

SPILOVERS IN EXCHANGE RATES AND THE EFFECTS OF GLOBAL SHOCKS ON EMERGING MARKET CURRENCIES

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Abstract

This paper provides an investigation into the spillover effects of exchange rate returns and volatility for developed and emerging market currencies, using data from 1997 to 2011. The results suggest that spillovers in exchange rate *returns* have increased steadily over time, in moderate reaction to economic events. In contrast, spillovers in total observed *volatility* (measured by squared returns) react more strongly to economic events, and this transmission has remained at a relatively high level since the global financial crisis. Furthermore, over the course of time, global shocks would appear to account for a larger proportion of aggregate exchange rate volatility (and the relative importance of domestic shocks has declined). The paper also considers whether the increase in volatility spillover is due to sudden shocks, or whether it is due to changes in the stochastic trend of the underlying volatility process. The results suggests that in most cases, this increase is due to sudden shocks, however, in certain instances country-specific events may perpetuate changes to the trend of the underlying volatility spillover.

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1. INTRODUCTION

The dynamic relationship between currencies that are traded on the foreign exchange market affect households, firms and government decision making. These markets allow for complex international linkages, where a change in the external value of a particular currency may lead to large adjustments to the relative prices of other currencies, and *vice versa*. In this paper, we seek to describe the nature of these spillovers for developed and emerging markets. Such an investigation is of particular importance to financial participants and policy makers, as it would describe the degree to which global shocks and international developments influence the external value of a currency. In addition, a measure of the spillover could also be used to partially assess currency risk (and its source), while providing information on the relative importance and potential impact of domestic and global events.

The construction of the initial spillover index follows the work of Diebold and Yilmaz (2009) who construct such an index for equity markets in different developed economies. They define spillover as the share of the forecast error variance in one market that is caused by shocks to other markets. Such an index is calculated from the variance decompositions and impulse response functions that utilise a vector autoregressive (VAR)

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modelling framework. We extend this methodological framework to distinguish between the effects of volatility shocks and changes to the characteristics of the stochastic trend in the underlying volatility process. This is achieved by incorporating the results of stochastic volatility models that utilise Bayesian inference and the particle filter of Liu and West (2001).

Using daily exchange rate data for 14 developed and emerging market currencies from November 1997 to November 2011, we are able to show that the spillover in *returns* are relatively stable, often increasing steadily over time. In the case of the EUR/USD exchange rate, we find that the spillover index for returns has remained relatively constant at 10% between 2002 and 2011, while the spillover between for the ZAR/USD exchange rate rose from less than 20% to over 60% over the same period.¹ In terms of the spillovers in total observed *volatility*, we note that this measure displays more erratic behaviour, as it reacts strongly to economic events. For example, we note that between 2000 and 2007, the volatility spillover index for the EUR/USD exchange rate experienced dramatic spikes, moving from less than 15% to over 75%, for short periods of time. In addition, at the onset of the recent global financial crisis, the spillover of volatility for most countries incurred a dramatic spike before returning to a level that is well above that which was experienced during the prior expansionary phase.

Based on the ordering the currencies in the model, we are also able to show that most of the shocks to African currencies are dominated by domestic events, while shocks to other currencies, such as the Swiss Franc, are dominated by events that affect global markets. This provides valuable guidance in terms of the need for hedging exposure to the respective currencies, as well as the appropriateness of a currency as a hedge to other types of risk. In the final part of this analysis, we are able to show that by distinguishing between the stochastic trend and the shocks to the volatility process, South Africa is one of the few countries that experienced a steady increase in the spillover of underlying latent volatility. This could possibly be attributed to the continued opening up of the economy to foreign influence, an increase in the proportion of portfolio flows (as a proportion of total foreign investment), and the recovery from a 'currency-specific' crisis in 2001.

In terms of this paper's contribution to the current body of literature, we show how the spillover index of Diebold and Yilmaz (2009) could be applied to the foreign exchange market to characterize the nature of spillovers within this market over certain periods of time. Thereafter, we show how it is possible to use this framework to describe these spillovers from advanced to emerging market currencies, for both returns and volatility. In addition, we also present an extension to the existing methodology to identify changes to the underlying structure of volatility spillovers that may have arisen in the presence of large shocks (*i.e.* over the period of the recent global financial crisis).² In the following sections, we consider the relevance of spillovers, contagion and the effects of increased financial integration before we describe the characteristics of the model that we use to calculate spillovers in various currencies. Thereafter, we provide details of the data, before discussing the results. Lastly, we provide a brief summary of our findings and their implications.

¹ The EUR/USD and ZAR/USD exchange rates refer to the exchange rate for the euro and United States Dollar, and the South African rand to United States Dollar, respectively.

² To the best of our knowledge, these techniques have not been previously applied to research into spillovers from one exchange rate to another.

2. SPILLOVERS, CO-MOVEMENT, CONTAGION AND THE EFFECTS OF FINANCIAL INTEGRATION

The literature on different types of exchange rate interdependencies incorporate studies of contagion across currencies and investigations into the co-movements of currency volatility over time (which may include the identification of a common volatility factor). While these topics are interrelated, it is important to note that the definitions for each of these phenomena are unique. For example, contagion has been narrowly defined as an increase in the co-movement of asset prices during a financial crisis (Forbes and Rigobon, 2002), while investigations into the co-movements of volatility over time largely focus on the degree to which the volatility in security a_t , at time t , may be related to the volatility in security b_t , at time t . Such investigations into the co-movements of volatility are of interest to financial participants as an increase in the co-movement over time would suggest that there are fewer opportunities for diversification when holding a portfolio of assets.^{3,4}

³ A brief review of the relevant research on exchange rate interdependencies from the contagion literature would suggest that there is little evidence of increased integration during a time of crisis. For example, Forbes and Rigobon (2002) suggest that the amount of co-movement during times of crisis is similar to that which arose during times of stability. Therefore, they suggest that there is no evidence of contagion during the Asian Crisis in 1997 (which affected markets in United States, Europe and Africa), and the Mexican peso crisis in 1994 (which rapidly affected other Latin American markets). In a further study that focuses on the interdependence of Latin American equity markets, Edward and Susmel (2001) suggest that while the interdependence of volatility is high, it is also consistent with what should be expected (which does not support the argument in favour of contagion). Furthermore, Forbes and Chinn (2003) have subsequently investigated the explanatory power of direct trade linkages and financial linkages where they consider the degree of co-movement between equity and bond markets. They suggest that trade linkages have been more important than financial linkages in influencing financial market interdependencies over the period from 1996 to 2000. However, in a study that considers the effects of more recent events, Cetorelli and Goldberg (2010) suggest that the increased globalisation of US banks has allowed domestic liquidity shocks in the United States to rapidly spread to other global capital markets. This may support the idea that financial linkages have provided an important channel for the transmission of recent shocks between countries (which may arise during a period of crisis). This argument is supported by Eichengreen *et al.* (2009) who suggest that financial market interdependence (across borders) has increased since the onset of the global financial crisis.

