Volatility Spillovers across South African Asset Classes during Domestic and Foreign Financial Crises

Andrew S. Duncan and Alain Kabundi

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February 2011

Abstract

This paper studies domestic volatility transmission in an emerging economy. Daily volatility spillover indices, relating to South African (SA) currencies, bonds and equities, are estimated using variance decompositions from a generalised vector autoregressive (GVAR) model (Pesaran and Shin 1998). The results suggest substantial time-variation in volatility linkages between October 1996 and June 2010. Typically, large increases in volatility spillovers coincide with 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. Bonds are a consistent net receiver of volatility spillovers. In comparison to similar research focussing on the United States (Diebold and Yilmaz 2010), volatility linkages between SA asset classes are relatively strong.

JEL Classification Numbers: G01, G1, F3.
Keywords: Asset Market Linkages, Dynamic Correlation, Financial Crisis, Generlised Vector Autoregression, Variance Decomposition, Volatility Spillover.

1 Introduction

This paper studies 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.[1] The consistent finding in this literature is that volatility spillovers are pronounced during financial crises. The analysis of domestic volatility transmission in an emerging market during periods of both tranquility and crisis contributes to a deeper understanding of cross-market linkages in general.

Analysis of volatility linkages in SA is a case in point. As depicted by plots of daily squared returns in Figure 1, 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. Knedlik and Scheufele

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[1]Early examples of such comparisons include Hamao, Masulis and Ng (1990) and King and Wadwhami (1990).

(2008) identify the following intervals as domestic currency crises: December 1995 – December 1996; June – July 1998; December 2001; and, June 2006. With the exception of June 2006, Duncan and Liu (2009) show that these crisis periods coincide with significant increases in rand/dollar volatility.[2] Similarly, from inspection of Figure 1, we observe marked increases in bond and/or equity volatility in time 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 East Asia (1997-8) and in the United States (dot-com 2000; subprime 2007-8).

The paper follows the analysis of Diebold and Yilmaz (2010). 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). They estimate the model for daily volatility proxies from United States (US) currency, bond, equity, and commodity markets, between January 1999 and January 2010. Diebold and Yilmaz 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 Diebold and Yilmaz, we find that 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. Consistently with other studies of volatility spillovers, we provide evidence of heightened volatility interdependence between SA asset classes during both domestic and foreign financial crises.

The remainder of this study 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, followed by our 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.

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[2]In addition, Duncan and Liu (2009) identify 26 September – 5 November 2008 as a crisis period in the rand.

2   Time-Varying Volatility Spillovers across Asset Classes

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 Wadwhami (1990) develop a partially-revealling 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.[3] Empirical estimation of the contagion model indicates significant interactions between realised returns in US, UK and Japanese equities. As expected, 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 international volatility spillovers in equity markets.[4] Similarly, there is evidence of volatility linkages between international currency, as well as bond markets.[5]

In comparison, there is limited research on domestic or international linkages in volatility *across* different asset classes. In what follows, we briefly review three notable contributions to this literature.[6] Although these papers follow vastly different

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[3] In contrast, Longin and Solnik (2001) argue that correlations are determinded by market trends, instead of volatility.

[4] 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] For examples of volatility spillovers in currency markets, refer to Engle, Ito and Lin (1990), Hong (2001), and Melvin and Melvin (2003). Studies of bond (or interest rate) volatility spillovers include Borio and McCauley (1996), Edwards (1998) and Edwards and Susmel (2003).

[6] 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).

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.[7] 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 *et al.* 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 – 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.[8] Dungey and Martin focus on interactions between currency and equity markets located in countries affected (directly or indirectly) by the East 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.[9]

In the third paper, Diebold and Yilmaz (2010) develop a variety of volatility spillover indices. The spillover indices are normalisations of forecast-error variance decompositions from a GVAR model of volatility proxies.[10] In contrast to traditional VAR specifications, GVAR allows for non-orthogonalised impulses; identification is achieved via

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

[8]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.

[9]Also refer to Dungey, Fry, González-Hermosillo, Martin and Tang (2010), who use Dungey and Martin's (2007) framework to study similarities between several recent financial crises.

[10]This method may be similarly applied to estimate spillovers in *returns* (see Diebold and Yilmaz 2009).

generalised impulse response functions.[11] 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 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 paper, a limitation of Fleming *et al.*'s approach is that it does not identify the *direction* of volatility transmission between asset classes. Although this problem is not encountered in Dungey and Martin's model, 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 to capture time-varying volatility spillovers between SA asset classes.

