ASSET PRICE VOLATILITY IN SOUTH AFRICAN MARKETS DURING FINANCIAL CRISES

by

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ABSTRACT

This thesis investigates the impact of domestic and foreign financial crises on volatility dynamics in South Africa (SA). In a sample ranging from January 1994 to March 2009, Chapter 2 provides empirical support for the theory that domestic currency crises are associated with significant structural changes in daily exchange rate volatility. Specifically, crisis periods coincide with large positive shifts in unconditional variance. Using this fact, we propose a new method - the structural change generalised conditional heteroskedasticity, or SC-GARCH, model - for identifying precise start- and end-dates for crises.

Chapter 3 studies volatility transmission within SA from October 1996 to June 2010. Using a generalised version of the vector autoregressive (VAR) approach, time-varying and bidirectional volatility spillover indices are estimated for domestic currency, bond and equity markets. The results identify equities as the primary source of volatility transfer to other asset classes. At different points in time, spillovers are responsible for anywhere between 7.5 and 65 percent of system-wide volatility. Local maxima in spillover magnitudes are estimated during domestic, as well as foreign-crisis periods.

Chapter 4 estimates time-varying comovement between SA and world volatilities during the period from 1994 to 2008. A dynamic factor model (FM) is used to extract three latent global volatility factors from a data panel which is representative of the world equity market portfolio. Relative to most other emerging markets, the global factors are poor predictors of volatility in SA. However, SA’s comovement with global volatility increases sharply in response to emerging market crises in Asia (1997-8) and Russia (1998). The global factors are also important determinants of domestic volatility during the latter stages of the US subprime crisis (2007-8).

Chapter 5 proposes the factor-augmented VAR as a parsimonious model for the transmission of foreign volatility shocks to SA equities. We compare international volatility transmission resulting from crises in Asia (1997-8) and the US (2007-8). Although the US crisis has a larger impact on the world equity market, the Asian shock leads to more dramatic increases in volatility in emerging economies, including SA.
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CHAPTER 1
INTRODUCTION

Recent financial crises, with origins in both developed and emerging countries, emphasise the unpredictability of investment in financial assets. These assets represent claims to uncertain future cash-flows. Under rational expectations and risk neutrality, the price of any asset is equated to the discounted value of its expected future dividends and capital value. But investors are risk-averse, and thus they prefer stable consumption streams over time. Consequently, assets with state-contingent payoffs trade at discount prices to risk-free alternatives in equilibrium.

Volatility is the reflection of uncertainty in financial markets. As a statistical concept, it measures the dispersion of asset returns from their expected values. Since asset price volatility is time-varying, volatility dynamics are linked with changes in the distribution of investors’ expectations over time. From an economic viewpoint, volatility is the sum of idiosyncratic and systematic components of risk. Whilst idiosyncratic risk is costlessly eliminated through diversification, systematic risk is unavoidable and encompasses fundamental variations in the economy’s earnings potential over time.

This thesis investigates possible connections between financial crises and time-varying volatility. Most definitions associate the typical crisis episode with a rare event, the beginning of which is accompanied by a dramatic loss in market value.\(^1\) Crises occur suddenly and unexpectedly. They may be triggered following revelations of a natural disaster, terrorist attack, or other bad news regarding fundamentals. Some crises are set into motion by irresponsible or misinterpreted policy decisions. They may result from coordinated speculative attacks or runs on bank capital. In other instances, markets crash due to a shared realisation that prices have become grossly overvalued. But regardless of how they are precipitated, crisis periods are characterised by extreme uncertainty regarding current and future prices. This uncertainty leads to erratic price discovery, and is manifest in the form of heightened volatility in the short-term.

The thesis focusses primarily on the behaviour of prices determined in South African (SA) financial markets. The models presented in Chapters 2 and 3, emphasise the domestic drivers for volatility dynamics. Chapter 2 analyses the changing character of volatility in the SA exchange rate for a sequence of local currency crises. In Chapter 3, we consider the interaction between volatility levels in SA currency, bond and equity markets during various domestic and foreign crisis periods. Thus, the first half of the thesis provides a perspective of financial volatility transmission within SA.

The second half of the thesis bears cognizance to the fact that SA is a small

\(^1\)For example, according to Kneulik (2006: 6), significant depreciation of the domestic exchange rate is a common element of most definitions of currency crisis.
emerging economy, with a well-developed financial system, and limited capital controls. As a consequence of these features, SA volatility may be expected to have some dependence on global volatility factors. Chapter 4 investigates this possibility by measuring the comovement of SA equity volatility with factors common to a large panel of countries that is representative of the world stock market. Building on this analysis, Chapter 5 presents a parsimonious model for describing the transmission of crisis-period shocks from foreign to domestic equity volatility. Given the generality of the models described in Chapters 4 and 5, the thesis has application not only to understanding volatility dynamics in SA, but also those in a large portion of the world’s capital markets. Chapter 6 concludes with a brief discussion of the implications of and possible extensions to our research. In what follows, we provide a more detailed overview of Chapters 2 to 5.

1.1 Transmission of Domestic Volatility within South Africa

At the heart of asset pricing theory lies the prediction that on average, the market rewards investors in proportion to the systematic riskiness of their asset portfolios. The extent of price volatility that is observed for a given asset indirectly reflects the degree of uncertainty that agents associate with that asset’s expected future payoff. By studying and characterising the dynamics of volatility, we obtain a measure of market uncertainty as it evolves over time.

The generalised autoregressive conditional heteroskedasticity (GARCH) approach (Engle 1982; Bollerslev 1986) is the benchmark empirical model for capturing time-conditional variance in financial returns. However, a drawback to the GARCH is that it assumes constant unconditional variance. The model is thus misspecified for time series exhibiting significant break points in the average level of volatility. In such cases, Diebold and Pauly (1987), Lastrapes (1989), and Lamoureux and Lastrapes (1990), show that the GARCH consistently overestimates the degree of persistence in volatility processes.

The latter problem is remedied in the structural change GARCH (SC-GARCH) approach (Wilson, Aggarwal and Inclán 1996, Aggarwal, Inclán and Leal 1999, Malik 2003 and Malik, Ewing and Payne 2005). The SC-GARCH augments the traditional GARCH specification with dummy variables controlling for discrete shifts in variance. The location of such shifts are detected endogenously using the iterative cumulative sum of squares (ICSS) algorithm (Inclán and Tiao 1994).

currency pairing. Given the chosen data frequency, the estimated model is sensitive to short-term variations in exchange rate volatility. Essentially, our application of the model amounts to a test of whether crises are accompanied by significant and large changes in the structure of foreign exchange market volatility.

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

Kurz (1994) proposes that the effects of exogenous uncertainty on volatility are in fact far outweighed by those of endogenous uncertainty. At times of crisis, heterogeneous behaviour results in extreme asymmetry in the distribution of market-wide expectations, leading to a cycle of aggressive adjustment in the exchange rate. Kurz’s (1994) view is consistent with the second-generation models of currency crisis (Obstfeld 1986). This class of models proposes that the currency market may at times be pulled into situations of crisis by endogenously driven and self-fulfilling speculation, even when economic fundamentals are relatively sound.

However, whether volatility arises from exogenous or endogenous sources is immaterial to our analysis. In either case, theory associates a crisis period with a phase of intensive price discovery, leading to heightened short-term volatility. Thus, the motivation for the modelling approach suggested in Chapter 2 is the claim that time-varying volatility dynamics of exchange rate returns should form an important element of our understanding of currency crises, particularly when such crises occur under floating exchange rate regimes. This claim is supported by Abiad (2003:45), who points out that a well-specified volatility model may provide the kind of information that has yet to be fully exploited in models of currency crises.

A prominent example of how volatility dynamics are successfully being in-

\[4\]
A similar statement can be made about equity prices. Using a mixed data sampling (MIDAS) modification of the GARCH, Engle, Ghysels and Sohn (2009) show that between 10 and 35 percent of daily fluctuations in US stock market volatility between 1885 and 2004 are forecasted by changes in industrial production and inflation.

\[5\]
In markets that are characterised by effective price controls, the relationship between uncertainty and volatility will be less than perfectly observed. Under fixed or managed exchange rate regimes, the central bank actively intervenes in the foreign exchange market in order to achieve a desired target for the exchange rate. Given such a policy, changes in uncertainty will be reflected not only in changes in exchange rate volatility, but also in changes in reserves and in short-term interest rates. Therefore, because neither reserves nor interest rates feature in our model, an important proviso of our analysis is that of a flexible exchange rate regime.
corporated in crisis modelling is through application of Markov-switching (MS) models (Hamilton 1989, 1990) with time-varying transition probabilities (Lee 1991; Diebold, Weinbach, and Lee 1994). The MS model specifies two unobservable state variables to represent periods of tranquillity and crisis. The main distinguishing characteristic of the crisis state is a high degree of exchange rate volatility (Abiad 2003:45). It is assumed that the state variables determine the behaviour of economic fundamentals. Consequently, the transition between the two different states of the economy is indirectly inferred and conditioned on observations of changes in the fundamentals. The onset of a crisis period is endogenously identified in the MS model as the point of transition from the tranquil state to the crisis state. Similarly, the end of the crisis is identified as the transition back from crisis to tranquility.

In a recent study, Knedlik and Scheufele (2008) compare the performance of the more traditional signals and probit/logit approaches with that of an MS model in identifying currency crises in SA. They construct an exchange market pressure (EMP) index (Girton and Roper 1977, Eichengreen et al. 1995) to detect four crisis periods in the domestic currency market between 1995 and 2006. The value of the EMP index is an increasing weighted function of depreciation in currency value, increases in short-term interest rates, and losses in foreign exchange reserves. The latter two variables capture attempts by the central bank to fend off speculative selling of the currency. Knedlik and Scheufele’s (2008) findings indicate that the MS approach compares favourably with the competing approaches. The MS model successfully identifies each of the EMP-detected crises in the SA rand; specifically December 1995-December 1996 (excluding September 1996), May-October of 1998, and December 2001. Furthermore, the MS approach is found to be successful in forecasting a crisis period in June 2006.

The SC-GARCH method of crisis identification is conceptually similar to that of the MS approach. As in the case of the MS model, the SC-GARCH treats volatility as being time varying, and uses this feature of the data to endogenously identify crisis periods. The main difference between these approaches is that whereas the MS model uses macro fundamentals to identify crises, the SC-GARCH represents a pure time-series approach. Although the fundamentals are undoubtedly important to our understanding of crises, fundamental models are in some respects difficult to implement empirically. A notable problem is that of low frequencies in the reporting of fundamental data. This makes it difficult for MS models to accurately estimate the timing of currency crises, especially since crises tend to be short-lived events. In contrast, financial volatility processes can be reliably estimated in data-driven models using data that is readily available in daily (or higher) frequencies.

Crisis dates obtained from the SC-GARCH model are broadly consistent with those given in the existing literature. Sub-intervals of the crises identified by

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Knedlik and Scheufele (2008) are associated with statistically significant increases in average volatility levels.\(^7\) In addition, our model identifies a currency crisis during September-November 2008 – a period which is previously undocumented in the literature. Relative to competing approaches, the SC-GARCH model indicates considerably shorter durations for crisis periods. The latter finding suggests an improvement in the precision with which crises are identified.

Having identified currency crises as periods of extreme volatility in the foreign exchange market, it is of interest to evaluate the impact (if any) that these crises have on volatility in other financial markets. Conversely, it is reasonable to suspect that exchange rate volatility may itself be influenced by shocks that originate from elsewhere in the domestic financial system. These observations provide the motivation for Chapter 3, where we model daily volatility spillovers across SA asset classes between October 1996 and June 2010.\(^8\) A volatility spillover is defined in this context as the share of lagged volatility in one asset which may be attributed to current volatility shocks in another asset. We estimate a variety of bidirectional, time-varying spillover indices to describe volatility interactions between SA currencies, bonds, and equities.

Our data-based approach is motivated by the absence of a coherent theory for cross-market volatility transmission. Models of contagion (King and Wadhwani 1990), information spillovers (Fleming, Kirby and Ostdiek 1998), and dynamic portfolio optimisation under information asymmetry (Kodres and Pritsker 2002), are indicative of volatility interdependence between markets. However, there is currently no compelling theoretical reason to restrict the direction of volatility transfer between markets located within a specific country. Hence, assessing the causality of volatility transmission in SA financial markets is regarded as an empirical issue.

The methodology is derived from a recent study by Diebold and Yilmaz (2011), which investigates domestic volatility transmission in the US. Spillover indices are calculated using generalised variance decompositions (Koop, Pesaran and Potter 1996; Pesaran and Shin 1998) from a vector autoregression (VAR) of volatility proxies. In contrast to structural (orthogonal) VARs, the generalised VAR (GVAR) produces unique impulse response functions. This is achieved by sequentially shocking each variable in the VAR in isolation, and using the estimated covariance matrix to determine the dynamic effects of the various shocks to the system. Hence, the hierarchy of causality is left unrestricted, with shocks to all variables simultaneously effecting all other variables. In our application, this translates to the construction of bidirectional spillover indices for each asset class measuring both volatilities transmitted and those received. Combining these estimates pro-

\(^7\)With the exception of the 2006 crisis.

\(^8\)A version of Chapter 3 appears as a peer-reviewed article in the *Economic Research Southern Africa Working Paper Series* (Duncan and Kabundi 2011a). The article is currently under review with *Economic Modelling.*
duces net and system-wide spillover indices that provide a rich characterisation of domestic volatility transmission.

Similar to Diebold and Yilmaz (2011), our spillover indices are estimated using two-year rolling window regressions. This allows us to capture the evolution of cross-market volatility dependence over time. In particular, we compare magnitudes of spillovers during crisis and non-crisis periods, providing a test for the hypothesis that domestic volatility linkages strengthen during crises. Furthermore, our results facilitate comparison between the dynamics of volatility transmission in SA, an emerging economy, with those in the developed economy of the US.

The results suggest substantial time-variation in volatility interactions. Local maxima in the spillover indices are associated with both domestic and foreign financial crises. Equities are the most important source of volatility spillovers to other asset classes. However, following the 2001 currency crisis, and up until mid-2006, currencies temporarily dominate volatility transmission in SA. Bonds are a consistent net receiver of volatility spillovers. In comparison to Diebold and Yilmaz’s (2011) findings for the US, cross-market volatility linkages are relatively strong in SA.

1.2 Transmission of Foreign Volatility to South Africa

Our investigation of domestic volatilities suggests that asset market linkages within SA have nonnegligible effects on pricing. Magnitudes of volatility spillovers increase considerably at times of crisis in SA’s exchange rate. However, volatility linkages also strengthen during crises in foreign financial markets.

The latter finding leads us to the hypothesis that SA equity volatility dynamics are dependent on foreign volatility. This idea may be conceptualised with reference to an international version of Merton’s (1973) intertemporal capital asset pricing model (ICAPM). Think of SA as representing a single asset within a globally diversified portfolio. In this setting, expected excess returns (in SA, as well as in all other countries) are proportional to time-varying volatility in the world market portfolio – the systematic risk associated with optimal investment behaviour. Correlation between volatilities in SA and the market portfolio determines the amount of systematic risk inherent to domestic investment.

Thus, the sensitivity of investors to global risk determines cross-country equity premia. Given plausible levels of risk aversion, observed premia are well in excess of those predicted when intertemporal marginal rates of substitution are used to discount uncertain future cash flows. This is the famous "equity premium puzzle" (Mehra and Prescott 1985, Hansen and Jagannathan 1991).9 Some of the more

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9 Refer to Hassan and van Biljon (2010) for evidence of a equity premium puzzle in the case of SA.
promising recent attempts to resolve the puzzle are based on models with countercyclical variations in the price of risk. One such model is presented by Campbell and Cochrane (1999). They suggest that external habit formation causes agents to be highly averse to especially bad states of the world. The modified preferences produce calibrated parameters that are broadly consistent with the empirical record of post-war US price data. In particular, the model predicts countercyclical variations in volatility. Thus, when a financial crisis induces a global recession, this can have a profound influence on systematic risk.

Within this context, Chapter 4 studies time-varying synchronisation between SA and global equity volatilities using monthly data from 1994 to 2008. A large-panel dynamic factor model (FM) is well-suited to this task. Using principal component analysis, latent common factors are extracted from a panel of volatility proxies for 25 developed and 20 emerging equity markets (including SA). For each market, we estimate the share of variance in volatility that is explained by the global factors. This proportion, which equals the relevant $R^2$-squared statistic obtained from the FM, measures the particular market’s comovement with global volatility, and hence its systematic risk. Its complement, the share of variance which is left unexplained by the FM, indicates the relative importance of idiosyncratic shocks to volatility. As in Chapter 3, a rolling-window estimation approach is used to estimate the model. This accounts for possible structural changes in volatility dynamics and produces smooth mappings of cross-sectional comovement over time.

In contrast to similar applications of the FM (Dungey and Martin 2007, Dungey et al. 2010, and Morana and Beltratti 2008), the cross-section that we consider is representative of the world equity market. For each country, comovement with the factors is estimated for the composite stock index, as well as for selected market sectors (financials, industrials, oil and gas, basic materials). The chosen data set ensures a high degree of generality in the results. Taken together, the panel constitutes over 95 percent of world market capitalisation. Hence, we may be fairly certain that the factors represent accurate proxies for the true drivers of global volatility. The chapter includes an analysis of the composition of the global volatility factors. Following the approach of Forni, Giannone, Lippi and Reichlin (2009) and Ludvigson and Ng (2007, 2009), the individual factors are sequentially regressed on a large set of macroeconomic and financial variables. The results provide an indication of the underlying sources for fluctuations in global systematic risk.

The optimal FM is found to include three global volatility factors. Composition analysis identifies Factor One as a developed market volatility factor. Factor One is also the most important foreign driver for SA volatility. On the other hand, Factor

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10A previous version of Chapter 4 appears as a peer-reviewed article in the *Economic Research Southern Africa Working Paper Series* (Duncan and Kabundi 2011b). The article is currently under review with the *Journal of Applied Econometrics.*
Two is correlated with volatility levels in Latin America, whilst Factor Three is associated with markets in emerging Asia. In addition, Factor One and Factor Two are proxies for uncertainty in global bond and commodity markets.

For both time- and cross-sectional dimensions, we find considerable variations in volatility comovement. Global volatility linkages are particularly strong during financial crises in Asia (1997-8), Russia (1998), and the US (2007-8). Emerging markets are less synchronised with world volatility than are developed markets. In particular, we observe decoupling between emerging and world volatilities between 2001 and 2007. Recoupling occurs during 2008, thus identifying emerging market investments as a temporary hedge against volatility spillovers from the subprime crisis.

Average volatility comovement for the SA composite index is estimated at 17 percent. This is exceptionally low, even in comparison to most other emerging markets. Similarly, with average comovement of 23.3 and 22.5 percent, respectively, SA basic materials and oil and gas stocks are little effected by global factors. In comparison, domestic financials and industrials have greater mean dependence on foreign volatility, with comovement of 30.6 and 36.7 percent, respectively.

Consistent with the results from Chapters 2 and 3, we find that the character of SA volatility is sensitive to the occurrence of crises. With the exception of financial stocks, comovement of all domestic indices reach their maxima during the latter stages of the subprime crisis. The Brazilian crisis also leads to sharp increases in foreign volatility dependence, particularly in the financial and industrial sectors.

Thus, Chapter 4 demonstrates the usefulness of the FM in capturing time-varying synchronisation of cross-market volatilities. However, a weakness of the FM is that it is not well suited to the analysis of shocks. This is due to our inability to disentangle innovations to the model’s observation and state equations (Koop and Korobilis 2009). Thus, although the FM emphasises linkages between increased dependence on global factors and the timing of major financial crises, it does not facilitate explicit modelling of volatility transmission during crisis periods. This is the objective of Chapter 5.

In contrast to the FM, shock identification is unambiguous in the context of VAR modelling. As a consequence, the VAR framework is a popular choice for studies of cross-market volatility transmission. For example, Engle, Ito and Lin (1990) combine GARCH and VAR models to derive impulse response functions for intra-daily volatility transmission in geographically dispersed foreign exchange markets. More recently, Diebold and Yilmaz (2009) use a Cholesky-restricted VAR to quantify return and volatility spillovers in a panel of seven developed and 12 emerging equity markets. Their analysis indicates system-wide volatility spillovers ranging between 40 and 75 percent from late 1995 to 2007. Consistent with the conclusions of this thesis, Diebold and Yilmaz’s (2009) paper shows that volatility spillovers increase in response to financial crises.
Two drawbacks of Diebold and Yilmaz’s (2009) analysis – and of the VAR approach in general – provide the motivation for our approach to modelling international volatility transmission. Firstly, there is a proliferation of parameters in the VAR which places an upper bound on the number of variables which may sensibly be included in the modelled system. This restriction limits the information content of the model and, for the intents and purposes of this thesis, would prevent us from considering international asset pricing in the proper context of a world equity market portfolio. Secondly, as we have already noted, impulse responses obtained from orthogonal VARs are not unique. For a system consisting of \( M \) variables, there exist \( M! \) alternative sets of identifying assumptions, each of which implies (possibly) different interactions between markets.

Chapter 5 simultaneously addresses the limitations of both the FM and the VAR through application of the factor-augmented VAR (FAVAR) approach. The FAVAR is originally proposed by Bernanke, Boivin and Eliasz (2005) to model the transmission of changes in monetary policy. Essentially, the model combines the parsimony of the FM with the convenience of shock identification associated with a VAR. As a result, it is ideally suited to studying dynamics in large systems characterised by complex interdependence amongst individual variables.

In our model, the stimulus for international volatility transmission during a crisis period is a foreign volatility shock which is assumed to have systematic implications on the world equity market portfolio. The shock is transmitted from the country (or group of countries) where the crisis originates. Given the systematic nature of the shock, volatility in the country of crisis is interpreted as an observable global volatility factor. The observable factor is added to the FM described in Chapter 4. This introduces direct dependence in cross-sectional volatility on the observable factor, thus controlling for global linkages with the market in crisis. The model also accounts for indirect international volatility transmission. An orthogonal VAR uses the shock to the observable factor to determine dynamics in the latent global factors. Depending on the factor loadings for individual countries, the displaced latent factors serve as conduits for volatility spillovers in world equity markets.

We follow the estimation approach suggested by Korobilis (2011) to account for changing volatility linkages over time. Specifically, Bayesian mixture innovations (Gerlach, Carter and Kohn 2000; Giordani and Kohn 2008) with non-informative priors are used to introduce time-varying parameters in the FAVAR. In so doing, the model endogenously controls for structural changes, thus enhancing the accuracy of estimated impulse responses.

The time-varying-parameter FAVAR (TVP-FAVAR) is estimated using the same data set analysed in Chapter 4. Shocks associated with several financial crises are modelled to ensure the robustness of our conclusions. In general, crises with origins either in developed, or in emerging countries, lead to qualitatively similar transmissions of volatility. For the sake of brevity, we limit our discussion
to comparison of the Asian emerging market crisis of 1997-8 with the developed market crisis originating in the US during 2007-8.

The results indicate significant differences in the patterns of volatility transmission for the two crises. Transmission of the Asian volatility shock is most evident in the case of emerging markets, although developed Australasia is also strongly effected. In comparison, the US crisis has a greater overall impact on world equity volatility. Large reactions to this event are measured for developed market volatilities in Europe and Canada. These findings suggest that volatility linkages are strong between markets which have similar characteristics.

