varepsilon^- : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	-	-	1.4446	-
			Skewed Student-t distribution statistic for residuals, ε_t		
Asymmetry	-0.1218	-0.1194	-0.1240	-0.1403	-0.1299
S.E.	(0.0210)	(0.01999)	(0.0211)	(0.0220)	(0.0219)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tail	4.9301	5.8672	4.9513	5.1010	4.94108
S.E.	(0.4074)	(0.4181)	(0.4111)	(0.4333)	(0.4059)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parameter	GARCH	IGARCH	GJR-GARCH	EGARCH*	APARCH
Information criteria and log-likelihood statistics					
SIC	2.3105	2.3134	2.3100	2.3022	2.3066
Log likelihood	-4430.78	-4440.50	-4425.83	-4406.49	-4414.91
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$					
Lag =10	6.1767	6.6374	6.2688	6.5545	7.9489
p-value	(0.8002)	(0.7592)	(0.7922)	(0.7667)	(0.6338)
Lag =20	15.744	16.768	15.313	17.711	17.294
p-value	(0.7324)	(0.6680)	(0.7582)	(0.6065)	(0.6338)
Lag =50	40.792	41.121	40.143	41.4338	42.023
p-value	(0.8203)	(0.8103)	(0.8392)	(0.8005)	(0.7814)
Mean equation squared standardised residuals serial correlation statistics, $Q_{LB(z_t^2)}$					
Lag =10	15.246	14.1025	13.339	23.893	31.764
p-value	(0.0545)	(0.0791)	(0.1007)	(0.0024)	(0.0001)
Lag =20	22.746	21.3818	21.314	30.3015	38.515
p-value	(0.2005)	(0.2606)	(0.2639)	(0.0346)	(0.0033)
Lag =50	43.494	41.880	42.609	54.557	61.117
p-value	(0.6578)	(0.7206)	(0.6927)	(0.2394)	(0.0968)
Joint Nyblom stability test statistics					
ω	27.304	27.548	27.568	27.393	27.635

Joint statistic of the Nyblom test of stability - H_0: Parameter is constant and H_1: Parameter is unstable. The asymptotic 1% and 5% critical values for joint Nyblom statistics are 0.75 and 0.47respectively.

Table B10: Comparative USD/ZAR Adaptive GARCH models estimation results

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Mean equation results			
γ	-0.0138	-0.0244	-0.0223
S.E.	(0.0064)	(0.0066)	(0.0068)
p-value	(0.0322)	(0.0002)	(0.0011)
κ	0.1009	0.1010	0.1009
S.E.	(0.0124)	(0.0111)	(0.0123)
p-value	(0.0000)	0.0000)	0.0000)
ν	-0.2252	-0.2208	-0.2265
S.E.	(0.0167)	(0.0170)	(0.0168)
p-value	(0.0000)	(0.0000)	(0.0000)
Variance equation results			
ω	0.4813	-4.3718	0.3020
S.E.	(0.1558)	(0.4654)	(0.1117)
p-value	(0.0020)	(0.0000)	(0.0069)
ψ_1	-0.6171	-0.4872	-0.4834
S.E.	(0.1577)	(0.2386)	(0.1186)
p-value	(0.0001)	(0.0413)	(0.0000)
ψ_2	0.2622	**	0.2110
S.E.	(0.0800)	**	(0.0646)
p-value	(0.0001)	**	(0.0011)
ρ_1	-0.4318	-0.3275	-0.2477
S.E.	(0.1536)	(0.1988)	(0.10816)
p-value	(0.0050)	(0.0995)	(0.0221)
ρ_2	**	0.3134	**
S.E.	**	(0.1665)	**
p-value	**	(0.0598)	**
$d-FIGARCH$	0.4010	0.3451	0.2893
S.E.	(0.0457)	(0.0464)	(0.0517)
p-value	(0.0000)	(0.0000)	(0.0000)
δ	-	-	1.9011
S.E.	-	-	(0.0778)
p-value	-	-	(0.0000)
α_1	0.2262	-0.5426	0.3363
S.E.	(0.0641)	(0.1187)	(0.1040)
p-value	(0.0004)	(0.0000)	(0.0012)
α_1^*	-	-	0.3693
S.E.		-	(0.1059)
p-value	-	-	(0.0005)
$\alpha_1+\alpha_1^*$	-	-	0.7056
θ_1	-	-0.0943	-
S.E.	-	(0.0220)	-
p-value	-	(0.0000)	-
θ_2	-	0.3067	-
S.E.	-	(0.0369)	-
p-value	-	(0.0000)	-
$\lvert\theta_1+\theta_2\rvert$	-	0.2124	-
$\lvert\theta_1-\theta_2\rvert$	-	0.4010	-
β_1	0.4924	0.8954	0.4890
S.E.	(0.0717)	(0.0379)	(0.0808)
p-value	(0.0000)	(0.0000)	(0.0000)

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Variance equation results (continued)			
$\alpha_1 + \beta_1$	0.7186	-	-
$\varepsilon^{+} : \alpha_1 + \beta_1$	-	-	0.8253
$\varepsilon^{-} : \alpha_1 + \alpha_1^{*} + \beta_1$	-	-	1.0419
$\varepsilon^{+} : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	1.1078	-
$\varepsilon^{-} : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	1.2964	-
Skewed Student-*t* distribution statistic for residuals, ε_t			
Asymmetry	-0.1445	-0.1402	-0.1564
S.E.	(0.0218)	(0.0261)	(0.0231)
p-value	(0.0000)	(0.0000)	(0.0000)
Tail	6.4358	5.7826	6.1575
S.E.	(0.5253)	(0.5299)	(0.5849)
p-value	(0.0000)	(0.0000)	(0.0000)
Information criteria and log-likelihood statistics			
SIC	2.2522	2.2538	2.2464
Log likelihood	-4301.85	-4296.43	-4282.17
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$			
Lag =10	10.106	10.703	10.618
p-value	(0.4312)	(0.3811)	(0.3880)
Lag =20	26.412	26.815	28.005
p-value	(0.1526)	(0.1406)	(0.1093)
Lag =50	55.596	56.300	55.791
p-value	(0.2722)	(0.2510)	(0.2662)

** Parameters are statistically insignificant at 1%, 5% and 10% levels – model is estimated without these trigonometric structural change variables.

Table B11: Comparative EUR/ZAR Adaptive GARCH models estimation results

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
		Mean equation results	
γ	-0.0035	-0.0320	-0.0150
S.E.	(0.0109)	(0.0203)	(0.0119)
p-value	(0.7522)	(0.1141)	(0.2096)
χ	0.6210	0.5446	0.5658
S.E.	(0.1116)	(0.1664)	(0.1704)
p-value	(0.0000)	0.0011)	0.0009)
ϕ	-0.6697	-0.5862	-0.5994
S.E.	(0.1060)	(0.1613)	(0.1661)
p-value	(0.0000)	(0.0003)	(0.0003)
τ		0.0196	
S.E.	*	(0.0247)	*
p-value		(0.4270)	
		Variance equation results	
ω	0.6152	-4.6439	0.4535
S.E.	(0.1319)	(0.6255)	(0.1159)
p-value	(0.0000)	(0.0000)	(0.0001)
ψ_1	**	**	**
S.E.	**	**	**
p-value	**	**	**
ψ_2	-0.2842	**	**
S.E.	(0.1071)	**	**
p-value	(0.0080)	**	**
ρ_1	**	**	-0.19277
S.E.	**	**	(0.0951)
p-value	**	**	(0.0429)
ρ_2	**	0.3336	0.1658
S.E.	**	(0.1064)	(0.0630)
p-value	**	(0.0017)	(0.0429)
$d-FIGARCH$	0.3052	0.1725	0.1974
S.E.	(0.0395)	(0.0385)	(0.0406)
p-value	(0.0000)	(0.0000)	(0.0000)
δ	-	-	1.8262
S.E.	-	-	(0.1175)
p-value	-	-	(0.0000)
α_1	0.2702	-0.4800	0.3049
S.E.	(0.0957)	(0.1319)	(0.1336)
p-value	(0.0048)	(0.0003)	(0.0225)
α_1^*	-	-	0.4879
S.E.		-	(0.1637)
p-value	-	-	(0.0029)
$\alpha_1+\alpha_1^*$	-	-	0.7928
θ_1	-	-0.0966	-
S.E.	-	(0.0321)	-
p-value	-	(0.0000)	-
θ_2	-	0.2565	-
S.E.	-	(0.0334)	-
p-value	-	(0.0000)	-
$\lvert\theta_1+\theta_2\rvert$	-	0.1599	-
$\lvert\theta_1-\theta_2\rvert$	-	0.3531	-
β_1	0.4558	0.9234	0.4014
S.E.	(0.1060)	(0.0321)	(0.1399)
p-value	(0.0000)	(0.0000)	(0.0041)

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Variance equation results (continued)			
$\alpha_1 + \beta_1$	0.7260	-	-
$\varepsilon^+ : \alpha_1 + \beta_1$	-	-	0.7063
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	-	-	1.1942
$\varepsilon^+ : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	1.0833	-
$\varepsilon^- : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	1.2765	-
Skewed Student-*t* distribution statistic for residuals, ε_t			
Asymmetry	-0.1432	-0.1471	-0.1469
S.E.	(0.0224)	(0.0233)	(0.0229)
p-value	(0.0000)	(0.0000)	(0.0000)
Tail	6.1736	5.8119	6.0879
S.E.	(0.5052)	(0.5162)	(0.5522)
p-value	(0.0000)	(0.0000)	(0.0000)

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Information criteria and log-likelihood statistics			
SIC	2.6105	2.6119	2.6067
Log likelihood	-5002.21	-4992.46	-4982.51
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$			
Lag =10	10.106	11.023	9.3863
p-value	(0.0170)	(0.2004)	(0.3108)
Lag =20	24.536	18.742	16.854
p-value	(0.1382)	(0.4079)	(0.5332)
Lag =50	48.151	44.498	39.4823
p-value	(0.4667)	(0.6171)	(0.8045)

* α_1 is statistically significant at the 5% (and 10%) level only when the ARCH-M parameter is included in the mean equation; although the latter is statistically insignificant.

** Parameters are statistically insignificant at 1%, 5% and 10% levels – model is thus estimated without these trigonometric structural change variables.

Table B12: Comparative GBP/ZAR Adaptive GARCH models estimation results

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Mean equation results			
γ	-0.0531	-0.0666	-0.0617
S.E.	(0.0170)	(0.0169)	(0.0161)
p-value	(0.0018)	(0.0001)	(0.0001)
κ	0.1025)	0.1033	0.1043
S.E.	(0.0151)	(0.0149)	(0.0149)
p-value	(0.0000)	(0.0000)	(0.0000)
ν	0.1806	0.1838	0.1778
S.E.	(0.0240)	(0.0236)	(0.0235)
p-value	(0.0000)	(0.0000)	(0.0000)
τ	0.0603*	-0.0534*	-0.0521*
S.E.	(0.0241)	(0.0228)	(0.0218)
p-value	(0.0125)	(0.0190)	(0.0170)
Variance equation results			
ω	0.6355	-5.6709	0.1927
S.E.	(0.1785)	(0.7889)	(0.0568)
p-value	(0.0004)	(0.0000)	(0.0007)
ψ_1	-0.3598	-0.3813	**
S.E.	(0.1630)	(0.1306)	**
p-value	(0.0273)	(0.0035)	**
ψ_2	**	**	**
S.E.	**	**	**
p-value	**	**	**
ρ_1	-0.3044	**	**
S.E.	(0.1460)	**	**
p-value	(0.0371)	**	**
ρ_2	**	**	**
S.E.	**	**	**
p-value	**	**	**
$d-FIGARCH$	0.3565	0.3813	0.2436
S.E.	(0.0425)	(0.1306)	(0.0513)
p-value	(0.0000)	(0.0035)	(0.0000)
δ	-	-	1.9827
S.E.	-	-	(0.0956)
p-value	-	-	(0.0000)
α_1	0.3381	-0.5021	0.4382
S.E.	(0.0694)	(0.1136)	(0.0947)
p-value	(0.0000)	(0.0000)	(0.0000)
α_1^*	-	-	0.3374
S.E.		-	(0.0899)
p-value	-	-	(0.0002)
$\alpha_1+\alpha_1^*$	-	-	0.7756
θ_1	-	-0.0911	-
S.E.	-	(0.0214)	-
p-value	-	(0.0000)	-
θ_2	-	0.2930	-
S.E.	-	(0.0329)	-
p-value	-	(0.0000)	-
$\lvert\theta_1+\theta_2\rvert$	-	0.2019	-
$\lvert\theta_1-\theta_2\rvert$	-	0.3841	-

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Variance equation results (continued)			
β_1	0.5450	0.9461	0.5395
S.E.	(0.0685)	(0.0233)	(0.0776)
p-value	(0.0000)	(0.0000)	(0.0000)
$\alpha_1 + \beta_1$	0.8831	-	-
$\varepsilon^{+} : \alpha_1 + \beta_1$	-	-	0.9777
$\varepsilon^{-} : \alpha_1 + \alpha_1^{*} + \beta_1$	-	-	1.3151
$\varepsilon^{+} : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	1.1480	-
$\varepsilon^{-} : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	1.3302	-
Skewed Student-*t* distribution statistic for residuals, ε_t			
Asymmetry	-0.0869	-0.0916	-0.0983
S.E.	(0.0218)	(0.0225)	(0.0225)
p-value	(0.0000)	(0.0000)	(0.0000)
Tail	6.8853	6.4529	6.8054
S.E.	(0.6362)	(0.6485)	(0.6966)
p-value	(0.0000)	(0.0000)	(0.0000)

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Information criteria and log-likelihood statistics			
SIC	2.5540	2.5558	2.5460
Log likelihood	-4884.81	-4884.19	-4869.22
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$			
Lag =10	11.920	12.294	13.596
p-value	(0.2905)	(0.2659)	(0.1922)
Lag =20	27.167	26.902	28.031
p-value	(0.1306)	(0.1381)	(0.1087)
Lag =50	55.909	56.203	55.313
p-value	(0.2626)	(0.2538)	(0.2811)

* Conditional variance

** Parameters are statistically insignificant at 1%, 5% and 10% levels – model is thus estimated without trigonometric structural change variables.