⁴ There is a great deal of literature that considers the extent of changes to the degree of correlation between measures of volatility for each individual currency. For example, Bollerslev (1990) tested the correlations of conditional volatility in different European currencies prior and post the European Monetary System (EMS). He found evidence that correlations in exchange rate volatility had significantly increased after the adoption of the EMS. In addition, King *et al.* (1994) note that while international equity markets go through periods of sustained co-movements, there are also periods when the correlation between them appears to be low. They suggest that this time-varying correlation of markets is hard to explain, or predict, with observable economic data. Similarly, in a study of early floating exchange rates, Baillie *et al.* (1993) make use of weekly data from 1922 to 1925 to show that there were no systematic effects in the volatility of one currency that could be used to predict the level of volatility of another currency, although there were several significant relationships around the time of the Bear Squeeze in March 1924 when volatility peaked on the French and Belgian francs. A number of papers have also sought to identify common volatility factors, using various combinations of volatility and factor models. Harvey *et al.* (1994) make use

While topics relating to contagion and changes to the common volatility in exchange rates would describe important interdependencies, this particular paper focuses on spillovers, which can be defined as the variation in one asset that is attributed, or *caused*, by shocks to another asset (Diebold and Yilmaz, 2009). Therefore, we are primarily concerned with the transmission, which allows for the behaviour of one currency to affect another. For example, where we are concerned with a volatility spillover, we are seeking to determine whether a shock to currency *b*'s volatility affects currency *a*'s volatility.⁵ This does not require that the two currencies include the same underlying volatility process, only that they influence one another.⁶

In a prominent early study that considered spillovers in volatility from one currency to another, Engle *et al.* (1990) find evidence of spillovers over short periods of time in the dollar/yen exchange rate, using a selection of impulse response functions. They termed

of a multivariate stochastic volatility model, where the two factors are used to explain the common variation in four exchange rates. They find that the one factor would appear to explain the variation in the volatility of the three European exchange rates, while the variation in the JPY/USD exchange rate is explained by the other factor. However, Alexander (1995) make use of an ARCH framework that is combined with a factor model (as per Engle and Kozicki, 1993) to suggest that few if any factors exist; and Klaassen (1999) use a GARCH specification, which is combined with a factor model (in a way that is different to that of Engle and Kozicki, 1993) to support to findings of Alexander (1995). In addition, McMillan and Ruiz (2009) suggest that for the three euro exchange rates, JPY/EUR, USD/EUR and GBP/EUR, there is some degree of time-varying commonality in the driving force behind volatility movement. For an emerging market context, Speight and McMillan (2001) find limited evidence of volatility spillovers in the conditional variance of six formerly socialist exchange rates of Eastern Europe (using data from the black market). Similarly, Ruiz (2009) tests for common volatility processes in 12 Latin American exchange markets, using the method of Engle and Kozicki (1993), and find little evidence of such, concluding that “the variances of each currency appear to be largely country specific”. This method was also applied in Farrell (2001) to investigate for common movements and spillovers between the dual exchanges in South Africa between 1985 and 1995. There was no evidence of a co-movement in volatility (while volatility from the commercial rand may have spilled over to the financial rand, but not *vice versa*). In a further study on the currency of an emerging market, Raputsoane (2008) consider the extent to which volatility in other exchange rates may describe volatility in the South African exchange rate, using an augmented Exponential GARCH model. Surprisingly, it is suggested that there is negative relationship in the co-movement of volatility in the South African rand and the currencies of developed and emerging European markets (while there appears to be no relationship between the volatility in the South African rand and the currencies in the Asian and Latin American markets). Additional research into the co-movements in the volatility of equity markets is considered in Longin and Solnik (1995), among others. In an interrelated piece of research, Kose *et al.* (2008) have suggested that during the period of globalisation (1985-2005), there has been some convergence of business cycle fluctuations with the respective groups of developed and emerging market economies. However, they also find that there is evidence of business cycle divergence (or decoupling) between the groups of developed and emerging economies.

⁵ There are several instances in the literature, where research into the co-movement of security prices (or their volatility) are termed spillovers. By using the above definition for co-movements and spillovers, we are able to distinguish between these areas of research.

⁶ We do of course acknowledge that an increase in the spillover in volatility or returns from one asset price to another, may increase the probability of realising some form of co-movement or contagion (if it were more prevalent during a crisis).

these events “Meteor Showers,” to describe the way volatility spills over into other markets that open in a different (subsequent) time zone. In a more general study, Baillie and Bollerslev (1991) suggest that while intra-day volatility patterns for the four largest currency pairs (at that time) were remarkably similar, there was little evidence of systematic spillovers from one of these currencies to another over this sample period (using Granger causality tests on the mean and variance of the variables). More recently, Melvin and Melvin (2003) use high frequency data to study the persistence of volatility in the DM/USD and JPY/USD exchange rates in five non-synchronous markets, to suggest that the spillovers in volatility are mostly region specific, and the extent of a spillover to other countries in other regions is not as large (*i.e.* whatever causes a volatility spike in one region today is related to higher-than-normal volatility in the same region tomorrow). Furthermore, McMillan *et al.* (2010) make use of the realised volatility approach to suggest that there is evidence of time-varying correlation across major developed world exchange rates. In addition, they also find that there is evidence of some cross-currency volatility spillover effects measured by Granger causality tests.⁷ This supports the earlier work of Black and McMillan (2004), who suggest that significant volatility spillovers are reported among the European series, which may be the result of an increase in the convergence of these economies.

While several studies have considered the effects of spillovers in other security markets, the methodological contribution of Diebold and Yilmaz (2009) is of particular relevance to our research question, as it establishes a framework for employing factorisation to the construction of spillover indices.⁸ In their paper, the spillover index was used to measure the proportion of the total variance of price returns (or volatility) that is explained by spillovers from other countries, on equity markets. They find that spillovers in the *volatility* of equities in various countries are highly responsive to dramatic events such as the Asian Crisis and the global financial crisis, while spillovers in the *returns* of equities are less responsive to financial or economic events.⁹

In a subsequent paper, Diebold and Yilmaz (2011) employ generalised impulse response functions to describe spillovers in volatility across US stock, bond, foreign exchange and commodities markets between 1999 and 2010. They suggest that despite

⁷ In particular, they find evidence of bi-direction causality between the USD/EUR and GBP/EUR, while there is evidence of causality running from JPY/EUR to GBP/EUR and possibly also from JPR/EUR to USD/EUR.

⁸ Additional research into spillovers in equity markets include Cheung and Ng (1996), who make use of high frequency data and a two-stage cross-correlation function to test for causation in variance to suggest that the evidence, for volatility in S&P 500 Granger causing volatility in the Nikkei 225, may be less than previously thought. Ng (2000) suggests that both regional and global shocks have significant spillover effects to many of the Pacific-Basin countries after estimating a spillover model that allows the unexpected return of any particular Pacific-Basin market to be driven by a local shock, a regional shock (from Japan) and a global shock (from the United States). Chow and Lawler (2003) compare the volatility on the NYSE and Shanghai, which is negatively correlated. They also note that each market would negatively Granger cause volatility in the other market (which is explained by the negative correlations in the macroeconomic fundamentals in these countries). Then lastly, Ramasamy and Yeung (2005) find that the direction and significance of Granger causality statistics can vary according to the sample of study when they consider the relationship between equity and foreign exchange markets in nine East Asian economies.