This conclusion is consistent with the results for SA. Magnitudes of domestic volatility responses are greatest in the case of the Asian crisis. In particular, the volatility of SA financial and industrial stocks increases dramatically in response to the Asian shock.
CHAPTER 2
MODELLING SOUTH AFRICAN CURRENCY CRISES AS STRUCTURAL CHANGES IN THE VOLATILITY OF THE RAND

2.1 Introduction

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

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

The applied methodology involves a two-step procedure. The first step is to statistically detect the full set of possible structural change points in rand volatility during the sample period. This is achieved through implementation of Inclán and Tiao’s (1994) iterative cumulative sum of squares (ICSS) algorithm. By repeatedly evaluating the relative magnitudes of consecutive changes in squared returns with respect to a critical value, the ICSS algorithm locates multiple points of discontinuity in the variance process. Having identified potential structural changes in the volatility of the rand, the second step is devoted to testing for the significance and modelling the effects (if any) of these changes on the variance process. We apply Bollerslev’s (1986) generalised autoregressive conditional heteroskedasticity (GARCH) model to capture the volatility in rand returns. The GARCH model has been shown to provide good approximations of the time-varying nature of volatility in financial returns (Diebold and Lopez 1995), and is thus considered appropriate for our application. Two GARCH models are estimated and compared. The first is the GARCH(1,1) model. This standard GARCH specification assumes that there are no structural changes in the unconditional variance of returns. The second model augments the conventional GARCH(1,1) by incorporating a set of structural changes.

\(^1\)In the context of this analysis, structural change refers to the occurrence of a sudden shift in variance, and not to a change in the domestic economic policy environment.
structural change dummy variables in the variance equation. Each dummy variable is constructed to measure the individual effect of one of the structural changes detected by the ICSS algorithm. In this way, the structural change GARCH (SC-GARCH) model controls for shifts in average volatility over time. Moreover, the model allows us to measure the significance and magnitudes of these shifts.

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

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

Our results indicate that using daily financial time series, the SC-GARCH model has the ability to identify periods of currency crisis. The SC-GARCH model is more precise than that of Knedlik and Scheufele’s (2008) Markov-switching (MS) model in identifying crises. Moreover, we identify a previously undocumented domestic currency crisis during 2008 (26 September–5 November).

The remainder of this chapter is structured as follows. In Section 2.2, we discuss our methodology. This is followed by data analysis in Section 2.3. The results of the analysis are presented in Section 2.4. Section 2.5 concludes the chapter.
2.2 Methodology

2.2.1 GARCH Modelling of Time-Varying Volatility Dynamics

Even though the GARCH model is certainly not the only model of its kind, it is generally regarded as the benchmark approach to financial volatility modelling.\(^2\) In general, volatility models like the GARCH are classified as pure time-series approaches in the sense that they are primarily designed to closely mimic the volatility process of returns, and not necessarily with reference to economic theory. Although they are technically different, most volatility models are based on similar principles. The majority of these models provide a measure of volatility persistence, a concept that is important to our analysis.

Regardless of the chosen model, a fundamental problem in measuring volatility is that it is a latent variable. Hence, typically applied measures such as realised variance or standard deviation of returns may at best be considered proxies of true volatility. For this reason, it is easy to obtain misleading results when modelling financial volatility. Furthermore, difficulties in modelling volatility are compounded by the stylised features of financial data. The typical distribution of financial returns displays fat tails, volatility clustering, and, in some cases, asymmetry.\(^3\)

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

\[
\begin{align*}
    r_t &= \mu + \varepsilon_t \\
    h_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1},
\end{align*}
\]

with coefficient restrictions \(\omega \geq 0, 0 \leq \alpha, \beta < 1,\) and \(\alpha + \beta \leq 1.\) \(r_t\) denotes the period-\(t\) realised return (calculated the log difference of the exchange rate), and \(\mu\) is the unconditional expectation of this return. The error term \(\varepsilon_t\) is assumed to be normally distributed with \(\varepsilon_t \sim N(0, h_t).\)\(^4\) Variance \(h_t\) is set conditional on its own lagged value, and on the square of the error term realised in period \(t - 1.\)

The true process underlying the volatility of returns is approximated in the model’s three estimated coefficients. The unconditional component of variance is given by the quotient, \(\sigma = \omega / (1 - \alpha - \beta).\) Conditional variance is captured in the

\(^2\)For a recent survey of volatility modelling, refer to Poon and Granger (2003).

\(^3\)We do not investigate possible asymmetry in the volatility of the rand. This represents a topic for future research.

\(^4\)Robust standard errors (Bollerslev and Wooldridge, 1992) are calculated to account for non-normality in financial data.
and $\beta$ coefficients, where $\alpha$ measures the “ARCH effect” – the sensitivity of the market’s reaction to breaking news – and $\beta$ the “GARCH effect” – the extent to which current price changes are influenced by historic volatility. The sum of $\alpha$ and $\beta$ represents the degree of persistence that shocks have in influencing the volatility process over time. If the value of this sum is close to one, we conclude that the volatility process has long memory.

In their survey of ARCH-type modelling, Bera and Higgins (1993: 342) report high persistence as a widespread finding of empirical research pertaining to financial volatility. However, they note that “. . . the consistent finding of very large persistence in variance in financial time series is perplexing because currently no theory predicts that this should be the case” This finding is at odds with the efficient market hypothesis, which proposes that news is instantly and fully reflected in prices (Hallwood and MacDonald, 2000:294-299). According to this theory, shocks should result in immediate, not persistent, market volatility.

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

This indicates that the standard GARCH model is open to misspecification, especially when applied to time series that exhibit unusually high volatility or outlying observations. Naturally, this is an important concern when modelling the volatility associated with sample periods that include currency crises.

### 2.2.2 Detecting Shifts in Unconditional Variance

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

The most commonly applied method for endogenous detection of break points in variance is the ICSS algorithm, developed by Inclán and Tiao (1994). The ICSS
procedure is a retrospective test that analyses relative variations in variance over time. A break in the variance process is assumed to result from the occurrence of a sudden, large and unexpected economic or political shock. When, following such a shock, the degree of variability from historically observed variance is sufficiently high, this implies that market volatility has undergone a structural change.

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

To test for shifts in unconditional variance over time, we begin by estimating the CUSUM of squared returns innovations. This quantity is given by

\[ C_k = \sum_{i=1}^{k} \varepsilon_i^2. \]

For a time series with \( T \) observations, the computed CUSUM statistics are normalised as

\[ D_k = \frac{C_k}{C_T} - \frac{k}{T}, \]

for \( k = 1, 2, ..., T \). Notice that \( D_0 = D_T = 0 \) by construction.

Inclán and Tiao (1994:914) show that \( D_k \) fluctuates around zero for time series with a high degree of homoskedasticity. They state that, in contrast, “when there is a sudden change in variance, the plot of \( D_k \) will exhibit a pattern going out of some specified boundaries with a high probability” This allows for the calculation of critical values for \( D_k \) beyond which we reject the null hypothesis of no significant shifts in variance. Our tests are based on a confidence level of 99 percent, implying a critical value of \( D_{k}^{01} = 1.628 \). Finding that

\[ \sqrt{T/2} |D_k| \geq D_{k}^{01} \]  

(2.1)

indicates the occurrence of a meaningful shift in variance with a high degree of probability. In this case, the exact location of the shift coincides with the value of \( t = k \) at which the absolute value of \( D_k \) is maximised.

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

The ICSS algorithm avoids masking effects, by means of an iterative application of the CUSUM test. Following the identification of a change in variance using the
conventional CUSUM test, $D_k$ statistics are reestimated prior to and following the detected break point. This process is repeated until $\sqrt{T/2}|D_k| < D_k^{01}$ for each interval between two consecutive changes in variance. Thus, the ICSS algorithm identifies a sequence $(sc_n)$ of structural change points in the variance of the time series, each coinciding with consecutive maximisations of the left hand side of inequality (2.1).

### 2.2.3 Accounting for Structural Changes in the GARCH Modelling Framework

A structural change in the market’s volatility process implies a discrete shift in the level of unconditional variance. Following their detection, structural changes should be incorporated in the chosen volatility model to avoid misspecification of the variance process.5

Suppose that the ICSS algorithm identifies a finite number $N$ of significant structural changes in variance. For $n = 1, \ldots, N - 1$, define $(I_n) = [sc_n, sc_n + x_n]$ as a sequence of disjoint volatility intervals with length $x_n = sc_{n+1} - sc_n$. Letting $I_0 = [t_0, sc_1]$ and $I_N = [sc_N, T]$, where $t_0$ and $T$ are the first and last observations in sample period, $\{\bigcup_{n=0}^N I_n\}$ forms a partition of the time series. Consecutive volatility intervals are characterised by unequal unconditional variances. Thus, where $\sigma^2_n$ is our estimate of unconditional variance for interval $I_n$, it follows that $\sigma^2_n \neq \sigma^2_{n+1}$.

In the SC-GARCH specification, the variance equation includes dummy variables that coincide with the various volatility intervals identified by the ICSS algorithm. The SC-GARCH(1,1) model takes the following form:

$$h_t^{SC} = \omega + \nu_1 \chi_1 + \cdots + \nu_N \chi_N + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^{SC},$$

where the mean equation remains unchanged, $h_t^{SC}$ is the structural change augmented conditional variance of returns, and where, for $n = 1, 2, \ldots, N$, dummy variables are defined as

$$\chi_n = \begin{cases} 1 & \text{for } t \in I_n \\ 0 & \text{for } t \notin I_n \end{cases}.$$

The set $(\nu_n)$ of structural change coefficients (SC-coefficients) measure the magnitude, direction and significance of the identified shifts in volatility.

The SC-GARCH specification has the flexibility to ensure that shifts in the average level of volatility do not impact on the estimation of $\alpha$ or $\beta$, the coefficients governing conditional variance. Hence, because the effects of structural changes are measured separately in the SC-GARCH model, it should be possible to obtain

---

5 An alternative treatment involves the removal of outliers from the data (see, for example, Kearns and Pagen, 1993). However, this method is not appropriate when modelling the volatility associated with currency crisis, and thus it is not applied in this thesis.
a closer approximation of the true volatility process by applying this method in place of the conventional GARCH approach. Wilson, Aggarwal and Inclán (1996), Aggarwal, Inclán and Leal (1999), Malik (2003) and Malik, Ewing and Payne (2005) consistently report a reduction in GARCH estimated volatility persistence when the SC-GARCH model is applied.

2.2.4 Identifying Currency Crises in the SC-GARCH model

The SC-GARCH model provides an effective method for estimating volatility dynamics in time series that are characterised by discrete shifts in variance. The model is thus particularly useful in analysing currency crises. This is due to the association between crisis periods and substantial spikes in market volatility (as discussed in Chapter 1). Since unusually high volatility is a distinguishing feature of most crises, the SC-GARCH model may be applied to identify the beginning and end points of crisis periods. The SC-GARCH model identifies the beginning of a crisis as a point in time at which unconditional variance displays a large positive shift away from its initial value. Such a shift represents a structural change in market volatility.

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

The identification problem is solved by specifying a threshold level for volatility that is unlikely to be exceeded under normal market conditions. The beginning of a crisis period is identified as a point of significant structural change in variance that results in the volatility threshold being exceeded. Similarly, the end of the crisis period coincides with a significant shift in variance to below the volatility threshold. Selection of an appropriate threshold for crisis identification is regarded as an empirical issue. We choose a crisis threshold for the SA exchange rate that is broadly consistent with Knedlik and Scheufele’s (2008) crisis identifications.

2.3 Data Analysis

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

In order to avoid losses of information, we use daily data to estimate the short-term volatility dynamics of the rand. Moreover, the choice of a daily frequency is also motivated by the fact that the accuracy of GARCH estimation is known to improve with increased data observations, especially when the model is applied to non-normal data (Engle, 2001:158). Our sample period comprises a total of 3,794 consecutive observations, beginning on 3 January 1994 and ending on 31 March 2009.\(^6\) The sample has been chosen to overlap with the period studied by Knedlik and Scheufele (2008), and therefore includes the four rand crises identified using their MS model. Specifically, these crisis dates are December 1995-December 1996 (excluding September 1996), May-October of 1998, December 2001 and April-June of 2006. This allows for the comparison of respective crisis periods identified by the MS and SC-GARCH approaches.

The analysis is based on the volatility of the rand relative to the US dollar. The dollar continues to be the most significant currency in the world economy. According to the Bank for International Settlements (2007), 86.3% of all foreign exchange market transactions involve the dollar. Similarly, the SA foreign exchange market is dominated by trade involving the dollar. Since the rand/dollar is the most significant exchange rate from the perspective of domestic market participants, our analysis is based on the volatility of this currency pairing.\(^7\)

Panel A of Figure 2.1 provides a plot of the daily rand/dollar exchange rate for the period under investigation. The start- and end-dates of the crises identified by Knedlik and Scheufele (2008) have been indicated on the graph. Each of the crises is associated with a loss of value in the rand relative to the dollar. However, the pattern of depreciation varies considerably for different crisis episodes. For example, whereas the 1996 (and to a lesser extent, the 1998) crisis is characterised by a relatively gradual depreciation in the rand, the 2001 crisis represents a very sudden adjustment in market value. This indicates that due to changes in the South African Reserve Bank (SARB)’s exchange rate policy, the rand is far more volatile during (and following) 2001 than it is in either 1996 or 1998.

During 1996 and 1998, the SARB intervened heavily in the forward exchange market to support the value of the rand and reduce market volatility. The policy of continuously defending the rand from market forces had the negative consequence that the SARB was forced to accumulate a very large net open forward position.

\(^6\)The data was obtained from the I-Net Bridge databank.

\(^7\)We gratefully acknowledge Brian Kahn from the South African Reserve Bank for his suggestion that we focus on modelling the volatility of the rand/dollar exchange rate.
The NOFP amounted to USD23.2 billion by the end of September 1998 (Myburgh Commission, 2002). The costliness of defending the rand during the 1990s may be regarded as a primary motivation for the change in policy stance that occurred in 2000. With the advent of inflation targeting, the SARB effectively abandoned the policy of consistently intervening in the foreign exchange market. Consequently, when pressure mounted against the domestic currency in the latter parts of 2001, foreign exchange market volatility increased substantially.

Figure 2.1. The rand/dollar exchange rate, its volatility, and domestic currency crises identified by Knedlik and Scheufele (2008)

Panel A. Rand/dollar exchange rate

Panel B. Squared returns for rand/dollar exchange rate

The effect of the policy change on market volatility can be observed in the plot of squared rand/dollar returns given in Panel B of Figure 2.1. The graph illustrates the increase in rand volatility following 2000, and, in particular, following the 2001 crisis. It is also evident from the graph that with the exception of June 2006, each of the periods identified by Knedlik and Scheufele (2008) is centred on what appears to be a large spike in volatility relative to the periods leading up to and following crisis. Analysis of the data suggests that in general, SA currency crises are indeed characterised by changes in domestic market volatility.

From the perspective that past crises were associated with heightened levels of volatility, Figure 2.1 is indicative of a rand crisis occurring during the latter
stages of 2008. The rand exhibited far greater volatility during 2008 than it did during any other part of the sample period. In the following section, we apply the SC-GARCH model in order to determine start- and end-dates for previously established crisis periods in the rand, and to test for the occurrence of a crisis in 2008.

2.4 Empirical Results

2.4.1 Detecting Break Points in the Variance of Rand/Dollar Returns

The ICSS algorithm is applied to the time series of innovations in rand/dollar returns. The locations of the endogenously detected break points in variance are summarised in Table 2.1. Application of the ICSS methodology indicates, at a confidence level of 99%, the occurrence of 19 significant shifts in the volatility of the rand during the sample period. A shift in rand volatility occurs on average once in every 190 trading days – a period of roughly 9 months.

This indicates that the domestic foreign exchange market exhibits a great deal of instability, especially in comparison to other studies of shifting variance in exchange rate returns. In comparison, Malik (2003), who uses the ICSS algorithm to investigate shifts in variance in foreign exchange markets between 1990 and 2000, reports only two shifts in the respective variances of returns to the French franc, Canadian dollar and German mark, and three shifts in the Japanese yen and British pound. Relative to these markets for major world currencies, the rand is characterised by exceptionally high volatility, implying a great deal of uncertainty in international transactions that involve the SA rand.

2.4.2 Comparison of GARCH and SC-GARCH Models of Rand Volatility

Panel A of Table 2.2 summarises the GARCH(1,1) estimation of rand/dollar volatility. The results suggest some cause for concern regarding model specification. The first problem is that the estimated \( \omega \) coefficient does not differ significantly from zero, implying that we are unable to calculate the unconditional variance of the rand using a simple GARCH approach. Of greater concern is that, although \( \alpha \) and \( \beta \) are both highly significant, they sum to a value of greater than unity. This violates the coefficient restrictions of the model and implies that the variance process estimated by means of a GARCH(1,1) model follows a non-stationary process over time.
Table 2.1. Identified structural changes in rand/dollar volatility

<table>
<thead>
<tr>
<th>Structural Change</th>
<th>Date of Change in Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>sc₁</td>
<td>31/3/1994</td>
</tr>
<tr>
<td>sc₂</td>
<td>11/5/1994</td>
</tr>
<tr>
<td>sc₃</td>
<td>20/2/1995</td>
</tr>
<tr>
<td>sc₄</td>
<td>2/6/1995</td>
</tr>
<tr>
<td>sc₅</td>
<td>15/2/1996</td>
</tr>
<tr>
<td>sc₆</td>
<td>16/5/1996</td>
</tr>
<tr>
<td>sc₇</td>
<td>14/3/1997</td>
</tr>
<tr>
<td>sc₈</td>
<td>10/6/1998</td>
</tr>
<tr>
<td>sc₉</td>
<td>20/7/1998</td>
</tr>
<tr>
<td>sc₁₀</td>
<td>21/1/1999</td>
</tr>
<tr>
<td>sc₁₁</td>
<td>27/1/2000</td>
</tr>
<tr>
<td>sc₁₂</td>
<td>20/9/2001</td>
</tr>
<tr>
<td>sc₁₃</td>
<td>12/12/2001</td>
</tr>
<tr>
<td>sc₁₄</td>
<td>23/1/2002</td>
</tr>
<tr>
<td>sc₁₅</td>
<td>23/8/2004</td>
</tr>
<tr>
<td>sc₁₆</td>
<td>17/11/2006</td>
</tr>
<tr>
<td>sc₁₇</td>
<td>22/10/2007</td>
</tr>
<tr>
<td>sc₁₈</td>
<td>26/9/2008</td>
</tr>
<tr>
<td>sc₁₉</td>
<td>6/11/2008</td>
</tr>
</tbody>
</table>

Notes. The reported structural change points represent significant shifts in the variance of rand/dollar returns at a confidence level of 99 percent. These points are endogenously estimated using Inclan and Tiao’s (1994) iterated cumulative sum of squares (ICSS) algorithm. Sample endpoints are not included in the list.

Results of the SC-GARCH(1,1) model are given in Panel B of Table 2.2. In contrast to the GARCH model, the estimated $\omega$, $\alpha$ and $\beta$ coefficients of the SC-GARCH specification are all significant and obey the coefficient restrictions of the model. Furthermore, the error term of the SC-GARCH does not show any significant signs of heteroskedasticity.

The above comparison indicates that because the SC-GARCH introduces dummy variables that measure discrete shifts in variance over time, it improves on the standard GARCH specification of exchange rate volatility. Furthermore, it calls into question the validity of previous studies of exchange rate volatility in SA. For example, Farrel (2001) applies the GARCH to estimate the volatility process of the commercial and financial rand exchange rates between between 1983 and 1998. His results suggest a very high degree of persistence in rand volatility, with reported $\alpha + \beta$ values ranging between 0.931 and 0.998. Estimation of the SC-GARCH model indicates far less persistence in rand volatility, with $\alpha$ and $\beta$ summing to a value of only 0.69.
Table 2.2. GARCH models of daily rand/dollar volatility

<table>
<thead>
<tr>
<th></th>
<th>( \omega )</th>
<th>( \alpha )</th>
<th>( \beta )</th>
<th>( \omega/(1 - \alpha - \beta) )</th>
<th>( \alpha + \beta )</th>
<th>( Q )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A. GARCH(1,1)</td>
<td>0.0112</td>
<td>0.0034</td>
<td>0.1486</td>
<td>0.8684</td>
<td>0.0040</td>
<td>1.0170</td>
</tr>
<tr>
<td></td>
<td>(0.0075)</td>
<td>(0.0023)</td>
<td>(0.0298)</td>
<td>(0.0252)</td>
<td>(3.1139)</td>
<td></td>
</tr>
</tbody>
</table>

Panel B. SC-GARCH(1,1)

<table>
<thead>
<tr>
<th></th>
<th>( \nu_1 )</th>
<th>( \nu_2 )</th>
<th>( \nu_4 )</th>
<th>( \nu_5 )</th>
<th>( \nu_7 )</th>
<th>( \nu_8 )</th>
<th>( \nu_9 )</th>
<th>( \nu_{11} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.2582</td>
<td>-0.0339</td>
<td>-0.0484</td>
<td>0.5152</td>
<td>-0.0353</td>
<td>1.7661</td>
<td>0.3457</td>
<td>0.0684</td>
</tr>
<tr>
<td></td>
<td>(0.1343)</td>
<td>(0.0097)</td>
<td>(0.0102)</td>
<td>(0.2529)</td>
<td>(0.0091)</td>
<td>(0.6601)</td>
<td>(0.1039)</td>
<td>(0.0188)</td>
</tr>
</tbody>
</table>

Table 2.3. Significant SC-GARCH structural change coefficients

<table>
<thead>
<tr>
<th></th>
<th>( \nu_{12} )</th>
<th>( \nu_{13} )</th>
<th>( \nu_{14} )</th>
<th>( \nu_{15} )</th>
<th>( \nu_{16} )</th>
<th>( \nu_{17} )</th>
<th>( \nu_{18} )</th>
<th>( \nu_{19} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.4634</td>
<td>3.1997</td>
<td>0.4083</td>
<td>0.2614</td>
<td>0.1476</td>
<td>0.3884</td>
<td>7.3386</td>
<td>0.9324</td>
</tr>
<tr>
<td></td>
<td>(0.1791)</td>
<td>(1.5565)</td>
<td>(0.0758)</td>
<td>(0.0513)</td>
<td>(0.0372)</td>
<td>(0.0808)</td>
<td>(4.3864)</td>
<td>(0.2328)</td>
</tr>
</tbody>
</table>

Notes. SC-GARCH is the acronym for "structural change generalised autoregressive conditional heteroscedasticity". Robust standard errors (Bollerslev and Wooldridge, 1992) relating to estimated coefficients are reported in brackets. The \( Q \)-statistic is an ARCH LM test for remaining heteroscedasticity in the estimated error term at a lag interval of 15.

2.4.3 Applying the SC-GARCH Model to Identify South African Currency Crises

The significant SC-coefficients estimated for the SC-GARCH(1,1) model of rand volatility are reported in Table 2.3. Of the 19 possible variance shifts detected by the ICSS algorithm, 16 are modelled as having a significant influence on the variance process of the rand at a 90% confidence level.