Table B13: Comparative JPY/ZAR Adaptive GARCH models estimation results

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Mean equation results			
γ	0.0080	-0.0071	-0.0092
S.E.	(0.0145)	(0.0131)	(0.0157)
p-value	(0.5793)	(0.5895)	(0.5595)
χ	0.5586	0.4682	0.4464
S.E.	(0.1300)	(0.1394)	(0.1570)
p-value	(0.0000)	0.0008)	0.0045)
ϕ	-0.6078	-0.5061	-0.4791
S.E.	(0.1268)	(0.1397)	(0.1590)
p-value	(0.0000)	(0.0003)	(0.0026)
Variance equation results			
ω	1.0994	-1.3792	0.7539
S.E.	(0.2434)	(0.3369)	(0.1891)
p-value	(0.0000)	(0.0000)	(0.0001)
ψ_1	**	-0.3349	**
S.E.	**	(0.1570)	**
p-value	**	(0.0330)	**
ψ_2	-0.3167	**	**
S.E.	(0.1725)	**	**
p-value	(0.0664)	**	**
ρ_1	**	**	**
S.E.	**	**	**
p-value	**	**	**
ρ_2	**	0.2464	**
S.E.	**	(0.1173)	**
p-value	**	(0.0357)	**
$d-FIGARCH$	0.3268	0.3526	0.2259
S.E.	(0.0415)	(0.0589)	(0.0426)
p-value	(0.0000)	(0.0000)	(0.0000)
δ	-	-	1.7866
S.E.	-	-	(0.1172)
p-value	-	-	(0.0000)
α_1	0.2884	-0.3411	0.3247
S.E.	(0.0702)	(0.1667)	(0.0897)
p-value	(0.0000)	(0.0408)	(0.0003)
α_1^*	-	-	0.4608
S.E.		-	(0.1255)
p-value	-	-	(0.0002)
$\alpha_1+\alpha_1^*$	-	-	0.7855
θ_1	-	-0.1008	-
S.E.	-	(0.0207)	-
p-value	-	(0.0000)	-
θ_2	-	0.2303	-
S.E.	-	(0.0326)	-
p-value	-	(0.0000)	-
$\lvert\theta_1+\theta_2\rvert$	-	0.1295	-
$\lvert\theta_1-\theta_2\rvert$	-	0.3311	-
β_1	0.4940	0.7942	0.4397
S.E.	(0.0747)	(0.0724)	(0.0952)
p-value	(0.0000)	(0.0000)	(0.0000)

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Variance equation results (continued)			
$\alpha_1 + \beta_1$	0.7824	-	-
$\varepsilon^+ : \alpha_1 + \beta_1$	-	-	0.7644
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	-	-	1.2252
$\varepsilon^+ : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	0.9237	-
$\varepsilon^- : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	1.1253	-
Skewed Student-*t* distribution statistic for residuals, ε_t			
Asymmetry	-0.1391	-0.1334	-0.1409
S.E.	(0.0226)	(0.0231)	(0.0228)
p-value	(0.0000)	(0.0000)	(0.0000)
Tail	7.1969	6.8026	7.2437
S.E.	(0.6856)	(0.6834)	(0.7499)
p-value	(0.0000)	(0.0000)	(0.0000)
Information criteria and log-likelihood statistics			
SIC	3.0431	3.0430	3.0352
Log likelihood	-5838.01	-5825.39	-5818.50
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$			
Lag =10	12.829	9.2524	6.3918
p-value	(0.1179)	(0.3215)	(0.6034)
Lag =20	22.895	18.419	16.974
p-value	(0.1947)	(0.4284)	(0.5249)
Lag =50	45.593	41.004	39.433
p-value	(0.5720)	(0.7527)	(0.8060)

** Parameters are statistically insignificant at 1%, 5% and 10% levels – model is thus estimated without these trigonometric structural change variables.

Table B14: Comparative NEER/ZAR Adaptive GARCH models estimation results

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Mean equation results			
γ	-0.0158	-0.0284	-0.0271
S.E.	(0.0074)	(0.0078)	(0.0078)
p-value	(0.0337)	(0.0003)	(0.0005)
κ	0.3303	0.3458	0.3325
S.E.	(0.0195)	(0.0203)	(0.0203)
p-value	(0.0000)	0.0000)	0.0000)
ν	0.0953	0.0934	0.0925
S.E.	(0.0131)	(0.0141)	(0.0133)
p-value	(0.0000)	(0.0000)	(0.0000)
Variance equation results			
ω	0.3965	-5.0730	0.2779
S.E.	(0.1379)	(0.6313)	(0.1072)
p-value	(0.0041)	(0.0000)	(0.0096)
ψ_1	-0.3987	**	-0.3758
S.E.	(0.1112)	**	(0.1092)
p-value	(0.0003)	**	(0.0006)
ψ_2	**	**	0.1479
S.E.	**	**	(0.0557)
p-value	**	**	(0.0080)
ρ_1	-0.2671	**	-0.2217
S.E.	(0.1088)	**	(0.0980)
p-value	(0.0141)	**	(0.0237)
ρ_2	**	0.4725	**
S.E.	**	(0.2504)	**
p-value	**	(0.0593)	**
$d - FIGARCH$	0.328	0.5022	0.2412
S.E.	(0.0432)	(0.0468)	(0.0516)
p-value	(0.0000)	(0.0000)	(0.0000)
δ	-	-	1.8471
S.E.	-	-	(0.0790)
p-value	-	-	(0.0000)
α_1	0.2662	-0.7409	0.4315
S.E.	(0.0681)	(0.1072)	(0.1106)
p-value	(0.0001)	(0.0000)	(0.0001)
α_1^*	-	-	0.5200
S.E.		-	(0.1275)
p-value	-	-	(0.0000)
$\alpha_1 + \alpha_1^*$	-	-	0.9515
θ_1	-	-0.1146	-
S.E.	-	(0.0220)	-
p-value	-	(0.0000)	-
θ_2	-	0.3365	-
S.E.	-	(0.0362)	-
p-value	-	(0.0000)	-
$\lvert\theta_1 + \theta_2\rvert$	-	0.2219	-
$\lvert\theta_1 - \theta_2\rvert$	-	0.4511	-
β_1	0.4965	0.8813	0.5352
S.E.	(0.0695)	(0.0508)	(0.0804)
p-value	(0.0000)	(0.0000)	(0.0000)

Parameter	A-FIGARCH	A-FIEGARCH	A-FIAPARCH
Variance equation results (continued)			
$\alpha_1 + \beta_1$	0.7627	-	-
$\varepsilon^+ : \alpha_1 + \beta_1$	-	-	0.9667
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	-	-	1.4867
$\varepsilon^+ : \lvert\theta_1 + \theta_2\rvert + \beta_1$	-	1.1032	-
$\varepsilon^- : \lvert\theta_1 - \theta_2\rvert + \beta_1$	-	1.3324	-
Skewed Student-*t* distribution statistic for residuals, ε_t			
Asymmetry	-0.1309	-0.1385	-0.1499
S.E.	(0.0212)	(0.0220)	(0.0229)
p-value	(0.0000)	(0.0000)	(0.0000)
Tail	5.8651	5.3855	5.6101
S.E.	(0.4320)	(0.4804)	(0.5117)
p-value	(0.0000)	(0.0000)	(0.0000)
Information criteria and log-likelihood statistics			
SIC	2.2992	2.2924	2.2884
Log likelihood	-4396.63	-4379.30	-4363.32
Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$			
Lag =10	6.8572	6.4213	7.8598
p-value	(0.7389)	(0.7787)	(0.6425)
Lag =20	17.623	16.209	18.959
p-value	(0.6122)	(0.7036)	(0.5245)
Lag =50	42.825	40.878	46.017
p-value	(0.7541)	(0.8177)	(0.6339)

** Parameters are statistically insignificant at 1%, 5% and 10% levels – model is thus estimated without these trigonometric structural change variables.

Table B15: Comparative SSC-GARCH models estimation results

Parameter	USD/ZAR	EUR/ZAR	GBP/ZAR	JPY/ZAR	NEER
			Mean equation results		
γ	-0.0180	-0.0107	-0.1592	-0.0153	-0.0029
S.E.	(0.0065)	(0.0113)	(0.0113)	(0.0155)	(0.0094)
p-value	(0.0056)	(0.5905)	(0.1592)	(0.3244)	(0.7531)
χ	-	0.5910	-	-	-
S.E.	-	(0.1259)	-	-	-
p-value	-	(0.0000)	-	-	-
ϕ	-	-0.6390	-	-	-
S.E.	-	(0.1202)	-	-	-
p-value	-	(0.0000)	-	-	-
			Variance equation results		
ω	1.0362	1.1512	0.9042	1.2690	1.1673
S.E.	(0.1281)	(0.1860)	(0.1419)	(0.2536)	(0.2120)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Structural breaks*	36	27	29	16	28
$D_1 - D_{XX}$	(-0.9815 : 9.6382)	(-0.9767 : 1.9025)	(-0.9319 : 4.5250)	(-1.226 : 8.9612)	(-1.1427 : 5.0133)
S.E.	(0.1010 : 3.2536)	(0.1636 : 1.0114)	(0.1143 : 2.0683)	(0.1990 : 2.6569)	(0.1855 : 2.1181)
p-value	(0.0000 : 0.0618)	(0.0000 : 0.0629)	(0.0000 : 0.0417)	(0.0000 : 0.0021)	(0.0000 : 0.0946)
α_1	0.0591	0.0449	0.0765	0.0749	0.0603
S.E.	(0.0151)	(0.0138)	(0.0175)	(0.0139)	(0.0158)
p-value	(0.0001)	(0.0011)	(0.0000)	(0.0000)	(0.0001)
β_1	0.4244	0.5913	0.5510	0.6923	0.5496
S.E.	(0.0538)	(0.0425)	(0.0514)	(0.0360)	(0.0464)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\alpha_1 + \beta_1$	0.4835	0.6362	0.6275	0.7672	0.6099
			Skewed Student-*t* distribution statistic for residuals, ε_t		
Asymmetry	-0.1120	-0.1123	-0.1006	-0.1096	-0.1152
S.E.	(0.0226)	(0.0229)	(0.0218)	(0.0237)	(0.0231)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tail	13.272	10.871	14.472	8.9142	10.510
S.E.	(2.6468)	(1.7411)	(2.9850)	(1.1235)	(1.6201)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
			Information criteria and log-likelihood statistics		
SIC	2.3670	2.6009	2.5740	3.0388	2.3785
Log likelihood	-4395.5	-4876.34	-4824.22	-5776.05	-4450.69
			Mean equation standardised residuals serial correlation statistics, $Q_{LB(z_t)}$		
Lag =10	10.442	4.6227	10.027	7.2943	113.977
p-value	(0.4026)	(0.7970)	(0.4382)	(0.6974)	(0.1741)
Lag =20	24.331	9.4906	26.855	11.957	21.326
p-value	(0.2282)	(0.9473)	(0.1394)	(0.5903)	(0.3782)
Lag =50	48.546	29.6334	57.087	43.867	47.541
p-value	(0.5319)	(0.9829)	(0.2285)	(0.7167)	(0.5726)

* To conserve space, D_{xx} is the number of significant change points plus unity. The information in parenthesis is the range for the relevant statistics for each dummy variable. The individual break point results may be requested from the author.

Table B16: Comparative SSC-GJR-GARCH models estimation results

Parameter	USD/ZAR	EUR/ZAR	GBP/ZAR	JPY/ZAR	NEER
			Mean equation results		
γ	-0.0228	-0.0001	-0.0279	-0.0049	-0.0122
S.E.	(0.0067)	(0.0110)	(0.0111)	(0.0157)	(0.0095)
p-value	(0.0007)	(0.9916)	(0.0121)	(0.7530)	(0.1999)
χ	-	0.5960	-	-	-
S.E.	-	(0.1427)	-	-	-
p-value	-	(0.0000)	-	-	-
ϕ	-	-0.6360	-	-	-
S.E.	-	(0.1374)	-	-	-
p-value	-	(0.0000)	-	-	-
κ	-	-	0.0959	-	-
S.E.	-	-	(0.0146)	-	-
p-value	-	-	(0.0000)	-	-
ν	-	-	0.1715	-	-
S.E.	-	-	(0.0229)	-	-
p-value	-	-	(0.0000)	-	-
			Variance equation results		
ω	0.9540	0.7185	0.9538	1.1850	0.9137
S.E.	(0.1223)	(0.1132)	(0.1676)	(0.2141)	(0.1797)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Structural breaks*	36	24	29	16	29
$D_1 - D_{XX}$	(-0.9428 : 9.7481)	(-0.6631 : 2.4383)	(-0.9184 : 4.0319)	(-1.1305 : 8.9780)	(-0.9002 : 5.3954)
S.E.	(0.1029 : 3.0534)	(0.0937 : 1.0092)	(0.1375 : 1.8229)	(0.1711 : 2.7049)	(0.1563 : 1.9411)
p-value	(0.0000 : 0.0400)	(0.0000 : 0.0512)	(0.0000 : 0.0992)	(0.0000 : 0.0009)	(0.0000 : 0.0793)
α_1	-0.0213	-0.0187	0.0073	-0.0209	-0.0349
S.E.	(0.0167)	(0.0118)	(0.0163)	(0.0105)	(0.0083)
p-value	(0.2032)	(0.1113)	(0.6655)	(0.0470)	(0.0000)
α_1^*	0.1429	0.1166	0.1266	0.1643	0.1598
S.E.	(0.0270)	(0.0227)	(0.0277)	(0.0232)	(0.0229)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\alpha_1 + \alpha_1^*$	0.1429**	0.1166**	0.1266**	0.1434	0.1249
β_1	0.4601	0.5929	0.6009	0.7077	0.5936
S.E.	(0.0538)	(0.5929)	(0.0474)	(0.0337)	(0.0430)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\varepsilon^+ : \alpha_1 + \beta_1$	0.4601**	0.5929**	0.6009**	0.6868	0.5587
$\varepsilon^- : \alpha_1 + \alpha_1^* + \beta_1$	0.6030**	0.7095**	0.7275	0.8511	0.7185
		Skewed Student-*t* distribution statistic for residuals, ε_t			
Asymmetry	-0.1360	-0.1210	-0.0899	-0.1288	-0.1337
S.E.	(0.0233)	(0.0231)	(0.0222)	(0.0245)	(0.0237)
p-value	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Tail	13.422	10.672	14.8667	9.2714	11.157
S.E.	(2.7237)	(1.6912)	(3.0720)	(1.2256)	(1.8448)
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
		Information criteria and log-likelihood statistics			
SIC	2.3626	2.5928	2.5481	3.0290	2.3708
Log likelihood	-4382.83	-4868.90	-4761.92	-5752.82	-4427.55
		Mean equation standardised residuals serial correlation statistics			
Lag =10	9.4247	3.3385	13.006	6.2790	12.582
p-value	(0.4923)	(0.9114)	(0.2234)	(0.7913)	(0.2480)
Lag =20	23.550	8.3981	27.580	16.826	20.171
p-value	(0.2626)	(0.9721)	(0.1197)	(0.6643)	(0.4473)
Lag =50	46.704	28.646	57.835	42.257	47.1191
p-value	(0.6064)	(0.9880)	(0.2085)	(0.7736)	(0.5897)

* See table B15. ** $\alpha_1$is statistically insignificant (or indifferent from zero) implying $\alpha_1 + \alpha_1^* = \alpha_1^*$, and $\alpha_1 + \beta_1 = \beta_1$.