⁹ Further details of this research and its relevance to our model is provided in section 3.

the significant fluctuations that were experienced in all markets, volatility spillovers only started to increase after it was apparent that a global financial crisis was in progress. Furthermore, as the crisis intensified so too did the volatility spillovers, where the spillovers from the stock market to other markets were of extreme importance. Duncan and Kabundi (2011a) have also considered the effect of spillovers in the South African equity markets, using a dynamic factor model. They suggest that spillovers in volatility across equities on respective global markets were particularly high during (and following) the financial crisis, however, for the period between crises (particularly from 2001 to 2007), the spillovers in volatility from developed equity markets to emerging equity markets appeared to be significantly lower. This finding is largely supported by Bonga-Bonga (2009), who uses a covered interest rate parity-based model of financial integration to show that during the time period from 1993 to 2008, the South African market became progressively more integrated into the world financial market, despite short periods of deviation.¹⁰

In contrast to many of the recent papers that consider the effects of spillovers in various security markets, our paper focuses exclusively on the spillovers (for returns and volatility) that may arise in the foreign exchange market. We utilise a slightly modified version of the spillover index that was applied to equity markets, as defined by Diebold and Yilmaz (2009), to consider the degree to which spillovers across currencies have affected different emerging market exchange rates between 1997 and 2010. Thereafter, we show how this methodological framework could be extended to distinguish between the effects of the volatility shocks and changes to the stochastic trend in the volatility process.

3. A FRAMEWORK FOR MODELLING SPILLOVERS IN THE FOREIGN EXCHANGE MARKET

3.1. A Country-Specific Measure for Spillovers

To model spillovers in returns and volatility for respective currencies on the foreign exchange market, we initially make use of the framework of Diebold and Yilmaz (2009), which relies on a Cholesky decomposition in which currencies are ordered according to trade volume. This form of factorisation would allow for the impact of shocks to more heavily traded currencies having same-day (and lagged) effects on less traded currencies. However, less traded currencies would only have lagged effects on the more heavily traded currencies. Such a decomposition is simple to derive yet rigorous and replicable. In addition, it also facilitates ease of understanding and improved transparency.

Spillovers would then arise when shocks to a foreign currency account for an unexpected change in the behaviour of a domestic currency, where the forecast errors from the moving average representation of the model are used to describe the unexpected changes. The forecast errors are then explained by either exogenous shocks to the domestic currency or spillovers from other currencies. This would imply that the spillover

¹⁰ Earlier research into spillovers in South Africa largely considered the effects of spillovers between local markets. For example, Duncan and Kabundi (2011b) make use of the framework of Diebold and Yilmaz (2011) to show that there has been substantial time variation in volatility linkages between October 1996 and June 2010, where large increases in volatility spillovers coincide with domestic and foreign financial crises. This is supported by Bonga-Bonga and Hoveni (2011) who suggests that there have been unidirectional volatility spillovers between the South African equity market and the foreign exchange market.

index is defined as the share of the forecast error variance that is attributed to the shocks to other currencies.¹¹

In terms of a more formal representation for the spillover in returns, consider the primitive form of the VAR model, which may be expressed as:

$$\mathbf{x}_t = \boldsymbol{\Pi} + \boldsymbol{\Gamma}_0 \mathbf{x}_t + \sum_{i=1}^p \boldsymbol{\Gamma}_i \mathbf{x}_{t-i} + \boldsymbol{\varepsilon}_t \quad (1)$$

where, \mathbf{x}_t is a $(k \times 1)$ vector of currency variables and each variable, x_t , is a time series with n observations of returns or volatility. The $(k \times k)$ $\boldsymbol{\Gamma}_0$ matrix assigns coefficients to the contemporaneous variables and must have a diagonal of zeros (as these are the coefficients on the contemporaneous dependent variables). The $(k \times k)$ $\boldsymbol{\Gamma}_i$ matrices would then assign coefficients to the i th lag, \mathbf{x}_{t-i} , and the errors, $\boldsymbol{\varepsilon}$, are contained in a $(k \times 1)$ vector that has elements that are assumed to be independently and normally distributed.

For the purposes of explanation, we remove the constant from the model, which implies that the assumed average returns are zero. The primitive model may now be rewritten in the standard form as:

$$\mathbf{x}_t = \sum_{i=1}^p \mathbf{B}_0 \boldsymbol{\Gamma}_i \mathbf{x}_{t-i} + \mathbf{B}_0 \boldsymbol{\varepsilon}_t, \quad (2)$$

where

$$\mathbf{B}_0 = [\mathbf{I} - \boldsymbol{\Gamma}_0]^{-1} \quad (3)$$

With the contemporaneous variables subtracted from both sides of the equation, all the remaining parameters in equation (2) may be identified using Ordinary Least Squares (OLS).¹² To derive parameter estimates for the primitive form in equation (1) from equation (2), we need to impose a number of restrictions on the values of the parameters as the primitive form of the model is under-identified. The most common method of doing so would be to impose a Cholesky decomposition on the \mathbf{B}_0 matrix, which allows us to derive unique estimates of the orthogonalised errors in equation (1).

Since we are primarily interested in the forecast errors, we may rewrite equation (2) as an infinite order Moving Average process, where the lag operator, \mathbf{L}^i , corresponds to the i th lag of the respective variable.¹³

$$\left(\mathbf{I} - \sum_{i=1}^p \mathbf{B}_0 \boldsymbol{\Gamma}_i \mathbf{L}^i \right) \mathbf{x}_t = \mathbf{B}_0 \boldsymbol{\varepsilon}_t$$

$$\mathbf{x}_t = \left[\mathbf{I} - \sum_{i=1}^p \mathbf{B}_0 \boldsymbol{\Gamma}_i \mathbf{L}^i \right]^{-1} \mathbf{B}_0 \boldsymbol{\varepsilon}_t$$

¹¹ By using the variance, the sign of a shock and the sign of its effect on other currencies do not affect the spillover index.

¹² Under the assumption of multivariate normal errors, this estimate coincides with the Maximum Likelihood and efficient Generalised Least Squares estimate (Davidson and MacKinnon, 2009).

¹³ To write the model as an infinite order moving average process, we would assume that the returns and volatility of the respective currencies are covariance stationary.

To simplify the notation we define,

$$\mathbf{A}(\mathbf{L}) \equiv \left[\mathbf{I} - \sum_{i=1}^p \mathbf{B}_0 \Gamma_i \mathbf{L}^i \right]^{-1} \mathbf{B}_0,$$

such that,

$$\mathbf{x}_t = \mathbf{A}(\mathbf{L})\boldsymbol{\varepsilon}_t,$$

and the forecast error ($\mathbf{e}_{t+1,t}$) from forecasting \mathbf{x}_{t+1} at time t , may then be expressed as,

$$\mathbf{e}_{t+1,t} = \mathbf{x}_{t+1} - \mathbf{E}_t(\mathbf{x}_{t+1}) = \mathbf{A}(\mathbf{L})\boldsymbol{\varepsilon}_{t+1}, \quad (4)$$

where $\boldsymbol{\varepsilon}_t$ are the orthogonalised errors with identity covariance matrix, $E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \mathbf{I}_k$. Hence, the error, $\varepsilon_{i,t}$, would describe the shock that is purely attributable to variable i ; and the degree to which this shock may spillover to variable j is described by the coefficients in the off-diagonal elements of the $\mathbf{A}(\mathbf{L})$ matrix.