In order to correctly interpret the magnitudes of the SC-coefficients, we need to convert them into measures of unconditional variance. This is done by summing the estimate of \( \omega \) with each of the respective significant SC-coefficients \( \nu_n \), and dividing by the complement of \( \alpha + \beta \):

\[
\sigma_n^2 = \frac{\omega + \nu_n}{1 - \alpha - \beta}
\]

where, as before, \( \sigma_n^2 \) denotes the unconditional variance associated with volatility.
Our application of the SC-GARCH model requires a volatility threshold to facilitate the identification of crisis periods. Selection of an appropriate threshold is an empirical issue. The threshold needs to be high enough to prevent the false identification of non-crisis periods. At the same time, the threshold should not be so high as to exclude the correct identification of known periods of crisis. Finally, the threshold should be dynamically calculated so that it evolves over time to reflect changes in factors (for example, market structure or exchange rate policy) that determine the amount of volatility that we expect to observe.

Given the above requirements, the crisis threshold proposed in this analysis is specified relative to the weighted average of unconditional variance preceding the consecutive points of structural change. To evaluate the importance of different structural changes, we calculate the ratio of individual shifts in variance relative to average unconditional variance. For volatility interval $I_n$, this ratio is given by

$$\rho_n = \frac{\sigma_n^2}{\hat{\sigma}_{n-1}^2},$$

where $\hat{\sigma}_{n-1}^2 = \sum_{i=1}^{n-1} (\sigma_i^2/x_i)$.

The unconditional variance estimated for each of the 20 detected volatility intervals that make up the sample period are summarised in Table 2.4. The weighted averages and ratios of unconditional variance are also reported in the table. Remarkably, 9 of the 14 volatility intervals that coincide with the sample period studied by Knedlik and Scheufele (2008) include an identified crisis episode. This overidentification of crisis periods is due to the fact that, while our volatility intervals are detected using daily data, Knedlik and Scheufele (2008) identify crises on the basis of monthly observations.

In the sample period considered by Knedlik and Scheufele (2008), we identify three structural changes in variance that each result in an extreme spike in market volatility. During this period, the average ratio of unconditional variance following a structural change is 3.8. In comparison, the respective ratios associated with volatility intervals $I_6$, $I_8$, and $I_{13}$, equal 12.12, 13.26 and 16.56, respectively. The latter structural changes are hence distinguishable by their extraordinary magnitudes from other significant shifts in variance. Accordingly, we select a crisis threshold ratio of 10 and thus obtain SC-GARCH identifications of domestic currency crises (as reported in Table 2.4.)

---

8 All of the insignificant SC coefficients (in this case, $\nu_3$, $\nu_6$, and $\nu_{10}$) are assumed to have a magnitude of zero.

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

10 Although it is chosen to be consistent with SA data, we acknowledge the arbitrariness of our
Each of the SC-GARCH identified crises coincides with part of a crisis period identified by Knedlik and Scheufele (2008). The first SC-GARCH crisis, coinciding with volatility interval $I_6$, captures the increase in volatility observed during the latter stages of the 1996 crisis. In this instance, the crisis is modelled as having lasted for a considerable period – 203 trading days, beginning on 16 May 1996 and ending on 13 March 1997. In comparison, the second crisis identified by the SC-GARCH model, as represented by volatility interval $I_8$, is more closely centred on the crisis period identified by Knedlik and Scheufele (2008). The duration of the volatility spike associated with the 1998 crisis is 26 trading days between 10 June 1998 and 19 July 1998. Results of the SC-GARCH estimation indicate that from the perspective of observed volatility, the rand crisis during 1998 was relatively short lived in comparison with the 1996 crisis. Coincidentally, with starting-date 12 December 2001 and ending-date 22 January 2002, the 2001 crisis is estimated as having identical duration to the 1998 crisis.

Although our findings are broadly consistent with those of Knedlik and Scheufele (2008), there are some notable differences between the SC-GARCH and MS crisis identifications. For instance, the SC-GARCH model fails to detect a crisis in June 1998. In this respect, our approach suffers from a common weakness in models of crisis identification (see Abiad 2003 for a discussion of crisis thresholds). The suggested threshold may not be appropriate for other currency pairings or other asset classes.
2006. This reflects the fact that although the rand lost 25% of its value in the first half of 2006, the depreciation was not characterised by the extent of market turmoil observed during previous crisis periods. A further cause for concern is the lack of accuracy with which the model identifies the 1996 crisis. Analysis of the data suggests that the rand was most volatile during February-May of 1996 (refer to Figure 2.2). In this case, the SC-GARCH model is late in its identification of the crisis. A possible reason for this may be the fact that foreign exchange market intervention played an important role in subduing market volatility during 1996. These findings suggest that the SC-GARCH model is not equally well suited to modelling all types of currency crises. The model is most informative when studying crises that are characterised by a high degree of short-term volatility. For instance, the SC-GARCH indicates that the high volatility associated with the 2001 crisis extended well into January 2002. From this perspective, the model's crisis identification may be regarded as more precise than that of Knedlik and Scheufele's (2008) MS model.

In addition to studying previously identified crises, our sample period includes the latter stages of 2008, a period of very high volatility in the rand. The ratio of unconditional variance associated with volatility interval $I_{18}$ is 24.6. This ratio easily exceeds the chosen threshold of 10 and is significantly greater than the ratios calculated for the 1996, 1998 and 2001 crises. Consequently, the SC-GARCH model indicates starting-date 26 June 2008 and ending-date 5 November 2008 as the most volatile crisis period in the SA foreign exchange market to date. The estimated duration of the 2008 crisis is 29 trading days.

### 2.5 Conclusion

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

The crisis periods identified by the SC-GARCH model (16 May 1996 – 13 March 1997; 10 June 1998 – 19 July 1998; 12 December 2001 – 22 January 2002; 26 September 2008 – 5 November 2008) are broadly consistent with those provided by Knedlik and Scheufele (2008). Notable differences between the two studies include: (i) SC-GARCH identified crises have shorter durations, and more precise start- and end-dates than MS identified crises; (ii) the SC-GARCH does not detect a crisis in the rand during 1996; and (iii) the sample period is extended to detect a crisis period in the rand during 2008.
CHAPTER 3
VOLATILITY SPILLOVERS ACROSS SOUTH AFRICAN ASSET CLASSES DURING FINANCIAL CRISES

3.1 Introduction

This chapter investigates volatility transmission across domestic asset classes in South Africa (SA). We investigate daily volatility relationships between SA currencies, bonds, and equities, from October 1996 to June 2010. Our objective is to characterise cross-market linkages in asset pricing through estimates of several volatility spillover indices. A volatility spillover is defined as the share of total variability in one asset class attributable to volatility surprises in another asset class. Estimated spillovers can be combined in a variety of ways, thus providing a rich source of information regarding magnitudes and directions of volatility transfer.

As far as we are aware, this is the first study of its kind to focus on spillovers across asset classes in an emerging market economy. According to De Santis and Imrohoroglu (1997: 561-2), "...the most commonly known characteristic of (emerging financial markets) is their high volatility compared to more developed markets". As noted by Bekaert and Harvey (1997), volatile financial markets may reflect high costs of raising capital in emerging economies. Richards (1996) suggests various possible explanations for elevated risk premiums in emerging market finance. These include: under-developed and segmented financial markets; over-reliance on commodity exports; instability in domestic policymaking; and, intermittent reversals of foreign portfolio investments. Furthermore, the high degree of risk inherent to emerging economies makes them particularly vulnerable to financial crises and contagion (Bae, Karolyi and Stulz 2003). In this context, comparisons of volatility linkages during crisis and non-crisis periods are of particular interest in the spillover literature. The consistent finding in this literature is that volatility spillovers are pronounced during financial crises.

Analysis of volatility linkages in SA is a case in point. As depicted by plots of daily squared returns in Figure 3.1 (located on page 35), domestic asset classes exhibit time-varying volatility. There are multiple episodes of extreme price instability for each asset class. The larger volatility spikes are generally associated with financial crises, either domestically or in the global economy. Furthermore, spells of heightened volatility often appear to be correlated across asset classes.

Consider, for instance, peaks in currency market volatility. The analysis in Chapter 1 associates domestic currency crises in 1996-7, 1998, 2001-2, and 2008 with significant increases in rand/dollar volatility. Similarly, from inspection of Figure 3.1, we observe marked increases in bond and/or equity volatility in time

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1Early examples of such comparisons include Hamao, Masulis and Ng (1990) and King and Wadhwani (1990).
periods that include currency crisis. In what follows, we use formal methods to assess volatility interactions between SA asset classes in periods of domestic currency crisis, as well as during major foreign crises in Asia (1997-8) and in the United States (dot-com 2000; subprime 2007-8).

The analysis follows a similar approach to Diebold and Yilmaz (2011). They introduce volatility spillover indices that are normalizations of forecast-error variance decompositions derived from a generalised vector autoregressive (GVAR) model (see, for example, Pesaran and Shin 1998). Diebold and Yilmaz (2011) estimate the model for daily volatility proxies from United States (US) currency, bond, equity, and commodity markets, between January 1999 and January 2010. They find that 12.6 percent of time-aggregated system-wide volatility is due to spillovers across asset classes. Rolling-window estimates indicate substantial time-variation in volatility transmission, with total spillovers reaching a maximum of roughly 32 percent during the recent US subprime crisis.

In comparison, we estimate time-aggregated spillovers which account for 26.6 percent of total volatility in SA asset classes. Similar to the US, we find that SA volatility spillovers are distinctly time-varying. However, our estimated spillovers frequently peak at levels in excess of 50 percent, which indicates that asset class volatility linkages are considerably stronger in SA than they are in the US. The analysis provides evidence of heightened volatility interdependence between SA asset classes during both domestic and foreign financial crises.

The remainder of the chapter is structured as follows. Section 2 briefly reviews the literature on volatility spillovers. Special emphasis is given to research focussing on spillovers across asset classes. In Section 3, we outline the methodology used in constructing volatility spillover indices. The data is analysed in Section 4. This is followed by a discussion of the empirical results in Section 5, including a detailed comparison of our findings to those of Diebold and Yilmaz 2010 in Subsection 5.4. Section 6 concludes.

3.2 Literature Review

Literature focussing on returns and volatility spillovers, dates back to the global equity market crash of October 1987. Interdependencies between national stock markets before and after the crash are well-documented. Hamao, Masulis and Ng (1990) introduce a simple generalised autoregressive conditional heteroskedasticity (GARCH) model to capture spillovers between US, United Kingdom (UK), and Japanese equity markets. They conclude that volatility surprises in foreign markets are a significant precursor to price volatility in the domestic market. Large volatility spillovers from the US to Japan are central to their results. Furthermore, they find that the significance, magnitude and frequency of measured spillovers, increases when the 1987 crash is included in their sample period.
King and Wadhwani (1990) develop a partially-revealing rational expectations model of cross-market contagion. In this model, idiosyncratic shocks to major equity markets have the potential to be misinterpreted as newsworthy events. When idiosyncratic shocks are large, as in the case of financial crises, they may result in drastic increases to correlations between markets, and positive feedback in short-term volatility transmission.\(^2\) Empirical estimation of the contagion model indicates significant interactions between realised returns in US, UK and Japanese equities. These interactions are strengthened amidst the volatility of the 1987 crash.

Several studies, employing a variety of methods and focussing on a wide range of countries, support the early findings of time-varying international volatility spillovers in equity markets.\(^3\) Similarly, there is evidence of changing volatility linkages between international currency, as well as bond markets.\(^4\)

Forbes and Rigobon (2002) focus the recent empirical debate on the distinction between interdependence and contagion in international asset prices. They define contagion as a significant increase in cross-market correlation, and show that time-varying volatilities in financial returns place an upward bias on correlation estimates.\(^5\) Having controlled for the volatility bias, they find evidence of significant comovement in international equity prices during various crises, but practically no indication of contagion. However, Corsetti, Pericoli and Sbracia (2005) observe that Forbes and Rigobon’s (2002) test introduces its own form of bias. This bias, which favours the interdependence hypothesis, results from imposing a constant variance ratio between common and idiosyncratic determinants of returns in the country where the crisis originates. By relaxing the latter assumption, Corsetti, Pericoli and Sbracia (2005) provide evidence of equity market contagion from Hong Kong to France, Italy, Phillipines, Singapore, and the UK during the Asian crisis.\(^6\)

There is limited research focussing on domestic or international linkages in

\(^2\)In contrast, Longin and Solnik (2001) argue that correlations are determined by market trends, instead of volatility.

\(^3\)See, for example: Choudhry (2004); Diebold and Yilmaz (2009); Engle, Ito and Lin (1992, 1994); Hamao, Masulis and Ng (1991); Karolyi (1995); King, Sentana and Wadhwani (1994); Koutmos and Booth (1995); Longin and Solnik (2001); Ng, Chang and Chou (1991); Susmel and Engle (1994); and Theodossiou and Lee (1993).


\(^5\)As reviewed by Pericoli and Sbracia (2003), many other definitions of contagion have been suggested in the literature. One such definition identifies contagion as the simultaneous increase in volatilities across markets (which need not be accompanied by increased correlation between these markets).

\(^6\)See also the closely related analysis of Pesaran and Pick (2007). They propose a contagion model which controls for interdependence and idiosyncratic risk. Using this model, they find that increases in interest rates lead to contagion during the collapse of the European exchange rate mechanism. However, there is no contagion in response to decreases in interest rates.
volatility across different asset classes. In what follows, we briefly review three notable contributions to this literature.\(^7\) Although these papers follow vastly different methodologies, applied to distinct crisis episodes, they share the conclusion that volatility linkages across asset classes grow stronger following major upheavals in financial markets.

Fleming, Kirby and Ostdiek (1998) propose two channels of possible interaction between correlated returns in equity, bond and money markets. The first, is the "common information" channel, where simultaneous changes to expected values in multiple markets lead to portfolio re-optimization. The second channel, referred to as "information spillovers", results when changing expectations in one market alter optimal hedging demands in other markets.\(^8\) Both channels, operating either independently, or in conjunction, provide possible explanations for volatility spillovers across asset classes. Using GMM to impose moment restrictions on a stochastic specification of volatility, Fleming, Kirby and Ostdiek (1998) estimate their model for US futures markets in a sample period ranging from January 1983 to August 1995. Their results suggest strong co-movements of volatility across all three asset classes. They find that market linkages are time-varying. Moreover, correlations between realised volatility in different asset classes increase following the 1987 crisis.

In the second paper, Dungey and Martin (2007) introduce a dynamic latent factor model of international asset price linkages. The model controls for a variety of global and domestic factors, each impacting on one or more asset classes. Cross-market factors included in each of the pricing equations, capture asset class contagion and spillovers.\(^9\) Dungey and Martin (2007) focus on interactions between currency and equity markets located in countries affected (directly or indirectly) by the Asian financial crisis from July 1997 to August 1998. Variance decompositions of the modelled factors indicate an important role for bidirectional contagion and spillovers in most countries, especially in the post-crisis period.\(^10\)

In the third paper, Diebold and Yilmaz (2011) develop a variety of volatility spillover indices. The spillover indices are normalisations of forecast-error variance decompositions from a GVAR model of volatility proxies.\(^11\) In contrast to tra-

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\(^7\) Other relevant studies – focussing primarily on cross-market linkages in returns – include: Granger, Huang and Yang (2000); Kaminsky and Reinhart (2002); and, Hartmann, Straetmans and de Vries (2004).

\(^8\) In related research, Kodres and Pritsker (2002) model information spillovers across countries in a partially-revealing rational expectations framework.

\(^9\) Dungey and Martin (2007) define contagion as contemporaneous comovements between asset classes. In contrast, and consistently with our definition, spillovers are intended to refer to market interactions which occur with a time lag.

\(^10\) Also refer to Dungey et al. (2010), which uses Dungey and Martin’s (2007) framework to study similarities between several recent financial crises.

\(^11\) This method may be similarly applied to estimate spillovers in returns (see Diebold and Yilmaz 2009).
ditional VAR specifications, GVAR allows for nonorthogonal impulses; identification is achieved via generalised impulse response functions. Generalised impulse responses fully incorporate the correlation structure between impulses and have the advantage that they are uniquely determined (i.e. invariant to reordering of the VAR). Application of GVAR facilitates complete characterisation of possible volatility interactions between markets. Diebold and Yilmaz (2011) apply this approach to measure directional volatility spillovers across US bond, equity, currency and commodity markets from January 1999 to January 2010. Their results indicate time-variation in volatility transmission, with increases in spillover magnitudes being observed during the US dot-com and subprime crises. In particular, they report a striking increase in spillovers coinciding with the subprime crisis.

Given the purpose of our investigation, a limitation of Fleming, Kirby and Ostdiek’s (1998) approach is that it does not identify the direction of volatility transmission between asset classes. Although this problem is not encountered in the model of Dungey and Martin (2007), the latter framework is not ideally suited to studies of domestic volatility transmission across asset classes. Consequently, we adopt the approach suggested by Diebold and Yilmaz (2011) to capture time-varying volatility spillovers between SA asset classes.

3.3 Methodology

3.3.1 Generalised Impulse Responses and Variance Decompositions

Let $Y_t = (y_{1t}, y_{2t}, ..., y_{Mt})$ denote a vector of endogenous proxies for period-$t$ volatility in $M$ distinct financial markets. Suppose that the dynamics of $Y_t$ are captured by the following VAR($p$) model:

$$Y_t = \sum_{k=1}^{p} \Phi_k Y_{t-k} + \epsilon_t,$$  \hspace{1cm} (3.1)

where the $\Phi_k$ are coefficient matrices and $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, ..., \epsilon_{Mt})$ is a vector of mean-zero error terms. We assume $\epsilon_t$ has a multivariate normal distribution, with $\epsilon_t$ independent of $\epsilon_s$ for $s \neq t$, and with nonsingular covariance matrix $E_{t-1} (\epsilon_t \epsilon_t') = \Sigma_{\epsilon} = \{\sigma_{ij}\}$ for $i, j = 1, 2, ..., M$.

Furthermore, suppose that (3.1) is a covariance stationary process. This implies

12 The GVAR approach is proposed by Gallant, Rossi and Tauchen (1993), Koop, Pesaran and Potter (1996), and Pesaran and Shin (1998).
the following infinite moving average representation for the system:

\[ Y_t = \sum_{k=0}^{\infty} A_k \epsilon_{t-k}. \]

By setting \( A_k = 0 \) for \( k < 0 \) and \( A_0 = I_M \), we establish the coefficient matrix \( A_k = \Phi_1 A_{k-1} + \Phi_2 A_{k-2} + \cdots + \Phi_p A_{k-p} \) recursively for \( k = 1, 2, \ldots \).\(^{13}\)

Within this framework, an impulse response function isolates the impact of a particular realisation of the error vector at time \( t \) (denoted \( \epsilon_t = \delta \)) on the period \( t + n \) expected outcome of the system. Specifically, we estimate the difference between, the \( n \)-period ahead expectation of \( Y_t \) conditional on \( \delta \), and the corresponding expectation of \( Y_t \) in the absence of any shocks.

Following Pesaran and Shin (1998), we define the generalised impulse response function (GI) by

\[
\psi_n = E_t (Y_{t+n}|\epsilon_t = \delta, F_{t-1}) - E_t (Y_{t+n}|F_{t-1}) = A_n \delta, \tag{3.2}
\]

where (3.2) is a function of the forecast period \( n = 0, 1, \ldots \) and the period-\( t \) shock \( \delta \), but its value is invariant to past observations in the information set \( F_{t-1} \).\(^{14}\)

Consider the system-wide impact of a shock to the \( j \)-th element of \( \epsilon_t \) (i.e. we set \( \epsilon_{jt} = \delta_j \) and \( \epsilon_{it} = 0 \) for all \( i \neq j \)). Given the assumed distributional properties of \( \epsilon_t \), we have the following conditional expectation:

\[
E_{t-1} (\epsilon_t|\epsilon_{jt} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \ldots, \sigma_{jj}, \ldots, \sigma_{mj})^\prime \sigma_{jj}^{-1} \delta_j = \frac{\Sigma \epsilon_j \delta_j}{\sigma_{jj}},
\]

where \( \epsilon_j \) denotes the \( j \)-th column of \( I_M \).

Consequently, the \( n \)-period ahead GI of \( Y_t \) conditional on \( \delta_j \) is given by

\[
\psi_{j,n} = E_t (Y_{t+n}|\epsilon_{jt} = \delta_j, F_{t-1}) - E_t (Y_{t+n}|F_{t-1}) = A_n \Sigma \epsilon_j \delta_j \]

and, letting \( \delta_j \) equal \( \sqrt{\sigma_{jj}} \), we obtain

\[
\psi_{j,n} = \frac{A_n \Sigma \epsilon_j}{\sqrt{\sigma_{jj}}}, \tag{3.3}
\]

\(^{13}\)Where \( I_M \) denotes the \( M \)-dimensional identity matrix.

\(^{14}\)Refer to Koop, Pessaran and Potter (1996) for a detailed discussion of history independence in (3.2).
for any \( j = 1, 2, \ldots, M \). Equation (3.3) measures the expected impact on \( Y_{t+n} \) of a one standard error shock to variable \( j \).

Suppose that we are interested in predicting the \( i \)-th element of \( Y_t \) with a forecast horizon of \( n \). We see from (3.3) that the expected cumulative impact on \( y_{i,t+n} \) of a period \( t \) shock \( \delta_j = \sqrt{\sigma_{jj}} \) is

\[
\varphi_{ji,n} = \sum_{\ell=0}^{n} e_i' \psi_{j,\ell},
\]

with covariance matrix

\[
cov(\varphi_{ji,n}) = \sum_{\ell=0}^{n} e_i' \psi_{j,\ell} \psi_{j,\ell}' e_i. \tag{3.4}
\]

In comparison, the total \( n \)-step ahead forecast-error and forecast-error covariance for \( y_{i,t+n} \) are given as:

\[
\xi_{i,n} = \sum_{\ell=0}^{n} e_i' A_{\ell} e_{t+n-\ell},
\]

\[
cov(\xi_{i,n}) = \sum_{\ell=0}^{n} e_i' A_{\ell} \Sigma_{\ell} A_{\ell}' e_i. \tag{3.5}
\]

Using (3.3), (3.4) and (3.5), we are now ready to define the \( n \)-step ahead generalised forecast-error variance decompositions (GF) for variable \( i \). Specifically, the contribution of innovations in variable \( j \) to the total forecast-error variance of \( i \) is given by

\[
\theta_{ij,n} = \frac{\sigma_{ii}^{-1} \sum_{\ell=0}^{n} (e_i' A_{\ell} \Sigma_{\ell} e_j)^2}{\sum_{\ell=0}^{n} e_i' A_{\ell} \Sigma_{\ell} A_{\ell}' e_i} = \frac{\sigma_{ji}}{\sigma_{ii}} \left[ \frac{cov(\varphi_{ji,\ell})}{cov(\xi_{i,n})} \right]. \tag{3.6}
\]

Notice that the values of (3.3) and (3.6) are uniquely determined, and thus invariant to the ordering of variables in the VAR. This is a special property of GI and GF analysis. Pesaran and Shin (1998) show that generalised impulse responses coincide with orthogonal impulse responses obtained through Cholesky factorisation only if \( j \) is the first variable included in the VAR.\(^{15}\)

\(^{15}\)A natural exception to this statement is provided if \( \Sigma_e \) is diagonal (implying orthogonality in the impulses), in which case GI coincide with orthogonalised impulse responses. Consult Lütkepohl (2007) for a detailed treatment of VAR models with orthogonal impulses.
3.3.2 Volatility Spillover Indices

Similar to Diebold and Yilmaz (2011), we construct volatility spillover indices using GF as defined in (3.6). In this context, \( \theta_{ij,n} \) measures the expected magnitude (in absolute terms) of \( n \)-horizon future volatility in asset class \( i \) which is attributable to period-\( t \) volatility in market \( j \).