Table B17: Model rankings - USD/ZAR

Model	BIC statistic	Log-Likelihood (LL) statistic	Loss Function (LF) statistic	$\alpha_1 + \beta_1$		Ranking		
				+ shocks	- shocks	BIC statistic	LL statistic	LF statistic
GARCH	2.2613	-4335.70	32226.05	1.0232	1.0232	5	7	10
IGARCH	2.2644	-4345.95	29917.12	1.0000	1.0000	8	8	4
GJR-GARCH	2.2625	-4333.92	32197.61	1.0031	1.0403	7	6	9
EGARCH	2.2612	-4327.28	31390.65	1.2706	1.3816	4	4	7
APARCH	2.2621	-4329.04	31873.27	1.0331	1.1491	6	5	8
A-FIGARCH	2.2522	-4301.85	29238.31	0.7186	0.7186	2	3	3
A-FIEGARCH	2.2538	-4296.43	30612.35	1.0689	1.2653	3	2	6
A-FIAPARCH	2.2464	-4282.17	30248.81	0.8253	1.0419	1	1	5
SSC-GARCH	2.3670	-4395.50	27846.80	0.4835	0.4835	9	10	1
SSC-GJR-GARCH	2.3626	-4382.83	29020.94	0.4601	0.6030	10	9	2

Table B18: Model rankings - EUR/ZAR

Model	BIC statistic	Log-Likelihood (LL) statistic	Loss Function (LF) statistic	$\alpha_1 + \beta_1$		Ranking		
				+ shocks	- shocks	BIC statistic	LL statistic	LF statistic
GARCH	2.6169	-5022.83	31170.50	0.9877	0.9877	9	9	8
IGARCH	2.6156	-5024.51	31828.44	1.0000	1.0000	8	10	10
GJR-GARCH	2.6170	-5018.86	31199.62	0.9591	1.0077	10	8	9
EGARCH	2.6146	-5006.02	29425.22	1.1806	1.3256	6	6	6
APARCH	2.6147	-5010.30	30082.51	1.0022	1.1182	7	7	7
A-FIGARCH	2.6105	-5002.21	29187.18	0.7260	0.7260	4	5	4
A-FIEGARCH	2.6119	-4992.46	29360.60	1.0833	1.2765	5	4	5
A-FIAPARCH	2.6067	-4982.51	28507.64	0.7063	1.1942	3	3	2
SSC-GARCH	2.6009	-4876.34	28600.13	0.6362	0.6362	2	2	3
SSC-GJR-GARCH	2.5928	-4868.90	27714.16	0.5929	0.7095	1	1	1

Table B19: Model rankings - GBP/ZAR

Model	BIC statistic	Log-Likelihood (LL) statistic	Loss Function (LF) statistic	$\alpha_1 + \beta_1$		Ranking		
				+ shocks	- shocks	BIC statistic	LL statistic	LF statistic
GARCH	2.5612	-4911.11	30125.23	1.0004	1.0004	8	9	10
IGARCH	2.5591	-4911.11	30055.86	1.0000	1.0000	5	10	9
GJR-GARCH	2.5610	-4906.56	29957.93	0.9728	1.0244	7	8	8
EGARCH	2.5591	-4898.77	29773.72	1.2131	1.3691	6	6	7
APARCH	2.5613	-4903.18	29538.03	1.0095	1.1828	9	7	5
A-FIGARCH	2.5540	-4884.81	28589.37	0.8831	0.8831	3	5	3
A-FIEGARCH	2.5558	-4884.19	29113.89	1.1480	1.3302	4	4	4
A-FIAPARCH	2.5460	-4869.22	29691.07	0.9777	1.3151	1	3	6
SSC-GARCH	2.5740	-4824.22	28239.52	0.6275	0.6275	10	2	2
SSC-GJR-GARCH	2.5481	-4761.92	27305.46	0.6009	0.7275	2	1	1

Table B20: Model rankings - JPY/ZAR

Model	BIC statistic	Log-Likelihood (LL) statistic	Loss Function (LF) statistic	$\alpha_1 + \beta_1$		Ranking		
				+ shocks	- shocks	BIC statistic	LL statistic	LF statistic
GARCH	3.0463	-5852.45	34268.85	0.9794	0.9794	9	9	7
IGARCH	3.0464	-5856.65	36330.26	1.0000	1.0000	10	10	10
GJR-GARCH	3.0436	-5842.98	34917.23	0.9282	1.0129	6	8	9
EGARCH	3.0448	-5841.31	33655.12	1.1539	1.3163	8	7	4
APARCH	3.0436	-5838.99	34491.34	0.9855	1.2754	6	6	8
A-FIGARCH	3.0431	-5838.01	32986.38	0.7824	0.7824	5	5	3
A-FIEGARCH	3.0430	-5825.39	33949.46	0.9237	1.1253	4	4	6
A-FIAPARCH	3.0352	-5818.50	33945.99	0.7644	1.2252	2	3	5
SSC-GARCH	3.0388	-5776.05	32674.72	0.7672	0.7672	3	2	2
SSC-GJR-GARCH	3.0290	-5752.82	32015.57	0.6868	0.8511	1	1	1

Table B21: Model rankings – NEER

Model	BIC statistic	Log-Likelihood (LL) statistic	Loss Function (LF) statistic	$\alpha_1 + \beta_1$		Ranking		
				+ shocks	- shocks	BIC statistic	LL statistic	LF statistic
GARCH	2.3105	-4430.78	32848.27	1.0270	1.0270	7	8	9
IGARCH	2.3134	-4440.50	29309.23	1.0000	1.0000	8	9	4
GJR-GARCH	2.3100	-4425.83	32874.85	0.9914	1.0577	6	6	10
EGARCH	2.3022	-4406.49	31316.31	1.2796	1.4446	4	4	6
APARCH	2.3066	-4414.91	31995.62	1.0339	1.2262	5	5	7
A-FIGARCH	2.2992	-4396.63	28828.23	0.7627	0.7627	3	3	3
A-FIEGARCH	2.2924	-4379.30	32553.94	1.1032	1.3324	2	2	8
A-FIAPARCH	2.2884	-4363.32	29877.84	0.9667	1.4867	1	1	5
SC-GARCH	2.3785	-4450.69	27949.30	0.6099	0.6099	9	10	2
SC-GJR-GARCH	2.3708	-4427.55	28566.99	0.5587	0.7185	10	7	1

Table B22: Timing of structural shifts in exchange rate returns variance

Break points	USD/ZAR	EUR/ZAR	GBP/ZAR	JPY/ZAR	NEER
06-Jan-19995	N	N	Y	N	N
24-Mar-1995	Y	N	N	N	N
09-May-1995	N	Y	N	N	Y
31-May-1995	N	Y	N	N	Y
20-Jul-1995	N	N	N	N	Y
16-Aug-1995	Y	N	N	N	N
03-Oct-1995	N	N	N	N	Y
21-Nov-1995	N	N	N	Y	N
12-Feb-1996	N	N	N	Y	N
13-Feb-1996	N	Y	N	N	N
14-Feb-1996	Y	N	N	N	N
21-Feb-1996	N	N	Y	N	Y
22-Feb-1996	Y	N	N	N	N
22-Apr-1996	N	Y	N	N	N
23-Apr-1996	Y	N	N	N	N
13-May-1996	N	N	Y	Y	Y
14-May-1996	Y	N	N	N	N
14-Jun-1996	Y	N	N	N	N
09-Jul-1996	N	Y	Y	N	N
31-Jul-1996	N	Y	N	N	N
07-Aug-1996	N	N	Y	N	N
23-Oct-1996	N	Y	Y	Y	Y
04-Feb-1997	Y	N	N	N	N
21-Feb-1997	N	Y	N	N	N
24-Feb-1997	N	N	N	N	Y
14-Mar-1997	N	N	Y	N	N
20-Mar-1997	Y	N	N	N	N
21-Jul-1997	Y	N	Y	N	N
19-Aug-1997	Y	N	N	N	N
22-Aug-1997	Y	N	Y	N	N
22-Oct-1997	N	Y	N	N	N
24-Oct-1997	Y	N	N	N	N
27-Oct-1997	N	N	Y	N	N
30-Oct-1997	N	N	N	N	Y
04-Nov-1997	Y	N	N	N	N
02-Jan-1998	Y	N	N	N	N
22-Jan-1998	Y	N	N	N	N
23-Jan-1998	N	N	N	N	Y
18-May-1998	N	N	N	N	Y
10-Jun-1998	N	Y	Y	N	Y
11-Jun-1998	Y	N	N	N	N
21-Jul-1998	N	Y	N	Y	Y
22-Jul-1998	Y	N	N	N	N

Break points	USD/ZAR	EUR/ZAR	GBP/ZAR	JPY/ZAR	NEER
31-Dec-1998	N	Y	N	N	N
04-Feb-1999	N	N	N	Y	N
08-Feb-1999	N	N	N	N	Y
09-Feb-1999	Y	N	Y	N	N
12-Jul-1999	Y	N	N	N	N
26-Jan-2000	Y	N	N	N	N
28-Mar-2000	N	N	N	N	Y
11-Apr-2000	N	N	Y	N	N
13-Jun-2000	N	N	Y	N	N
14-Sep-2000	N	N	Y	N	N
04-Jan-2001	Y	N	N	N	N
26-Apr-2001	Y	N	N	N	N
20-Sep-2001	N	N	N	N	Y
21-Sep-2001	Y	N	N	N	N
13-Nov-2001	N	N	Y	N	N
27-Nov-2001	N	Y	N	N	Y
24-Jan-2002	N	Y	Y	N	Y
28-Jan-2002	Y	N	N	N	N
28-Feb-2002	N	Y	N	N	N
18-Mar-2002	N	N	Y	Y	Y
20-Mar-2002	Y	N	N	N	N
13-Dec-2002	Y	N	N	N	N
26-Jun-2003	N	N	Y	N	N
12-Dec-2003	N	Y	N	N	N
15-Dec-2003	Y	N	N	N	N
15-Jan-2004	N	N	Y	N	N
19-Jan-2004	N	N	N	Y	Y
28-Apr-2004	N	N	N	Y	N
11-May-2004	N	Y	N	N	N
13-May-2004	N	N	Y	N	Y
12-Aug-2004	Y	N	N	N	N
12-Jul-2005	N	Y	N	N	N
13-Jul-2005	N	N	Y	Y	Y
20-Sep-2005	N	N	Y	N	N
23-Sep-2005	N	Y	N	N	N
12-Dec-2005	N	N	N	Y	N
18-Apr-2006	N	N	N	Y	N
20-Apr-2006	N	Y	N	N	Y
24-Apr-2006	Y	N	N	N	N
23-Jun-2006	N	N	Y	N	N
16-Aug-2006	N	Y	N	N	N
02-Nov-2006	N	Y	N	N	Y
07-Nov-2006	Y	N	N	N	N
24-Nov-2006	N	N	Y	N	N
13-Mar-2007	N	N	N	Y	N
24-Jul-2007	N	N	N	Y	N

Break points	USD/ZAR	EUR/ZAR	GBP/ZAR	JPY/ZAR	NEER
09-Oct-2007	N	N	Y	N	N
11-Jan-2008	N	Y	N	N	N
14-Jan-2008	Y	N	N	N	N
09-Apr-2008	N	N	N	N	Y
03-Sep-2008	Y	N	N	N	N
15-Sep-2008	N	Y	N	N	N
02-Oct-2008	N	N	N	Y	Y
03-Oct-2008	Y	N	Y	N	N
30-Oct-2008	N	Y	N	N	Y
03-Nov-2008	Y	N	N	N	N
11-Dec-2008	N	Y	N	N	N
19-Jan-2009	N	N	Y	N	N
15-May-2009	N	N	N	Y	N
02-Oct-2009	N	Y	N	N	N
26-Oct-2009	N	N	Y	N	N
05-Nov-2009	N	N	N	N	Y

'Y' denotes a significant volatility break point; 'N' denotes no-break.

Appendix C

Figure C1: Daily returns, r_t (expressed as percent)

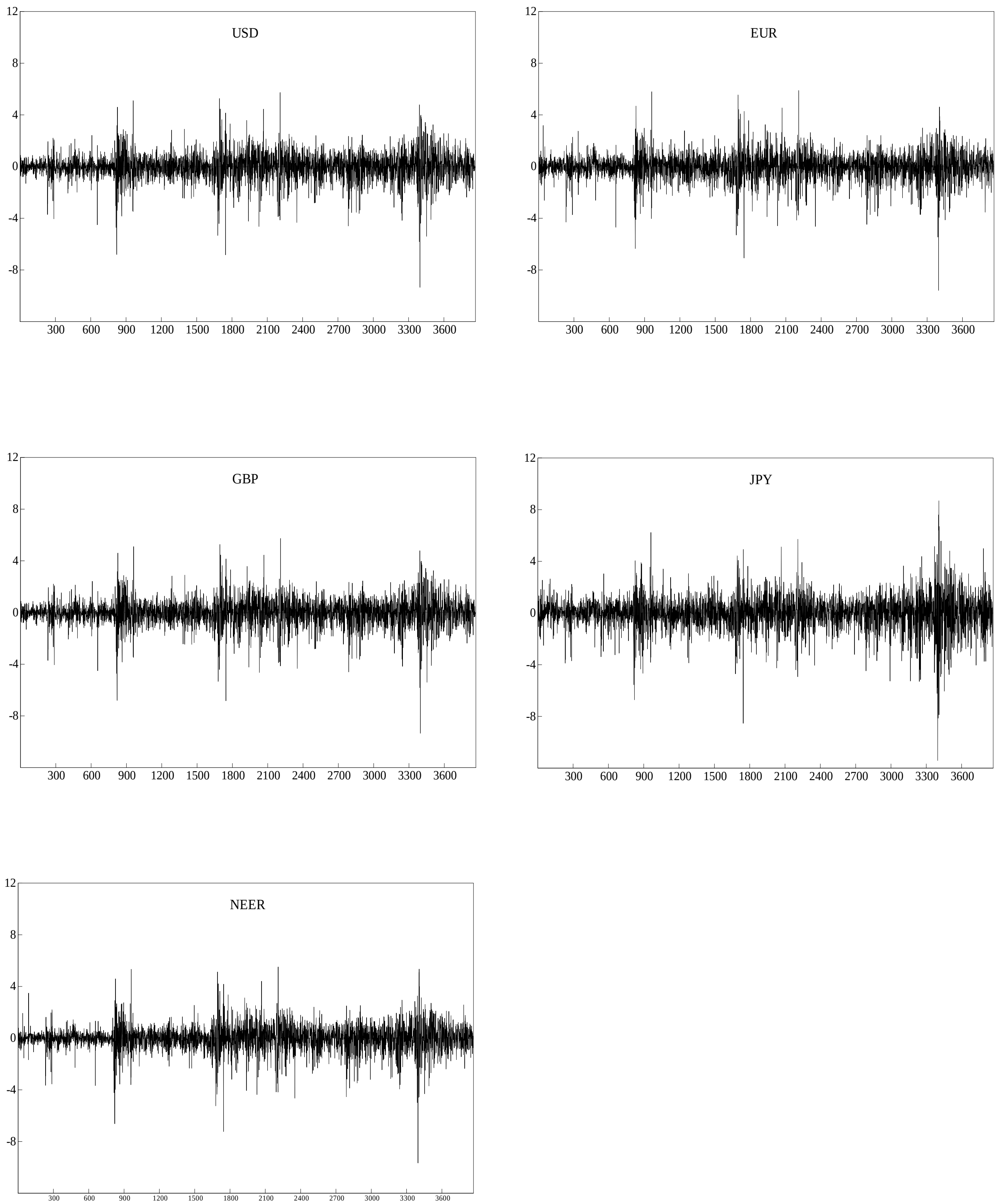


Figure C2: Absolute value of daily returns, $|r_t|$ (expressed as percent)

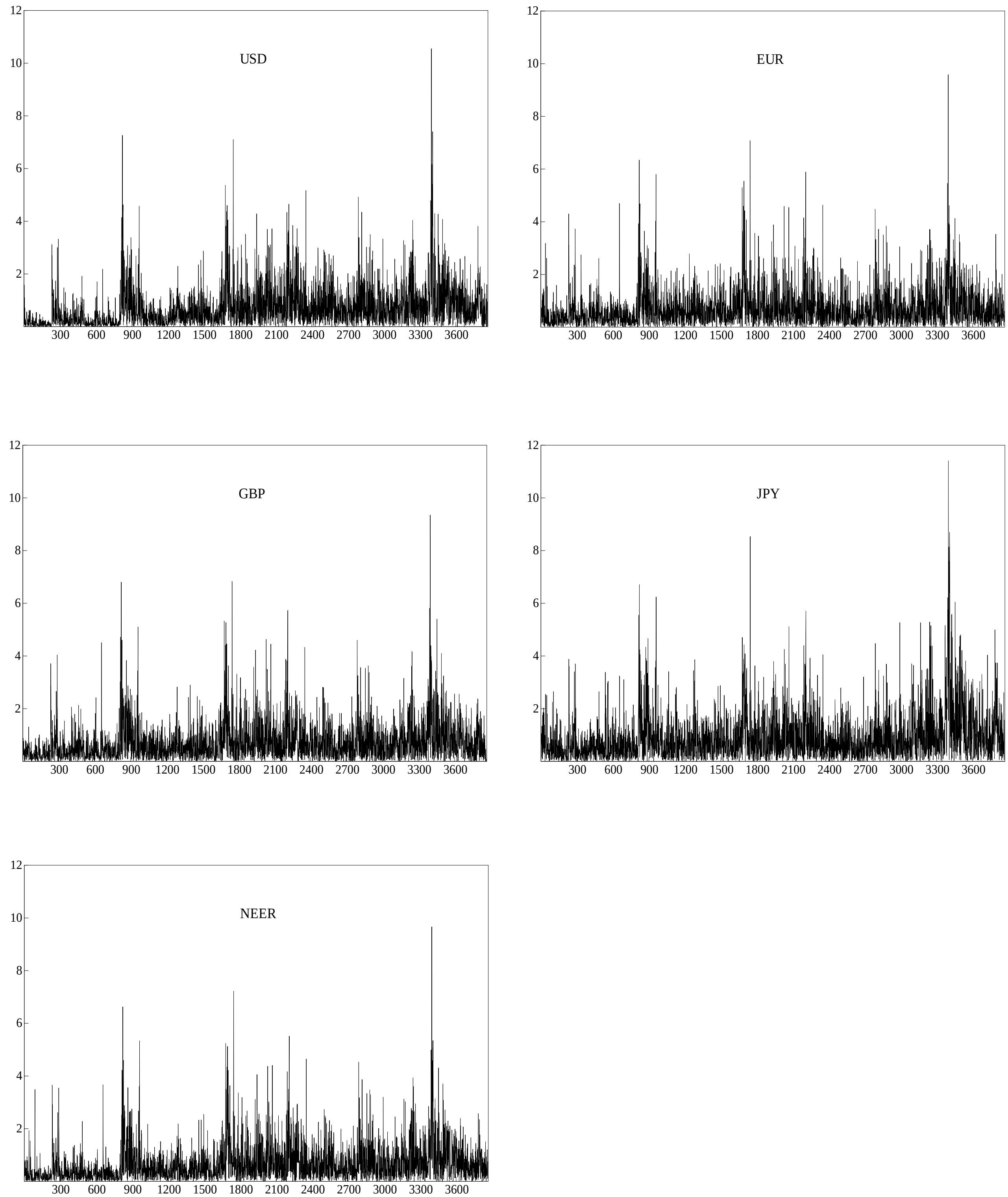


Figure C3: Daily squared returns, r_t^2 (expressed as decimal)