3 Methodology

3.1 Generalised Impulse Responses and Variance Decompositions

Without loss of generality, we let $x_t = (x_{1t}, x_{2t}, ..., x_{mt})$ denote a vector of endogenous proxies for period-t volatility in m distinct financial markets. Suppose that the dynamics of x_t are captured in a linear system. The VAR(p) model of this system is given by

$$x_t = \sum_{k=1}^{p} \Phi_k x_{t-k} + \epsilon_t \tag{1}$$

where the Φ_k are coefficient matrices and $\epsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}..., \varepsilon_{mt})$ is a vector of mean-zero error terms. We assume ϵ_t has a multivariate normal distribution, with ϵ_t independent of ϵ_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 (1) is a covariance stationary process. This implies the following infinite moving average representation for the system:

$$x_t = \sum_{k=0}^{\infty} A_k \epsilon_{t-k} \tag{2}$$

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[11] The GVAR approach is proposed by Gallant, Rossi and Tauchen (1993), Koop, Pesaran and Potter (1996), and Pesaran and Shin (1998).

Here, 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 $k = 1, 2, \ldots$[12]

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 x_t conditional on δ, and the corresponding expectation of x_t in the absence of any shocks.

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

$$\begin{aligned} \psi_n &= E_t\left(x_{t+n}|\epsilon_t = \delta, \Omega_{t-1}\right) - E_t\left(x_{t+n}|\Omega_{t-1}\right) \\ &= A_n \delta \end{aligned} \tag{3}$$

where (3) is a function of the forecast period $n = 0, 1, \ldots$ and the period-t shock δ, but its value is invariant to past observations Ω_{t-1}.[13]

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

$$\begin{aligned} E_{t-1}\left(\epsilon_t|\varepsilon_{jt} = \delta_j\right) &= \left(\sigma_{1j}, \sigma_{2j}, \ldots, \sigma_{jj}, \ldots, \sigma_{mj}\right)' \sigma_{jj}^{-1} \delta_j \\ &= \frac{\Sigma_\epsilon e_j \delta_j}{\sigma_{jj}} \end{aligned}$$

where e_j denotes the j-th column of I_m.

Consequently, the n-period ahead GI of x_t conditional on δ_j is given by

$$\begin{aligned} \psi_{j,n} &= E_t\left(x_{t+n}|\varepsilon_{jt} = \delta_j, \Omega_{t-1}\right) - E_t\left(x_{t+n}|\Omega_{t-1}\right) \\ &= \frac{A_n \Sigma_\epsilon e_j \delta_j}{\sigma_{jj}} \end{aligned}$$

and, letting δ_j equal $\sqrt{\sigma_{jj}}$, we obtain

$$\psi_{j,n} = \frac{A_n \Sigma_\epsilon e_j}{\sqrt{\sigma_{jj}}} \tag{4}$$

for any $j = 1, 2, \ldots, m$. Equation (4) measures the expected impact on x_{t+n} of a one standard error shock to variable j.

Suppose that we are interested in predicting the i-th element of x_t with a forecast horizon of n. We see from (4) that the expected cumulative impact on $x_{i,t+n}$ of a period t shock $\delta_j = \sqrt{\sigma_{jj}}$ is

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

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[12] Where I_m denotes the m-dimensional identity matrix.

[13] Refer to Koop *et al.* (1996) for a detailed discussion of history independence in (3).

with covariance matrix

$$cov(\varphi_{ji,n}) = \sum_{\ell=0}^{n} e_i' \psi_{j,\ell} \psi_{j,\ell}' e_i \tag{5}$$

In comparison, the *total* n-step ahead forecast-error and forecast-error covariance for i are given as:

$$
\begin{aligned}
\xi_{i,n} &= \sum_{\ell=0}^{n} e_i' A_\ell \epsilon_{t+n-\ell} \\
cov\left(\xi_{i,n}\right) &= \sum_{\ell=0}^{n} e_i' A_\ell \Sigma_\epsilon A_\ell' e_i
\end{aligned}
\tag{6}
$$

Using (4), (5) and (6), 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

$$
\begin{aligned}
\theta_{ij,n} &= \frac{\sigma_{ii}^{-1} \sum_{\ell=0}^{n} \left(e_i' A_\ell \Sigma_\epsilon e_j\right)^2}{\sum_{\ell=0}^{n} e_i' A_\ell \Sigma_\epsilon A_\ell' e_i} \\
&= \frac{\sigma_{jj}}{\sigma_{ii}} \left[\frac{cov(\varphi_{ji,\ell})}{cov\left(\xi_{i,n}\right)} \right]
\end{aligned}
\tag{7}
$$