Forecast-error variance decompositions derived from orthogonal VARs have the convenient property that they sum to unity. However, in general \( \sum_{j=1}^{M} \theta_{ij,n} \neq 1 \), and thus we cannot think of \( \theta_{ij,n} \) as a share of total variance in \( i \). To allow for such an interpretation, we normalise the values obtained from (3.6) as

\[
\tilde{\theta}_{ij,n} = \frac{\theta_{ij,n}}{\sum_{j=1}^{M} \theta_{ij,n}},
\]

such that \( \sum_{j=1}^{M} \tilde{\theta}_{ij,n} = 1 \) and \( \sum_{i,j=1}^{M} \tilde{\theta}_{ij,n} = M \).

In what follows, we suppress the variable forecast horizon \( n \) implicit in our spillover indices for notational convenience. Define \( \tilde{\theta}_{ii} \) as the share of asset class \( i \)’s volatility arising from own-shocks. Similarly, for \( i \neq j \), we let \( \tilde{\theta}_{ij} \) denote the percentage volatility spillover to asset class \( i \) originating from shocks to variable \( j \).

Using these definitions, it is possible to measure volatility spillovers across all asset classes as a relative share of total volatility in the system. The total volatility spillover index is given by

\[
\Theta_{System} = 100 \cdot \frac{\sum_{i,j=1}^{M} \tilde{\theta}_{ij}}{M} = 100 \cdot \frac{\sum_{i,j=1}^{M} \tilde{\theta}_{ij}}{M}. \quad (3.8)
\]

It is also of interest to study the net effects of cross-market volatility transmission. Each asset class plays two possible roles at any given point in time: (i) the source of volatility spillovers to other asset classes; and, (ii) the destination for volatility spillovers from other markets. If, for example, the first (second) role predominates in the case of asset class \( i \), then we regard \( i \) as a net transmitter (receiver) of volatility spillovers to (from) other asset classes.

To compute net spillover indices, we first need to estimate gross spillovers transmitted and received by each asset class. The expected gross volatility spillovers received by asset class \( i \) from volatility surprises in other markets is calculated as

\[
\Theta_{i\rightarrow j} = 100 \cdot \frac{\sum_{j=1}^{M} \tilde{\theta}_{ij}}{M} = 100 \cdot \sum_{j=1}^{M} \tilde{\theta}_{ij}. \quad (3.9)
\]
Next, we reverse the roles and consider volatility spillovers expected to be transmitted from market \( i \) during the forecast window. Gross volatility spillovers from \( i \) to other asset classes is given as follows:

\[
\Theta_{i\rightarrow j} = 100 \cdot \frac{\sum_{j=1}^{M} \theta_{ji}}{\sum_{j=1}^{M} \sum_{j\neq i} \theta_{ji}^{2}} = 100 \sum_{j=1}^{M} \sum_{j\neq i} \theta_{ji}.
\]  \hspace{1cm} (3.10)

Subtracting (3.9) from (3.10) we get the net volatility spillovers for asset class \( i \):

\[
\Gamma_{i} = \Theta_{i\rightarrow j} - \Theta_{i\rightarrow j},
\]  \hspace{1cm} (3.11)

For values of \( \Gamma_{i} > 0 \), we conclude that asset class \( i \) is a net transmitter of volatility to the financial system. Conversely, if \( \Gamma_{i} < 0 \), we expect to observe net volatility injections to asset class \( i \) from other parts of the system.

### 3.4 Data Analysis

We model volatility spillovers between three SA asset classes: currencies, bonds, and equities. Unlike Diebold and Yilmaz (2011), we do not include commodity volatility in our model. As a small economy, SA is a price-taker in the global commodity market, and thus it is inappropriate to consider commodity volatility as being endogenously determined in domestic markets.\(^{16}\)

Consistent with Chapter 2, we use returns to the SA rand/US dollar exchange rate as a proxy for domestic currencies. For bonds and equities, we base our study on yields to SA 10-year government bonds and returns on the Johannesburg Stock Exchange (JSE) composite market index, respectively.

Volatility is an unobservable variable. Squared returns, range-based measures and intra-daily realised variances are commonly used proxies for financial volatility (Andersen and Bollerslev 1998). Due to unavailability of, either intra-daily, or high and low price quotes for SA asset classes, squared returns/yields are chosen to measure volatility.\(^{17,18}\) Closing prices are sampled on a daily basis in order to capture high-frequency variations in the time series.

---

\(^{16}\)This does not imply that SA asset classes are immune to volatility spillovers from world commodity markets (especially given the importance of domestic commodity production). Unfortunately, the employed methodology does not allow for easy inclusion of exogenous variables in the model.

\(^{17}\)We assume that returns/yields have zero expected values. Thus, we derive volatility proxy \( x_{it} = \sigma_{it}^{2} = \frac{1}{2} \left[ \sum_{j=1}^{M} \theta_{ij} \right] \) from period-\( t \) realised returns. A similar proxy is created for bond yields.

\(^{18}\)In contrast, Diebold and Yilmaz (2011) use range-based proxies for volatility.
The sample period is, to some extent, limited by data availability for the bond market. Regular quotes for daily bond interest rates are available from 1 October 1996, which marks the beginning of our sample. The sample ranges to 4 June 2010, and has a duration of 3411 concurrent observations.\(^{19}\) Missing observations in a single series are replaced with the previous day’s volatility. Trading holidays across all three markets are removed from the sample. Furthermore, three extreme outliers are deleted from the time series to avoid biasing our estimations. Table 3.1 provides details of these outliers. Descriptive statistics for the log-transformations of daily squared returns are given in Table 3.2. On average, equities are the most volatile asset class, followed by bonds and then currencies. However, variations in log volatility (measured by the standard deviation) are greatest for currencies. All three time series shows signs of non-normality.

<table>
<thead>
<tr>
<th>Date</th>
<th>Currencies</th>
<th>Bonds</th>
<th>Equities</th>
</tr>
</thead>
<tbody>
<tr>
<td>28/10/1997</td>
<td>2.07</td>
<td>5.78</td>
<td>161.03</td>
</tr>
<tr>
<td>14/12/2001</td>
<td>49.57</td>
<td>196.05</td>
<td>23.43</td>
</tr>
<tr>
<td>15/10/2008</td>
<td>253.22</td>
<td>0.01</td>
<td>52.45</td>
</tr>
</tbody>
</table>

Table 3.1. Extreme outliers in daily squared returns

<table>
<thead>
<tr>
<th></th>
<th>Currencies</th>
<th>Bonds</th>
<th>Equities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-1.75</td>
<td>-1.58</td>
<td>-1.03</td>
</tr>
<tr>
<td>Median</td>
<td>-1.34</td>
<td>-1.45</td>
<td>-0.67</td>
</tr>
<tr>
<td>Maximum</td>
<td>4.67</td>
<td>4.16</td>
<td>4.13</td>
</tr>
<tr>
<td>Minimum</td>
<td>-13.04</td>
<td>-5.61</td>
<td>-12.66</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>2.47</td>
<td>1.74</td>
<td>2.29</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.90</td>
<td>-0.14</td>
<td>-1.05</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>4.18</td>
<td>2.54</td>
<td>4.86</td>
</tr>
</tbody>
</table>

Table 3.2. Summary statistics of log-transformed daily squared returns

Figure 3.1 plots the daily squared returns of SA asset classes. Some patterns are discerned from visual inspection of the data. An eyeball test is indicative of volatility clustering in returns/yields, a stylised feature of financial time series (Bollerslev, Chou and Kroner 1992). Time-varying volatility dynamics are punctuated by repeated observations of extraordinary spikes in volatility. Furthermore, spells of heightened volatility often appear to be correlated across asset classes.

Periods of extreme turbulence in one or more SA asset classes are typically associated with financial crises, either domestically or in the global economy. For instance, large spikes in currency volatility are located in June–July 1998, December 2001, and October 2008. Each of these periods is associated with crisis in the

\(^{19}\)All data is obtained from the I-Net Bridge databank.
domestic currency market (as discussed in Chapter 2). The latter period follows shortly after the demise of Lehman Brothers in September 2008, a landmark event in the 2007-8 US subprime crisis.

Peaks in bond volatility follow a similar pattern to those for currencies. June–July 1998 and December 2001 provide striking examples of correlation between currency and bond volatility. Instability in bond yields during these periods may be attributed to the South African Reserve Bank’s (SARB) attempts at defending the rand against speculators (Myburgh Commission 2002). In comparison, the bond market’s response to currency market turmoil during October 2008 is less pronounced. The changing response of bond yields to currency volatility is perhaps reflective of the SARB’s shift towards a more freely floating exchange rate regime during the latter parts of the sample period.

Equities appear to be more volatile than either currencies or bonds. The data suggests vulnerability of the JSE to volatility injections from foreign crises. Large shocks to equity volatility are observed during October 1997, April 2000 and October/November 2008. The first of these shocks is contiguous to the spread of Asian crisis to Hong Kong (Kaminsky and Schmukler 1999). The second shock occurs during the bursting of the US dot-com bubble (Ofek and Richardson 2003). Finally, the volatility shock towards the end of 2008 overlaps with the end of the US subprime crisis.

We leave the investigation of internationally propagated volatility to Chapters 4 and 5. However, in what follows, we do investigate changes in SA volatility transmission coinciding with both domestic and foreign crises.

3.5 Empirical Results

The reported results are based on multivariate least squares estimations of the GVAR, with an autoregressive lag selection of 18 periods (approximately three-and-a-half weeks). This lag structure is chosen to minimise the Akaike information criterion and is considered reasonable given that volatility persistence is a stylised feature of financial time series (Bollerslev, Chou and Kroner 1992). Similar to Diebold and Yilmaz (2011), a forecast horizon of 10 periods (or two weeks) is maintained throughout our analysis.

The results are presented in four subsections. We begin by considering time-aggregated volatility spillover indices estimated for the full sample period. This is followed by the results of rolling-window estimations of time-varying volatility spillovers. Next, we analyse changes in volatility spillovers coinciding with domestic and/or foreign financial crises. Finally, we benchmark our findings regarding SA volatility transmission to Diebold and Yilmaz’s (2010) study of spillovers across US asset classes.
3.5.1 Time-Aggregated Volatility Spillovers

Using (3.6) and (3.7), we estimate time-aggregated volatility spillovers across SA asset classes. Percentages of overall volatility arising from shocks to variable \( j \) are given in the respective columns of Table 3.3; the rows report the sensitivity of asset class \( i \) to the various shocks. Thus, own-variance shares appear along the diagonal of Table 3.3, whilst the volatility spillover to market \( i \) transmitted from market \( j \), is measured in off-diagonal entry \( ij \). Time-aggregated estimates of total-, gross- and net volatility spillover indices, obtained from (3.8), (3.9), (3.10) and (3.11), are summarised in Table 3.4.

Consider first volatility spillovers received. Relative to other asset classes, bond volatility is most susceptible to outside influence. Roughly 44 percent of bond volatility is transmitted from the currency market; equity volatility contributes a further 11.5 percent of total variability in bond yields. Spillovers to currencies and equities are small in comparison. Bond and equity spillovers are responsible for only 6.9 and 4.8 percent of rand volatility, respectively. And, with time-aggregated spillovers of 3.8 and 1 percent from currencies and bonds, the JSE is – at least on average – practically immune to volatility injections from other asset classes.

Next, compare the different sources of volatility transmission. With gross spillovers of 47.8 percent, currencies are by far the most important contributor to outside volatility.\(^{20}\) However, only a small portion (3.8 percent) of these spillovers are destined for the equity market. We observe a similar pattern for bond spillovers: 6.9 percent of the total 7.9 percent gross bond spillover is received by the currency market. Gross spillovers from the equity market are estimated at 16.3 percent. Similarly to currency spillovers, the bulk of transmitted equity volatility is received by the bond market (11.5 percent).

Our time-aggregated estimates emphasise the importance of volatility flows between currencies and bonds. This interpretation is supported by correlation analysis of the VAR estimated error terms. As reported in Table 3.5, significant positive correlation of 0.47 between currency and bond innovations indicates a relatively close relationship between these variables. In comparison, correlations between currencies and equities (0.17), and equities and bonds (0.20) are weak, but still significantly positive.

Taken together, our results imply that currencies and equities are net transmitters of volatility to bonds. Furthermore, the estimated net volatility spillover indices suggest substantial imbalances in volatility transmission – particularly between currencies and bonds (with net spillovers of 36.1 and -47.62 percent, respec-

\(^{20}\) Care should be taken in the interpretation of gross volatility spillovers. System-wide volatility is given by \( 100 \cdot \sum_{i,j=1}^{M} \tilde{\theta}_{ij} = 100 \cdot M \) percent, where, as before, \( M \) denotes the number of variables included in the VAR. Total volatility in our model is thus 300 percent, and potential spillovers from asset class \( i \) has a maximum value of 200 percent.
Figure 3.1. Squared daily returns for SA asset classes

Table 3.3. Time-aggregated volatility spillovers for SA asset classes

<table>
<thead>
<tr>
<th></th>
<th>Currencies</th>
<th>Bonds</th>
<th>Equities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Currencies</td>
<td>88.31</td>
<td>6.93</td>
<td>4.76</td>
</tr>
<tr>
<td>Bonds</td>
<td>44.04</td>
<td>44.46</td>
<td>11.50</td>
</tr>
<tr>
<td>Equities</td>
<td>3.77</td>
<td>0.99</td>
<td>95.24</td>
</tr>
</tbody>
</table>

Table 3.4. Time-aggregated gross-, net-, and total volatility spillover indices

<table>
<thead>
<tr>
<th></th>
<th>Currencies</th>
<th>Bonds</th>
<th>Equities</th>
<th>System-wide</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross spillovers transmitted</td>
<td>47.82</td>
<td>7.92</td>
<td>16.26</td>
<td></td>
</tr>
<tr>
<td>Gross spillovers received</td>
<td>11.69</td>
<td>55.54</td>
<td>4.76</td>
<td></td>
</tr>
<tr>
<td>Net spillovers</td>
<td>36.13</td>
<td>-47.62</td>
<td>11.50</td>
<td></td>
</tr>
<tr>
<td>Total spillovers</td>
<td></td>
<td></td>
<td></td>
<td>24.00</td>
</tr>
</tbody>
</table>
This conclusion is consistent with the estimated total volatility spillover index of 24 percent. Just less than a quarter of system-wide price/interest rate variability is due to volatility spillovers. These findings suggest significant interdependence in volatility across SA asset classes.

### 3.5.2 Time-Varying Volatility Spillovers

To allow for possible time-variation in volatility transmission between SA asset classes, we estimate volatility spillovers using rolling-window regressions. Similar to Diebold and Yilmaz (2011), the duration of our rolling window is 200 periods (or 40 weeks). By shifting the estimation window one observation at a time, we obtain 3211 consecutive sets of results. These results track the sensitivity of volatility transmission to significant domestic and global economic events, especially in the presence of various structural breaks.

We begin this part of the analysis by considering interactions between the different variables included in the model. Correlation coefficients for time-varying volatility spillovers transmitted from the various asset classes are presented in Table 3.6. All of the estimated correlations are significant at the 99 percent confidence level. Positive relations are observed between spillovers coming from any single source. These relationships are strong when volatility is transmitted from either currencies (0.81) or equities (0.82).

The interaction of spillovers originating in different asset classes is indicative of cross-market relationships. Volatility spillovers from currencies are positively correlated with spillovers from bonds – particularly when volatility is being transmitted from these asset classes to equities (correlation, in this case, equals 0.66). In contrast, equity spillovers are negatively related to volatility transmissions from other asset classes. The suggestion is thus, that, at any given moment in time, volatility transmission is likely to be dominated either by a combination of currency and bond spillovers, or by equity spillovers on their own.
Table 3.6. Correlations between time-varying spillovers transmitted across SA asset classes

<table>
<thead>
<tr>
<th>Currency spillovers to:</th>
<th>Bonds</th>
<th>Equities</th>
<th>Currencies</th>
<th>Equities</th>
<th>Currencies</th>
<th>Bonds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bonds</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equities</td>
<td>0.81</td>
<td>1.00</td>
<td>(78.74)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Currencies</td>
<td>0.09</td>
<td>0.16</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4.97)</td>
<td>(8.96)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equities</td>
<td>0.50</td>
<td>0.66</td>
<td>0.31</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(32.52)</td>
<td>(50.08)</td>
<td>(18.39)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Currencies</td>
<td>-0.59</td>
<td>-0.49</td>
<td>-0.07</td>
<td>-0.40</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>(-41.54)</td>
<td>(-31.54)</td>
<td>(-4.01)</td>
<td>(-24.87)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bonds</td>
<td>-0.59</td>
<td>-0.56</td>
<td>-0.21</td>
<td>-0.49</td>
<td>0.82</td>
<td>1.00</td>
</tr>
<tr>
<td>(-41.5)</td>
<td>(-38.17)</td>
<td>(-12.06)</td>
<td>(-31.44)</td>
<td>(-82.28)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes. Estimated t-statistics are given in parentheses.

To gain a deeper understanding of relationships between different asset classes, we measure time-varying correlations between innovations from the VAR. Figure 3.2 compares these dynamic correlations with their time-aggregated equivalents (as reported in Table 3.5). In each case, it is evident that correlations between different assets are not constant over time. As shown in Panel A of Figure 3.2, correlation between currencies and bonds tends to move above its average value of 47 percent during crisis periods. In the Asian crisis of 1997-8, correlation reaches 60 percent. Subsequent to the currency crisis of 2001, currency-bond correlation again peaks, this time at just less than 80 percent. Comovement between currency and bond volatility during the latter period is clearly visible in Figure 3.1. Lastly, correlation between currencies and bonds again reaches a high of roughly 60 percent during the 2007-8 subprime crisis.

The analysis is similar when we consider the relationship between currency and equity innovations in Panel B. There are many instances where the correlation coefficient is above the time-average of 17 percent. Periods of crisis depict stronger volatility relationships between currencies and equities. This is especially evident in the period following the 2001 currency crisis, with currency-equity correlation almost reaching the 70 percent mark. Once again, time-variation in correlation mimics the pattern of daily squared returns for these two assets in Figure 3.1.

Finally, Panel C exhibits the relationship between bond and equity innovations. Similar to Panel A and B, time-varying correlations surpass their time-aggregated equivalent of 20 percent in periods of crisis. The correlation coefficient attains its maximum during the Asian crisis, which corresponds to a period of high volatility in equities and, to a lesser extent, in bonds. The currency crisis of 2001 is associated
with a local maximum in bond-equity correlation. Close inspection of Panel C suggests that the strength of the relationship between bond and equity innovations is decreasing over time.

This analysis give us a glance of the time-varying dynamics in the volatility transmission mechanism across SA asset classes. Unlike what is shown in Table 3.5, the relationship between different assets in SA depends on the state of the financial market. Periods of higher volatility leads to higher correlation across markets, while periods of lower volatility correspond to lower correlations in volatilities.

These findings provide a first indication of increased volatility linkages between SA asset classes during domestic and/or foreign crises. To deepen the analysis, we proceed by discussing in turn rolling-window estimates of gross volatility spillovers originating from currencies, bonds, and equities.

Panel A of Figure 3.3 plots volatility spillovers transmitted from currencies. Similarly to the time-aggregated estimates, time-varying currency spillovers tend
to have greater impact on bonds than equities. Gross spillovers from the foreign exchange market increase considerably during/following periods of domestic currency crises. For instance, in the period from the December 2001 currency crisis to October 2002, average spillovers from the rand account for 56.7 and 41.6 percent of the volatility in bonds and equities, respectively. Similarly, we see that currency spillovers to bonds by far exceed spillovers to equities during the subprime crisis.

Figure 3.3. Time-varying transmissions of volatility spillovers

Panel A. Spillovers from Currencies

Panel B. Spillovers from Bonds

Panel C. Spillovers from Equities

Gross volatility spillovers originating in the bond market are shown in Panel B of Figure 3.3. In keeping with our previous results, bond spillovers are typically small in magnitude. Up to April 2003, bond spillovers transmitted to currencies consistently dominate those to equities. In particular, volatility spillovers to the rand are relatively high for protracted periods surrounding the 1998 and 2001
currency crises. Following these periods, spillovers to currencies are substantially reduced (with the exception of a short-lived spike in July 2007). As far as the equity market is concerned, we observe moderate spikes in bond transmitted spillovers during 2001-2 and in the middle of 2005.

Time-variation in gross volatility spillovers from equities is evident in Panel C of Figure 3.3. Equity spillovers are prominent between the beginning of the sample period and November 2001. Massive injections of volatility from the equity market coincide with both Asian and US dot-com crises. Remarkably, average spillovers transmitted from equities between October 1997 and May 1998 (which includes the Asian crisis) contribute to 92.2 percent of volatility in currencies and 88 percent in bonds. Similarly, we see that equity spillovers assume the dominant role in volatility transmission between June 2006 and the end of the sample. Spillovers from equities to the bond market predominate in this period (and exceed corresponding spillovers received by bonds from currencies). Given the relative importance of equity volatility at the beginning and end of the sample, the protracted lull in gross spillovers between December 2001 and May 2006 is perhaps surprising. From inspection of Panels A, B, and C of Figure 3.3, it is evident that the 2001 currency crisis has the effect of temporarily altering the dynamics of domestic volatility transmission in SA.

Table 3.7 reports average values of time-varying net- and total volatility spillover indices. These averages are based on a large number of estimations (3211 consecutive sets of result), and thus, are likely to provide more accurate measures of volatility linkages than the time-aggregated spillover indices reported in Table 3.4. Relative to the time-aggregated results, rolling-window estimations indicate a reversal in the roles of volatility transmission played by currencies and equities, while the behaviour of the bond market remains practically unchanged. With average net spillovers of 55.6 percent, the equity market is the only net contributor to volatility in other asset classes. Specifically, equities are responsible for net volatility transfers of 9.8 percent to currencies and 45.8 percent to bonds. Regarding system-wide volatility, average time-varying total spillovers are measured at 34.9 percent. In comparison, time-aggregated spillovers of only 24 percent indicate substantially weaker cross-market relationships. In our interpretation, time-aggregated spillover indices misrepresent both the direction of net volatility transmission, as well as the magnitude of volatility linkages between SA asset classes.

<table>
<thead>
<tr>
<th>Currencies</th>
<th>Bonds</th>
<th>Equities</th>
<th>System-wide</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net spillovers</td>
<td>-9.81</td>
<td>-45.77</td>
<td>55.58</td>
</tr>
<tr>
<td>Total spillovers</td>
<td></td>
<td></td>
<td>34.87</td>
</tr>
</tbody>
</table>

Table 3.7. Average time-varying, net-, and total volatility spillover indices

Time-varying net volatility spillover indices are depicted in Figure 3.4. Equities are net transmitters of volatility on 76.2 percent of all trading days. In comparison, positive net spillovers from currencies occur only 40.1 percent of the
time. However, between 11 November 2001 and 7 June 2006, the currency market temporarily dominates volatility transmission in SA (with average net bond and equity spillovers measuring -29.1 and -11.5 percent, respectively, during this period). Also evident, is the passive role played by bonds in volatility transmission. The bond market is a net receiver of spillovers on 96.3 percent of trading days.