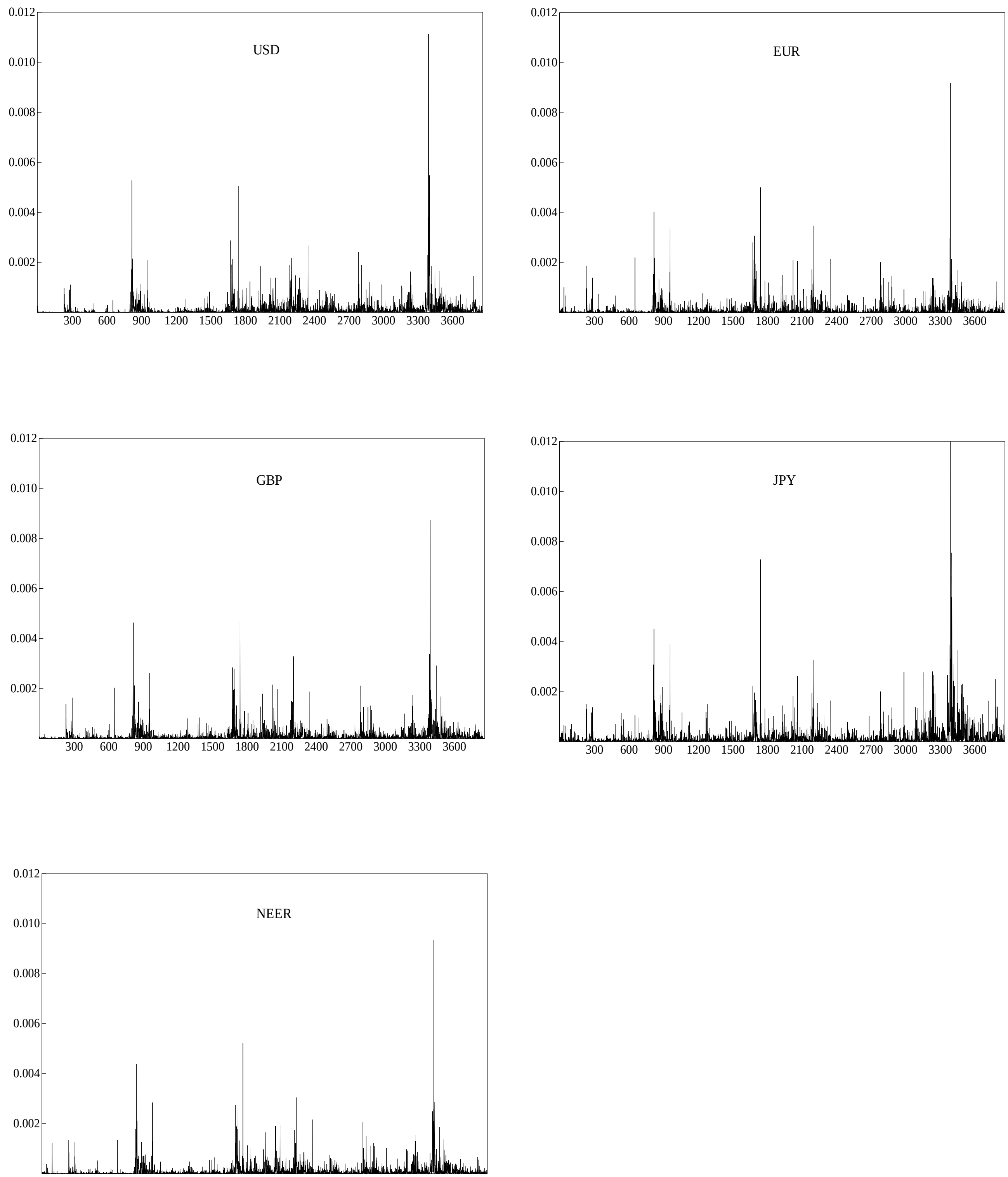


Figure C4: Daily returns, r_t, correlograms (ACF) (36 lags)

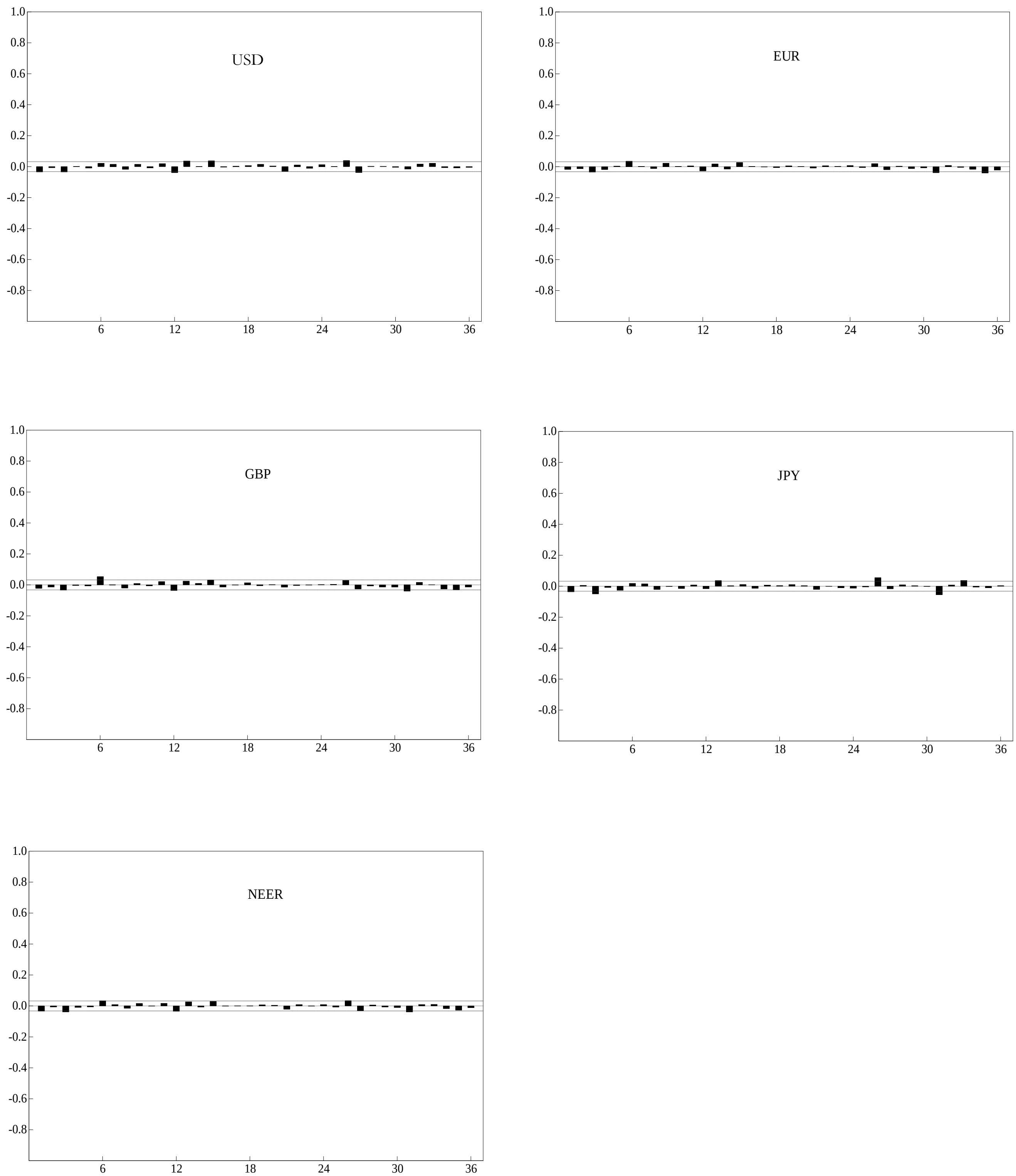


Figure C5: Absolute values of daily returns, $|r_t|$, correlograms (ACF) (36 lags)

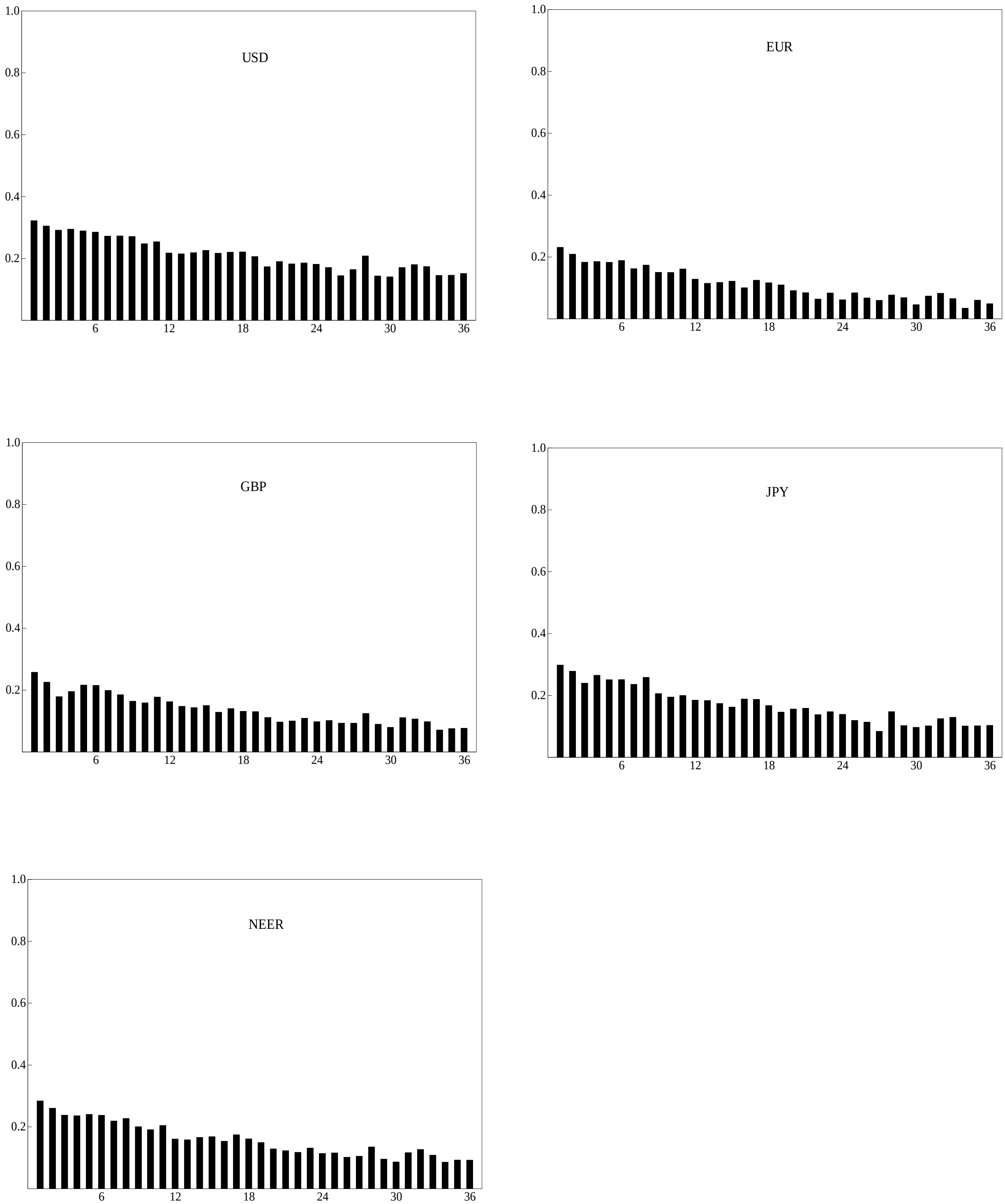


Figure C6: Squared daily returns, r_t^2, correlograms (ACF) (36 lags)