Notice that the values of (4) and (7) 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 orthogonalised impulse responses obtained through Cholesky factorisation only if j is the first variable included in the VAR.[14]

3.2   Volatility Spillover Indices

Similar to Diebold and Yilmaz (2010), we construct volatility spillover indices using GF as defined in (7). 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 orthogonalised 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 (7) as

$$\tilde{\theta}_{ij,n} = \frac{\theta_{ij,n}}{\sum_{j=1}^{m} \theta_{ij,n}} \tag{8}$$

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[14]A natural exception to this statement is provided if Σ_ϵ is diagonal (implying orthogonality in the impulses), in which case GI coincide with orthogonalised impulse responses. Consult Lütkpohl (2007) for a detailed treatment of VAR models with orthogonal impulses.

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 forecast horizon variable 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

$$\Lambda_{VSO} = 100 \cdot \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{m} \tilde{\theta}_{ij}}{\sum_{i,j=1}^{m} \tilde{\theta}_{ij}} = \frac{100}{m} \cdot \sum_{\substack{i,j=1 \\ i \neq j}}^{m} \tilde{\theta}_{ij} \tag{9}$$

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: 1) the *source of* volatility spillovers *to* other asset classes; and, 2) the *destination for* volatility spillovers *from* other markets. If, for example, role one (two) 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

$$\Lambda_{i \leftarrow j} = 100 \cdot \frac{\sum_{\substack{j=1 \\ j \neq i}}^{m} \tilde{\theta}_{ij}}{\sum_{j=1}^{m} \tilde{\theta}_{ij}} = 100 \cdot \sum_{\substack{j=1 \\ i \neq j}}^{m} \tilde{\theta}_{ij} \tag{10}$$

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:

$$\Lambda_{i \rightarrow j} = 100 \cdot \frac{\sum_{\substack{j=1 \\ j \neq i}}^{m} \tilde{\theta}_{ji}}{\sum_{j=1}^{m} \tilde{\theta}_{ji}} = 100 \cdot \sum_{\substack{j=1 \\ j \neq i}}^{m} \tilde{\theta}_{ji} \tag{11}$$

Subtracting (10) from (11) we get the net volatility spillovers for asset class i:

$$\Gamma_i = \Lambda_{i \rightarrow j} - \Lambda_{i \leftarrow j} \tag{12}$$

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.

4   Data Analysis

We model volatility spillovers between three SA asset classes: currencies, bonds, and equities. Unlike Diebold and Yilmaz (2010), 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.[15]

SA and global foreign exchange markets are dominated by trade involving the US dollar (Bank for International Settlements 2007). Since the rand/dollar is the most significant exchange rate from the perspective of domestic market participants, we use returns to this pairing as a proxy for 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) all-share index, respectively.[16]

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] Consistently with Diebold and Yilmaz, we use daily data to capture high-frequency variations characteristic of financial time series.

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

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[15]As correctly pointed out by a referee, 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.

[16]Log returns are calculated as $r_{it} = 100 \cdot (s_{it} - s_{it-1})$, where s_{it} denotes the relevant period-t log-transformed closing price for asset class i. Bond yields are given by $y_t = 100 \cdot \left(\frac{b_t - b_{t-1}}{b_{t-1}} \right)$, where b_t is the period-t bond rate.

[17]We assume that returns/yields have zero expected values. Thus, we derive volatility proxy $x_{it} = \hat{\sigma}_{it}^2 = E_{t-1} \left[r_{it}^2 \right]$ from period-t realised returns. A similar proxy is created for bond yields.

[18]In contrast, Diebold and Yimaz (2010) use range-based proxies for volatility.

[19]All data is obtained from the I-Net Bridge databank.

are removed from the sample. Furthermore, three extreme outliers are deleted from the time series to avoid biasing our estimations. Table 1 provides details of these outliers.

Descriptive statistics for the log-transformations of daily squared returns are given in Table 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.

Figure 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 domestic currency market (as identified by Knedlik and Scheufele 2008, and Duncan and Liu 2009). The latter period follows shortly after the demise of Lehman Brothers in September 2008, a landmark event in the 2007-8 US subprime crisis (Brunnermeier 2009).

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 Commision 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 contagion 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 East Asian crisis to Hong Kong (Kaminsky & 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.