By way of example, consider a bivariate first-order model for two currencies, which has the vector of forecast errors ($\mathbf{e}_{t+1,t}$). After expanding equation (4), we could write,

$$\begin{pmatrix} e_{1,t+1} \\ e_{2,t+1} \end{pmatrix} = \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{pmatrix} \quad (5)$$

Since, $E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \mathbf{I}_2$, this gives us the covariance matrix,

$$\begin{aligned} E(\mathbf{e}_{t+1}\mathbf{e}_{t+1}') &= \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix} \begin{pmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{pmatrix}' \\ &= \begin{pmatrix} a_{0,11}^2 + a_{0,12}^2 & a_{0,11}a_{0,21} + a_{0,12}a_{0,22} \\ a_{0,11}a_{0,21} + a_{0,12}a_{0,22} & a_{0,21}^2 + a_{0,22}^2 \end{pmatrix} \end{aligned} \quad (6)$$

Diebold and Yilmaz (2009) then define the ‘‘own variance’’ as the fraction of the forecast error variance from forecasting $x_{1,t}$ that is due to shocks relating to $x_{1,t}$ and the ‘‘cross variance’’ as the forecast error variance in $x_{1,t}$ that is attributed to shocks from the other variable, $x_{2,t}$. The ‘‘cross variance’’ is what is referred to as the spillover effect, where the total spillover is the sum of spillover effects that relate to the two variables. Hence,

$$\text{TotalSpillover} = a_{0,21}^2 + a_{0,12}^2 \quad (7)$$

One is then able to derive a spillover index, which reflects the proportion of the total forecast error variance (*i.e.* the sum of the forecast variance for all currencies at all forecast horizons) that is explained by total spillovers (Diebold and Yilmaz, 2009),

$$\begin{aligned} S &= \frac{a_{0,21}^2 + a_{0,12}^2}{a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2} \times 100 \\ &= \frac{a_{0,21}^2 + a_{0,12}^2}{\text{trace}(\mathbf{A}_0\mathbf{A}_0')} \times 100 \end{aligned} \quad (8)$$

This may be generalised to a multivariate case for several currencies, with an H -step ahead forecast horizon. Hence,

$$S = \frac{\sum_{h=0}^H \sum_{i=1}^k \sum_{j=1}^k a_{h,ij}^2}{\sum_{h=0}^H \text{trace}(\mathbf{A}_h \mathbf{A}_h')} \times 100 \quad (9)$$

where $a_{h,ij}^2$ indicates the spillovers from currency j to currency i , that pertains to the h -step ahead forecast error.

3.2. A Regional Measure for Spillovers

In this paper, we extend this framework by also estimating *regional* spillover indices for groups of exchange rates, to describe the combined spillovers to certain regions. In this case, the regional spillover index is defined as the share of forecast error variance in region A that is explained by shocks to region B . This index may be used to investigate the proportion of the spillover in emerging markets that is explained by shocks to developed economies (and *vice versa*). Again, the ordering of the Cholesky decomposition is based on trade volume in the respective currencies, and conveniently all developed currencies have a higher trade volume than all emerging market currencies in our sample. This makes the notation (and programming) quite simple, as the first a currencies belong to region A (developed economies), while the following $k - a$ currencies belong to region B (emerging markets). Thus, we may express this index by equation (10) where the subscripts i and j refer to the i th and j th variables in the Cholesky ordering.¹⁴

$$S_A = \frac{\sum_{h=1}^H \sum_{i=1}^a \sum_{j=a+1}^k a_{h,ij}^2}{\sum_{h=0}^H \sum_{i=1}^a \sum_{j=1}^k a_{h,ij}^2} \times 100 \quad (10)$$

And for region B :

$$S_B = \frac{\sum_{h=0}^H \sum_{i=a+1}^k \sum_{j=1}^a a_{h,ij}^2}{\sum_{h=0}^H \sum_{i=a+1}^k \sum_{j=1}^k a_{h,ij}^2} \times 100 \quad (11)$$

And similarly for an H -step ahead forecast with k variables we calculate the *individual* currency spillover index for currency i as:

$$S_i = \left[1 - \frac{\sum_{h=0}^H a_{h,ii}^2}{\sum_{h=0}^H \sum_{j=0}^k a_{h,ij}^2} \right] \times 100 \quad (12)$$

Therefore, equation (12) would suggest that the individual spillover index would reflect the share of the variance of the forecast errors that relates to currency i , which is explained by shocks to all other currencies in the model. While the regional spillover

¹⁴ The forecast horizon, h , in the spillover index for region A (S_A) would begin at 1 as the contemporaneous shocks are restricted to only occur in the direction from region A to region B . Contemporaneous spillovers from emerging markets to developed markets are in other words ruled out.

index reflects the share of forecast error variance in currencies included in region B that is explained by shocks to the currencies that are included in region A .¹⁵

3.3. *Attributing Volatility Spillovers to Shocks or Changes to the Underlying Stochastic Trend*

Most financial assets display relatively high levels of serial dependency in their volatility, where one large movement is often followed by another. Early evidence of such characteristics in asset prices was reported as early as Mandelbrot (1963), and after a period of rapid development in the 1980s, researchers are now able to generate reasonably accurate forecasts for inter-day volatility (Andersen and Bollerslev, 1998; Engle and Patton, 2001).

Models for the volatility of exchange rates have largely been dominated by autoregressive conditional heteroskedasticity (ARCH) models that were originally proposed by Engle (1982), and generalised ARCH (GARCH) models, that were developed by Bollerslev (1986).¹⁶ However, the use of stochastic volatility models, which have been used to price options since the mid-1980s have recently taken “centre stage in econometric analysis of volatility forecasting” (Shephard and Andersen, 2008). In addition, a further benefit of this framework is that by modelling volatility as a latent stochastic process, one is able to distinguish between the effects of volatility shocks and changes in the stochastic trend of the process, which is essentially the objective of this part of the study.¹⁷

Stochastic volatility models adopt a state-space framework where the state of the latent volatility may be estimated with the use of a recursive algorithm, such as the Kalman filter.¹⁸ However, where the latent process exhibits non-linear or non-Gaussian properties, the application of the Kalman filter is not suitable, particularly when the model incorporates a number of unknown parameters (Petris *et al.*, 2009). Early work by Pitt and Shephard (1999) on the auxiliary particle filter circumvents the problem of non-linearities and non-Gaussian state variables by using importance sampling to assign weights to each randomly generated particle, where an auxiliary variable is sampled for each of these particles. This algorithm is able to choose the particles that give higher likelihood values for observing the actual data conditional on the state variables (Petris *et al.*, 2009; Prado and West, 2010).