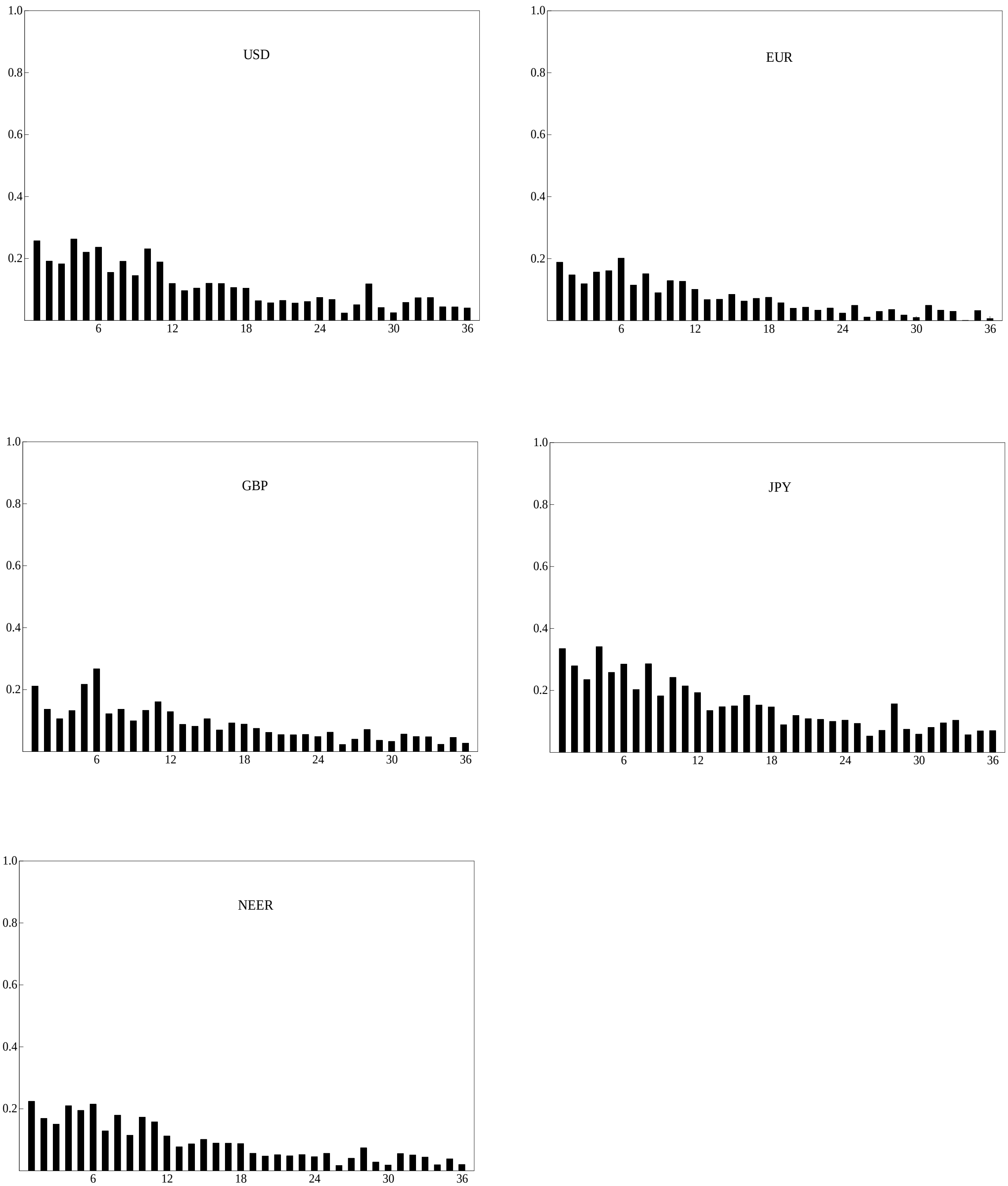
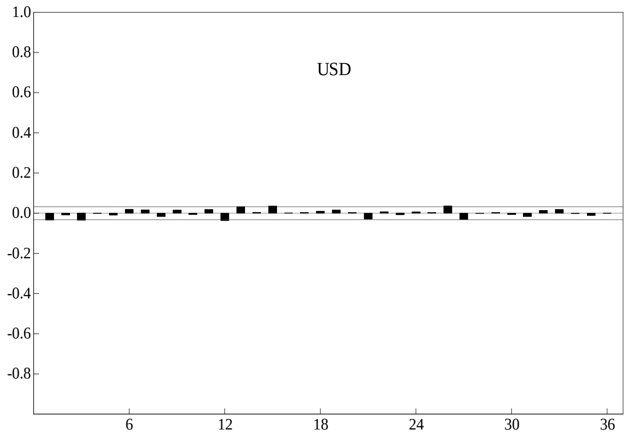
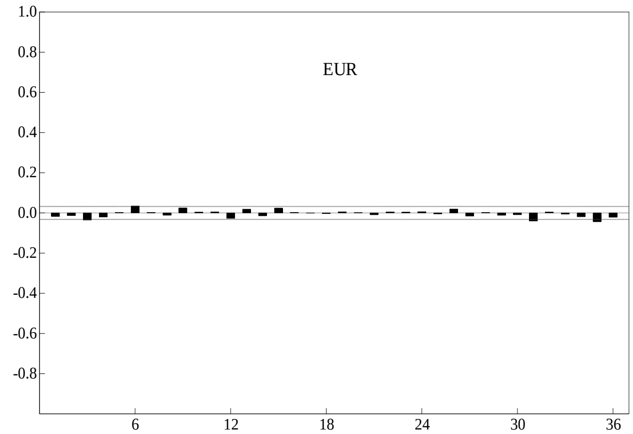
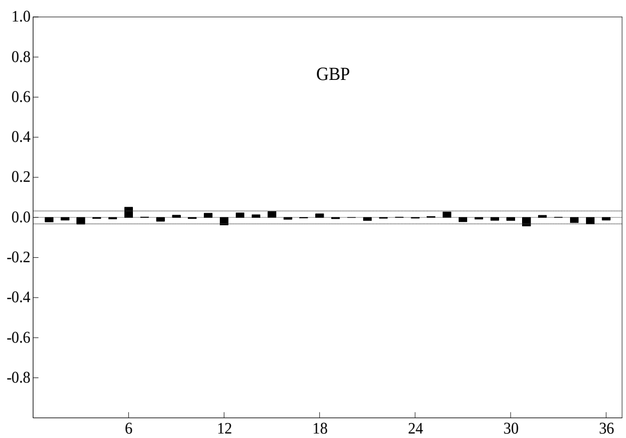
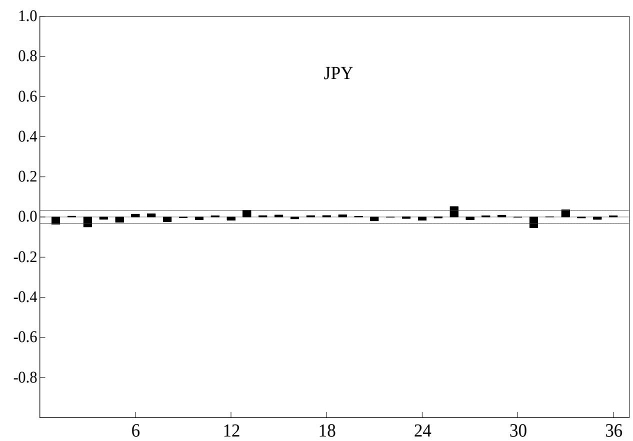


Figure C7: Daily returns, r_t, correlograms (PACF) (36 lags)









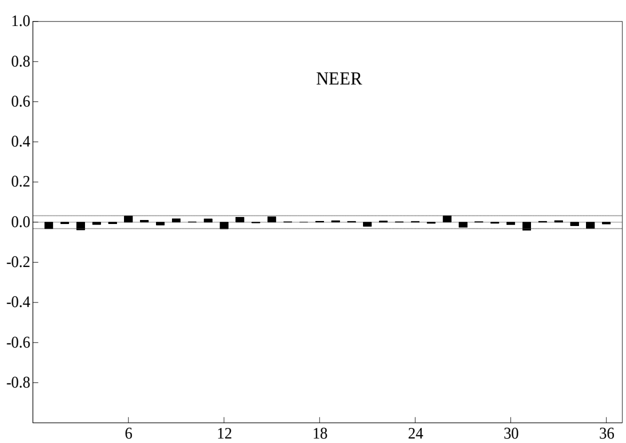


Figure C8: Absolute values of daily returns, $|r_t|$, correlograms (PACF) (36 lags)

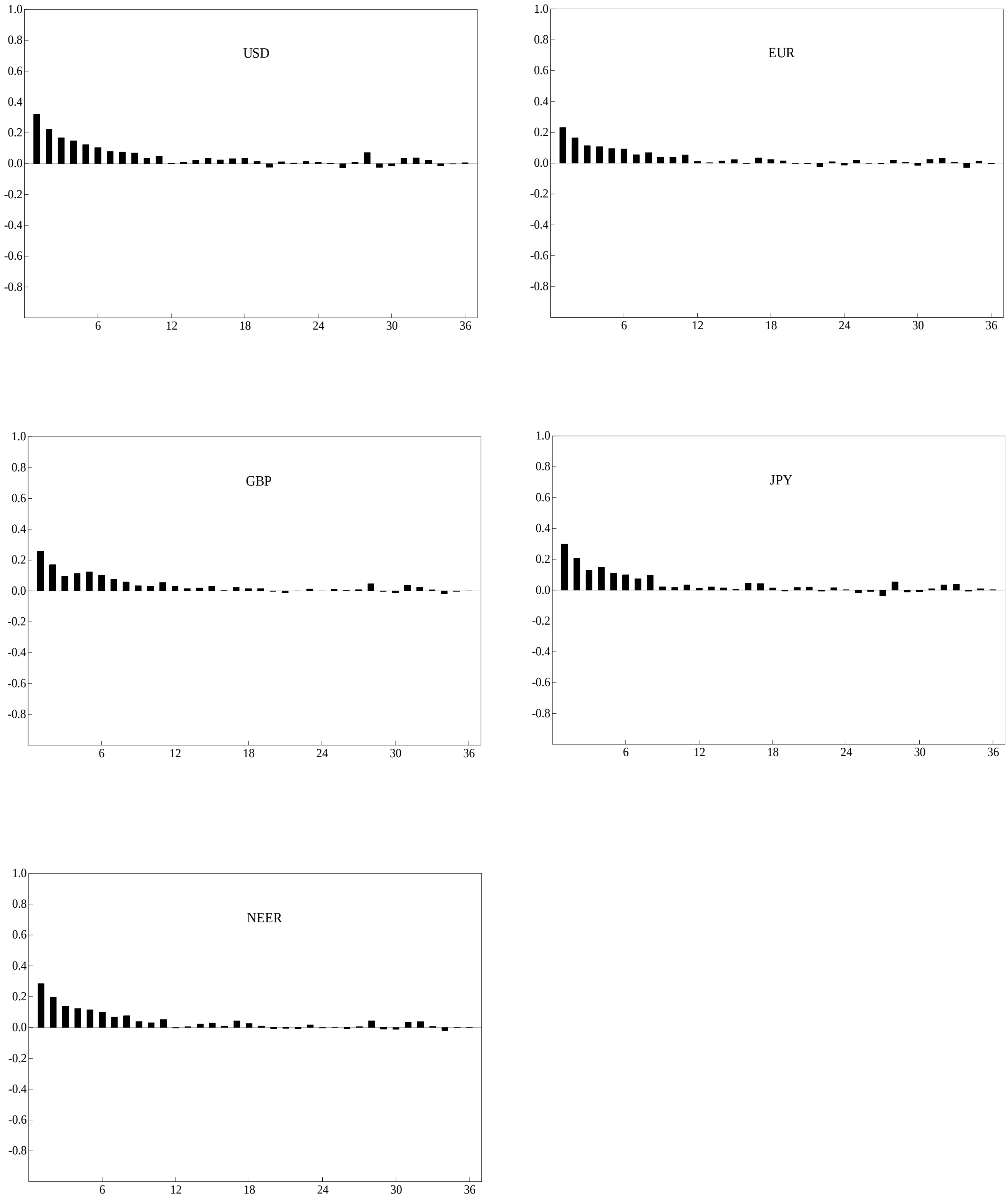


Figure C9: Squared daily returns, r_t^2, correlograms PACF) (36 lags)