The investigation of internationally propagated volatility is beyond the scope of this paper. However, in what follows, we do investigate changes in SA volatility transmission coinciding with both domestic and foreign crises.

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5 Empirical Results

The reported results are based on multivariate least squares estimations of (1), with an autoregressive lag selection of 18 periods (approximately three-and-a-half weeks).[20] 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 (2010), 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.

5.1 Time-Aggregated Volatility Spillovers

Using (7) and (8), 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; the rows report the sensitivity of asset class i to the various shocks. Thus, own-variance shares appear along the diagonal of Table 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 (9), (10), (11) and (12), are summarised in Table 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.[21]

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[20]The relevant programme codes are available from the authors on request.

[21]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

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 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 (0.2) 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, respectively). 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.

5.2   Time-Varying Volatility Spillovers

To allow for possible time-variation in volatility transmission between SA asset classes, rolling-window estimations of the various volatility spillover indices are provided below. Similar to Diebold and Yilmaz (2010), 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 6. All of the estimated correlations are significant at a confidence interval of 99 percent. 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 interesting. Volatil-

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i has a maximum value of 200 percent.

ity 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.

To gain a deeper understanding of relationships between different asset classes, we measure time-varying correlations between innovations from the VAR. Figure 2 compares these dynamic correlations with their time-aggregated equivalents (as given in Table 5).

In each case, it is evident that correlations between different assets are not constant over time. Hence, the picture portrayed in Table 5 is misleading. For example, in Panel A of Figure 2 correlation between currencies and bonds tends to move above its average value of 47 percent during crisis periods. In the East 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. Comovemet between currency and bond volatility during the latter period is clearly visible in Figure 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 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 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.

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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 given in Figure 3.

Panel A of Figure 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.

Gross volatility spillovers originating in the bond market are shown in Panel B of Figure 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. 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 East Asian and US dot-com crises. Remarkably, average spillovers transmitted from equities between October 1997 and May 1998 (which includes the East 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, it is evident that the 2001 currency crisis has the effect of temporarily altering the dynamics of domestic volatility transmission in SA.

Table 7 reports average values of time-varying net- and total volatility spillover indices. These averages are based on a large number of estimations (3211 sets of results in our study), and thus, are likely to provide more accurate measures of volatility linkages

than the time-aggregated spillover indices reported in Table 4.

Relative to our time-aggregated results, rolling-window estimations indicate a reversal in the roles of volatility transmission played by currencies and equities, while the role of bonds 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. In net terms, equity spillovers account for 9.8 percent of currency and 45.8 percent of bond volatility, respectively. 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.

Time-varying net- and total volatility spillover indices are depicted in Figure 4 and Figure 5, respectively. 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.

In keeping with the analysis presented in this subsection, we see sharp increases in the dynamic total spillover index coinciding with the East 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.

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 East 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 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

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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 spillover dynamics.

Table 9 reports estimates of average time-varying net- and total volatility spillover indices during the identified crisis periods. Table 9 is comparable to the full-sample averages given in Table 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 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 East Asian crisis.

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 East Asian crisis. Similarly, the rand 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".

5.4   Comparison with Diebold and Yilmaz's Results

Our paper is comparable to Diebold and Yilmaz's (2010) study of volatility spillovers across US asset classes. To aid the comparison, we focus on Diebold and Yilmaz's sample period, 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 10. Diebold and Yilmaz 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.[22] 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.

In what follows, we compare time-varying volatility spillovers estimated for SA and the US. Figure 6 is taken from Diebold and Yilmaz (2010: 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 5 (here, the vertical dotted lines identify the start and end-points of Diebold and Yilmaz's sample period).[23] 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, 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 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

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

[23]As mentioned previously, estimated GIs and GFs are invariant to past observations Ω_{t-1}. Thus, our results are unaffected by resampling.

impact on volatility transmission in the US than it does in SA. Future research should focus on understanding the differential impact of global financial crises on volatility transmission in emerging markets.

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, *et al.* 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 Wadwhami'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.

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 paper contributes to this literature by considering domestic volatility transmissions in South Africa.

We apply a generalised vector authoregressive (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 December 2001, 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 advanced economies to SA asset classes. It is equally relevant to find the degree of synchronization of volatility between SA and other emerging market economies. A further refinement to the current investigation would be to compute volatility spillover indices using intra-daily data.[24] Lastly, to facilitate more general conclusions regarding emerging economies, it would be constructive for future research to investigate volatility spillovers across a broad panel of emerging asset classes.