Figure 3.5 shows time-variation in system-wide volatility spillovers. In keeping with the analysis presented in this subsection, we see sharp increases in the dynamic total spillover index coinciding with the Asian, dot-com and (to a lesser extent) subprime crises, as well as during the 1998, 2001, 2006, and 2008 domestic currency crises. The following subsection provides a more detailed analysis of time-variation in volatility spillovers during periods of financial crisis.

**Figure 3.4. Time-varying net volatility spillovers**
time. However, between 11 November 2001 and 7 June 2006, the currency market temporarily dominates volatility transmission in SA (with average net bond and equity spillovers measuring -29.1 and -11.5 percent, respectively, during this period). Also evident, is the passive role played by bonds in volatility transmission. The bond market is a net receiver of spillovers on 96.3 percent of trading days.

Figure 3.5 shows time-variation in system-wide volatility spillovers. In keeping with the analysis presented in this subsection, we see sharp increases in the dynamic total spillover index coinciding with the Asian, dot-com and (to a lesser extent) subprime crises, as well as during the 1998, 2001, 2006, and 2008 domestic currency crises. The following subsection provides a more detailed analysis of time-variation in volatility spillovers during periods of financial crisis.
3.5.3 Volatility Spillovers during Domestic and Foreign Financial Crises

In this subsection, we compare volatility linkages between SA asset classes during periods of crisis and tranquility. The crisis periods of interest are various currency crises in the domestic economy (1998, 2001, 2006 and 2008), as well as foreign crises in Asia (1997-8) and the US (dot-com 2000; subprime 2007-8). Identification of crisis periods falls outside of the objectives for this study. Consequently, we adopt crisis dates suggested in the literature, as summarised in Table 3.8. Determination of crisis dates is open to a degree of subjectivity; even when formal identification methods are used, start- and end-dates for crisis episodes are at best imprecise. Furthermore, the impact period which a specific crisis may have on volatility transmission is uncertain (especially, for foreign crises). For these reasons, it is difficult to isolate changes in volatility transmission resulting from a particular crisis episode. Nevertheless, our results provide some indication of the connection between domestic spillover dynamics and financial crises.

Table 3.9 reports estimates of average time-varying net- and total volatility spillover indices during the identified crisis periods. These results are comparable to the rolling-window spillovers given in Table 3.7. The average total spillover for the full sample period is 34.9 percent. We measure similar averages for total spillovers during both the subprime (34.7 percent) and the 2006 currency (38.2

Figure 3.5. Time-varying total volatility spillovers for SA asset classes
percent) crises. All other crises are associated with total spillovers in excess of 43 percent. Maximum total spillovers of 65 percent are observed during the Asian crisis.

<table>
<thead>
<tr>
<th>Crisis period:</th>
<th>Start / End dates:</th>
<th>Reference:</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001 currency crisis</td>
<td>12/12/2001 - 22/1/2002</td>
<td>Chapter 2</td>
</tr>
</tbody>
</table>

Table 3.9. Volatility spillovers across SA asset classes during domestic and global crises

<table>
<thead>
<tr>
<th>Crisis period:</th>
<th>Average net spillovers:</th>
<th>Average total spillovers:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Currencies</td>
<td>Bonds</td>
</tr>
<tr>
<td>Asian crisis</td>
<td>-98.63</td>
<td>-92.72</td>
</tr>
<tr>
<td>1998 currency crisis</td>
<td>-68.27</td>
<td>-65.95</td>
</tr>
<tr>
<td>US dot-com crisis</td>
<td>-74.59</td>
<td>-47.03</td>
</tr>
<tr>
<td>2001 currency crisis</td>
<td>50.82</td>
<td>-47.87</td>
</tr>
<tr>
<td>2006 currency crisis</td>
<td>-7.22</td>
<td>-75.12</td>
</tr>
<tr>
<td>US subprime crisis</td>
<td>-23.80</td>
<td>-59.13</td>
</tr>
<tr>
<td>2008 currency crisis</td>
<td>-23.36</td>
<td>-68.87</td>
</tr>
</tbody>
</table>

Average net spillovers during crises affirm the dominant role of equities in domestic volatility transmission. Net spillovers transmitted to bonds range from 47 percent during the dot-com crisis, to 92.7 percent in the Asian crisis. Similarly, the SA exchange rate is a net receiver of volatility from equities during all crisis periods, with the exception of the 2001 currency crisis. The obvious implication is that SA’s vulnerability to currency crises may be rooted in volatility dynamics of domestic equities. This interpretation seems especially appropriate for the 1998 currency crisis, during which time spillovers from equities account for 68.3 percent of net volatility in the rand.

The results summarised in this subsection support the general conclusion that periods of both domestic and global financial crisis are characterised by heightened interdependence of volatility in SA asset classes. This conclusion parallels the observation of Bae, Karolyi and Stulz (2003: 718-9) that cross-market contagion is asymmetric, particularly when the news is especially bad:

"... if panic grips investors as... returns fall and leads them to ignore fundamentals, one would expect large negative returns to be contagious in a way that small negative returns are not".
3.5.4 Comparison with Diebold and Yilmaz’s Results

Our study is comparable to Diebold and Yilmaz’s (2011) analysis of volatility spillovers across US asset classes. To aid the comparison, we focus on the sample period analysed in Diebold and Yilmaz (2011), which begins on 25 January 1999 and ends on 29 January 2010. For the sake of brevity, the discussion is restricted to net and total volatility spillover indices.

The respective time-aggregated results for US and SA asset classes are summarised in Table 3.10. Diebold and Yilmaz (2011) report system-wide volatility spillovers of 12.6 percent for US asset classes. On a net basis, US equities generate 5 percent of total volatility in other asset classes. On the other hand, with a net volatility receipt equal to 2.8 percent, currencies are the most vulnerable to cross-market spillovers. Commodities and bonds each get 1.7 and 0.6 percent of their net variability in the form of spillovers. In contrast, the total volatility spillover index for SA is 26.6 percent – more than double the value of the US index. Net spillovers transmitted by currencies are estimated at 52.6 percent; bonds, receive net spillovers of 53.7 percent. The balancing positive net spillover of 1.1 percent is derived from equities.

Table 3.10. Comparison of time-aggregated spillover indices for SA and US asset classes

<table>
<thead>
<tr>
<th></th>
<th>Currencies</th>
<th>Bonds</th>
<th>Equities</th>
<th>Commodities</th>
<th>System-wide</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States:</td>
<td>-2.8</td>
<td>-0.6</td>
<td>5.0</td>
<td>1.7</td>
<td>12.6</td>
</tr>
<tr>
<td>South Africa:</td>
<td>52.6</td>
<td>-53.7</td>
<td>1.1</td>
<td>N/A</td>
<td>26.6</td>
</tr>
</tbody>
</table>


In what follows, we compare time-varying volatility spillovers estimated for SA and the US. Figure 3.6 is taken from Diebold and Yilmaz (2011: 23), and graphs the dynamic total volatility spillover index for US markets. As before, the corresponding index for SA asset classes is depicted in Figure 3.5 (here, the vertical dotted lines identify the start and end-points of Diebold and Yilmaz’s 2011 sample period). Comparison of the estimated spillover indices suggests both similarities and divergences across the two countries.

We start by considering the period from the beginning of the sample to the end of 2002. US volatility spillovers twice break through the 20 percent threshold in this time frame: once, during the dot-com crisis, and, secondly, towards the end of 2001. Increases in SA volatility spillovers occur at similar times. However,

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21 Note that, because Diebold and Yilmaz (2011) study four asset classes, total system-wide volatility equals 400 percent, and the maximum volatility contribution of any single asset class is 300 percent.

22 As mentioned previously, estimated GIs and GFs are invariant to past observations $F_{t-1}$. Thus, our results are unaffected by resampling.
in comparison to the US, changes in SA spillovers are far more dramatic. For instance, the SA spillover index more than doubles in value in 2000, ultimately reaching a maximum of over 60 percent during the dot-com bubble. This leads us to the perverse conclusion that, although the dot-com crisis originates in US financial markets, this event has greater relative impact on volatility transmission in SA than it does in the US.

Between 2003 and mid-2006, we observe relative declines in volatility spillovers, both in SA and in the US. It seems reasonable that the decline in spillovers is partly due to an absence of major domestic or global financial crises. This period corresponds to the end of the Great Moderation in the global economy, with lower volatility in output, inflation, interest rates and investment.

Finally, we note that the period from late 2006 to the end of the sample includes the three most significant recorded spikes in US volatility spillovers. The US index twice reaches a maximum value of approximately 32 percent during 2008. Diebold and Yilmaz (2011) associate the recent surge in US volatility spillovers with the occurrence of the 2007-8 subprime crisis. In comparison, we observe peaks of roughly 50 percent in the SA spillover index at similar points in time. When viewed from the perspective of past shocks to volatility spillovers, we conclude that the subprime crisis has a greater relative impact on volatility transmission in the US than it does in SA.

Figure 3.6. Time-varying total volatility spillover index for US asset classes

In summary, comparisons of both time-aggregated and time-varying spillover indices suggest far greater volatility interdependence between SA asset classes than between their US counterparts. There are several possible explanations for observing comparatively stronger volatility linkages in SA. Typically of an emerging economy (Richards 1997), SA’s financial markets are far more volatile than are US markets. Greater domestic volatility implies that significant price adjustments occur more frequently. When these adjustments are unusually large and negative, there is a tendency for cross-market interactions to strengthen (Bae, Karolyi and Stulz 2003). This increases the probability of idiosyncratic shocks to one asset class being misinterpreted as newsworthy to the pricing of other asset classes (in a similar vein to King and Wadhwani’s 1990 contagion model). Other justifications relate to differences in microstructure of SA and US financial systems. For instance, SA financial markets are small and illiquid in comparison to US markets. The consequence is that domestic and/or foreign shocks are not easily absorbed, and thus, are more likely to have systemic effects. Also relevant, is the possibility that SA investors are less sophisticated, and receive lower quality information, than their US counterparts.

### 3.6 Conclusion

Are there important linkages in volatilities across different asset classes? Several studies provide evidence in favour of volatility interdependence between asset classes in developed countries. This chapter contributes to this literature by considering domestic volatility transmissions in SA, an emerging market economy.

We apply a generalised vector autoregressive (GVAR) model to estimate a variety of time-aggregated- and time-varying daily volatility spillover indices for SA currencies, bonds and equities between October 1996 and June 2010. Our results suggest strong interactions in volatility across SA asset classes (particularly in comparison to corresponding relationships between their US counterparts). Roughly a quarter of system-wide time-aggregated volatility is due to cross-market spillovers.

Furthermore, we document substantial time-variation in volatility linkages. In general, equities are identified as the primary source of volatility spillovers to other asset classes. However, beginning with the currency crisis of 2001-2, and up until June 2006, currencies temporarily dominate volatility transmission in SA. Bonds are fairly constant in their role as net receivers of volatility from other asset classes. Finally, we find that, in general, increases in volatility spillovers coincide with periods of domestic as well as global financial crises.

Given the latter finding, one would like to assess the importance of volatility spillovers from foreign economies to SA asset classes. It is equally relevant to find the degree of volatility synchronization between SA and world capital markets. We pursue these objectives in Chapters 4 and 5 of this thesis.
CHAPTER 4
GLOBAL FINANCIAL CRISES AND TIME-VARYING
COMOVEMENT IN WORLD EQUITY MARKETS

4.1 Introduction

Chapter 3 considers the relationship between the South African (SA) equity market and other domestic asset classes. We find that equities are the dominant source for volatility spillovers within the domestic economy. A natural extension, is to consider interactions between volatilities in SA and foreign markets.

In this chapter, a large-panel dynamic factor model (FM) is used to study volatility comovement between domestic and world equity markets. Global volatility factors are extracted from a panel of volatility proxies for 25 developed and 20 emerging markets. The panel includes data for the composite index from each country, as well as indices relating to particular market sectors in those countries (specifically, the basic materials, financial, industrial, and oil and gas sectors). Based on the global factors, and using monthly observations from 1994 to 2008, the FM quantifies time-variation in systematic and idiosyncratic components of variance in volatility. Taking world volatility as a proxy for non-diversifiable risk, volatility comovement measures the sensitivity of equity prices to globally systemic events. The results of this investigation are very general: They relate not only to SA, but also to each of the other 44 countries included in the panel.

The study is motivated by dynamic linkages between national stock markets. As discussed in Chapter 3, volatility linkages tend to strengthen during global financial crises, causing large degrees of interdependence and spillovers across internationally integrated markets. Moreover, Ramachand and Susmel (1998), Ball and Touros (2000), Morana and Belltratti (2008), and others, provide evidence of a non-spurious positive relationship between volatility levels and correlations in cross-country returns. The implication is that crises are associated with reduced benefits to international diversification and high risks to global financial stability. With these concerns in mind, the chapter investigates the association between variations in volatility comovement and the timing of financial crises. We measure and catalogue the responses of volatilities in the cross-section to crises in Asia (1997-8), Russia (1998), Brazil (1999), and the United States (US; 2000, 2007-8).

Papers closely related to this chapter include Dungey and Martin (2007), Dungey et al. (2010), and Morana and Beltratti (2008). Based on results from dynamic factor analyses, these authors document significant linkages between international asset markets. Furthermore, they provide evidence of close synchronisation in volatility transmission during crisis periods.

Relative to the above-mentioned studies, the key contributions of the current analysis are as follows. Firstly, the cross-section under consideration has been ex-
tended to a total of 45 equity markets, constituting over 95 percent of world market capitalisation.\footnote{In comparison, Dungey and Martin (2007) and Dungey \textit{et al.} (2010) base their studies on panels consisting of six countries. The analysis in Morana and Beltratti (2008) pertains to only four developed markets.} Benefits associated with the larger panel include: Increased precision in latent factor extraction (Stock and Watson 2002); Greater generality of results pertaining to both developed and emerging markets; And, a closer approximation of the true drivers for \textit{global} volatility.

Secondly, our treatment of dynamics deviates from the traditional approach of pre-specifying non-crisis and crisis sample periods, and subsequently comparing results for the sub-samples. Instead, we follow a similar estimation strategy to that used in Chapter 3. Specifically, our results are derived from a sequence of two-year rolling-window regressions of the FM. Estimated in this way, the model may be interpreted as a variant of the time-varying-parameter FM (refer to Del Negro and Otrok 2008, Koop and Korobilis 2009). This approach allows for a smooth mapping of cross-sectional volatility comovement through time. Permitting the parameters to evolve gradually in response to changes in the data enhances model fit, and avoids the problems discussed in Chapter 2 with \textit{a priori} identification of structural breaks and crisis periods.

Thirdly, we analyse the underlying composition of the latent global volatility factors. Similar to Forni, Giannone, Lippi and Reichlin (2009) and Ludvigson and Ng (2007, 2009), we sequentially regress individual members from a comprehensive set of internationally relevant financial and fundamental variables on each of the identified factors. Thus, we provide an association between unobservable volatility factors and observable time series. This clarifies the relative importance of financial and fundamental indicators in global volatility transmission, and represents a first step towards a structural interpretation for this process.

The main results are summarised as follows. We identify three global factors for world volatility. Comovement of volatilities with the factors differs considerably across countries and over time. We find that volatilities in Germany, the United Kingdom (UK), and the US display consistently high degrees of comovement with the first of the identified global factors. Moreover, there appears to be a positive trend in the strength of volatility linkages between these major markets. In comparison, French and Japanese volatilities are largely idiosyncratic in nature. In the case of emerging markets, comovement is high for Brazil, Mexico, Thailand and Turkey. However, in general, emerging market volatility is characterised by low comovement relative to developed markets.

For SA, the FM indicates weak synchronisation with world volatility, even in comparison to other emerging markets. On average, the global factors account for only 17.3 percent of variations in the volatility of the SA composite index. The corresponding statistics for individual market sectors in SA range between
22.5 percent in the case of the oil and gas stocks, and 36.7 percent for industrial stocks. This provides evidence of sectoral dependence in SA’s comovement with world volatility.

For the majority of countries, including SA, comovement between global factors and domestic volatilities increases considerably during the Asian, Russian, and US subprime crises. We observe decoupling of SA and other emerging markets from global factors between 2001 and 2007. However, there is clear evidence of recoupling with world volatility in 2008. Thus, the benefits to diversification associated with investing in emerging markets during the subprime crisis are short-lived.

With regards factor composition, we find that financial variables are more closely associated with global factors than are fundamentals. Factor One is generally important to volatility dynamics in developed countries; Factor Two is correlated with Latin American emerging markets, particularly Mexico; and Factor Three is a driver of volatility conditions in Asian emerging economies. Furthermore, Factor One and Factor Two are identified as proxies for volatility conditions in global bond and commodity markets.

The remainder of the chapter is organised as follows. Section 4.2 provides a short review of the relevant literature. In Section 4.3, we introduce the FM and discuss its estimation. Details of data and the extraction of global factors appear in Section 4.4. This is followed by discussion of the results in Section 4.5. Section 4.6 concludes the chapter.

### 4.2 Literature Review

Several existing papers use dynamic factor analysis to investigate international asset market linkages. Dungey and Martin (2007) provide a theoretical motivation for a FM that captures pricing relationships between equity and currency markets. GARCH specifications for conditional factor volatilities reflect the time-varying characteristics of financial data. The model is applied to a panel of six countries effected by the Asian crisis (Australia, Indonesia, Korea, Malaysia, Thailand, and the US). The results suggest a high degree of comovement in volatilities during the crisis period. Spillovers and contagion in asset market returns contribute meaningfully to increases in domestic volatilities from pre-crisis to crisis levels. This includes a significant volatility injection from the US to Australia – countries not directly associated with the onset of the crisis.


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2Chapter 7 provides two appendices to the current chapter.

3From a purely theoretical view point, Kodres and Pritsker (2002) provide a clear justification for the applicability of the FM to studies of asset market linkages.
Consistently, the authors report an important role for spillovers and contagion for all the countries included in their panel (Argentina, Brazil, Canada, Mexico, Russia, and the US).\footnote{Dungey et al. (2010) perform a robustness test wherein the panel is extended to include Australia, Germany, Japan, and the United Kingdom. The results of this test are similar to those for the smaller panel.} Significant international market linkages are measured for every crisis period. Volatility linkages are especially prominent during the Russian debt and US subprime crises.

Using the conditional capital asset pricing model (Merton 1973) as a theoretical foundation, Morana and Beltratti (2008) propose a close connection between stock market linkages and financial integration. FMs are used to assess degrees of comovement between equity prices, returns, volatilities, and correlations in Germany, Japan, the UK, and the US. Results from three sub-samples – specifically, 1973-1982, 1983-1992, and 1993-2004 – indicate a trend towards greater volatility interdependence between European and US markets. In contrast, Japanese asset price dynamics are driven predominantly by idiosyncratic factors. With regards to comovement in volatility, Morana and Beltratti (2008) identify two common factors, with the first of these factors explaining important shares of variances in domestic volatilities.

\section*{4.3 Methodology}

The key advantage of the FM-methodology lies in its ability to maximise information content without sacrificing parsimony. Principal component analysis allows for the extraction of common factors that explain the majority of variations in cross-sectional data. With closely integrated markets, the number of factors needed to explain variability in world volatility is naturally small.

A disadvantage of the FM is that the common factors are unobservable, and thus difficult to interpret. To address this limitation, Forni, Giannone, Lippi, and Reichlin (2009) and Ludvigson and Ng (2007, 2009) investigate factor composition by regressing a large set of observable variables on the individual factors. We follow a similar approach to identify the drivers of volatility comovement in world equity markets.

\subsection*{4.3.1 The Factor Model}

This analysis applies the FM to a vector $Y_t = (y_{1t}, y_{2t}, ..., y_{Mt})'$ of proxies for period-$t$ volatility in $M$ distinct stock indices. The cross-section is chosen to be representative of the world equity market portfolio (in terms of cumulative market capitalisation). We assume that $Y_t$ follows a covariance stationary process
standardised to have zero mean and unit variance. The model decomposes each member of $Y_t$ into two components. The first component, is a common vector $F_t = (f_{1t}, f_{2t}, \ldots, f_{Kt})$ of $K$ distinct global volatility factors, where $K << M$. Since the factors are mutually orthogonal, they satisfy $E(f_{it}f_{jt}) = 0$ for all $i \neq j$. We refer to $F_t$ as a set of "global" factors because it is constructed using all the information contained in $Y_t$. The explanatory power of $F_t$ for variations in the dependent variable $y_{mt}$ measures period-$t$ comovement between volatility levels in market $m$ and world equities.

The second component, is a vector $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{Mt})$ of idiosyncratic volatility factors and measurement errors, with $E(\varepsilon_{mt}f_i) = 0$ for all $i, m,$ and $E(\varepsilon_{mt}\varepsilon_{nt}) = 0$ for $m \neq n$. The idiosyncratic factors may be weakly autocorrelated, but serial dependence vanishes as $M \rightarrow \infty$. Supposing that the FM is correctly specified, the relative size of $\varepsilon_t$ is inversely related to the degree of volatility integration in world equities during period $t$. Consistently large values for $\varepsilon_{mt}$ over time indicate that volatility in market $m$ is driven predominantly by domestic news.

The model takes the following form:

$$Y_t = \Lambda F_t + \varepsilon_t,$$

where we suppress the intercept term, and $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_M)'$ is a $M \times K$ matrix of constant factor loadings ($\lambda_m$ represents a $K \times 1$ column vector of parameters). Since $F_t$ is unobservable, its value is approximated using an autoregressive representation. In the case of our FM, the optimal lag order of one is determined by minimising the Bayesian information criterion. Thus, we have the following state equation:

$$F_t = AF_{t-1} + \zeta_t,$$

where $A$ is a $K \times K$ coefficient matrix, and $\zeta_t$ a $K \times 1$ vector of residuals.

### 4.3.2 Estimation and Factor Composition

$R$-squared statistics obtained from (4.1) measure the variance shares of $Y_t$ that are explained by global volatility factors. These statistics provide proxies for time-aggregated volatility comovement in the cross-section. However, it is well-known that stock market volatility is time-varying. Furthermore, as discussed in Chapter 3, empirical evidence points to non-constant volatility linkages between national stock markets, especially in sample periods that contain financial crises. A suitable means of capturing volatility dynamics is provided by the time-varying-parameter FM (TVP-FM; Del Negro and Otrok 2008, Koop and Korobilis 2009). But, in the absence of sensible restrictions on the model, parameter flexibility often leads to over-parameterisation.
As an alternative to the TVP-FM, we estimate the constant-parameter FM by means of 24-period (two-year) rolling-window regressions. The use of rolling-window regressions has two advantages. Firstly, similar to the TVP-FM, rolling-window factor loadings are continuously re-estimated to reflect changes in the data through time. Providing for possible structural change in the volatility process increases the flexibility of the model and improves estimation accuracy. Furthermore, rolling-window estimation conveniently sidesteps the difficulties associated with the identification of financial crisis periods. The second advantage is that, by consecutively shifting the estimation window forward through time, we obtain a sequence of $R^2$-squared statistics for each dependent variable. These sequences provide cross-sectional mappings of volatility comovement as a continuous function of time.

With regards the composition of factors, we consider world equity volatility as being correlated with a vector $Z_t = (z_{1t}, z_{2t}, ..., z_{Lt})'$ of $L$ possible variables. $Z_t$ contains a combination of volatility proxies for financial and fundamental indicators. Financial variables are likely to matter due to the interconnectedness of global equity portfolios. Interconnectivity of investors creates the possibility for volatility contagion and spillovers between countries, even when these countries have seemingly independent domestic fundamentals. However, to the extent that equity prices ultimately reflect economic reality, fundamental volatility is also expected to play a role in financial volatility transmission. For example, using quarterly data, Diebold and Yilmaz (2008) provide evidence of one-way causality from GDP volatility to equity volatility across a broad cross-section of countries.