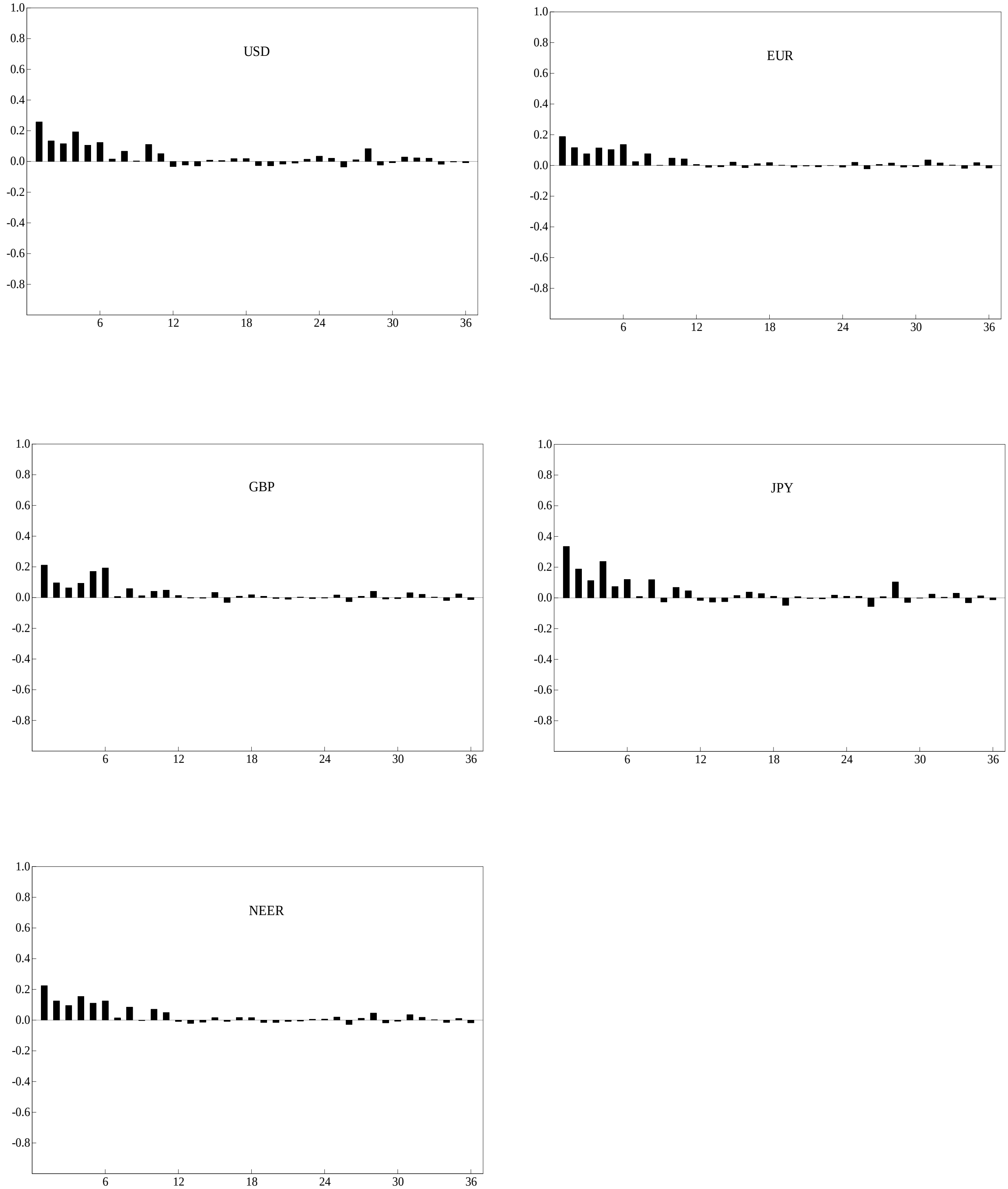


Figure C10: Daily returns histogram polygon

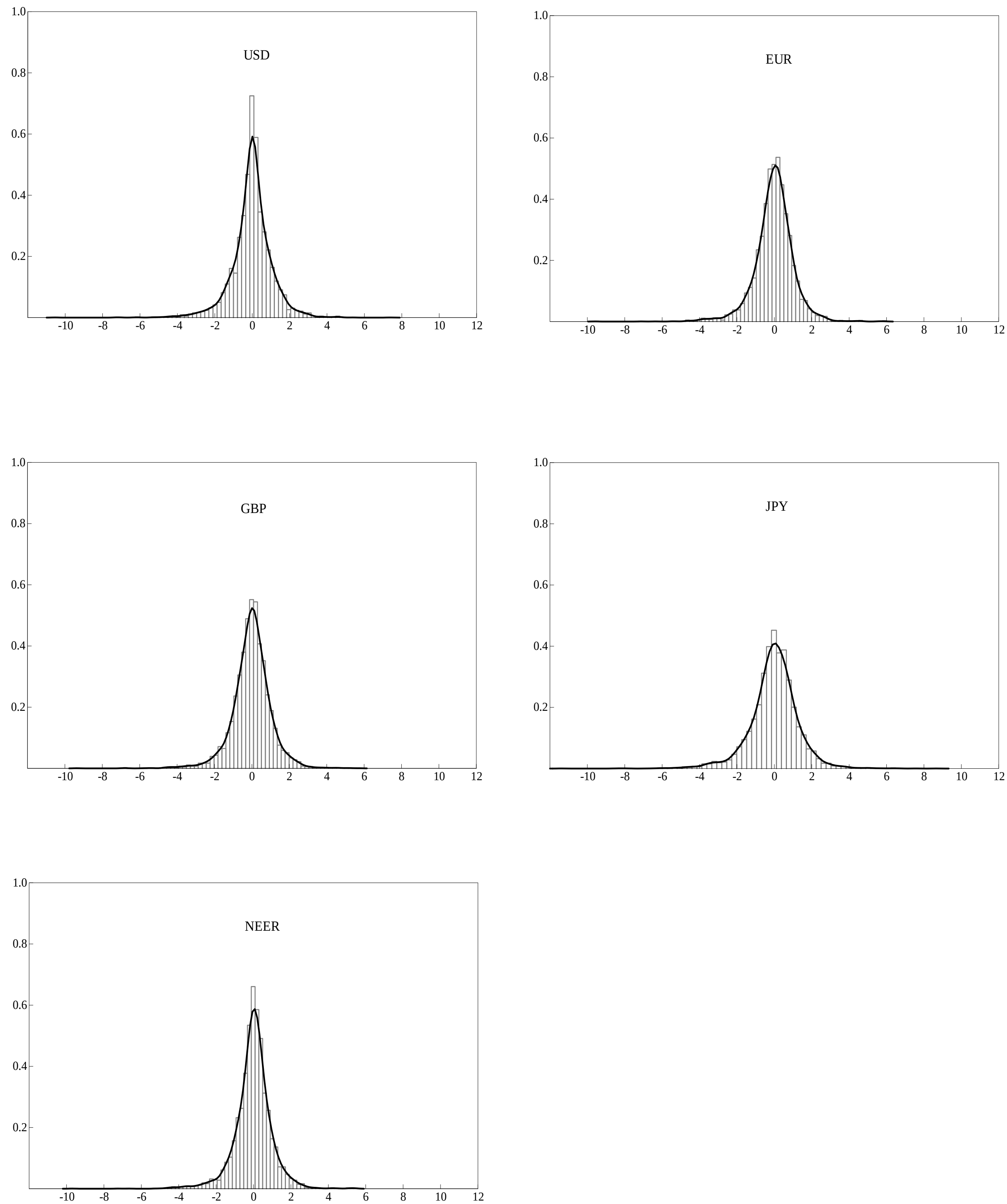
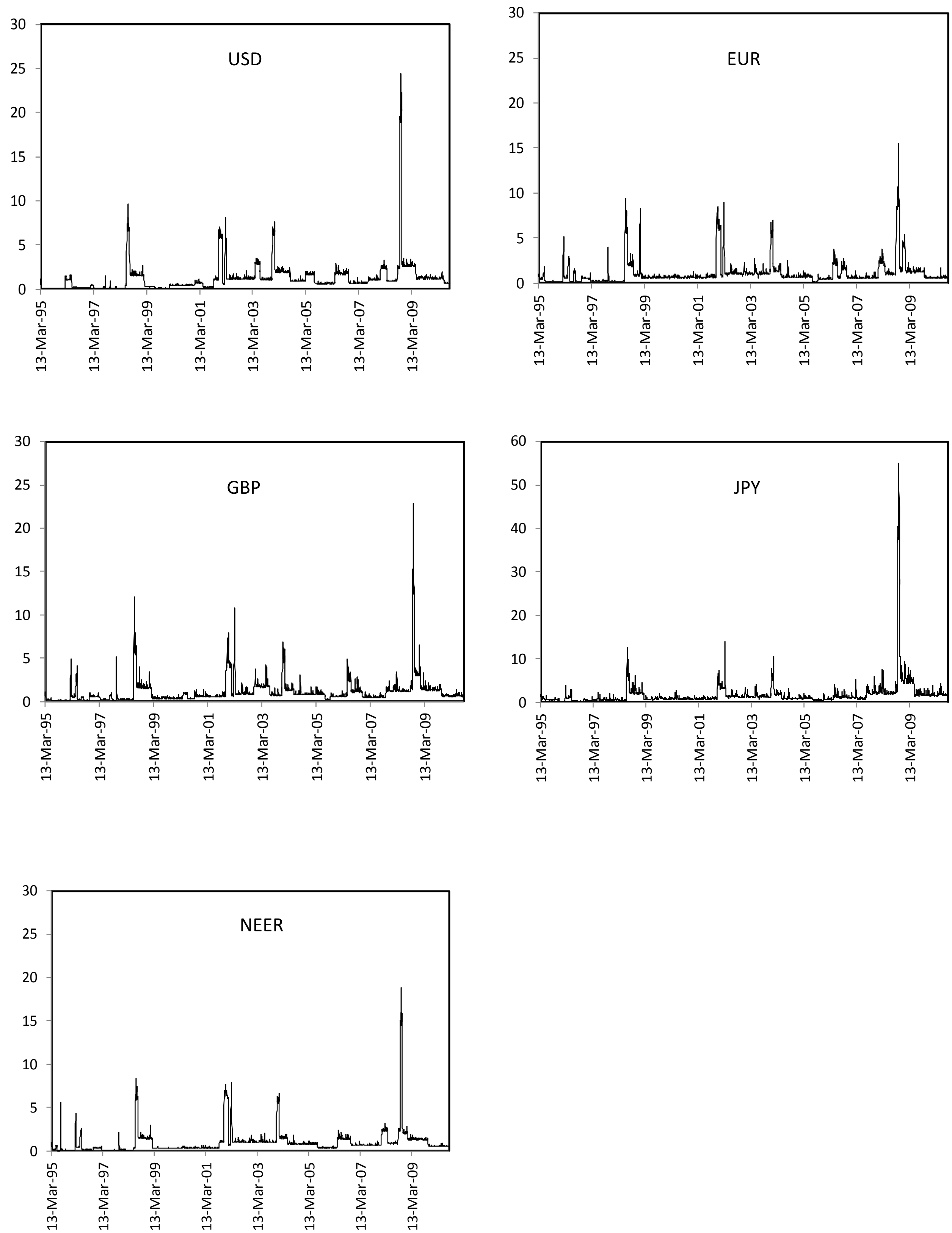


Figure C11: Conditional volatility



Appendix D

D.1 Standard Volatility Models

D.1.1 Variance and standard deviation

Volatility measures the intensity of randomness of a variable or phenomenon. Strictly speaking, there is no best measure of volatility and the value of measure depends on how it is used. Historically, variance, σ^2, and standard deviation, σ, are the most popular numerical measures of dispersion and volatility in economics and finance.

(Population) *variance* in the rate of return, r_t, is the average of the square of the distance of each data point from the mean, and is given by

$$\sigma^2 = \frac{1}{n}\sum_{t=1}^{n}(r_t - \bar{r})^2 , \tag{D1}$$

where r_t is the rate of return or relative change in the spot exchange rate, e_t, represented by the formula[96]

$$r_t = \ln\left(\frac{e_t}{e_{t-1}}\right) * 100 , \tag{D2}$$

$\bar{r}$ is the mean rate of return defined by

$$\bar{r} = \frac{1}{n}\sum_{k=1}^{n} r_k , \tag{D3}$$

and n is the length of the interval. The sample variance of returns r_t, given by

$$\hat{\sigma}^2 = \frac{1}{n-1}\sum_{t=1}^{n}(r_t - \bar{r})^2 , \tag{D4}$$

is a bias corrected or unbiased estimator of the population while equation (D1) is a biased estimator. Equation (D1) in large samples is an unbiased estimate of σ^2 but tends to underestimate the true population variance in small samples. The sample *standard deviation estimator*, $\hat{\sigma}$, is the positive square root of equation

[96] The rate of return is expressed as an approximate percentage in this study.

(D4). The standard deviation has an advantage over the variance in that it is an indicator of variability that is measured in the same units as the original observations. Both measures, however, can and have been shown to produce inaccurate measures of volatility in financial data for two main reasons. Firstly, they are appropriate for normal and *t*-distributions and some other symmetrical distributions (Poon and Granger, 2003), which is questionable for daily exchange rates where these parameters are time-varying (Frommel and Menkhoff, 2003). A second problem is their sensitivity to outliers, particularly for short intervals (Menkhoff, 2003). A single outlier can raise the standard deviation and in turn, distort the picture of the spread. One would expect infrequent jumps and collapses in the international price of a currency, in particular, that of a small open economy with a float exchange rate regime such as South Africa, undermining the accuracy of variance and standard deviation estimates.[97]

D.1.2 High-low variation estimations

To reduce the influence of outliers or extremes, Parkinson (1980) and Garman and Klass (1980) propose the *high-low variation* or *extreme-value variance* as a measure of volatility.[98] The high-low variation is defined by the following formula:

$$\sigma_{HL} = \max(r_t) - \min(r_t) \qquad \text{(D5)}$$

where σ_{HL} is the high-low variation (extreme-value variance), and $\max(r_t)$ and $\min(r_t)$ represent the maximum and minimum daily returns respectively. Extreme-value estimators are superior to the conventional variance and standard deviation estimators discussed above because they incorporate the range or dispersion of prices observed over the entire day, not just a snapshot at a specific point in the day (Wiggins, 1991). Parkinson (1980) shows that the use of the extreme-value method provides superior estimates – about $2\frac{1}{2}-5$ times better than the traditional standard deviation method – depending on how you chose to measure the difference between the extreme values. Estimators using the high-low variation approach are seen to have relative efficiencies that are considerably higher, at least eight times better than the classical variance parameter, $\hat{\sigma}^2$ (Garman and Klass, 1980).[99] In Wiggins (1991), extreme-value estimators in a discrete time are at least five times more efficient than the close-close estimator when an outlier screen is applied to the data.[100] The general conclusion then is that because high-low variation is less sensitive to outliers, it is therefore more efficient in small samples.

[97] For a summary of prediction models built on historical sample standard deviations, see Poon and Granger (2003).

[98] See Wiggins (1991) for a more general discussion of the high-low variation.

[99] The relative efficiency of an arbitrary estimator $\hat{y}$ is measured by the ratio $Eff(\hat{y}) = \mathrm{var}(\hat{\sigma}^2)/\mathrm{var}(\hat{y})$.

[100] An outlier screen involves applying a screen for errors in high and low prices because without direct observation of actual transactions, it is impossible to know whether these high- and low-price data represent actual trades or recording errors. Close-to-close are the comparative closing prices of a financial asset.

D.1.3 Maximum likelihood estimations of variance

An alternative procedure to exploit or moderate the impact of extremes is the maximum likelihood estimation (MLE) procedure. MLE is a technique that identifies the population that is 'most likely' to have generated the sample. Put differently, the method of maximum likelihood, as the name indicates, involves estimating the unknown parameters in such a manner that the probability of observing the given *r*'s is as high (or maximum) as possible.[101] Briefly, let

$$f(r \mid \theta) \tag{D6}$$

denote the probability density function (PDF) that specifies the probability of observing data vector *r* given the parameter vector $\theta = (\bar{r}, \sigma^2)$. In reality, because we have observed the data, we are faced with the inverse problem of determining the PDF that is most likely to have produced the observed sample data. To solve this problem, the likelihood function, $L(\theta)$, is defined by reversing the roles of the data vector *r* and the parameter θ, that is,

$$L(\theta \mid r) = f(r, \theta) \tag{D7}$$

and the MLE for $\theta = (\bar{r}, \sigma^2)$ is

$$\theta_{MLE} = (\bar{r}_{MLE}, \sigma^2_{MLE}) . \tag{D8}$$

Formally, the probability density function for a normally distributed variable with given mean and variance is

$$f(r \mid \theta) = \frac{1}{\sigma\left(\sqrt{2\pi}\right)} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} \frac{(r_t - \bar{r})^2}{\sigma^2} \right\}. \tag{D9}$$

If the data vector *r* is known or given but the parameter θ is unknown, the function in (D9) is called a likelihood function written as

$$LF(\theta) = \frac{1}{\sigma\left(\sqrt{2\pi}\right)} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} \frac{(r_t - \bar{r})^2}{\sigma^2} \right\}. \tag{D10}$$

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[101] The $r's$ are rates of return represented by equation (D2). In the case of a normal distribution, the maximum is unique whereas the MLE need not exist nor be unique.

Partial differentiation of the logarithm of the likelihood function in (D10) with respect to $\bar{r}$ and σ^2, and equating each partial derivative to zero, we calculate the maximum likelihood estimator $\theta_{MLE} = (\bar{r}_{MLE}, \sigma^2_{MLE})$.[102]

Controlled simulation studies established that, for reasonable sample sizes, this procedure yields essentially unbiased estimates with the highest degree of efficiency (Ball and Torous, 1984). Ball and Torous (1984), however, raise a number of caveats regarding the practical limitations of this and all other proposed high-low estimators of security price volatility. Firstly, their usefulness depends critically on the actual security price dynamics being governed by the posited diffusion process.[103] Secondly, questions exist whether observed security price highs and lows correspond to actual security price highs and lows. Finally, security price volatility estimation procedures must more fully integrate the closed market effect.[104]

Additional historical statistical measures of volatility that are resilient to outliers include the mean absolute deviation or average deviation and the interquartile range, amongst others.

D.2 Sophisticated GARCH Class Conditional Volatility Models

D.2.1 <u>Symmetrical linear ARCH and GARCH Models</u>[105]

ARCH (p) Model

The *ARCH*(*p*) process proposed by Engle (1982) is the simplest case in the ARCH family. The conditional variance is

$$h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 \tag{D11}$$

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[102] Since the logarithm is a continuous strictly increasing function over the range of the likelihood, the values which maximise the likelihood function will also maximise the logarithm function. For the mathematically inclined reader, see and Ball and Torous (1984) for a detailed discussion of the theory, evidence and application. Myung (2003) provides a tutorial exposition on the MLE for researchers who practice mathematical modelling but are unfamiliar with the estimation method.

[103] In the context of this paper, a diffusion process is the past evolution of exchange rate volatility following a shock, or how market participants actually form expectations about the future volatility of the exchange rate after a shock.

[104] Weekend effect (or closed market effect) is when financial asset prices display significantly lower or negative returns over the period between Friday's close and Monday's close.

[105] In linear models, the dependent variable is linearly related to the explanatory variable but the relationship between the two is not exact. In analytic geometry, the graph of a linear function in the Cartesian coordinate plane is a straight line and has an equation that can be written in the form: $y = mx + b$. Equations whose graphs are not straight lines are termed non-linear functions. A non-linear data generating process is one that can be written in the form $y_t = f(u_t, u_{t-1}, u_{t-2} \ldots)$ where u_t is an *iid* error term and f is a non-linear function (Campbell *et al.*, 1997). A more specific definition of a non-linear data generating process given by Campbell *et al.* (1997) is $y_t = g(, u_{t-1}, u_{t-2}, u_{t-3} \ldots) + \sigma^2(u_{t-1}, u_{t-2}, u_{t-3}, \ldots)$ where g is a function of past error terms only and σ^2 is a variance term. Model $y_t = g(\bullet) + \sigma^2(\bullet)$ is non-linear in mean and variance.

for $p > 0$ and where p is the lag on the disturbance term, ε_t.[106] In specification (D11), the conditional volatility at time t depends on the realisation of ε in the past periods up to lag p. Thus a large (small) shock in period t-1 can lead to a large (small) conditional variance in period t, its impact depending on the magnitude of α_1. By a simple extension of this argument, this will have an effect on the conditional volatility in later periods but the effect dies out progressively, that is, $\alpha_1 > \alpha_2 > \ldots > \alpha_p$. The unconditional (or stationary) variance

$$E\left[h_t^2\right] = {}_u\hat{\sigma}^2 = \frac{\omega}{\left(1 - \sum_{k=1}^{p} \alpha_k\right)} \tag{D12}$$

is also the long-run variance in this case.[107] In the long run we assume that the conditional variances are constant and equal to the long run variance.[108] For h_t^2 to be nonnegative, whatever the values of ε_{t-k}^2, and ${}_u\hat{\sigma}^2$ to be finite and nonnegative, we must have $\omega > 0$, $\alpha_k \geq 0$ and $0 \leq \sum_{k=1}^{p} \alpha_k < 1$. When $\alpha_k = 0$, the conditional variance is constant and the series ε_{t-k}^2 is conditionally homoscedastic. ARCH accounts for three stylised facts associated with times series of asset prices and associated with returns (Patterson, 2000): a) conditional variances change over time, sometimes quite substantially; b) there is volatility clustering – large (small) changes in unpredictable returns tend to be followed by large (small) changes of either sign; and, c) the unconditional distribution of returns has fat tails giving a relatively large probability of outliers relative to normal distribution.[109]

GARCH(p,q) Model

Another possibility, analogous to an autoregressive distributed lag model, to avoid long lag lengths on ε_t^2 in equation (D11), is to include lags of h_t^2, since, for example, h_{t-1}^2 is implicitly an infinite lag of ε_t^2 in equation (D11). And to avoid problems with negative variance parameter estimates, a fixed lag structure is typically imposed. Such models in the ARCH family are termed Generalised ARCH (GARCH) models, an extension of the basic ARCH model. The original GARCH(*p,q*) model introduced by Bollerslev (1986), is given by