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[24]Financial volatility is a high-frequency phenomenon. Thus, use of intra-daily data is likely to provide a more accurate picture of volatility interdependence, particularly during financial crises. We thank a referee for this suggestion.

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Table 1. Extreme outliers in daily squared returns

Date	Currencies	Bonds	Equities
28/10/1997	2.07	5.78	161.03
14/12/2001	49.57	196.05	23.43
15/10/2008	253.22	0.01	52.45

Table 2. Summary statistics of log-transformed daily squared returns

	Currencies	Bonds	Equities
Mean	-1.75	-1.58	-1.03
Median	-1.34	-1.45	-0.67
Maximum	4.67	4.16	4.13
Minimum	-13.04	-5.61	-12.66
Standard deviation	2.47	1.74	2.29
Skewness	-0.9	-0.14	-1.05
Kurtosis	4.18	2.54	4.86

Table 3. Time-aggregated volatility spillovers for SA asset classes

	Currencies	Bonds	Equities
Currencies	88.31	6.93	4.76
Bonds	44.04	44.46	11.5
Equities	3.77	0.99	95.24

Table 4. Time-aggregated gross-, net-, and total volatility spillover indices

	Currencies	Bonds	Equities	System-wide
Gross spillovers transmitted	47.82	7.92	16.26	
Gross spillovers received	11.69	55.54	4.76	
Net spillovers	36.13	-47.62	11.5	
Total spillovers				24 %

Table 5. Correlations between VAR estimated innovations

	Currency innovations	Bond innovations	Equity innovations
Currency innovations	1		
Bond innovations	0.47 (31.13)	1	
Equity innovations	0.17 (9.84)	0.2 (11.94)	1

Note: Estimated t-statistics given in parentheses.

Table 6. Correlations between time-varying spillovers transmitted across SA asset classes

		Currency spillovers to:		Bond spillovers to:		Equity spillovers to:	
		Bonds	Equities	Currencies	Equities	Currencies	Bonds
Currency spillovers	Bonds	1					
to:	Equities	0.81 (78.74)	1				
Bond spillovers	Currencies	0.09 (4.97)	0.16 (8.96)	1			
to:	Equities	0.5 (32.52)	0.66 (50.08)	0.31 (18.39)	1		
Equity spillovers	Currencies	-0.59 (-41.54)	-0.49 (-31.54)	-0.07 (-4.01)	-0.4 (-24.87)	1	
to:	Bonds	-0.59 (-41.5)	-0.56 (-38.17)	-0.21 (-12.06)	-0.49 (-31.44)	0.82 (82.28)	1

Note: Estimated t-statistics are given in parentheses.

Table 7. Average time-varying net- and total volatility spillover indices

	Currencies	Bonds	Equities	System-wide
Net spillovers	-9.81	-45.77	55.58	
Total spillovers				34.87 %

Table 8. Identification of crisis periods

Crisis period:	Start /	End dates	Reference:
East Asian crisis	20/10/1997	31/5/1998	Kaminsky and Schmuckler (2002)
1998 currency crisis	10/6/1998	19/7/1998	Duncan and Liu (2009)
US dot-com crisis	28/2/2000	7/6/2000	Dungery *et al.* (2010)
2001 currency crisis	12/12/2001	22/1/2002	Duncan and Liu (2009)
2006 currency crisis	1/6/2006	30/6/2006	Knedlik and Scheufele (2008)
US subprime crisis	1/7/2007	31/10/2008	Brunnermeier (2009)
2008 currency crisis	26/9/2008	5/11/2008	Duncan and Liu (2009)

Table 9. Volatility spillovers across SA asset classes during domestic and global crises

Crisis period:	Average net spillovers:			Average total spillovers:
	Currencies	Bonds	Equities	System-wide
East Asian crisis	-98.63	-92.72	191.35	65.05
1998 currency crisis	-68.27	-65.95	134.22	50.75
US dot-com crisis	-74.59	-47.03	121.62	46.48
2001 currency crisis	50.82	-47.87	-2.96	43.39
2006 currency crisis	-7.22	-75.12	82.34	38.22
US subprime crisis	-23.80	-59.13	82.92	34.66
2008 currency crisis	-23.36	-68.87	92.23	44.78

Table 10. Comparison of time-aggregated spillover indices for SA and US asset classes

	Net spillovers:				Total spillovers
	Currencies	Bonds	Equities	Commodities	
United Sates:	-2.8	-0.6	5	-1.7	12.6 %
South Africa:	52.6	-53.7	1.1	–	26.6 %