In estimating factor composition, members of $Z_t$ are sequentially regressed on each of the individual factors:

$$z_{ilt} = \kappa_{li} + \gamma_{li} f_{il} + \eta_{ilt},$$

where, for $l = 1, 2, ..., L$ and $i = 1, 2, ..., K$, $\kappa_{li}$ and $\gamma_{li}$ are estimated coefficients, and $\eta_{ilt}$ is a residual term. The $R^2$-squared statistics from (4.2) measure the strength of the relationship between observable variables and latent factors.

### 4.4 Data Analysis

The accuracy of the FM depends critically on the size of the chosen data panel. Stock and Watson (2002) demonstrate that when the ratio of the number of variables to factors is large, extraction of latent factors is achieved with a high degree

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5 The length of the estimation window has been limited to 24 periods in order to adequately capture dynamics in the data. The reported results are robust to alternative window specifications of 36 and 48 periods. Results relating to the latter alternatives are available from the author upon request.
of precision. Moreover, the use of a large data set is important to obtain a true representation of global volatility factors. Hence, we base our analysis on a large panel consisting of data for 25 developed and 20 emerging equity markets. Up to five volatility proxies from each market are included in the panel. These proxies relate to the various countries’ composite stock indices and, where available, individual market sectors relating to stocks in basic materials, financial, industrial, and oil and gas firms. In total, the data set contains 191 time series from January 1994 to December 2008. On average, the cross-section constitutes over 95 percent of annual world market capitalisation during the sample period.

The panel data allows for comparison of volatility comovement across individual countries. Our primary interest is in analysing volatility comovement in SA equities. However, it is also of interest to draw comparisons between SA and other countries, including globally significant groupings of equity markets. To facilitate such an analysis, we construct twelve strategic market indices consisting of different combinations of markets included in the panel. Most significant among the constructed indices, are those relating, respectively, to the developed markets, the emerging markets, and the world as a whole. Comovement of these indices with global factors is discussed at length in Section 4.5.2. The remaining indices represent subsets of developed markets (in Australasia, Europe, and the G7) and emerging markets (in Asia, the BRICS, the E7, Europe, and Latin America). The discussion of volatility comovement in the latter indices appears in Appendix B. The various strategic indices are constructed as weighted averages of returns for individual countries. The relevant weight for each country is calculated as that country’s share of market capitalisation relative to all markets included in the index. The weights are updated annually to reflect changes in relative market sizes over time. Changing shares of world market capitalisation for the indices are depicted in Figure 4.1.

As in Chapter 3, volatility proxies are constructed as squared returns of observed closing stock prices. We use the monthly data frequency to avoid problems related to asynchronous trading hours across countries located in different time-

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6 The data is sourced from Datastream. Market typology emphasises the stage of development of the different equity markets, and not necessarily the development of the countries that host those markets. Our categorisation is consistent with the FTSE country classification review for 2010 (obtained from the FTSE website: http://www.ftse.com/Indices/Country_Classification/Downloads/FTSE_Country_Matrix_June2011_Post_2010_Changes.pdf). Refer to Table A.1 in Appendix A (Chapter 7.1) for a detailed specification of the data panel.

7 The calculation of market capitalisation in the panel relative to the world is based on data obtained from the World Bank’s website (http://data.worldbank.org/indicator/CM.MKT.LCAP.CD). No market capitalisation data is available for Taiwan.

8 BRICS refers to Brazil, Russia, India, China, and SA. The E7 is a collection of seven major emerging markets. Refer to Table A.2 in Appendix A for details of the strategic indices’ compositions.
zones. An added benefit of monthly data, is that it allows for inclusion of fundamentals in the factor composition analysis. A total of 67 macroeconomic variables are used to evaluate equity volatility dependence on real activity. These variables include volatility proxies for log differences in bond yields, consumer price indices, commodity prices, exchange rates, industrial production, and interest rates.\footnote{Table A.3 in the Appendix A provides list of the macroeconomic variables included in the factor composition analysis.} We also consider factor composition with respect to financial variables. The set of financial indicators consists of the 45 individual stock markets included in the data panel, as well as the constructed strategic indices.

![Figure 4.1. Shares of world market capitalisation for strategic market indices](image)

Source. The World Bank.

### 4.4.1 Volatility Dynamics

Volatility plots for the strategic market indices are displayed in Figure 4.2. Comparison of the graphs indicates that emerging markets are more volatile than developed markets. The latter observation is consistent with the notion of a positive
risk-premium in emerging finance (as discussed in Chapter 3). Clearly, all markets exhibit considerable time-variation in volatility. In this respect, there appear to be similarities in the timing of large volatility shocks across different markets. For three-quarters of all composite indices, October 2008 represents the most volatile period in the sample, demonstrating the global impact of the subprime crisis on equity pricing. In the case of the Asian Tigers (excluding Taiwan), the highest level of volatility is recorded when the Asian crisis spreads to Hong Kong during October 1997. The second largest spike in volatility of the emerging index occurs at roughly the same time. The most volatile period in Latin America coincides with the beginning of the Russian crisis in August 1998. The considerable effect of this crisis on the developed and BRICS indices is evident from the relevant volatility plots. Markets in emerging Europe are especially volatile during December 1999. This period is also associated with above-average volatilities in developed Europe and the E7. Finally, we identify the period from the 9/11 terrorist attack in September 2001 to July 2002 as a turbulent period in developed European, G7, and world indices.

Volatility proxies for SA equities are depicted in Figure 4.3. Notably, each of the four market sectors displays greater volatility than the composite index. On the other hand, the composite index is generally less variable than the emerging market benchmark. Domestic volatility reaches a maximum during the Russian crisis. In particular, this crisis episode appears to have a large impact on the industrial and financial sectors. High volatility is also observed in SA during the subprime crisis. The only exception to this occurs in financial stocks. Due to the absence of meaningful exposures to subprime debt, SA banks and other firms in the financial sector are relatively unaffected by the 2007-8 crisis. Compared to the other market sectors, there is a low degree of time-variation in the volatility of oil and gas stocks. This suggests that relative changes in volatility during the various crisis periods are small in comparison to other sectors.

4.5 Empirical Results

R-squared statistics obtained from the FM measure variance shares of volatilities explained by fluctuations in global volatility factors. At one extreme, if the estimated R-squared value is zero, the FM suggests that domestic volatility dynamics are independent of foreign volatilities. On the other hand, an R-square of unity indicates that volatility is imported in totality. This provides a natural index for volatility comovement in SA and other equity markets. Of central interest to our analysis, are variations in comovement over time and across countries. Thus, two-year rolling-window estimates of the FM are particularly useful, as they provide consecutive snapshots of volatility linkages in the cross-section.

In what follows, we provide details regarding the selection global factors to be
4.5.1 Number of Global Volatility Factors

There are various methods for determining the appropriate number of factors to include in the FM. Application of the Bai and Ng (2002) approach to our data set indicates that there are five common factors (detected by means of the lowest $IC_{p2}$). In contrast, the principal component approach suggests only two factors, given that the third factor explains less than 5% of variations in the panel. However, we base

included in the FM. Subsequently, we discuss the results of the FM estimation, first as it relates to the constructed strategic market indices, and then with respect to individual countries. Comovement of SA equity volatilities with global factors is analysed in Section 4.5.4. This is followed by a summary of results from the factor composition analysis.

Figure 4.2. Volatility plots for strategic market indices
Our factor selection on the test developed by Alessi, Barigozzi and Capasso (2010), which improves on the Bai and Ng (2002) method in terms of robustness. The latter test suggest the inclusion of three global volatility factors in the FM.\footnote{Results for the various approaches to selecting the number of common factors are available from the author upon request.}
4.5.2 Comovement in Developed, Emerging and World Volatilities during Financial Crises

Estimating the FM using the full sample period, comovement is estimated at 87 percent for the world, 86 percent for developed markets, and 69 percent for emerging markets. This implies consistently high degree of interdependence between domestic and foreign volatility levels. However, the generality of this conclusion is conditional on the stability of international volatility linkages.

Two-year rolling-window regressions of the FM suggest instability in volatility transmission over time. Figure 4.4 depicts time-varying volatility comovement for the three indices. Also identified, are periods of major financial crisis that are contained in the sample. For each index, there is a clear association between the timing of financial crises and local maxima in comovement.

Aggregating across the rolling regressions, the global factors explain 72, 70, and 57 percent of volatilities in the world, developed, and emerging indices. The developed and world comovement plots are highly correlated. This is expected, as developed markets constitute an average of 90.5 percent of the panel’s market capitalisation. Comovement in developed markets exceeds comovement in emerging markets in two-out-of-every-three periods. The main exception to this occurs from 1996 to 1999, during which time increases in emerging comovement precede similar increases in comovement for developed markets. High sensitivity of emerging volatility to global factors in the late 1990s is due to the recurrence of financial crises with origins in emerging countries.

Global factors explain only 13 percent of emerging volatility in December 1995,
the first estimation point. However, comovement increases rapidly in subsequent periods, peaking at 73 percent during March to June of 1997. The latter period coincides with growing speculative pressure on the Thai baht, culminating in its eventual devaluation on 2 July 1997. This marks the beginning of the Asian crisis. The corresponding turning point in developed comovement occurs in October 1997, when Hong Kong loses 30 percent of its market value. Volatility linkages weaken during the first half of 1998, as relative stability returns to world markets.

But, recovery from the Asian crisis is short-lived. A further four major global shocks arrive within the space of two years. The Russian crisis begins on 17 August 1998 with the announcement of a deferral in government debt repayments. Uncertainty mounts in world bond markets in September 1998, when Long-Term Capital Manangement receives a bailout package in the US. This is followed by currency crisis in Brazil, and ultimate devaluation of the real on 15 January 1999. Finally, the bursting of the US dot-com bubble occurs between February and June 2000. We observe a dramatic response in volatility linkages during the time interval corresponding with these events. Emerging comovement reaches its maximum value of 98 percent in August 1998. Comovement of 92 percent is recorded for the developed index in the same period. Following this, comovement exceeds 88 percent for all three indices up until June 2000, indicating a sustained period of commonality in the drivers for developed and emerging volatility transmission.

In contrast, we see signs of divergence in the determinants of emerging and world volatility levels between 2001 and 2007. Whilst global factors continue to predominate in developed volatility transmission, there is rising importance of idiosyncratic factors in the case of emerging markets. Lower sensitivity to foreign volatility is the result of emerging markets’ financial and fiscal reforms, greater policy discipline, and accumulation of foreign exchange reserves. Coinciding with the September 2001 terrorist attacks, developed comovement increases from 58 to 87 percent. Developed market volatility linkages continue to strengthen, with comovement reaching 95 percent in July 2004. During the same period, emerging comovement declines from 70 percent to 56 percent (including a momentary fall to below 15 percent in November 2003). The developed and emerging comovement plots continue to move in opposite directions during 2005 to 2006. Following a temporary decline to 21 percent between January and April 2006, developed comovement begins to rise again in the lead-up to the US subprime crisis. As funding difficulties associated with two Bear Sterns’ hedge funds become public in June 2007, developed comovement reaches 63 percent. At the same stage, with comovement of only 14 percent, emerging markets appear to be unaffected by the crisis.

The next major shock occurs during January 2008 when rating agency Fitch downgrades US monoline insurer Ambac, thus generating heightened uncertainty regarding the sustainability of structured credit contracts. The uncertainty spills over into the equity market, and consequently comovement in the developed index
jumps from 51 to 93 percent. In this case, emerging markets are also significantly affected, with comovement more than doubling in value, from 20 to 53 percent. Following the failure of Lehman Brothers in mid-September, developed comovement increases further, reaching its sample maximum of 98 percent in October. At this point, the connection between developed and emerging comovement is firmly reestablished, with global factors explaining 92 percent of the variations in emerging market volatility.

In summary, we provide evidence of heightened volatility comovement during financial crises in both developed and emerging economies. We observe signs of decoupling in emerging market volatility from global factors during 2001 to 2007. Hence, emerging markets provide an effective hedge against systematic risk associated with the early stages of the subprime crisis. But the benefits to diversification are temporary, as global factors ultimately dominate volatility transmission during the latter stages of 2008.

4.5.3 Variations in Volatility Comovement across Individual Countries

Figure 4.5 depicts volatility comovement plots (sequences of time-varying $R^2$ statistics) for each of the 45 markets included in the panel. Comparison of these plots suggest three time-trends that are common to the majority of countries. Volatility comovement is increasing from the beginning of the estimation period until 2000. This period includes a spell of especially strong dependence on global factors from 1998 to 2000. For some markets (notably, Germany, Netherlands, the UK, and the US), the trend towards stronger international volatility linkages continues up until the end of 2004. But, in general, the importance of global volatility factors diminishes between 2001 and the beginning of 2007, suggesting a lower degree of systematic volatility in individual equity markets. The latter period is followed by unanimous increases in comovement measures during 2008, with $R^2$-squared values approaching unity for many countries.\(^{11}\)

To ease comparison across different countries, we analyse averages of time-varying $R^2$-squared statistics. The average comovement measures are reported in Table 4.1. Consistent with the conclusion reached in the previous subsection, the results indicate that volatility is most closely synchronised with global factors in developed markets. In particular, European volatility is strongly comoving with world volatility. Average comovement exceeds 60 percent for Germany, Netherlands, and the UK, and 51 percent for Belgium, Italy, Spain, and Switzerland.

\(^{11}\)Two exceptions to this finding, are Israel and Philippines, where comovement is relatively low in 2007-8. Due to missing data observations (refer to Appendix A, Table A.1), we are unable to estimate volatility comovement for Czech Republic, Pakistan, and Singapore for the full duration of 2008.
Figure 4.5: Volatility comovement in developed equity markets
Figure 4.5 (continued). Volatility comovement in emerging equity markets
These values are greater than estimated comovement of 51 percent for the US. This is perhaps surprising, since US equities account for an overwhelming share of world market capitalisation (a sample average of 42 percent). However, a degree of idiosyncrasy in US volatility is to be expected given the frequency of large shocks with origins in the US economy (for example, Long-Term Capital Management, the dot-com bubble, and sub-prime crisis). Hong Kong and Singapore complete the list of ten developed markets with greatest dependence on world volatility levels, with average comovement statistics of 49 and 51 percent, respectively.

<table>
<thead>
<tr>
<th>Developed Markets:</th>
<th>Emerging Markets:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Netherlands</td>
<td>Brazil</td>
</tr>
<tr>
<td>Germany</td>
<td>Brazil</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>Thailand</td>
</tr>
<tr>
<td>Italy</td>
<td>Mexico</td>
</tr>
<tr>
<td>Switzerland</td>
<td>Hungary</td>
</tr>
<tr>
<td>Spain</td>
<td>Chile</td>
</tr>
<tr>
<td>Belgium</td>
<td>Argentina</td>
</tr>
<tr>
<td>United States</td>
<td>India</td>
</tr>
<tr>
<td>Singapore</td>
<td>Malaysia</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>Russia</td>
</tr>
<tr>
<td>Denmark</td>
<td>Indonesia</td>
</tr>
<tr>
<td>Greece</td>
<td>Poland</td>
</tr>
<tr>
<td>Canada</td>
<td>Czech Republic</td>
</tr>
<tr>
<td>Portugal</td>
<td>Taiwan</td>
</tr>
<tr>
<td>South Korea</td>
<td>Pakistan</td>
</tr>
<tr>
<td>Australia</td>
<td>Sri Lanka</td>
</tr>
<tr>
<td>Austria</td>
<td>Columbia</td>
</tr>
<tr>
<td>France</td>
<td>South Africa</td>
</tr>
<tr>
<td>Norway</td>
<td>Philippines</td>
</tr>
<tr>
<td>Sweden</td>
<td>China</td>
</tr>
<tr>
<td>Japan</td>
<td></td>
</tr>
<tr>
<td>Israel</td>
<td></td>
</tr>
<tr>
<td>Ireland</td>
<td></td>
</tr>
<tr>
<td>New Zealand</td>
<td></td>
</tr>
<tr>
<td>Finland</td>
<td></td>
</tr>
</tbody>
</table>

Notes. Reported statistics are average R-squared's from two year rolling window regressions of the volatility proxy for each country’s composite stock index on the global volatility factors.

Not all developed markets are well-integrated with global factors. In particular, the results for France and Japan have important implications. These markets constitute considerable portions of world market capitalisation (sample averages of 4 percent for France and 12 percent for Japan). However, with time-aggregated comovement of only 39 and 27 percent, global factors are relatively poor predictors...
of volatilities in these countries. Compared with other major markets, Figure 4.5 indicates relatively low levels of volatility comovement in France during 1996 to mid-2001. In this respect, France appears to be one of few countries in Europe (and in the world) that successfully escapes volatility spillovers from the Asian, Brazilian, and Russian crises. In contrast, we observe that between 2002 and the end of the sample period, France’s comovement dynamics are similar to those for Denmark, Spain and the US. These observations suggest that France has become more integrated with world financial markets over time.

In the case of Japan, volatility linkages appear fairly robust from 1997 to 2000, and also during 2007-8. Sensitivity to global factors during the first period is related to common exposures between the financial sectors in Japan and countries immediately affected by the Asian crisis.\textsuperscript{12} In the second period, the increase in volatility comovement coincides with the onset of the subprime crisis. But, in the absence of financial crises, we find that Japanese volatility is predominantly driven by idiosyncrasies, thus corroborating Morana and Beltratti’s (2008) conclusion of weak synchronisation between Japanese and developed market volatilities. The relative importance of domestic shocks to the Japanese market may be attributed to structural problems inherited from the disinflationary experience of the 1990s (the so-called "lost decade" in Japan). Other developed markets with low average degrees of comovement include Finland (20 percent), Ireland (22 percent), Israel (22 percent), and New Zealand (20 percent). All of these markets constitute less than one percent of developed market capitalisation (refer to Table A.1 in Appendix A).

Among emerging markets, global factors are important determinants of volatility in Latin America. This may be attributed to the proximity and economic integration of countries in this region with major developed markets in Canada and the US. Most notably, average comovement equals 54 percent for Brazil and 47 percent in the case of Mexico. The comovement plots for these markets – which are not dissimilar to those for Canada and the US – peak at values of approximately 90 percent during 1998 to 2000, and 2008. Parallel increases in foreign volatility dependence are also observed for Argentina and Chile, thus identifying Latin America as a receiver of volatility injections subsequent to crises in Asia, Russia, and the US. Spikes in volatility comovement occur at roughly the same times for most emerging markets in Asia and Europe. On average, half of the variance in volatility for Thailand is explained by variations in global factors. The factors are related to 44 percent of average volatility in Hungary and 49 percent in Turkey.

Excluding crisis periods, the determinants of volatility in China, Philippines, and SA, are predominantly idiosyncratic in nature. With average comovement of only 13 percent, China is the country least affected by global factors. Low

\textsuperscript{12}The most notable Japanese failure during the Asian crisis occurs on 24 November 1997, when Yamaichi Securities announces its bankruptcy (Kaminsky and Schmukler 1999).
synchronisation with world volatility, in spite of the growing size of the Chinese market, is due to the imposition of strict domestic capital controls. Continued accumulation of foreign exchange reserves and double digit growth rates may also contribute to China’s insulation from smaller shocks to the global financial system. Low comovement in Philippines (15 percent) is reflective of its small size relative to other emerging markets (a sample average of 2.2 percent of emerging market capitalisation). Average comovement of 17 percent for SA indicates the importance of domestic shocks to volatility transmission.

4.5.4 Volatility Comovement in South Africa

Figure 4.6 graphs the estimates of volatility comovement for SA equities. Relative to other emerging economies, global factors are poor predictors of SA volatility. Estimated comovement for the emerging index exceeds that for the SA composite index in 95.5 percent of all periods. Excluding the latter stages of the subprime crisis, more than half of SA’s composite volatility is idiosyncratically determined. Similar to the emerging index, the Russian and US subprime crises are associated with local maxima in SA’s synchronisation with foreign volatility. Moreover, SA’s comovement mimics that of other emerging markets between 2001 and 2007. During this time the explanatory power of global factors declines across all domestic indices. Recall from the analysis in Chapter 3, that the latter period is characterised by domestic volatility transmission from the currency market to the equity market. The suggestion is thus, that exchange rate volatility and vulnerability to currency crises are important contributors to idiosyncratic risk in SA equities.

Figure 4.6 provides some evidence of sectoral dependence of volatility comovement in SA. On average, the global factors account for 36.7 and 30.6 percent of volatilities in industrials and financials, respectively. Comovement in these sectors exceeds that of the aggregate market by a large margin during the Russian crisis. For stocks in basic materials and oil and gas, average comovements of 23.3 and 22.5 percent indicate a low degree of dependence on foreign volatilities.

4.5.5 Factor Composition

Table 4.2 reports results of sequentially regressing volatility proxies in the panel and the set of strategic market indices on the individual global volatility factors. In general, the greatest \( R \)-square statistics are estimated when regressing financial variables on the first factor. Factor One accounts for 86, 85, and 65 percent respectively, of variations in world, developed and emerging market volatility. In comparison, none of the corresponding statistics for Factor Two and Factor Three exceed 5 percent. For individual countries, Factor One is most closely related to volatilities in Japan, the UK, and the US (with respective \( R \)-squares of 59, 58, and
65 percent). Thus, we conclude that Factor One is best identified as a developed financial market volatility factor.