The application of the auxiliary particle filter is usually combined with a Markov Chain Monte Carlo (MCMC) algorithm that can deal with unknown parameters in

¹⁵ All of the spillover indices were calculated in the Matlab programming language; using code that was written by the authors.

¹⁶ See, Sarno and Taylor (2002) for a review of volatility models that have been used to describe exchange rate behaviour.

¹⁷ These models are built on the premise that volatility is an unobserved state variable that incorporates its own stochastic element (Andersen *et al.*, 2006). While, stochastic volatility models are more computationally costly they have been found to provide impressive in-sample descriptions of the data, when compared to more heavily parametrised GARCH models (Kim *et al.*, 1998).

¹⁸ The Kalman filter effectively bases estimates of the state of the latent process at time t on the posterior distribution at time $t - 1$ in a relatively straightforward manner.

non-linear and non-Gaussian models.¹⁹ However, when making use of an MCMC algorithm with an auxiliary particle filter, one would need to execute the entire algorithm a large number of times (for each observation in the data set), as the filter is a recursive tool (Petris *et al.*, 2009). Liu and West (2001) present a solution to this problem by allowing for parameter learning, where a vector of unknown parameters is included in the target distribution. In such a case, one draws a set of random particles at each data point from the prior distribution, for both the state variable and the unknown parameters (in which one allows for an artificial evolution of the static unknown parameters).²⁰

Hence, it has been suggested that these Sequential Monte Carlo (SMC) algorithms, which are employed in the Liu and West (2001) algorithm, are better suited to the purpose of studying unobserved state variables in models that encounter unknown parameters, non-linearities, and non-Gaussian data (Petris *et al.*, 2009).²¹

(i) *Particle Filters in the Estimation of Stochastic Volatility* To estimate the stochastic volatility model for currency returns, we define a simple state-space model where we denote the return series as y_t , the volatility of the series is h_t , and the shocks to the volatility process are assumed to be independently distributed innovations, ε_t . The structure of the model is assumed to be autoregressive of order one, with the inclusion of a constant, where the volatility equation contains its own stochastic innovations, v_t (which largely distinguishes this model from one that use the ARCH framework). The innovations to returns, ε_t , are assumed to have a student's- t distribution (as a number of periods display high return variance), and the innovations to volatility, v_t , are assumed to be independently normally distributed.²²

The model may then be described as follows.²³

$$y_t = \sqrt{h_t} \varepsilon_t \tag{13}$$

$$\log(h_t) = \alpha + \beta \log(h_{t-1}) + v_t \tag{14}$$

where

$$E(y_t | h_t) = \sqrt{h_t} E(\varepsilon_t) = 0$$

$$E(y_t^2 | h_t) = h_t E(\varepsilon_t^2) = h_t \sigma_\varepsilon^2$$

¹⁹ The MCMC algorithm is extremely useful when there are a relatively large number of parameters in the model.

²⁰ See, Prado West (2010) and Petris *et al.* (2009) for a detailed textbook description on the application of the Liu and West (2001) filter.

²¹ The SMC method allows us to sequentially estimate the joint probability distribution of the state of the latent volatility and the unknown parameters, all conditional on the observed variable. This algorithm does not require that the model makes use of new Markov Chains to be re-estimated for each observation in the data set.

²² See, figure D.4, which suggests that the variance in returns are particularly high during certain periods.

²³ See, Jacquier *et al.* (1994), Kim *et al.* (1998) and Lopes and Tsay (2011), who make use of similar structures.

and

$$E(\log(h_t) | h_{t-1}) = \alpha + \beta \log(h_{t-1})$$

$$E((\log(h_t))^2 | h_{t-1}) = E(v_t^2) = \tau_v^2$$

such that:

$$y_t | h_t \sim t_{df}(\mathbf{0}, h_t \sigma_\varepsilon^2) \quad (15)$$

$$\log(h_t) | h_{t-1} \sim N(\alpha + \beta \log(h_{t-1}), \tau_v^2) \quad (16)$$

The unknown static parameters, $(\alpha, \beta$ and $\tau_v)$, are then collected in the vector, θ , where knowledge of the degrees of freedom for the stochastic term in the measurement equation is given as, $\varepsilon_t \sim t_{df}$. We then follow the approach of Lopes and Tsay (2011), who estimate the model with different degrees of freedom, before proceeding to generate the final posterior probability distribution by integrating over all the previous models. The objective is to estimate the joint probability distribution of the unobserved volatility h_t and the parameters in θ , conditional on the observed returns y_t , which may be expressed using Bayesian inference,

$$p(h_t, \theta | y_t) \quad (17)$$

For each time period, t , we sequentially produce a Monte Carlo generated series of $n = 100,000$ particles for the unobserved stochastic volatility process and the unknown parameters, $\{h_{t-1}^{(i)}, \theta_{t-1}^{(i)}\}_{i=1}^N$, that approximate the density in (17) as per Lopes and Tsay (2011).²⁴ Each particle is then assigned a weight ($w^{(i)}$):

$$w^{(i)} \propto p(y_t | (E[\log(h_{t-1}^{(i)})], m^{(i)}))$$

$$m^{(i)} = a\theta^{(i)} + (1-a)\bar{\theta}$$

where $m^{(i)}$ is a weighted average of the parameter particle $\theta^{(i)}$ (and the average parameter particle value is given as $\bar{\theta}^{(i)} = \frac{1}{N} \sum_{j=1}^N \theta^{(j)}$) with weights a and $(1-a)$. The weights (or shrinkage constant) is set at $a = 0.95$ as in Lopes and Tsay (2011). This shrinkage constant is what allows the Liu and West (2001) filter to incorporate an artificial evolution of the parameter estimates without losing information.

The Liu and West (2001) algorithm then proceeds as follows. For each time period:

1. Resample a new set of particles, $\{\tilde{h}_{t-1}^{(i)}, \tilde{\theta}_{t-1}^{(i)}\}_{i=1}^N$ by assigning the weights, $w^{(i)}$, to the previous set of particles, $\{h_{t-1}^{(i)}, \theta_{t-1}^{(i)}\}_{i=1}^N$.
2. Propagate the re-sampled parameter vector $\{\tilde{\theta}_{t-1}^{(i)}\}_{i=1}^N$ to $\{\hat{\theta}_t^{(i)}\}_{i=1}^N$ via the normal distribution $N(\tilde{m}^{(i)}, V)$ where $V = (1-a^2) \sum_{j=1}^N (\theta_{t-1}^{(j)} - \theta)(\theta_{t-1}^{(j)} - \theta)'$.
3. Propagate new state particles $\{\tilde{h}_{t-1}^{(i)}\}_{i=1}^N$ to $\{\hat{h}_t^{(i)}\}_{i=1}^N$ via the density $p(h_t | \tilde{h}_{t-1}^{(i)}, \tilde{\theta}_t^{(i)})$.

²⁴ The t -subscript on θ refers to the period (or observation) for which the set of particles were drawn. Hence, θ is still assumed to be a vector of static parameters.