Source: Estimates of US spillovers as reported by Diebold and Yilmaz (2010: 22).
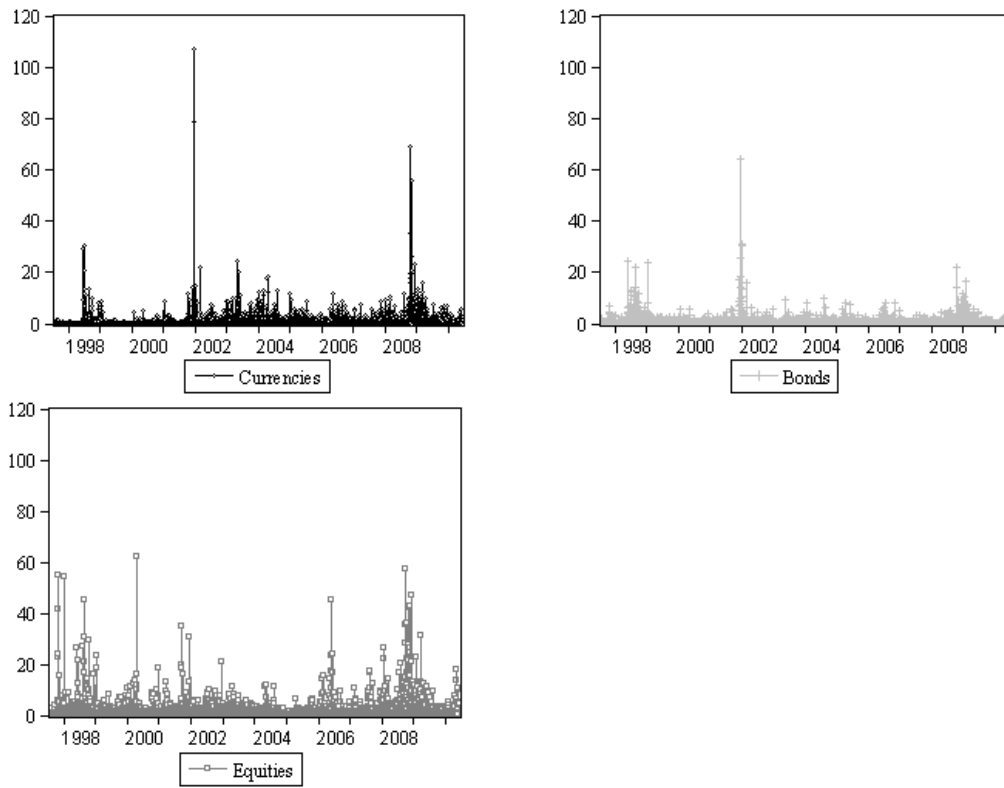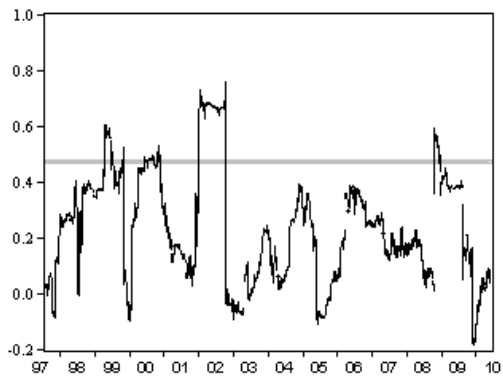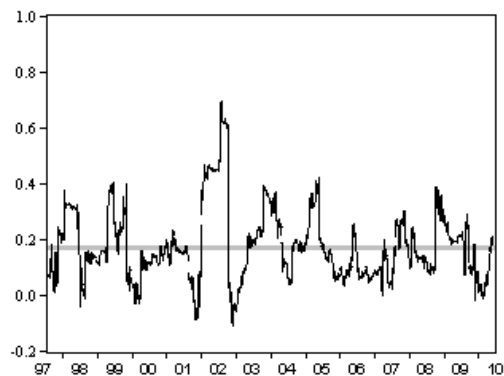
Figure 1. Squared daily returns for SA asset classes