In contrast, the relative importance of the second and third factors is most evident for regional groupings of the emerging markets. Factor Two explains 19 percent of volatility changes in emerging Europe and 32 percent in Latin America. For individual countries, $R^2$-squares of 30 percent for Mexico and 15 percent for Russia indicate correlation of these markets with Factor Two. On the other hand, with a variance share of 22 percent, Factor Three is of greatest relative consequence to volatility levels in Asia. $R^2$-squared statistics ranging between 24 and 35 percent are estimated for Hong Kong, Singapore, South Korea, and Thailand.
Table 4.2. Factor composition results for selected financial variables

<table>
<thead>
<tr>
<th>Strategic Indices:</th>
<th>Factor One</th>
<th>Factor Two</th>
<th>Factor Three</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asian Emerging</td>
<td>0.41</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Asian Tigers (ex. Taiwan)</td>
<td>0.32</td>
<td>0.01</td>
<td>0.22</td>
</tr>
<tr>
<td>Australasian Developed</td>
<td>0.68</td>
<td>0.05</td>
<td>0.01</td>
</tr>
<tr>
<td>BRICS Emerging</td>
<td>0.55</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Developed</td>
<td>0.85</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>E7</td>
<td>0.56</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Emerging</td>
<td>0.65</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>European Developed</td>
<td>0.75</td>
<td>0.00</td>
<td>0.06</td>
</tr>
<tr>
<td>European Emerging</td>
<td>0.22</td>
<td>0.19</td>
<td>0.03</td>
</tr>
<tr>
<td>G7</td>
<td>0.81</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Latin American Emerging</td>
<td>0.41</td>
<td>0.32</td>
<td>0.00</td>
</tr>
<tr>
<td>World</td>
<td>0.86</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Individual Countries:**

<table>
<thead>
<tr>
<th>Country</th>
<th>Factor One</th>
<th>Factor Two</th>
<th>Factor Three</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brazil</td>
<td>0.45</td>
<td>0.08</td>
<td>0.03</td>
</tr>
<tr>
<td>Germany</td>
<td>0.30</td>
<td>0.04</td>
<td>0.09</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>0.26</td>
<td>0.01</td>
<td>0.24</td>
</tr>
<tr>
<td>Japan</td>
<td>0.59</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td>Mexico</td>
<td>0.28</td>
<td>0.30</td>
<td>0.00</td>
</tr>
<tr>
<td>Russia</td>
<td>0.24</td>
<td>0.15</td>
<td>0.01</td>
</tr>
<tr>
<td>Singapore</td>
<td>0.31</td>
<td>0.10</td>
<td>0.27</td>
</tr>
<tr>
<td>South Korea</td>
<td>0.14</td>
<td>0.00</td>
<td>0.35</td>
</tr>
<tr>
<td>Thailand</td>
<td>0.30</td>
<td>0.01</td>
<td>0.33</td>
</tr>
<tr>
<td>UK</td>
<td>0.58</td>
<td>0.00</td>
<td>0.10</td>
</tr>
<tr>
<td>United States</td>
<td>0.65</td>
<td>0.07</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**South Africa:**

<table>
<thead>
<tr>
<th>Category</th>
<th>Factor One</th>
<th>Factor Two</th>
<th>Factor Three</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic Materials</td>
<td>0.27</td>
<td>0.01</td>
<td>0.15</td>
</tr>
<tr>
<td>Composite Index</td>
<td>0.37</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Financials</td>
<td>0.22</td>
<td>0.50</td>
<td>0.01</td>
</tr>
<tr>
<td>Industrials</td>
<td>0.60</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Oil and Gas</td>
<td>0.17</td>
<td>0.02</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Notes. Reported statistics are R-squared's from regressing the indicator variable on the individual factor.
Correlation of SA variables with the global factors is relatively high for an emerging market. With $R$-squares of 60 percent for industrials and 37 percent for the composite index, Factor One is the best predictor of domestic volatility dynamics. Half of volatility in the financial sector is explained by Factor Two. Regressing basic materials on Factor Three produces a $R$-square of 15 percent. Compared with other sectors, oil and gas stocks are weakly correlated with the factors.

Relationships between global volatility factors and fundamental indicators are considered in Table 4.3. The explanatory power of Factor One is greatest for volatility proxies from a variety of bond and commodity market indices. Thus, in addition to capturing volatility conditions in developed markets, Factor One represents a proxy for commodity and bond price volatilities. Although the global volatility factors are constructed to be mutually orthogonal, Table 4.3 indicates a similar interpretation for the composition of Factor Two with respect to global fundamentals. The highest $R$-square statistics for the first and second factors (66 and 61 percent, respectively) are estimated when the Dow Jones (UBS/AIG) commodity index is the dependent variable. Moreover, Factor One and Factor Two both explain meaningful shares (between 31 and 38 percent) of volatility in bond indices recorded by Barclays and J.P. Morgan.

With respective $R$-squares of 50 and 41 percent, Factor Two is also relevant to volatility in the US/Russian nominal exchange rate and the SA 10-year government bond yield (with respective $R$-squares of 50 and 41 percent). Unique to Factor Two, is the fact that it has greater explanatory power for fundamental variables than it does for financial variables.

In regressions of fundamental indicators on Factor Three, all resulting $R$-squared statistics are less than or equal to 13 percent in magnitude. This makes it difficult to draw firm conclusions regarding factor composition. Fundamentals most closely related to Factor Three are US capacity utilisation and industrial production. Of secondary importance, are the Euro marginal lending rate and trade-weighted-index (both with $R$-squares of 11 percent), and the price of platinum (with an $R$-square of 8 percent).

4.6 Conclusion

In this chapter, we investigate comovement of monthly volatilities in world equity markets with global volatility factors during 1994 to 2008. Three global factors are extracted from a panel of 45 national stock markets which constitutes over 95

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\(^{13}\) In the interest of brevity, the reported results relate only to variables with the highest estimated $R$-squared statistics for each factor. Complete results of the composition analysis (for both financial and fundamental variables) are available from the author upon request.
Table 4.3. Factor identification using fundamental variables

<table>
<thead>
<tr>
<th>Factor One</th>
<th>#1 DJ UBS/AIG Commodity Futures Index</th>
<th>0.66</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#2 US Corporate Bond Yield (BAA)</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>#3 Goldman Sachs Commodity Index</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>#4 Barclays Euro Inflation-Linked Bond Index</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>#5 Industrial Commodities Index</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>J.P. Morgan Emerging Market Bond Spread</td>
<td>0.36</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Factor Two</th>
<th>#1 DJ UBS/AIG Commodity Futures Index</th>
<th>0.61</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#2 US Dollar/Russian Ruble Exchange Rate</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>#3 SA 10-Year Government Bond Yield</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>#4 J.P. Morgan Emerging Market Bond Spread</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>#5 Barclays Euro Inflation-Linked Bond Index</td>
<td>0.31</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Factor Three</th>
<th>#1 US Capacity Utilisation</th>
<th>0.13</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#2 US Industrial Production</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>#3 Euro Marginal Lending Rate</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>#4 Euro Trade-Weighted-Index</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>#5 Platinum Spot Price</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Notes. Reported statistics are R-squared’s from regressing the indicator variable on the individual factor. Results for the top 5 variables (in terms of explanatory power) for each factor are reported.

As a group, the emerging markets are less synchronised with world volatility than are developed markets. In particular, we observe decoupling between emerging and world volatilities between 2001 and 2007. Recoupling occurs during 2008, thus identifying emerging market investments as a temporary hedge against volatility spillovers from the US subprime crisis.

There is a large degree of heterogeneity in volatility linkages for different countries in the panel. Whilst developed markets in Germany, Hong Kong, Singapore, the UK, and the US are closely integrated with global factors, volatilities in France and Japan are predominantly driven by idiosyncrasies. There is also considerable variance in comovement across emerging markets. Foreign volatilities are influential to equity pricing in Brazil, Mexico, Thailand and Turkey, but less so in countries such as China and Philippines. Similarly, the majority of volatility in SA is driven by country specific factors.

We provide evidence of sectoral dependence in the impact of global factors on SA volatilities. Generally, industrial firms are the most sensitive to changes in foreign volatilities. Global factors are also relatively important determinants of
volatility in the financial sector. In comparison, basic materials and oil and gas stocks are less integrated with foreign volatility.

In Chapter 5, our focus shifts to developing a structural interpretation of international volatility transmission. As a first step in this direction, this chapter analyses the composition of the global volatility factors. Factor One, which is identified as a developed market volatility factor, is the most important foreign driver of volatility in SA. On the other hand, Factor Two is correlated with volatility levels in Latin America, whilst Factor Three is associated with markets in emerging Asia. In addition, Factor One and Factor Two are proxies for uncertainty in global bond and commodity markets. The latter finding suggests an extension of the current analysis to account for asset market linkages which may exist across different asset classes.
CHAPTER 5
INTERNATIONAL TRANSMISSION OF EQUITY VOLATILITY DURING DEVELOPED AND EMERGING MARKET FINANCIAL CRISES

5.1 Introduction

Chapter 4 develops a factor model (FM) of volatility in world equity markets. The FM identifies three latent global factors that account for commonality in cross-country volatilities. A key finding for the majority of countries, including South Africa (SA), is that high degrees of comovement in volatility coincide with periods of major financial crisis.

Building on this framework, the current chapter develops a parsimonious model to describe crisis-period transmission of shocks to stock market volatility. The analysis relates to the same data panel and sample period discussed in Chapter 4. This panel consists of 25 developed and 20 emerging markets – a representative proxy for the world equity market portfolio. The model allows us to capture crisis-period volatility spillovers received by any country included in the panel. Consistent with the focus of the thesis, the objective of this chapter is to analyse and compare foreign volatility transmission to SA equities during crises originating in emerging and developed financial markets. In particular, we discuss and compare the impacts of major crises in Asia (1997-8) and the United States (US; 2007-8).

The model represents a version of Bernanke, Boivin and Eliasz’s (2005) factor-augmented vector autoregression (FAVAR) approach. In our FAVAR, unobserved global factors similar to those studied in Chapter 4 form the conduits for international volatility transmission. The stimulus for this transmission is simulated by shocking observed volatility for the country (or group of countries) where financial crisis originates. This specification is consistent with the view that major crises signal a temporary increase in systematic risk, with global consequences to equity pricing.

Similar to previous chapters, our estimation approach is cognizant of the time-varying nature of cross-market volatility interactions. Consistent with Korobilis (2011), we use the method of Bayesian mixture innovations (Gerlach, Carter and Kohn 2000; Giordani and Kohn 2008) with non-informative priors to introduce time-varying parameters in the FAVAR. By controlling for heteroskedasticity and evolving linkages between international asset markets, time-varying estimation increases the accuracy of the obtained impulse response functions.

A key contribution of the chapter is to synthesize the use of VARs and FMs in studies of cross-market linkages in asset pricing. Individually, these approaches feature prominently in the literature. Diebold and Yilmaz (2009) provide an application of the VAR which serves as a motivation for our chosen methodology.
They use an orthogonal VAR to construct volatility spillover indices similar to those developed in Chapter 3. The spillovers indices are estimated for a panel consisting of seven developed and 12 emerging equity markets. The paper reports system-wide volatility spillovers ranging between 40 and 75 percent from late 1995 to 2007. Local maxima in the volatility spillover plots coincide with periods of financial crisis.\(^1\)

However, there are important limitations to both the VAR and the FM. In the case of the VAR, proliferation of parameters restrains the number of variables that may sensibly be included in the analysis.\(^2\) This limits the information content of the model and makes infeasible the specification of a global model for volatility transmission. Moreover, identification of shocks in the VAR is not invariant to ordering of the chosen variables.\(^3\) Implicit in the model of Diebold and Yilmaz (2009), is a set of structural assumptions regarding the causality of volatility transmission in the panel. Since their panel includes a large number of variables, this implies a high degree of uncertainty regarding the true model governing volatility linkages. In contrast to VARs, the precision of FMs is proportional to the size of the data panel. But, as noted by Koop and Korobilis (2009), difficulties in identifying structural shocks in the FM complicates impulse response analysis. The time-varying-paramater FAVAR (TVP-FAVAR) combines the two approaches to provide a highly parsimonious specification of dynamics in large systems and a convenient setting for shock identification.

Our results identify significant cross-market volatility linkages during both the Asian and US crises. However, the nature of these linkages is dependent on the origin of the crisis. World volatility is more profoundly impacted by the US crisis. In particular, this event leads to large increases in volatility in developed Europe and Canada. On the other hand, most emerging markets (including SA), and developed markets in Australasia, are more sensitive to the volatility shock which coincides with the Asian crisis. These findings are indicative of high degrees of financial integration between markets which: (i) are at similar stages in their development; and, (ii) are in geographic proximity to each other.

Consistent with the FM from Chapter 4, the TVP-FAVAR indicates varying sensitivities of SA market sectors to foreign volatility. Specifically, stocks in the domestic industrial and financial sectors are more susceptible to foreign volatility spillovers than are those in basic materials and oil and gas.

The remainder of the chapter is organised as follows. Section 5.2 introduces

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\(^1\) Chapter 4 demonstrates the usefulness of the FM in assessing cross-market synchronisation in volatility dynamics, and reviews the relevant literature.

\(^2\) As an exception, refer to Banbura, Gianonnie and Reichlin (2010) for an example of a Bayesian time-varying-paramater VAR which is applied to panels consisting of up to 130 variables.

\(^3\) As demonstrated in Chapter 3, generalised impulse response functions (Pesaran and Shin 1998) produce a unique identification scheme in the VAR and, thus, provides a possible solution to this problem.
the FAVAR and its time-varying extension. Section 5.3 provides details of model identification and estimation. The data is briefly summarised in Section 5.4. This is followed by a discussion of the results in Section 5.5. Section 5.6 concludes the chapter.

5.2 Methodology

5.2.1 The FAVAR

As before, suppose that for $t = 1, \ldots, T$, $Y_t = (y_{1t}, \ldots, y_{Mt})'$ is a vector of volatility proxies relating to $M$ distinct equity indices. We choose $M$ to be large, so that the panel is representative of the world equity market portfolio. In the standard FM given in (4.1), $Y_t$ depends on a set of $K$ latent volatility factors $F_t = (f_{1t}, \ldots, f_{Kt})'$, where $K << M$. Consistent with Chapter 4, we use principal component analysis to estimate the unobserved factors, thus implying $E(f_{it} f_{jt}) = 0$ for all $i \neq j$.

In addition to their dependence on global volatility factors, the elements of $Y_t$ are assumed conditional on $X_t$ in the FAVAR. The latter variable is a proxy for observable equity volatility in the country (or group of countries) where financial crisis originates. Ultimately, shocks to $X_t$ provide the stimulus for volatility transmission in the model. For simplicity, we restrict $X_t$ to be a singleton. However, this definition is easily extended to allow for higher dimensions of the observable volatility factor.

The FAVAR’s measurement equation has the following VAR representation:

$$
\begin{bmatrix}
Y_t \\
X_t
\end{bmatrix} =
\begin{bmatrix}
\Lambda^F & \Lambda^X \\
0 & 1
\end{bmatrix}
\begin{bmatrix}
F_t \\
X_t
\end{bmatrix} + \epsilon_t,
$$

(5.1)

where $\Lambda^F$ is a $M \times K$ factor loading matrix, and $\Lambda^X$ is a $M \times 1$ vector of parameters measuring the dependence of $Y_t$ on $X_t$.\footnote{Since volatility is a necessarily latent variable, labelling $X_t$ as an observable factor is a slight abuse of terminology.} The error term $\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{M,t}, 0)'$ satisfies $E(\epsilon_m f_{kt}) = 0$ for all $m, k$ and $t$, and $E(\epsilon_{i,t} \epsilon_{j,s}) = 0$ for all $i \neq j$ and $t \neq s$. In particular, we assume $\epsilon_t \sim N(0, H)$, with $H = \text{diag}(\exp(h_1), \ldots, \exp(h_M), 0)$. Since the errors are independently distributed, (5.1) is conveniently estimated as a series of univariate regressions.

The FAVAR state equation is captured by the following VAR($p$) process:

$$
\begin{bmatrix}
F_t \\
X_t
\end{bmatrix} = \sum_{i=1}^{p} A_i \begin{bmatrix}
F_{t-i} \\
X_{t-i}
\end{bmatrix} + \zeta_t,
$$

(5.2)

where the $A_i$’s are $(K + 1) \times 1$ coefficient vectors for $i = 1, \ldots, p$, and $\zeta_t \sim N(0, \Omega)$.

\footnote{For notational convenience, the intercept term is suppressed in (5.1) and in future equations.}
5.2.2 Introducing Time-Varying Parameters in the FAVAR

We show in Chapter 4 that comovement between international equity markets fluctuates considerably over time. In particular, dependence of domestic volatility on foreign shocks tends to increase during financial crises. This implies that parameter flexibility is a key feature for any model of international volatility transmission. Following Korobilis (2011), we introduce time-varying parameters in the FAVAR to allow for possible structural changes in international volatility linkages.

In principal, each of FAVAR coefficient matrices may be allowed to vary over time. However, complete generality comes at a heavy computational cost and leads to proliferation of parameters. Hence, we limit the time-varying components of the model to three sets of parameters in state equation (5.2). The collection of $A_i$'s is modified as $A_t = (A_{1,t}, ..., A_{p,t})$. Similar to Cogley and Sargent (2005), Primiceri (2005), and Korobilis (2011), the covariance of $\zeta_t$ is decomposed as $\Sigma_t = B_t^{-1}\Sigma_t B_t^\top$. Here, $B_t$ is a $(K + 1) \times (K + 1)$ lower triangular matrix with ones along its diagonal and $\Sigma_t = \text{diag}(\exp(\sigma_{1,t}), ..., \exp(\sigma_{K+1,t}))$. We denote the $j^{th}$ column of $B_t$ by $b_{j,t}$.

The procedure for capturing time-variation in these parameters is based on a random walk model which incorporates mixture innovations with non-informative Bayesian priors for parameter change. For notational convenience, define $\phi_{j,t} \equiv \{A_t, b_{j,t}, \sigma_{j,t}\}$, where $j = 1, ..., K + 1$. Each element of $\phi_{j,t}$ is modelled as $\phi_{j,t} = \phi_{j,t-1} + \eta_{\phi,t}$, where $\eta_{\phi,t} \sim N(0, Q_{\phi})$ are identically and independently distributed innovations. The indicator variable $J_{j,t}^\phi$, which follows a Bernoulli distribution, equals one with probability $\pi_{j,\phi}$ and zero with probability $(1 - \pi_{j,\phi})$. Thus, the specification nests models with fully time-varying ($\pi_{j,\phi} = 1$) and constant ($\pi_{j,\phi} = 0$) parameters. When $\pi_{j,\phi} \in (0, 1)$, the parameters for variable $\phi$ are subject to random changes which are reflective of dynamics in the data.

5.2.3 Impulse Responses and Variance Decompositions

To derive impulse response functions, we rewrite the time-varying FAVAR in terms of structural shocks $\Delta_t = (\delta_t^Z, \delta_t^G)$ to the measurement and state equations. Letting $\epsilon_t = (W) \delta_t^Z$, $\zeta_t = (B_t^{-1}\Sigma_t) \delta_t^G$, and defining $Z'_t = (Y'_t, X'_t)$, $G'_t = (F'_t, X'_t)$, we obtain

$$Z_t = \Lambda G_t + W \delta_t^Z \quad (5.3)$$

$$C_0 G_t = \sum_{i=1}^{p} A_i G_{t-p} + (B_t^{-1}\Sigma_t) \delta_t^G, \quad (5.4)$$

---

6Refer to Gerlach, Carter and Kohn (2000) and Giordani and Kohn (2008) for details regarding mixture innovation models and their benefits relative to other time-varying approaches.
where $W$ is a matrix satisfying $WW' = H$ and $\Lambda = \begin{bmatrix} \Lambda^F & \Lambda^X \\ 0 & 1 \end{bmatrix}$. $C_0$ is a $(K+1) \times (K+1)$ lower triangular Cholesky decomposition matrix, imposing the identifying restriction $E(F_t X_t) = 0$. Substituting (5.4) into (5.3) produces:

$$Z_t = \Lambda \left( C_0^{-1} \sum_{i=1}^p A_{i,t} G_{t-p} \right) + \varpi_t$$

$$\varpi_t = \left( C_0^{-1} \Lambda B^{-1}_{t-1} \Sigma_t \right) \delta_t^G + W \delta_t^Z. \quad (5.5)$$

Notice, from the definition of $H$, that the bottom row of $W$ contains only zeros. Consequently, $X_t$ is independent of $\delta_t^Z$; so changes in $X_t$ are proportional to structural shocks in the state equation.

Variance decompositions for $Y_t$ are derived from (5.5). For $i = 1, \ldots, M$, we have:

$$V_t (y_{i,t}) = c_{0,i} \lambda_i \Omega_t \lambda_i' r_{0,i} + \exp(h_i), \quad (5.6)$$

where $c_{0,i}$ and $\lambda_i$ are the $i^{th}$ rows of $C_0^{-1}$ and $\Lambda$, respectively. Expression (5.6) clarifies the possible sources for volatility disturbances in the model. The first term measures market $i$’s direct and indirect exposure to a shock in $X_t$. Our assumption here is that the shock is sufficiently large to have systematic effects on pricing in foreign markets. This hypothesis typifies the kinds of shocks associated with recent financial crises. Cholesky factorisation of (5.4) implies that the shock to $X_t$ impacts on $F_{t+1}$. Market $i$ reacts to the change in $F_{t+1}$, conditional on its sensitivity to global factors. Notice that the latter channel of volatility transmission operates independently of the degree of bilateral integration between volatilities $y_{i,t}$ and $X_t$. Finally, volatility shocks that are idiosyncratic to market $i$ make up the second term in (5.6).

### 5.3 Model Identification and Estimation

Given that our analysis is based on the same data set analysed in Chapter 4, the optimal number of unobserved factors remains unchanged. Thus, the FAVAR is specified with three orthogonal factors in $F_t$, each capturing a different dimension of commonality in international volatility dynamics. Common dynamics in the system are driven by shocks to a fourth, observable volatility factor denoted by $X_t$. Shocks to $X_t$ are identified recursively by means of the Cholesky decomposition matrix $C_0$ in (5.4). The identification scheme places a contemporaneous restriction on the state equation. The unobserved factors $F_t$ only respond to shocks in $X_t$ with a one-period time lag. However, as discussed in Bernanke, Boivin and Eliasz (2005), the model does allow for instantaneous effects on selected variables in panel $Y_t$. Specifically, $Y_t$ is partitioned into subsets of slow- and fast-moving variables. Similar to the factors, the slow variables do not react immediately to shocks. But, shock transmission is instant in the case of the fast variables.
The identity of the observable global volatility factor is crisis-dependent, and should reflect the origins of the various crisis episodes under investigation. Choice of $X_t$ should also ensure that shocks relate to a market (or collection of markets) which is large enough to have global significance. Although they are small individually, taken together the emerging markets constitute close to 20 percent of world market capitalisation (refer to Figure 4.1). Hence, the emerging market strategic index discussed in Chapter 4 is incorporated in the FAVAR as the source for foreign volatility shocks during the Asian crisis. For the latter crisis, we assume that volatility transmission to emerging markets occurs more quickly than it does to developed markets. This motivates the selection of emerging markets as fast-moving variables. Furthermore, the definition of the fast-moving category is expanded to account for regional integration with crisis afflicted markets. Thus, Australia, Hong Kong, Japan, New Zealand, Singapore, and South Korea are also assumed to be fast variables. In the case of the subprime crisis, we specify US volatility as a global factor, and we assume that volatilities in developed markets are fast-moving.

5.4 Data

The data panel used in estimation is identical to the panel discussed in Chapter 4. The sample period spans January 1994 to December 2008. The panel consists of 191 monthly squared returns from 25 developed and 20 emerging equity markets. In addition to the various countries’ composite stock indices, the panel includes volatility proxies for selected market sectors (specifically, industrials, oil and gas, financials, and basic materials). The various strategic market indices discussed in Chapter 4 and defined in Appendix A are also included in the estimation panel.

5.5 Empirical Results

5.5.1 Volatility Transmission during Emerging and Developed Crises

To ensure robustness of our results, we estimate impulse response functions relating to several distinct crises in the sample period. We find that the patterns of international volatility transmission are qualitatively similar for different crises which originate either in developed, or in emerging markets. However, there are important differences between the two categories of crises. To illustrate these differences, we compare impulse response functions estimated for the Asian and US subprime crises.
To simulate the Asian crisis we evaluate the impact of a one-unit standard deviation shock to volatility in the strategic index for emerging markets. This shock is chosen to coincide with the devaluation of the Thai baht in July 1997. The subprime crisis is modelled using a similar shock to US volatility. In this case, the shock occurs in January 2008, when ratings agency Fitch downgrades US monoline insurer Ambac.

Figure 5.1 shows the impulse responses of strategic indices and individual markets following the Asian crisis. The generated shock to the emerging index is short-lived and has narrow confidence bands. Although there is a small (but significant) positive effect on volatility after two periods, the main impact of the shock occurs contemporaneously. As a consequence, we see significant increases in volatility during the impact period for all strategic indices, with the exception of developed Europe where volatility is unchanged. Consistent with the source of the crisis, the response of emerging Asia is large and positive, with a value of approximately 0.75 standard deviation units (SDUs). Sizeable volatility injections are also observed for the other emerging indices. Specifically, initial responses are measured at just less than one-SDU for the E7, 0.9-SDUs for the BRICS, 0.75-SDUs for Latin America, and 0.55-SDUs for emerging Europe. The magnitude of the latter impulse responses exceed those for the developed indices, which are all less than 0.25-SDUs in value. Volatility in the world index increases by close to 0.4-SDUs, thus suggesting a global impact of the crisis on equity pricing.