4. Re-sample both state variable and parameter particles $\{(h_t, \theta_t)^{(i)}\}_{i=1}^N$ from the propagated particles $\{(\hat{h}_t, \hat{\theta}_t)^{(i)}\}_{i=1}^N$, where each of the (i) particles is assigned the weight,

$$w_t^{(i)} \propto \frac{p(y_t | \hat{h}_t^{(i)}, \hat{\theta}_t^{(i)})}{p(y_t | E(\hat{h}_{t-1}^{(i)}), \tilde{m}^{(i)})}$$

The posterior distribution following the addition of each observation point is then stored before we repeat the algorithm after including an additional observation point. Once the algorithm has run through the entire data set, we are able to generate a filtered estimate of the underlying latent volatility process. In this exercise, the estimate is only filtered and not smoothed, in the sense that only past observations were included in the information set, on which the probability distribution is conditional upon.²⁵

3.4. Other Methods That Are Not Considered as a Part of This Investigation

An alternative method for deriving the spillover index is provided in Diebold and Yilmaz (2011). They make use of generalised impulse response functions (GIRF) of Pesaran and Shin (1997) to describe the spillovers in returns and volatility for different asset classes within a country (e.g. from bonds to equities, and vice versa). In this case, the GIRF that describes the behaviour of variable x_t after a shock to this variable is identical to the impulse response functions of a VAR model that makes use of a Cholesky decomposition, where variable x_t is placed first in the ordering (Kim, 2009).

Hence, the GIRF essentially describes the effects of shock to a particular variable, x_t , after allowing for all the other variables to have contemporaneous effects on variable x_t . Such a method would be appropriate in a study were all the variables may exhibit some form of contemporaneous behaviour (as would occur between various asset prices in a single country). However, in our case we would not expect for shocks to an emerging market currency (such as the South African rand) to have contemporaneous effects on the euro (over the specified sample period). Therefore, we believe that the use of the Cholesky decomposition would be an appropriate method for considering the spillovers in exchange rates between developed and emerging countries.

4. EXCHANGE RATE DATA AND LAG LENGTH SELECTION

The model includes three groupings of currencies, chosen according to their trade volume and relevance. In addition, we are primarily interested in the effects of floating exchange rates, preferably independently, but managed floats would also be of interest. In the case of managed floats, or periods of central bank intervention, we would expect that this would reduce the spillover index for the respective currency as such an event would clearly constitute a country specific innovation that cannot be explained by spillovers from other currencies. We classify the exchange rate regimes according to the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions* (IMF, 2009).

The data were obtained from Thompson Reuters Datastream through the WM/Reuters channel, for exchange rates that are quoted at (or around) 16H00 in London. "This time reflects the middle of the 'global day' and the time of highest

²⁵ For further details on the filtering algorithm see Lopes and Tsay (2011) and Liu and West (2001).

Table 1. Exchange rate regimes – selected currencies ordered according to trade volume

Code	Currency	1998	2001	2004	2007	2010
USD	US Dollar	IF	IF	IF	IF	IF
EUR	Euro	IF	IF	IF	IF	IF
JPY	Japanese Yen	IF	IF	IF	IF	IF
GBP	British Pound Sterling	IF	IF	IF	IF	IF
AUD	Australian Dollar	IF	IF	IF	IF	IF
CHF	Swiss Franc	IF	IF	IF	IF	IF
CAD	Canadian Dollar	IF	IF	IF	IF	IF
KRW	Korean Won	IF	IF	IF	IF	IF
MXN	Mexican Pesos	IF	IF	IF	IF	IF
INR	Indian Rupee	IF	MF	MF	MF	MF
ZAR	South African Rand	IF	IF	IF	IF	IF
BRL	Brazilian Real	MF	IF	IF	IF	IF
NGN	Nigerian Naira	MF	MF	MF	MF	MF
EGP	Egyptian Pound	MF	P	MF	MF	MF
KNS	Kenyan Shilling	MF	MF	MF	MF	MF

Source: IMF Annual Report on Exchange Arrangements and Exchange Restrictions, 1998-2010 and Bank of International Settlements Triennial Central Bank Survey 2010.

IF: independent float; MF: managed float; P: peg or currency board.

liquidity in the foreign exchange market” (Datastream, 2011). It is important for the study that all exchange rates are quoted at the same time, as we wish to avoid the “meteor shower” effects that were demonstrated by Engle *et al.* (1990).²⁶ We use six advanced country currencies, four emerging market currencies and five African currencies (summary statistics are provided in Table E2). All of these currencies use the US dollar as a base currency. The advanced country currencies are chosen according to their trade volume, as reported by Bank of International Settlements (BIS, 2010). We then select four of the most traded emerging market and African currencies according to their trade volume and relevance (in terms of the exchange rate regime).²⁷ The sample thus consists of daily exchange rate data on 14 currencies from 15 November 1997 to 15 November 2011. The selected currencies are listed in Table 1, where they are ordered by trade volume (which corresponds to that of the initial VAR model).

The exchange rates are converted into daily continuously compounded returns, using the first difference of the natural logarithm. The initial measure of observed volatility is then obtained from the squared returns.²⁸ Note that as the variables are expressed as returns, they have in effect been standardised (they have no units of measurement). Hence, there is no need to convert the squared returns into standard deviations.²⁹

Although the use of squared returns is a common proxy, it has been suggested that it is a poor estimate of realised volatility as it is “plagued by large idiosyncratic errors” (Andersen *et al.*, 2006). That is, it captures and amplifies all the day-to-day noise in the

²⁶ Meteor showers refer to volatility spillovers across time zones.

²⁷ The paper does not provide an outright definition of emerging markets, but we selected from the countries that are included in the widely quoted MSCI Emerging Markets Index (MSCI, 2011).

²⁸ Diebold and Yilmaz (2009) use a volatility estimate for equities based on the difference between open-close prices and bid-ask spreads, while Diebold and Yilmaz (2011) use the difference between daily high and low prices. We do not have access to this type of data and follow Duncan and Kabundi (2011b) who use squared returns as a measure of total observed volatility.

²⁹ Summary statistics for the distributions of each exchange rate is provided in the Appendix.

exchange rates and will consequently have a very high *noise-to-signal* ratio. This provides further motivation for the use of stochastic volatility models that describe the underlying latent volatility of the process.

To determine the optimal lag length, we utilise the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). The largest negative value for these test statistics was produced by the second-order VAR model for exchange rate returns. Hence, two lags of each variable have been used in the models that consider the spillovers in returns. To model the volatility of exchange rates, the AIC suggests a lag order that is greater than 10, while the BIC suggests that this model should also be expressed as a second-order VAR. Hence for simplicity, and to save degrees of freedom, we make use of a VAR(2) model for both returns and volatility.