Figure 2. Time-aggregated and dynamic correlations between SA asset classes

Panel A. Correlations between Currency and Bond innovations

Panel B. Correlations between Currency and Equity innovations

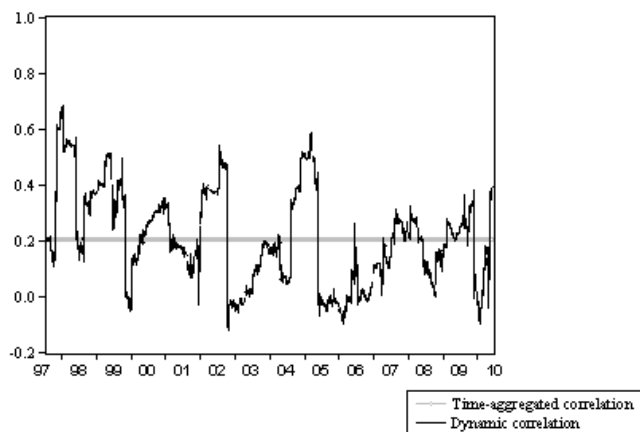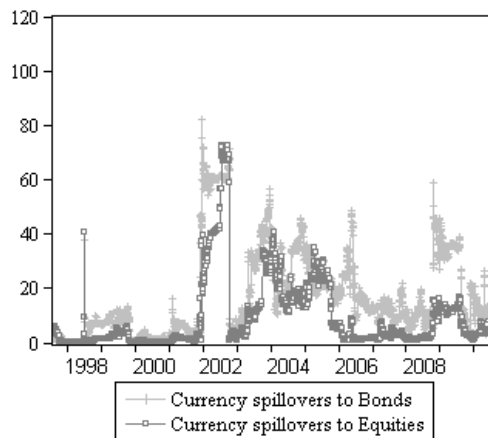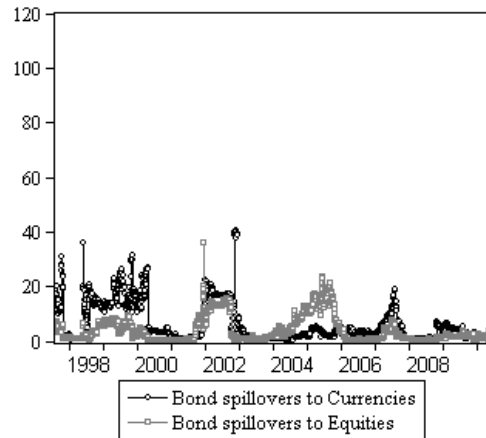Panel C. Correlations between Bond and Equity innovations

Time-aggregated correlation
Dynamic correlation

Figure 3. Time-varying transmissions of volatility spillovers

Panel A. Spillovers from Currencies

Currency spillovers to Bonds
Currency spillovers to Equities

Panel B. Spillovers from Bonds

Bond spillovers to Currencies
Bond spillovers to Equities

Panel C. Spillovers from Equities

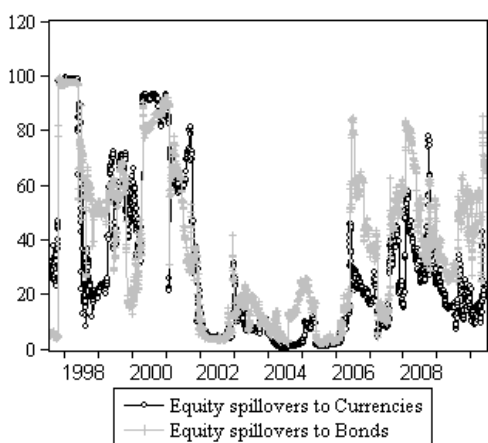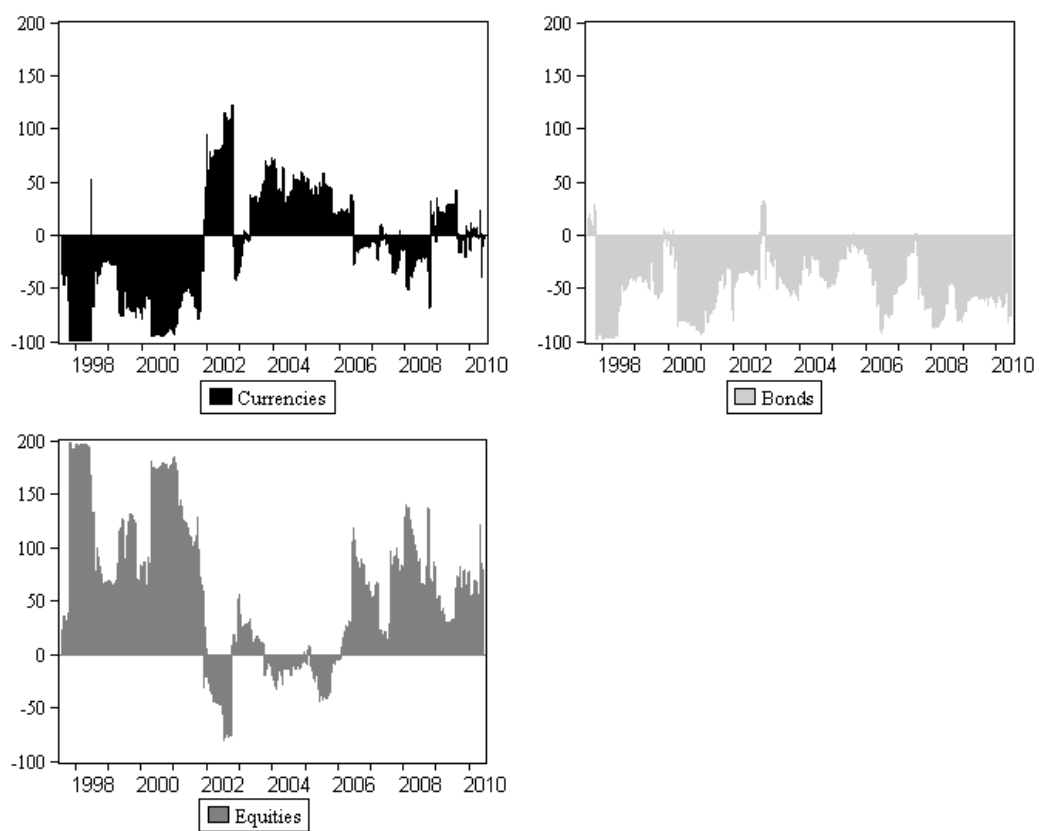Equity spillovers to Currencies
Equity spillovers to Bonds