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[106] Here, the terms 'disturbances', 'errors', 'shocks', 'residuals' and 'news' can be treated as synonymous.
[107] See Engle (1982) for mathematical proof. Patterson (2000) easily motivates Engle's complex proof of equation (15).
[108] Empirical evidence has shown changes in the unconditional variance, contrary to the assumption of constant unconditional variance. Heaney and Pattenden (2005) suggest the KL (Kokoszka and Leipus) test to check for the stability of the unconditional variance before estimating the ARCH family model parameters.
[109] The conditional distribution of ε_t is assumed normal and the fat tail property of ARCH models relates to the unconditional distribution of ε_t. Patterson (2000) shows that kurtosis increases nonlinearly with α_1.

$$h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 \tag{D13}$$

$$p > 0\,,\; q \geq 0\,,\; \omega > 0\,,\; \alpha_k \geq 0\,,\; \beta_j \geq 0 \text{ and } \left(\sum_{k=1}^{p} \alpha_k + \sum_{j=1}^{q} \beta_j \right) < 1\,,$$

where p refers to the lag on the disturbance term, ε_t^2, and q to the lag on the conditional variance, h_t^2.[110] This GARCH specification allows the conditional variance to follow an autoregressive and moving average (ARMA) process, which is a more parsimonious specification to capture the time series properties in volatility. The lag orders of the autoregressive (AR) and moving average (MA) components are denoted by p and q correspondingly.[111] If the conditions for the constant term and coefficients are met, then the unconditional variance

$$E\left[h_t^2\right] =_u \sigma^2 = \frac{\omega}{\left(1 - \sum_{k=1}^{p} \alpha_k - \sum_{j=1}^{q} \beta_j \right)} \tag{D14}$$

is nonnegative and finite.[112] For $q = 0$, the process reduces to the ARCH(p) process, and for $p = q = 0$, ε_t is simply white noise. The GARCH(*p,q*) process allows for both a longer memory and a more flexible lag structure which Bollerslev (1986) describes as corresponding to some sort of adaptive learning mechanism. In the vast empirical findings, GARCH(1,1) is the most commonly used structure for many financial times series analysis and it is difficult to beat a GARCH(1,1) in a <u>forecasting</u> contest for exchange rates – Hansen and Lunde (2004) find this for exchange rates but that the GARCH(1,1) is clearly inferior to models that can accommodate a leverage effect in their analysis of IBM stock returns. Two methods can be used to determine the appropriate orders of p and q. Akgiray (1989) and Cao and Tsay (1992) use a general-to-specific procedure by starting with a model with p and q set equal to large values, and testing down using

[110] Note that for h_t^2 to be interpreted as a (conditional) variance, it must always be nonnegative; sufficient conditions are that the constant term and coefficients satisfy $\omega > 0$, $\alpha_k \geq 0$ and $\beta_j \geq 0$. Stationarity of the unconditional variance imposes the condition $\left(\sum_{k=1}^{p} \alpha_k + \sum_{j=1}^{q} \beta_j \right) < 1$. The latter result is due to Bollerslev (1986) theorem 1.

[111] The GARCH(1,1) model represented by $\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 \sigma_{t-1}^2$ can be rewritten as $\varepsilon_t^2 = a_0 + (a_1 + b_1)\varepsilon_{t-1}^2 - b_1\left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right) + \left(\varepsilon_t^2 - \sigma_t^2\right)$ and GARCH(1,1) is an ARMA(1,1) model in squared form where $(a_1 + b_1)$ is the coefficient of the AR term while $-b_1$ is the coefficient of the MA term.

[112] The unconditional variance for the GARCH process can be motivated in the same way as for the ARCH process, although its formal proof is also quite complex – see Bollerslev (1986, theorem 1).

likelihood-ratio-type restrictions. Brooks and Burke (1998) suggest the modified information criteria approach.

Bollerslev's (1986) original GARCH(1,1) is a restricted model. A more general GARCH(1,1) model removes the $\left(\sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j\right) < 1$ condition and if $\left(\sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j\right) \geq 1$, then unconditional variance is nonstationary; that is, it has a unit root. The speed of mean reversion depends on the magnitude of $\left(\sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j\right)$. Generally speaking, the closer the value of $\left(\sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j\right)$ to 1, the longer it takes for volatility to revert to its mean implying volatility persistence; a value greater than 1 means that the volatility process is not mean reverting, that is, it is explosive. The GARCH model is popular not only for its simplicity in specification and its parsimonious nature in capturing time series properties of volatilities, but also because it is a generalisation of other measures of volatility presented below.

IGARCH (p,q) Model

In some empirical applications, the condition $0 \leq \sum_{k=1}^{p}\alpha_k < 1$ for ARCH(*p*), or $0 \leq \sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j < 1$ for GARCH(*p,q*) models, is not met. Engle and Bollerslev (1986) show that if $\sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j = 1$,[113] then shocks to conditional variance are persistent in the sense that current information remains important for forecasts of all horizons because if there is a large positive shock to ε_{t-1} and so to ε_{t-1}^2, then the conditional variance, h_t^2, increases and the shock is always remembered, in stark contrast to where the shock dies out when $\sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j < 1$. In the GARCH(1,1) model, if $\alpha_1 + \beta_1 = 1$, equation (D13) is an integrated GARCH (IGARCH) or nonstationary, because $\alpha_1 + \beta_1 = 1$ implies a unit root for ε_t^2.[114] In such a case, shocks to conditional variance die out slowly in contrast to the mean reverting volatility when $\alpha_1 + \beta_1 < 1$. To account for persistence of volatility, a limitation of the standard GARCH model, Bollerslev and Mikkelsen (1996)

[113] This condition can also be written as an approximation; that is, $\sum_{k=1}^{p}\alpha_k + \sum_{j=1}^{q}\beta_j \approx 1$.

[114] The terms 'nonstationary', 'random walk', and 'unit root' can be treated as synonymous here. 'Stationary time series' and 'time series integrated of order zero' mean the same thing and 'nonstationary time series' and 'time series integrated of order one or greater' are equivalent because the time series has to be differenced twice or more times to make it stationary. Integrated GARCH in this context means the latter. See Bollerslev and Engle (1993) for applications of IGARCH in exchange rates and, Engle and Mustafa (1992) for examples of stock returns that exhibit persistence in shocks.

developed the IGARCH model. Using the lag or backshift operator, $\alpha(L)=\alpha_1 L^1+\ldots+\alpha_p L^p$ and $\beta(L)=\beta_1 L^1+\ldots+\beta_q L^q$, equation (D13) can be rewritten as

$$h_t^2=\omega+\alpha(L)\varepsilon_t^2+\beta(L)h_t^2. \tag{D15}$$

By adding ε_t^2 to and subtracting $\beta(L)\varepsilon_t^2$ from both sides of (D15), moving h_t^2 to the right-hand side, and $\alpha(L)\varepsilon_t^2$ to the left-hand side, the GARCH(*p,q*) process in (D13) may also be expressed as an ARMA (*m,p*) process in ε_t^2 :

$$[1-\alpha(L)-\beta(L)]\varepsilon_t^2=\omega+[1-\beta(L)](\varepsilon_t^2-h_t^2). \tag{D16}$$

When the $[1-\alpha(L)-\beta(L)]\varepsilon_t^2$ polynomial contains a unit root, that is, the sum of all the α_k and the β_j equals unity, we have the IGARCH(*p,q*) model. The IGARCH in (D16) can be rewritten as

$$\phi(L)(1-L)\varepsilon_t^2=\omega+[1-\beta(L)](\varepsilon_t^2-h_t^2) \tag{D17}$$

where $\phi(L)=[1-\alpha(L)-\beta(L)](1-L)^{-1}$ is of order $[\max(p,q-1)]$. The conditional variance is obtained by rewriting equation (D17) in terms of h_t^2:

$$h_t^2=\frac{\omega}{[1-\beta(L)]}+\left\{1-\phi(L)(1-L)[1-\beta(L)]^{-1}\right\}\varepsilon_t^2. \tag{D18}$$

Conditional variance is now a hyperbolic function representing a gradual decay in the effects of shocks. An integrated model has been shown to be powerful for prediction over a short horizon, as it is not conditioned on a mean level volatility, and as a result it adjusts to changes in unconditional volatility quickly (Poon and Granger, 2003).

D.2.2 Asymmetrical Nonlinear GARCH Models

A number of empirical studies provide evidence that positive and negative shocks have an asymmetric impact on conditional volatility. A 'leverage effect' – when stock prices change induces an inverse change in its volatility – is an additional property of financial time series (Black, 1976). As the conditional variance in the GARCH models discussed above depends on the squared shock, positive and negative shocks of the same magnitude have the same effect on conditional volatility and these models cannot capture such asymmetric effects of positive and negative shocks. The nonlinear extensions of the GARCH presented below were designed to allow for different effects of 'good news' (positive shocks) and 'bad news' (negative shocks) or other types of asymmetries.

EGARCH (p,q) Model

Nelson (1991) identifies several drawbacks in the above symmetrical nonlinear GARCH models. The first is a negative correlation between current returns and future returns volatility found in some empirical studies.[115] Secondly, GARCH models impose parameter restrictions that are often violated by estimated coefficients and that may unduly restrict the dynamics of the conditional variance process. A third problem is the difficulty of interpreting whether shocks to conditional variances persist or not because the usual norms measuring persistence often do not agree. The exponential GARCH (EGARCH) model proposed by Nelson (1991) which constitutes the first introduction of an asymmetric effect between negative and positive shocks in an econometric model of volatility, is specified as

$$\ln h_t^2 = \omega + \sum_{k=1}^{p} \alpha_k g(z_{t-k}) + \sum_{j=1}^{q} \beta_j \ln h_{t-j}^2 \; . \tag{D19}$$

The asymmetry effect is introduced by the nonlinear function

$$g(z_t) \equiv \theta_1 z_t + \theta_2 \left(|z_t| - E|z_t| \right) \tag{D20}$$

where z_t is the scaled or standardised shock, the term $\theta_2 \left(|z_t| - E\left[|z_t|\right] \right)$ – deviations between realised and actual expected – represents the magnitude effect and the term $\theta_1 z_t$ is the sign effect – negative or positive shock. An important difference between the EGARCH and the standard GARCH models discussed in the preceding subsections is that the effect of a shock on volatility in the latter depends only on the size of the shock and ignores its sign. By construction, $g(z_t)$ has zero mean and so do its two components, $\theta_1 z_t$ and $\theta_2 \left(|z_t| - E\left[|z_t|\right] \right)$. From equation (2), $z_t = \dfrac{\varepsilon_t}{h_t}$; that is, the purely random or white noise is the innovations divided by the conditional standard deviation. Under the normality assumption, $E|z_t| = \sqrt{2/\pi} \approx 0.798$.

[115] It has been suggested that an unexpected fall in the price of a financial asset, which is 'bad news', increases predictable volatility more than the same size unexpected increase in price (Patterson, 2000), illustrating the trade-off between risk and return; that is, investing in or holding an asset can render higher profits only if the asset is subject to the possibility of losses.

Adopting $\ln h_t^2$, a function of time and lagged z_t's, as the conditional variance still ensures that the conditional variance is nonnegative. In contrast to the GARCH specifications, the EGARCH model allows negative and positive shocks to have different effects; that is, it allows financial markets to respond asymmetrically to 'bad news', a negative shock $(z_t < 0)$, and 'good news', a positive innovation $(z_t > 0)$, even though the observed shocks are of same magnitude or absolute value implying that the market gets nervous when asset prices fall unexpectedly. For $0 < z_t < \infty$, $g(z_t)$ is linear with slope $\theta_1 + \theta_2$ and the slope becomes $\theta_1 - \theta_2$ when $-\infty < z_t < 0$. Different assumptions about θ_1 and θ_2 illustrate the sign and magnitude effects. *Magnitude effect:* If we assume that $\theta_2 > 0$ and $\theta_1 = 0$, the innovation in $\ln(\sigma_{t+1}^2)$ is positive (negative) when the magnitude of z_t is larger (smaller) than its expected value. *Sign effect:* However, a supposition that $\theta_2 = 0$ and $\theta_1 < 0$ gives rise to a positive (negative) innovation in the conditional variance when return innovations are negative (positive). The absolute values of $\theta_1 + \theta_2$ and $\theta_1 - \theta_2$ capture the asymmetry in response to positive and negative z_t shocks. A leverage effect is present if θ_1 is negative. For the conditional volatility process to be stationary it is required that $|\beta_1| < 1$ (Nelson, 1991). Thus, the EGARCH model summarised in equations (D19) and (D20) overcomes the first drawback of the GARCH model. And, because there are no constraints on the magnitudes of the coefficients in equations (D19) and (D20), oscillatory behaviour is permitted because β_j can be negative or positive. The log formulation of conditional volatility in the EGARCH(*p,q*), a key difference from the GARCH (*p,q*), guarantees that all conditional volatilities will be nonnegative and thus, no restrictions on the parameters are necessary.

The exponential GARCH model, originally introduced by Nelson (1991), is re-expressed in Bollerslev and Mikkelsen (1996) as follows:

$$\ln h_t^2 = \omega + [1 - \beta(L)]^{-1}[1 + \alpha(L)]g(z_{t-1}). \tag{D21}$$

If bad news increases volatility more than good news, we say there is a *leverage effect* for the *i*-th order. Note that the left-hand side is the natural logarithm of the conditional variance. This implies that the leverage effect is exponential and that forecasts of the conditional variance are guaranteed to be non-negative as in the original model. The presence of leverage effects can be tested by the hypothesis that $\alpha_i^* < 0$; α_i^* is the leverage or asymmetric parameter. The impact is asymmetric if $\alpha_i^* \neq 0$. Estimating the re-specification of the Nelson model, equation (D21), will yield identical estimates to those of the original Nelson model, equations (D19) and (D20) - except for the intercept term ω which will differ depending upon the distributional assumption and the order p. For example, in a $p=1$ model with normal distribution, the difference will be $\alpha_1\sqrt{2/\pi}$. If the conditions for constant term and coefficients are met, then the unconditional variances are:

$$_u\sigma_+^2 = \frac{\omega}{\left(1-\left|\theta_1+\theta_2\right|-\beta_1\right)} \text{ for positive shocks} \tag{D22}$$

$$_u\sigma_-^2 = \frac{\omega}{\left(1-\left|\theta_1-\theta_2\right|-\beta_1\right)} \text{ for negative shocks.} \tag{D23}$$

To compute volatility forecasts using EGARCH requires a distributional assumption or a numerical simulation, making applications of EGARCH more difficult. An additional complication of the EGARCH model relates to comparing its historical and forecasting performance to that of the GARCH models presented above and below; the fact that the ranking of models based on information criteria depends on the unit of measurement of the dependent variable y, one should exercise caution when using information criteria to select between a model with dependent variable y and one with say, $\ln y$ (or any variant of y).