5. RESULTS

5.1. *The Spillover Index for Returns and Total Observed Volatility (Squared Returns)*

To calculate the time-varying spillover effects, we calculate spillover effects for a subsample (or window) of the entire data set. We then roll this sample forward, keeping the size of the window constant. To ensure that the results are not overly sensitive to the window size, we report on the use of a 260-day (one year) and 780-day (three years) window.³⁰ As would be expected, a large window provides a smoother spillover index and a smaller window provides more information on short-term movements.³¹

The initial results are reported for four indices: *(i)* the overall spillover index; *(ii)* the Africa spillover index (excluding South Africa); *(iii)* the emerging markets spillover index; and *(iv)* the individual currency spillover indices. The overall index reflects the sum of spillovers into all currencies as a share of total forecast error variance. The emerging markets index reflects the percentage share of forecast error variance in the emerging market currencies that are attributed to shocks from advanced economies. The Africa spillover index would then reflect the spillovers from both developed economies and emerging markets into African currencies. Lastly, the individual indices measure the percentage share of the forecast error variance in the respective currency that is explained by shocks to all other currencies.

Each index is plotted with two different forecast-horizons, 10 days ($H = 10$) and 2 days ($H = 2$). The graphs report the spillover index at the end of the sampling window so that the spillover index reported for, say, January 2008 reflects the estimated spillover between January 2007 to January 2008 for the 1-year sample window. In the latter part of the paper, we focus attention on the 3-year sample windows with a 10-day forecast horizon ($H = 10$), as this would be more consistent with the existing literature, and they would

³⁰ The results for the 780-day window time-varying spillover index are reported in this paper. You can find the results for the 260-day window in the additional online Appendix. We also estimated the models based on a 160-day rolling window, but due to the short window/small sample, the resulting index contained too much noise to provide any useful information. The use of 260- and 780-day windows is consistent with previous studies, where Diebold and Yilmaz (2009) used a rolling 200-week (approximately four years) window for their estimations on weekly returns.

³¹ While the larger window size would potentially provide more accurate parameter estimates (as the number of observations/degrees of freedom would be larger), this benefit would need to be offset against the increased possibility of experiencing a structural break (or large change) within the window, which would detract from the accuracy of the parameter estimates.

appear to provide more meaningful results. It should be noted that the results for volatility spillovers are based on the squared returns measure of volatility.³²

(i) *Return Spillovers* Figure A.1 displays the indices for spillovers in returns for all countries, emerging markets, African countries and South Africa, using the 780-day window.³³ These results suggest that in most cases, return spillovers increased gradually over the entire sample period, peaking prior to the global financial crisis, before stabilising at a relatively high level. This corresponds with the results of Diebold and Yilmaz (2009), who detect a similar pattern in equity markets. The overall sample peaks at about 45%, the emerging markets peak at about 40%, African countries at 12% and South Africa at about 60%.

Furthermore, during the early part of the sample, the South African spillover index closely resembles the overall spillover index, where in 2007, they are both just below 40%. Thereafter, the overall spillover index then appears to stabilise at this level, while the South African spillover index continues to increase at a slightly lower rate until mid-2008. This has meant that spillovers to South African returns have gone from below the average to being one of the highest, where an extremely large portion of the forecast error variance may currently be explained by shocks that emanate from other currencies. In addition, our results also suggest that the African spillover index appears to move quite independently of the others.

It is also important to note that the results for South Africa are not purely attributed to a sudden increase in trading volumes for the South African currency. The rand accounted for 0.7% of the total foreign exchange market turnover in 2010, which is equivalent to the proportion of trading volumes in 2004 (and lower than in 2001 and 2007 when it accounted for 0.9% of the foreign exchange market turnover) (BIS, 2010). This would provide an early indication that this rapid increase in the spillover index may be the result of changes to structural factors, where at the start of the sample, the currency was largely influenced by South African specific factors, while in the latter part of the sample, the same proportion of the total trade volume is largely influenced by global factors. These global factors are likely to include global risk and risk appetite, which will affect the optimal portfolio allocation of international investors. A large body of research has found evidence of so-called risk-on/risk-off portfolio flows that are driven by global risk appetite and can dominate the pattern of global portfolio flows.³⁴

With regards to the results to other individual countries, not reported here, we note that the characteristics of the South African spillover index is similar to that of other emerging market currencies, such as the Brazilian, Mexican, Korean, Hungarian, Russian, Polish and Turkish spillover indices. There is no obvious common denominator between these economies (such as size, openness or policy) other than the fact that they all fall in the category of emerging markets.³⁵

³² The corresponding indices for the stochastic volatility model are reported in section 5.2.

³³ We include the results for South Africa as a further analysis of spillovers for this particular country provide interesting results.

³⁴ See, for example Forbes and Warnock (2012), Bruno and Shin (2012) and McCauley (2012).

³⁵ The fact that the South African spillover index is greater than the *emerging markets spillover index* in figure A.1 may be partly attributed to the fact that the South Africa index includes shocks

As in Diebold and Yilmaz (2009), we find that the return spillovers never appear to decline to the relatively low levels from the early part of the sample, which suggests that there has been a consistent increase in financial market integration. As noted above, this is also in support of the findings in Kose *et al.* (2008), Cetorelli and Goldberg (2010), Duncan and Kabundi (2011b) and Eichengreen *et al.* (2009). In addition, we also show that the trend in the return spillovers was highest during the period prior to 2007. This increase in the trend appears to have declined since the onset of the crisis and has stabilised at a relatively high level.³⁶

(ii) *Volatility Spillovers* The initial results for the spillovers in volatility (measured by squared returns) are contained in figure B.2. They indicate that volatility spillovers are much more abrupt and extreme, for all indices. This was also found to be the case for spillovers in global equity markets by Diebold and Yilmaz (2009). While Diebold and Yilmaz do not speculate in the cause of this abruptness in volatility spillover, one feasible explanation could be that so-called contagion during crises causes the volatility to spill over across currencies. In particular, there is a spike at the time of the recent global financial crisis, where it jumps by approximately 30% points. The index remains at a higher level for the preceding period, while this spike is still included in the three-year rolling sample window. The fact that volatility spillovers increase sharply (and become more volatile themselves) during the financial crisis is of no great surprise.³⁷

As with returns, the overall, emerging markets and South African volatility indices appear to display similar characteristics. We suspect that the high levels of all spillover indices at the beginning of the sample (remember, the index is reported at the end of the sample window) is due to the Asian crisis and the dot-com bubble that affected economic activity in the late 1990s and early 2000s. The results also suggest that there was a gradual increase in spillovers leading up to the recent global financial crisis. These findings concur with the existing literature on financial integration and the financial crisis.³⁸

When we compare the volatility indices to the return indices, we notice that they also display a wider gap between indices that are estimated at different forecast horizons ($H=2$ and $H=10$). This would imply that the more immediate response of financial participants may differ to their longer term response. However, using a microstructure approach, Evans and Lyons (2008) suggest that the peak in return variance caused by the arrival of news is reached after 60-90 minutes. One possible way to reconcile our results with the existing microstructure literature would be to consider the indirect channel

from other emerging markets, whereas the emerging markets index does not (*i.e.* it only includes spillovers from advanced economies into emerging markets).