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Figure 4. Time-varying net volatility spillovers

Figure 5. Time-varying total volatility
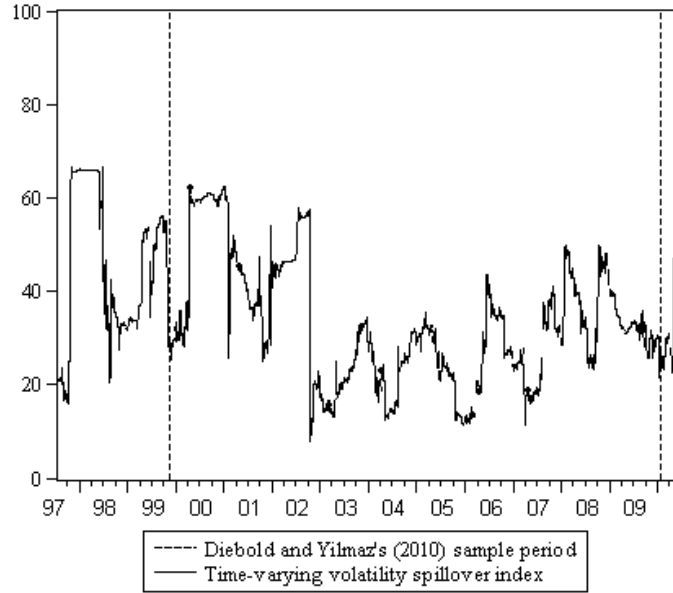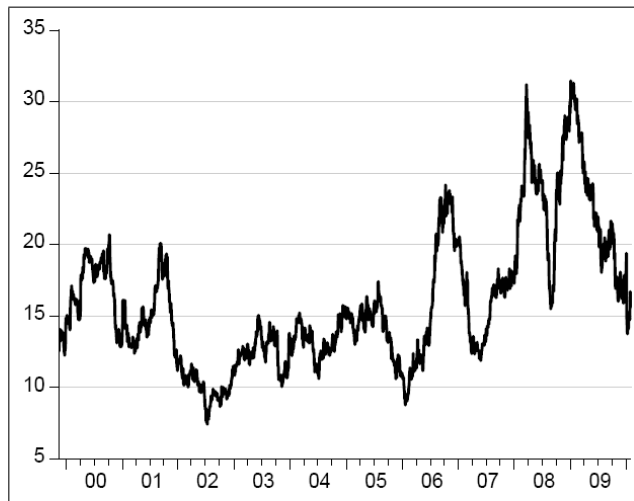spillover index for SA asset classes

Figure 6. Time-varying total volatility
spillover index for US asset classes

Source: Diebold and Yilmaz (2010: 23).

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