There is less uniformity in the effect of the crisis on individual markets. Countries which are largely unaffected by the crisis include Australia, Brazil, France, Hong Kong, South Korea, and Taiwan. Other than the latter three countries, volatility increases in all of the Asian developed and emerging markets. Positive responses also occur in the remaining emerging markets, as well as in the developed markets of Canada, Greece, Spain, Switzerland, and the US. Small negative reactions are estimated for European developed markets in Germany, Italy, Netherlands, and the UK. In a few instances (for example, Malaysia), after initially increasing, volatility decreases significantly one month following the shock, before increasing again in the next period.

The impulse responses relating to the US subprime crisis are plotted in Figure 5.2. The simulated shock to US volatility converges to zero after one period and appears to be well-behaved. Once again, this crisis causes volatility to increase significantly in all of the strategic indices. Relative to the Asian crisis, the magnitude of the initial impact declines to less than 0.25-SDUs for all emerging indices, as...
Figure 5.1 (continued). International volatility transmission during the Asian crisis
well as for developed Australasia and the Asian Tigers (ex. Taiwan). Volatility in the remaining developed indices increases by between 0.55- and 0.75-SDUs as a result of the subprime crisis. This implies a considerably larger response for the majority of developed markets during the latter crisis period. A positive response of 0.6-SDU in the world index indicates that the global effects of the subprime crisis are significantly greater than those of the Asian crisis.

Among those countries depicted in Figure 5.2, the only negative response to the US volatility shock occurs in the case of South Korea. There are no meaningful reactions in volatility levels for Brazil, Hong Kong, Hungary, Singapore, and Thailand. Small positive effects are measured for the rest of the emerging markets, as well as for Australia, Greece, and Japan. The impact of the crisis is most evident for developed markets in Europe. Volatility increases by approximately 0.8-SDU in Germany, 0.5-SDU in Netherlands, Spain, and the UK, and 0.3-SDU in Canada and France. These results imply a high degree of dependence in European and Canadian volatility on US shocks.

5.5.2 Foreign Shocks to South African Equity Volatility

Reactions of SA equity volatility in response to the Asian and US subprime crises are shown in Figure 5.3. The Asian crisis leads to a positive and significant initial response of 0.2-SDUs in the SA composite index. Impulse responses with similar magnitudes are estimated for stocks in basic materials and oil and gas. In comparison, the crisis has a more substantial impact on the financial and industrial sectors, with volatility increasing by about 0.7-SDUs in both instances.

In the case of the subprime crisis, changes in SA volatility are small in comparison to the earlier crisis period. With an estimated impulse of negative 0.1, volatility in the composite index decreases in response to crisis in the US. Furthermore, oil and gas stocks are practically unaffected. However, volatility does increase by between 0.15- and 0.2-SDUs in basic materials, financials and industrials.

The analysis suggests sectoral dependence in the transmission of foreign volatility shocks to SA. Consistent with the results from Chapter 4, stocks in financial and industrial firms are found to be more sensitive to changes in foreign volatility than are those in basic materials and oil and gas. Moreover, we find that the behaviour of equity volatility in SA is typical of that for other emerging markets. Specifically, foreign volatility dependence is greater for shocks transmitted from other emerging markets than it is for shocks originating in the US.
Figure 5.2. International volatility transmission during the US subprime crisis
Figure 5.2. (continued). International volatility transmission during the US subprime crisis
Figure 5.3. Transmission of foreign volatility to SA equities

Panel A. Asian crisis

Panel B. US subprime crisis
5.6 Conclusion

This chapter presents a structural model of international volatility transmission in world equity markets. The model represents an application of the time-varying-parameter factor-augmented VAR (TVP-FAVAR) approach (Bernanke, Boivin and Eliasz 2005; Korobilis 2011). It provides a parsimonious alternative to conventional VAR modeling of dynamic asset market linkages (see, for example, Diebold and Yilmaz 2009). The TVP-FAVAR incorporates two channels of volatility transmission. The first channel captures direct linkages between any given market and the source of a global shock to volatility. The second channel operates indirectly, via the impact of such a shock on the set of latent global volatility factors.

We use the TVP-FAVAR to compare the effects on world equity volatility of financial crises in Asia (1997-8) and the US (2007-8). Both crises lead to significant increases in the short-term volatility of strategic groupings of equity markets. Volatility transmission from the Asian crisis is pronounced for emerging markets, as well as for developed markets in Australasia. Relative to the Asian crisis, the US crisis has a greater impact on world equity volatility. In particular, the US shock has a considerable positive effect on volatility in developed markets in Europe and Canada. These findings are indicative of countries’ sensitivity to crises originating in markets with similar characteristics to their own. Furthermore, the results suggest that regional financial linkages play a significant role in international volatility transmission.

Similar to other emerging markets, the reaction of SA volatility is greater in response to the Asian crisis. A small decrease in volatility is measured for the domestic composite index following the US crisis. Oil and gas stocks are practically unaffected by the US shock. In all other cases, volatility increases following both crises. The most notable of these increases occur in the financial and industrial sectors.
CHAPTER 6
CONCLUSION

The past three decades bear witness to recurring financial crises. These events precipitate sudden and large losses in asset values, costly institutional reforms, and disruptions to the efficient allocation of savings. Crises create extreme uncertainty regarding future investment prospects, thus creating an intimate connection between their occurrence and heightened volatility. This connection forms the basis for the various analyses included in this thesis. The focus is on modelling asset pricing dynamics as they pertain to South Africa (SA) – a small, open and emerging economy with a sophisticated financial system.

Chapter 2 models domestic currency crises as structural changes in the volatility of the SA rand/United States (US) dollar exchange rate. Our application of the structural change generalised autoregressive conditional heteroskedasticity (SC-GARCH) model represents a novel approach for the identification of crisis periods.\textsuperscript{1} This method is data-driven and exploits the high frequency price changes which are characteristic of financial securities. Hence, it provides crisis dates that are more precise than those from competing approaches which typically use low-frequency macroeconomic data as inputs. The obtained crisis dates are broadly consistent with those provided in the literature (Bhundia and Ricci 2005; Knedlik and Scheufele 2008).\textsuperscript{2} Furthermore, we provide evidence of an undocumented domestic currency crisis occurring from 26 September to 5 November, 2008.

The successful application of the SC-GARCH approach to model SA currency crises highlights a number of possible refinements to the current research. It may be constructive to contrast model performance when attempting to identify crises which have differing characteristics. Such an exercise would facilitate comparisons of crisis-period volatility dynamics across countries and asset classes. The comparison may also help to refine the choice of a robust volatility-threshold for identifying the typical crisis episode. Another useful pursuit is the development of a multivariate version of the SC-GARCH model. This would allow us to account for volatility interactions between different markets (similar to traditional multivariate GARCH models), whilst also controlling for (possibly asynchronous) shifts in the variances of individual asset prices. Finally, it may be possible to adapt the model so that it provides an effective early-warning system for future financial crises. Obtaining accurate predictions of crises is the holy grail for financial forecasters. According to Poon and Granger (2003: 497-8), this elusive objective may be achievable with the use of a model that controls for extreme observations and which makes use of options or high frequency data.

\textsuperscript{1}There are several existing applications of the model to the analysis of asset prices with non-constant average volatilities (see, for example, Wilson, Aggarwal and Inclán 1996). But, the focus on crisis identification is unique to this thesis.

\textsuperscript{2}However, the SC-GARCH model does not detect a previously identified crisis during July 2006.
Chapter 3 extends the analysis of SA’s crisis-period volatility to a multivariate setting. Applying the methodology recently proposed by Diebold and Yilmaz (2011), bidirectional and time-varying volatility spillover indices are computed for currency, bond and equity markets. The estimated indices provide compelling evidence of volatility transfers. Equities are the predominant source of volatility spillovers to other asset classes. However, following the currency crisis at the end of 2001 and up until 2006, the majority of domestic spillovers originate in the foreign exchange market. In contrast to other asset classes, bonds are found to be a consistent net receiver of volatility injections. The occurrence of domestic and foreign crises exaggerate the time-varying nature of volatility linkages, since these events coincide with local maxima in system-wide spillovers. In comparison to a similar analysis for the United States (US; Diebold and Yilmaz 2011), interactions between SA asset classes are characterised by relatively strong volatility linkages.

An obvious limitation to Chapter 3’s analysis is the absence of an explicit explanation for why we observe volatility linkages between markets. The development of the theory of financial connectedness represents an important agenda for future research. Recent applications of network topology to finance and economics suggest one of the possible avenues for progress towards a workable theory. Another shortcoming of our analysis is its lack of generality. The differences that we document between SA and the US indicate the need for a comprehensive comparison of volatility spillovers within emerging and developed markets. Furthermore, a holistic model of volatility transmission should take into account the effects of both national and international market linkages on domestic asset pricing.

From a methodological point of view, we may consider estimating dynamic volatility spillover indices by means of time-varying parameters. This would involve augmenting the time-varying vector autoregression (VAR) approach (see, for example, Primiceri 2005) to allow for generalised impulse response analysis. The time-varying VAR is likely to provide a robust and theoretically appealing alternative to the rolling-window regressions used in the thesis. However, the practicality of this model is somewhat limited by proliferation of parameters when applied to larger systems of variables.

In Chapter 4, we use a large-panel dynamic factor model (FM) to investigate the dependence of SA equities on global volatility factors. Relative to a large number of other emerging markets, the factors are poor predictors of volatility fluctuations in SA. The implication is that, on average, the majority of domestic volatility is due to idiosyncratic risk. In contrast, systematic risk represents a key driver for SA volatility dynamics during crises in Asia (1997-8), Russia (1998) and the US (2007-8).

\textsuperscript{3}Important examples of network theory applied to financial markets include: Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010); Adamic, Brunetti, Harris, and Kirilenko; Allen, Babus, and Carletti (2010); Billio, Getmansky, Lo, and Pelizzon (2010); Bonanno, Caldarelli, Lillo, and Mantegna (2003); and Boss, Elsinger, Summer, Thurner (2004).
The latter finding motivates the development of a structural model for international volatility transmission. Hence, Chapter 5 proposes a time-varying version of the factor-augmented VAR (FAVAR; Bernanke, Boivin and Eliasz 2005; Korobilis 2011) to simulate the effects of the Asian and US subprime crises on global volatility. Although the US crisis has a larger impact on the world equity market, the Asian shock leads to more dramatic increases in volatility in emerging economies, including SA.

The data analysed in Chapters 4 and 5 are monthly observations. Monthly data facilitates the inclusion of macroeconomic variables in Section 4.5.5’s factor composition analysis, and avoids the problem of asynchronous trading hours in international equity markets. However, it may also lead to significant losses of information, given the high frequency of changes in financial asset prices. A natural test for robustness is reestimating the FM and FAVAR using weekly observations. It may also be important to test for the sensitivity of these models to the choice of volatility proxy. Since range-based and intra-daily realised variances are less noisy alternatives to squared returns (Andersen and Bollerslev 1998), the use of these measures is likely to produce more accurate estimations. Finally, we could consider the inclusion of bonds, currencies, or other asset classes in the analysis. Presumably, enlarging the panel of volatility proxies would result in global volatility factors which are closer approximations for true systematic risk in world asset markets. This would also facilitate the study of volatility spillovers across a broad range of markets for varying assets and with differing locations.

\footnote{The consistent use of squared returns in this thesis is due to constraints on data availability.}
The market typology used in Chapters 4 and 5 is consistent with FTSE’s market classification review of 2010. The markets included in the data panel are listed in Table A.1, along with details of missing data observations and indices. Relative market capitalisations for the various markets, used to calculate mean weights of the developed and emerging market indices, are also reported. Table A.2 provides details regarding the mean proportions of individual market returns constituting the various other strategic market indices. Finally, Table A.3 identifies the fundamental indicators that are used in the factor composition analysis given in Section 4.5.5.

### Table A.1. Market typology, mean market capitalisations, and missing observations

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<td>Israel</td>
<td>0.3%</td>
<td></td>
<td></td>
<td>Pakistan</td>
<td>0.3%</td>
<td></td>
<td>1/1994 - 12/2001</td>
</tr>
<tr>
<td>Italy</td>
<td>2.0%</td>
<td></td>
<td></td>
<td>Philippines</td>
<td>2.2%</td>
<td></td>
<td>7/2008 - 12/2008</td>
</tr>
<tr>
<td>Japan</td>
<td>13.2%</td>
<td></td>
<td></td>
<td>Poland</td>
<td>1.4%</td>
<td>B, F, I, O</td>
<td></td>
</tr>
<tr>
<td>Netherlands</td>
<td>1.9%</td>
<td></td>
<td></td>
<td>Russia</td>
<td>6.3%</td>
<td>B, F, I, O</td>
<td>1/1994 - 8/1994</td>
</tr>
<tr>
<td>New Zealand</td>
<td>0.0%</td>
<td>1</td>
<td>1/1994 - 12/2001</td>
<td>South Africa</td>
<td>12.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Norway</td>
<td>0.3%</td>
<td>1/1994 - 12/1995</td>
<td></td>
<td>Sri Lanka</td>
<td>0.1%</td>
<td>B, O</td>
<td></td>
</tr>
<tr>
<td>Portugal</td>
<td>0.2%</td>
<td></td>
<td></td>
<td>Taiwan</td>
<td>N/A</td>
<td>O</td>
<td></td>
</tr>
<tr>
<td>Singapore</td>
<td>0.0%</td>
<td>3/2008 - 12/2008</td>
<td></td>
<td>Thailand</td>
<td>3.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>South Korea</td>
<td>1.2%</td>
<td></td>
<td></td>
<td>Turkey</td>
<td>2.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spain</td>
<td>2.1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sweden</td>
<td>1.1%</td>
<td>O</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Switzerland</td>
<td>2.6%</td>
<td>O</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>United Kingdom</td>
<td>8.7%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>United States</td>
<td>47.8%</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Data source: Datastream. Mean relative market capitalisations are based on own calculations from market capitalisation data obtained from the World Bank’s online database. Key for missing indices: B = Basic Materials; F = Financials; I = Industrials; O = Oil and Gas.
<table>
<thead>
<tr>
<th>Strategic Index</th>
<th>Countries and Approximate Mean Weightings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asian Emerging:</td>
<td>China (44%), India (21.5%), Indonesia (6%), Malaysia (19%), Pakistan (0.6%), Sri Lanka (0.3%), Thailand (9%).</td>
</tr>
<tr>
<td>Asian Tigers (ex. Taiwan):</td>
<td>Hong Kong (55%), Singapore (16.5%), South Korea (28.5%).</td>
</tr>
<tr>
<td>Australasian Developed:</td>
<td>Australia (10%), Hong Kong (12%), Japan (68%), New Zealand (0.3%), Singapore (3%), South Korea (6.5%).</td>
</tr>
<tr>
<td>BRICS Emerging:</td>
<td>Brazil (20%), China (32%), India (16%), Russia (9%), South Africa (23%).</td>
</tr>
<tr>
<td>Developed:</td>
<td>All developed markets (as listed in Table A.1).</td>
</tr>
<tr>
<td>E7 Emerging:</td>
<td>Brazil (20%), China (32%), India (17%), Indonesia (5%), Mexico (12%), Russia (9%), Turkey (5%).</td>
</tr>
<tr>
<td>Emerging:</td>
<td>All emerging markets (as listed in Table A.1).</td>
</tr>
<tr>
<td>European Developed:</td>
<td>Austria (0.7%), Belgium (2%), Denmark (1%), Finland (2%), France (15%), Germany (13%), Greece (1%), Ireland (0.8%), Italy (7%), Netherlands (6.5%), Norway (1%), Portugal (0.7%), Spain (7%), Sweden (3.5%), Switzerland (8.5%), United Kingdom (29.5%).</td>
</tr>
<tr>
<td>European Emerging:</td>
<td>Czech Republic (15%), Hungary (10.5%), Poland (24.5%), Turkey (50%).</td>
</tr>
<tr>
<td>G7 Developed:</td>
<td>Canada (4%), France (5%), Germany (5%), Italy (2%), Japan (16%), United Kingdom (10%), United States (58%).</td>
</tr>
<tr>
<td>Latin American Emerging:</td>
<td>Argentina (13%), Brazil (46%), Chile (14%), Colombia (2%), Mexico (25%).</td>
</tr>
<tr>
<td>World:</td>
<td>All developed markets (90.5%), all emerging markets (9.5%).</td>
</tr>
</tbody>
</table>

Data source: Datastream; approximate mean weights are based on own calculations from World Bank market capitalisation data.
<table>
<thead>
<tr>
<th>Bond Indices:</th>
<th>Money Supply:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barclays euro inflation-linked bond index</td>
<td>European M3</td>
</tr>
<tr>
<td>Barclays United States (US) govt. inflation linked index</td>
<td>US M1</td>
</tr>
<tr>
<td>Barclays world govt. inflation linked index</td>
<td>US M2</td>
</tr>
<tr>
<td>Citigroup world govt. bond index</td>
<td></td>
</tr>
<tr>
<td>J.P. Morgan emerging market bond spread</td>
<td>Brazilian industrial production (IP)</td>
</tr>
<tr>
<td>J.P. Morgan global govt. bond index</td>
<td>Canadadian IP</td>
</tr>
<tr>
<td>J.P. Morgan US govt. bond yield to maturity</td>
<td>European employment</td>
</tr>
<tr>
<td>US AAA corporate bond yield</td>
<td>European IP</td>
</tr>
<tr>
<td>US BAA corporate bond yield</td>
<td>European leading indicator (LEAD)</td>
</tr>
<tr>
<td></td>
<td>French IP</td>
</tr>
<tr>
<td>Commodity Prices:</td>
<td>G7 employment</td>
</tr>
<tr>
<td>Brent crude oil spot</td>
<td>G7 IP</td>
</tr>
<tr>
<td>Dow Jones UBS/AIG commodity futures index</td>
<td>German IP</td>
</tr>
<tr>
<td>Economist all commodities index</td>
<td>Japanese IP</td>
</tr>
<tr>
<td>Economist food index</td>
<td>Mexican IP</td>
</tr>
<tr>
<td>Economist metals index</td>
<td>South Korean IP</td>
</tr>
<tr>
<td>Economist industrial commodities index</td>
<td>United Kingdom IP</td>
</tr>
<tr>
<td>Gold spot</td>
<td>US capacity utilisation</td>
</tr>
<tr>
<td>Goldman Sachs Commodity Index</td>
<td>US coincident indicator</td>
</tr>
<tr>
<td>Industrial Commodities Index</td>
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</tr>
<tr>
<td>Platinum spot</td>
<td></td>
</tr>
<tr>
<td>Consumer Price Indices (CPI) and Inflation:</td>
<td></td>
</tr>
<tr>
<td>Brazilian Inflation</td>
<td></td>
</tr>
<tr>
<td>Chinese Inflation</td>
<td></td>
</tr>
<tr>
<td>European CPI</td>
<td></td>
</tr>
<tr>
<td>G7 CPI</td>
<td></td>
</tr>
<tr>
<td>Indian Inflation</td>
<td></td>
</tr>
<tr>
<td>Russian CPI</td>
<td></td>
</tr>
<tr>
<td>Russian Inflation</td>
<td></td>
</tr>
<tr>
<td>South African Inflation</td>
<td></td>
</tr>
<tr>
<td>US CPI</td>
<td></td>
</tr>
<tr>
<td>Interest Rates:</td>
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</tr>
<tr>
<td>Chinese discount rate</td>
<td></td>
</tr>
<tr>
<td>European 10-year govt. bond rate</td>
<td></td>
</tr>
<tr>
<td>European marginal lending rate</td>
<td></td>
</tr>
<tr>
<td>European repo</td>
<td></td>
</tr>
<tr>
<td>South African 10-year govt. bond rate</td>
<td></td>
</tr>
<tr>
<td>South African repo rate</td>
<td></td>
</tr>
<tr>
<td>US 10-year govt. bond rate</td>
<td></td>
</tr>
<tr>
<td>US Federal funds rate</td>
<td></td>
</tr>
</tbody>
</table>

Data source: Inet Bridge.
APPENDIX B
TIME-VARYING VOLATILITY COMOVEMENT OF STRATEGIC MARKET INDICES

Figure B.1 depicts time-varying volatility comovement for nine indices of equity market groupings that are of strategic importance to international investors. As expected, there are similarities between comovement plots for individual countries that constitute the various indices, and the comovement plots for the indices themselves. Time-aggregated $R$-squared statistics of 80 and 58 percent for European developed and emerging indices, are consistent with our conclusion in Section 5.4.3 that European volatility is closely integrated with global factors. By implication, these markets are especially sensitive to foreign volatility shocks. In contrast, developed and emerging markets in Australasia are much less effected by foreign volatilities.\footnote{This statement does not apply to the Asian Tigers (excluding Taiwan), where integration with world volatility is relatively high.}

More generally, comparison of comovement for the E7 and G7 suggests that volatility linkages in major emerging markets are generally weaker than the corresponding linkages for important developed markets. Nevertheless, increases in E7
comovement lead those for the G7 from the beginning of the estimation period up until the Asian crisis. The regional impact of the Asian crisis is evidenced by large spikes in comovement for all Australasian indices during this period. Developed Europe and Latin America also appear to be significantly impacted by the Asian flu. Increasing volatility linkages during the Russian crisis are most perceptible for emerging Asia, BRICS, the E7, the G7, and Latin America. On the other hand, the dot-com crisis has a noticeable impact on volatility transmission in emerging Europe. We observe a uniform decline in comovement across all indices following the dot-com crisis. This decline is relatively persistent for the Asian emerging, Australasian developed, BRICS, E7, and Latin American indices, indicating a degree of decoupling from global volatility factors. From 2006 onwards, recoupling with the factors is led by increases in comovement for the developed indices of Australasia, Europe, and the G7. Relative to the other indices, increases in comovement associated with US subprime crisis are delayed for markets in emerging Asia, the BRICS, the E7, and, to some extent, Latin America. Thus, these indices are identified as possible hedges against systematic global volatility during the early stages of the subprime crisis.
REFERENCES


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zones. An added benefit of monthly data, is that it allows for inclusion of fundamentals in the factor composition analysis. A total of 67 macroeconomic variables are used to evaluate equity volatility dependence on real activity. These variables include volatility proxies for log differences in bond yields, consumer price indices, commodity prices, exchange rates, industrial production, and interest rates.\textsuperscript{9} We also consider factor composition with respect to financial variables. The set of financial indicators consists of the 45 individual stock markets included in the data panel, as well as the constructed strategic indices.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure41.png}
\caption{Shares of world market capitalisation for strategic market indices}
\end{figure}

Source. The World Bank.

\subsection{4.4.1 Volatility Dynamics}

Volatility plots for the strategic market indices are displayed in Figure 4.2. Comparison of the graphs indicates that emerging markets are more volatile than developed markets. The latter observation is consistent with the notion of a positive

\textsuperscript{9}Table A.3 in the Appendix A provides list of the macroeconomic variables included in the factor composition analysis.
Figure 4.5. Volatility comovement in developed equity markets
Figure 4.5 (continued). Volatility comovement in emerging equity markets.