GJR-GARCH(p,q) Model

This popular model, proposed by Glosten, Jagannathan, and Runkle (GJR) (1993), is an alternative device to the nonlinear EGARCH model. Asymmetries are introduced by dividing the shocks into two intervals – positive and negative parts of the innovation process. In the GJR-GARCH (1,1) model, an extension of GARCH, conditional variance is a linear function of the squared positive and negative parts of the innovations:

$$h_t^2 = \omega + \sum_{k=1}^{P}\left(\alpha_k\varepsilon_{t-k}^2 + \alpha_k^* S_{t-k}^-\varepsilon_{t-k}^2\right) + \sum_{j=1}^{q}\beta_j h_{t-j}^2 \tag{D24}$$

where S_{t-k}^- is a dummy variable that takes the value unity when α_k^* is negative and zero when it is positive. The impact of positive shocks is captured by α_k while $\alpha_k+\alpha_k^*$ measures the negative innovations response. A nice feature of the GJR model is that the null hypothesis of no leverage effect is easy to test. Indeed, $\alpha_1^* = \ldots = \alpha_k^* = 0$ implies that the news impact curve is symmetric, that is past positive shocks have the same impact on today's volatility as past negative shocks. If the conditions for constant term and coefficients are met, then the unconditional variances are:

$$ {}_u\sigma_+^2 = \frac{\omega}{\left(1-\alpha_1-\beta_1\right)} \text{ for positive shocks} \tag{D25}$$

$$ {}_u\sigma_-^2 = \frac{\omega}{\left(1-\alpha_1-\alpha_1^*-\beta_1\right)} \text{ for negative shocks.} \tag{D26}$$

When $\alpha_k^* \neq 0$, the GJR model covariance stationarity condition is

$$\sum_{k=1}^{p}\alpha_k\left[1+\left(\alpha_k^*\right)^2\right]+\sum_{j=1}^{q}\beta_j<1 \tag{D27}$$

Engle and Ng (1993) find that the EGARCH model estimates a conditional variance that is too high and more volatile than the GJR-GARCH model, although it captures most of the asymmetry. Since the exchange rates of the rand tend to be high during brief crisis periods and volatility moderates during the longer normal periods, the EGARCH model might be too extreme in the tails. Consequently, the GJR model, might be a more reasonable model to use for estimating volatility over extended periods and the EGARCH is more appropriate for approximating volatility during crisis.[116] In addition, because the dependent variable in the GJR model is same as that of the other models presented above – excluding the EGARCH model – ranking based on information criteria is apt.

APARCH Model

The asymmetric power ARCH, APARCH(*p*,*q*), model introduced by Ding, Granger, and Engle (1993), can be expressed as:

$$h_t^\delta=\omega+\sum_{k=1}^{p}\alpha_k\left(\left|\varepsilon_{t-k}\right|-\alpha_k^*\varepsilon_{t-k}\right)^\delta+\sum_{j=1}^{q}\beta_j h_{t-j}^\delta \tag{D28}$$

[116] Similar to the EGARCH model, the GJR-GARCH model of Glosten, Jagannathan, and Runkle (GJR) (1993) also captures asymmetry but volatility forecasting is not as straightforward as one needs to consider the sign of shock in the future.

where $\omega > 0$, $\delta \geq 0$, $\alpha_k \geq 0$, $-1 < \alpha_k^* < 1$, and $\beta_j \geq 0$. The parameter δ plays the role of a Box-Cox power transformation of the conditional standard deviation process and the asymmetric absolute residuals,[117] while α_k^* reflects the so-called leverage effect. When $\alpha^* > 0$ (< 0), negative (positive) shocks give rise to higher volatility than positive (negative) ones. A benefit of this model is that it combines the flexibility of a varying exponent with the asymmetry coefficient to account for the 'leverage effect'. If $\omega > 0$ and $\sum_{k=1}^{p} \alpha_k E(|z| - \alpha_k^* z)^{\delta} + \sum_{j=1}^{q} \beta_j < 1$, a stationary solution

$$E\left[h_t^{\delta}\right] =_u \sigma^2 = \frac{\omega}{\left(1 - \sum_{k=1}^{p} \alpha_k \left(|z| - \alpha_k^* z\right)^{\delta} - \sum_{j=1}^{q} \beta_j\right)} \tag{D29}$$

exists. If $\alpha_k^* = 0$, $\delta = 2$ and z_t has a zero mean and unit variance, then we have the customary standard stationarity condition of the GARCH(1,1) model $\alpha_1 + \beta_1 < 1$. But if $\alpha_k^* \neq 0$ and/or $\delta \neq 2$, the stationarity condition will depend on the assumption made on the innovation process.

D.2.3 Fractionally Integrated GARCH-type Models

FIGARCH

Baillie *et al.* (1996) proposed the FIGARCH which captures a finite persistence of volatility shocks; *id est.*, long memory behaviour and a hyperbolic or slow rate of decay for the influence of lagged squared innovations. The FIGARCH(p, d, q) model is obtained by adding an exponent d to the first difference operator $(1 - L)$ in the IGARCH model (equation (C17)):

$$\phi(L)(1 - L)^d \varepsilon_t^2 = \omega + [1 - \beta(L)](\varepsilon_t^2 - h_t^2) \tag{D30}$$

implying

$$h_t^2 = \frac{\omega}{[1 - \beta(L)]^{-1}} + \left\{1 - \phi(L)(1 - L)^d [1 - \beta(L)]^{-1}\right\}\varepsilon_t^2 \tag{D31}$$

[117] The Box-Cox method, developed by statisticians Box and Cox (1964) is one particular way of parameterising a power transform; this method is used to automatically identify a suitable power transformation for the data which can make big improvements in model fit.

where $0 \le d \le 1$ and the fractional differencing parameter, d, indicates the rate of decay; that is, the speed at which shocks die out over time.[118] It can be shown that $\omega > 0$, $0 \le d \le (1 - 2\phi_1)$ and $0 \le \beta_1 \le (\phi_1 + d)$ is necessary and sufficient to ensure that the conditional variance of the FIGARCH $(1, d, 1)$ is positive almost surely for all *t* (Baillie *et al,* 1996). Although mean reverting, shocks to h_t^2 will die out at a slow hyperbolic rate of decay determined by d in the variance equation, while the short-run dynamics are modeled by the conventional AR(1) and MA(1) parameters in the GARCH model variance equation. Here, the FIGARCH-Chung version of the FIGARCH model is estimated.[119]

FIEGARCH

Bollerslev and Mikkelson (1996) extend the fractional integration idea to the EGARCH model. Similar to the GARCH model, the EGARCH equation (C21) can be extended to account for long memory by factorising the autoregressive polynomial $[1 - \beta(L)] = \phi(L)(1 - L)^d$ where all roots of $\phi(z) = 0$ lie outside the unit circle. The fractionally integrated EGARCH - FIEGARCH(*p,d,q*) – is specified as follows:

$$\ln h_t^2 = \omega + \phi(L)^{-1}(1 - L)^d \left[1 + \alpha(L)\right] g(z_{t-1}). \tag{D32}$$

The asymmetry effect, $g(z_t)$, is specified in equation (C20).

FIAPARCH

In the literature surveyed, the GJR-GARCH model does not appear to have been extended to the long-memory framework. It is, however, nested in the asymmetric power ARCH (APARCH) class of models. Tse's (1998) FIAPARCH(*p,d,q*) model, a fractional integration augmentation of the APARCH model, equation (C28), can be written as:

$$h_t^\delta = \omega + \left\{1 - \left[1 - \beta(L)\right]^{-1} \phi(L)(1 - L)^d \right\}\left(\left|\varepsilon_t\right| - \alpha^* \varepsilon_t\right)^\delta . \tag{D33}$$

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[118] $\phi(L)$ is defined in the symmetric IGARCH model discussion above.

[119] Chung (1999) proposes to truncate $\lambda(L) = \left\{1 - \left[1 - \beta(L)\right]^{-1} \phi(L)(1 - L)^d \right\}\varepsilon_t^2$ at the size of the information set (T - 1) and to initialise the unobserved $\left(\varepsilon_t^2 - h_t^2\right)$ at 0 (this quantity is small in absolute values and has a zero mean). Truncation means limiting the number of digits right of the decimal point, by discarding the least significant ones.

APPENDIX E

Figure E1: Foreign exchange returns levels: Response to 100-basis-point repo rate shock

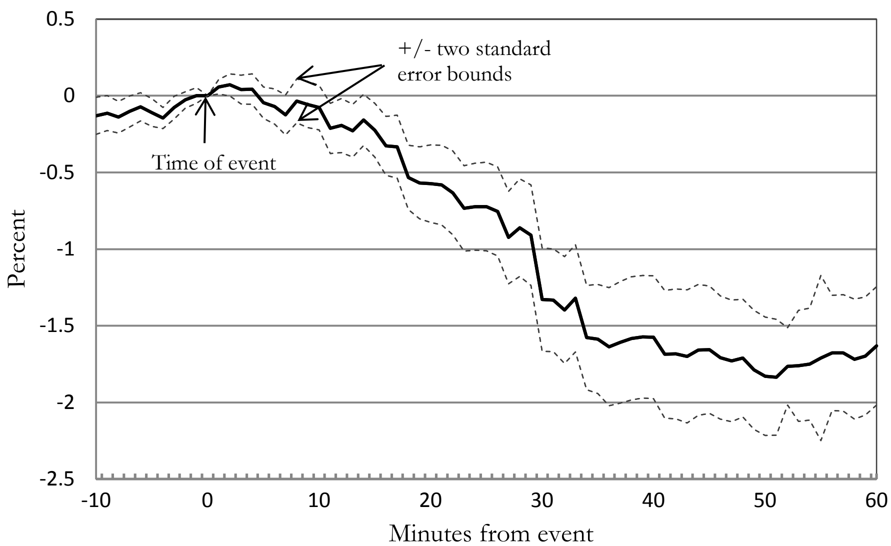
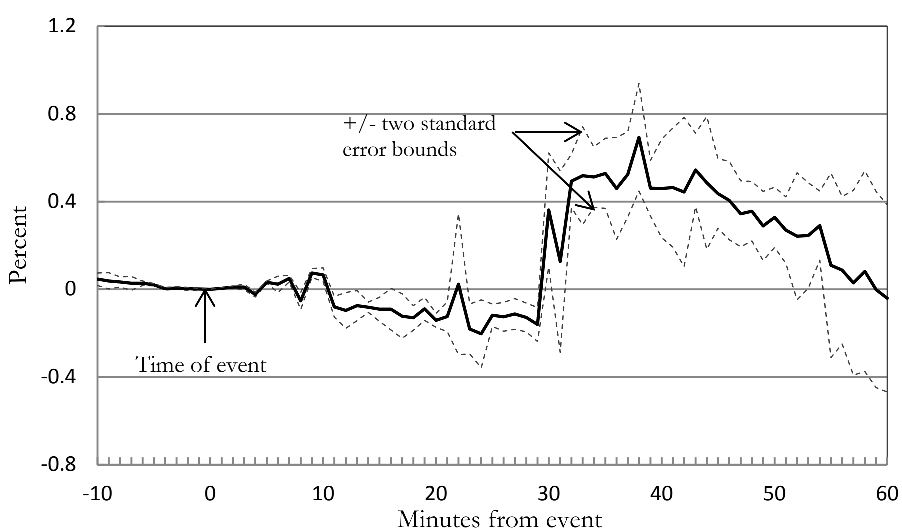


Figure E2: Foreign exchange returns conditional volatility: Response to 100-basis-point repo rate shock



APPENDIX F

Table F1: Repo rate scheduled embargo and decision announcement times

Scheduled MPC press conference date and time	Repo rate pronouncement time after start of event
2009/06/25 - *15h00*	13:48
2009/08/13 - *15h00*	12:10
2009/09/22 - *15h00*	11:42
2009/10/22 - *15h00*	11:23
2009/11/17 - *15h00*	13:04
2010/01/26 - *15h00*	8:32
2010/03/25 - *15h00*	11:12
2010/05/13 - *15h00*	14:14
2010/07/22 - *15h00*	14:35
2010/09/09 - *15h00*	16:35
2010/11/18 - *15h00*	15:59
2011/01/20 - *15h00*	16:38
2011/03/24 - *15h00*	16:23
2011/05/12 - *15h00*	14:10
2011/07/21 - *15h00*	16:45
2011/09/22 - *15h00*	18:06
2011/11/10 - *15h00*	16:02
2012/01/19 - *15h00*	17:54
2012/03/29 - *15h00*	18:42
2012/05/24 - *15h00*	16:40
2012/07/19 - *15h00*	17:30
2012/09/20 - *15h00*	19:17
2012/11/22 - *15h00*	19:30
2013/01/24 - *15h00*	19:13
2013/03/20 - *12h00*	19:09
2013/05/23 - *15h00*	17:51
2013/07/18 - *15h00*	20:.07
2013/09/19 - *15h00*	20:18
2013/11/21 - *15h00*	18:48
2014/01/29 - *15h00*	19:55
2014/03/27 - *15h00*	21:16
Time range	08:32 – 21:16
Average time to repo rate announcement	16:14

End Notes

[a] The series needs to have constant mean; mean is a measure of central tendency; *id est*, the location of the distribution.

[b] The series must have constant and finite variance; variance is a measure of dispersion, *id est*, the variability or spread in the data.

[c] The autocovariances for any given lag are constant; *id est*, the autocovariances depend only on the distance(s) between two observations. In the context of a single series, autocovariance is the similarity between observations as a function of the time separation between them or a measure of linear dependence between observations.

[d] A moment is a summary statistic of a probability distribution. Mean, variance, skewness and kurtosis are the first, second, third and fourth moments of a distribution respectively.

The arithmetic mean for a sample is the average value of the observations r_t series: $\mu = \frac{\sum X}{N}$ (population mean) or $\bar{X} = \frac{\sum X}{n}$ (sample mean). The mean is the most commonly used measure of central tendency. The mean, however, is affected by extreme values in the data set while the median and mode are not.

The median is the middle value (or average of the two middle values) of the observations or series when all items are arranged in either descending or ascending order in terms of values: Median = the $\frac{n+1}{2}$ *th* item in the data array. The median is a robust measure of the centre of the distribution that is less sensitive to outliers than the mean.

The mode is the value that occurs most frequently in the data.

Max and min are the maximum and minimum values respectively of the series in the current sample.

Standard deviation (std. dev.) is a measure of dispersion or spread in a series is $\sigma = \sqrt[+]{\sigma^2}$ (population standard deviation) or $s = \sqrt[+]{s^2}$ (sample standard deviation) where the variance is $\sigma^2 = \frac{\sum(x-\mu)^2}{N}$ (population variance) or $s^2 = \frac{\sum\left(X-\bar{X}\right)^2}{n-1}$ (sample variance).

Skewness is a measure of asymmetry of the distribution of the series around its mean. Skewness can be measured by the third moment divided by the cube of the standard deviation: $Sk = \frac{\sum f(X-\mu)^3}{\sigma^3}$ for populations and $Sk = \frac{\sum f\left(X-\bar{X}\right)^3}{s^3}$ for samples. For a symmetric distribution, $Sk = 0$.

Kurtosis measures the peakedness or flatness of the distribution of the series. Kurtosis can be measured by the fourth moment divided by the standard deviation raised to the fourth power: $K = \frac{\sum f(X-\mu)^4}{\sigma^4}$ for populations and $K = \frac{\sum f\left(X-\bar{X}\right)^4}{s^4}$ for samples. For a normal distribution, the K value is 3, and such a probability density function (PDF) is called mesokurtic. A peaked curve is called leptokurtic $(K > 3)$ and a flat one platykurtic $(K < 3)$.

JB test statistic: $JB = \frac{n}{6}\left(\hat{S}^2 + \frac{\left(\hat{K}-3\right)^2}{4}\right)$ where $\hat{S}$ denotes the sample skewness and $\hat{K}$ the sample kurtosis. $JB_{asy} \sim \chi^2_{(2)}$; that is, the *JB* statistic given in the *JB* test equation follows the chi-square distribution with 2 degrees of freedom asymptotically (that is, in large samples). For a normal distribution, the statistic equals zero and larger statistics show greater non-normality.

[e] In linear models, the dependent variable is linearly related to the explanatory variable but the relationship between the two is not exact. In analytic geometry, the graph of a linear function in the Cartesian coordinate plane is a straight line and has an equation that can be written in the form: $y = mx + b$. Equations whose graphs are not straight lines are termed non-linear functions. A non-linear data generating process is one that can be written in the form $y_t = f(u_t, u_{t-1}, u_{t-2} \ldots)$ where u_t is an *iid* error term and f is a non-linear function (Campbell *et al.*, 1997). A more specific definition of a non-linear data generating process given by Campbell *et al.* (1997) is $y_t = g(, u_{t-1}, u_{t-2}, u_{t-3} \ldots) + \sigma^2 (u_{t-1}, u_{t-2}, u_{t-3}, \ldots)$ where g is a function of past error terms only and σ^2 is a variance term. Model $y_t = g(\bullet) + \sigma^2(\bullet)$ is non-linear in mean and variance.

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