³⁶ To ensure that our results are robust, we estimated four different orderings of the Cholesky decomposition, which are reported in figure (C.3). The different orders include: the original order based on trade volume, the exact reverse order and two orderings where the top five currencies were rearranged and the bottom five currencies were rearranged. The alternative orderings gave remarkably similar results. The only slight exception is the reverse ordering which estimated lower spillover effects but similar developments over time. However, this reverse ordering is arguably not realistic as it allows shocks to less traded currencies such as the South African rand to have immediate impacts on more traded currencies like the euro while restricting the less traded currencies from responding to contemporaneous shocks to the more traded currencies.

³⁷ Similar results have been reported in Duncan and Kabundi (2011b) and the references therein.

³⁸ See, Eichengreen *et al.* (2009).

through which news travels. For example, a shock to EU equity markets may affect the volatility of the euro. This shock may not have a direct impact on the South African rand, but it may very well affect volatility in South African equity markets through equity market spillovers. This volatility in equity markets may then spillover to the South African currency, as suggested by Duncan and Kabundi (2011b). Hence, currency traders would still act on the arrival of unexpected news after a relatively short period of time, but this information may only reach them after a delay.³⁹

In summary, the spillover indices for returns and volatility seem to support the current literature's findings for other asset classes, where spillovers in returns increase gradually over the sample with no abrupt movements, while volatility spillovers displays no clear trend but strong reactions to financial events. Unfortunately, little research has been done into the reasons for this different behaviour of return spillovers vs. volatility spillovers. In the following sections we explore volatility spillovers more closely to determine whether the abrupt changes in volatility spillovers are caused by changes in the underlying volatility process or the short term noise. Such an insight may provide guidance for future research into the causes of the sudden changes in volatility spillovers.

5.2. *The Effects of Volatility Shocks and Changes in the Stochastic Volatility Trend*

(i) *Results from the Stochastic Volatility Model* Stochastic volatility models may be used to remove the noise from an observed measure of volatility to produce an estimate of the underlying trend in the latent volatility process. In this way, it could also be used to isolate (or remove) the effects of shocks to the volatility process. The calculation of a separate spillover index that use stochastic volatility models enables us to determine whether the change in the spillover index for total observed volatility (that use the squared returns measure) may be attributed to the underlying (more persistent) element of volatility, or whether these changes are due to volatility shocks.

This is an area of potential interest, since the period that preceded the recent global financial crisis was characterised by increasing levels of excessive debt⁴⁰ and other relatively 'slow moving' events (such as those that may have resulted in slight changes to the structure of an economy). Therefore, it would be of interest to determine whether the changes to the measure of underlying volatility that is described by the stochastic volatility model have impacted on the spillover in volatility from one country to another, or whether the spillover index is largely attributed to volatility shocks to these currencies.

Figure D.4 plots the stochastic volatility estimates with the squared returns for South Africa. The estimates for the other countries stochastic volatility (and squared returns) are not reported here.⁴¹ As expected, the squared returns appear to exaggerate the effects of

³⁹ A further interesting finding from the microstructure approach is that Evans and Lyons (2008) have suggested that approximately 30% of volatility in exchange rates can be attributed to the arrival of macroeconomic news. Therefore, as there would be an increase in the rate of macroeconomic news arrivals during a crisis, we would expect that there would be an increase in the volatility of all currencies, which would create an environment that is conducive to an increase in the spillover of volatility.

⁴⁰ See, Reinhart and Rogoff (2009).

⁴¹ The posterior estimates of the parameters that are contained in the θ vector are reported in the online Appendix, which also contains additional diagnostic information for these models.

spikes in the reported measure of volatility when compared to the stochastic volatility estimates which are slightly smoother.⁴²

(ii) *The Spillover Index for the Stochastic Trend in Volatility* In what follows, we refer to the index based on the stochastic volatility proxy as the *underlying volatility spillover index* and the index based on the squared returns proxy as the *squared returns spillover index*. These results are provided in figures E.5 and E.6.

The results from this investigation display a number of interesting characteristics. Firstly, the underlying volatility spillover index appears to be less smooth than the squared returns spillover index. Secondly, underlying volatility spillover index does not respond as strongly to the financial crisis. And lastly, this index is estimated to be very high for most currencies, spillovers consistently explain approximately 80% of the variance in the *underlying* volatility process, but only 15-30% of the variance in the observed measure of volatility during periods of relative tranquility, and between 50% and 80% during periods of financial turmoil. The underlying volatility spillover index is also higher than what Diebold and Yilmaz (2009) found for volatility spillovers in equity markets (40-80%).

Closer inspection of figure E.5 reveals that both spillover estimates react to the financial crisis of 2008 and also appear to have been high in the aftermath of the dot-com bubble that burst in 2001. In addition, the squared returns spillover index displays a positive trend between these events, with a slightly higher growth rate than the underlying volatility spillover index. These findings would suggest that the squared returns index is dominated by global shocks, which facilitate greater cross-country linkages during financial crises that could foster an environment that is conducive to contagion. In contrast, the underlying volatility process shows no such effects of contagion, as the spillover between currencies during crises occurs at approximately the same rate, as during periods of benign economic activity.

A further interesting result is contained in figure E.6, which suggests that the underlying volatility spillover index for South African volatility has displayed a clear positive trend (which is very similar to the spillover index that incorporates shocks to the volatility process). Notably, no other currencies display this positive trend in underlying volatility spillovers. In addition, the South African index also differs to other countries in that the underlying volatility spillovers have been relatively low (around 30%) at times. These values were experienced towards the end of 2001 and the beginning of 2002, after the bursting of the dot-com bubble, and another albeit slower reduction in the spillover index happened in 2006. Both these events took place during periods when the South African rand was experiencing some sort of currency crisis (Knedlik, 2006; Knedlik and Scheufele, 2008). This is an important finding, as it suggests that the South African rand crisis of 2001-2002 may have affected some of the structural factors in the economy, which impacted on the trend of the volatility process; causing it to act more independently of other currencies (*i.e.* we cannot attribute this event to a unique volatility shock). In addition, we also note that it took approximately six to eight years before the spillovers in the underlying volatility spillovers returned to

⁴² The extreme variation in the squared returns for several currencies is less visible due to the scale of the y-axis, which is adapted to capture the outliers in volatility in 2008 and 2002.

comparative global levels, at the time of the global financial crisis.⁴³ Furthermore, it appears as if the South African rand was converging on the respective global level (at a relatively slow pace), possibly as a result of increased financial integration. However, following the onset of the global financial crisis of 2008, this convergence was accelerated (at an above average rate).

Another currency in our sample that provides a highly interesting case study is the Swiss Franc (CHF). It appears that the announcement on 6 of September 2011 that the Swiss National Bank (SNB) would put a ceiling on the CHF/EUR exchange rate has greatly affected its squared returns spillover index. Spillovers in exchange rate noise dropped by 25 percentage points after this announcement and are now lower than at any other point in our sample. There is also a slight dip in the spillovers for underlying volatility, although one would have possibly expected to see a larger decline as this index should respond to more permanent interventions (or structural changes) in the exchange rate.⁴⁴

5.3. Implications for Financial Practitioners

The finding that the underlying volatility trends are characterised by consistently high spillover levels would suggest that the long-term currency volatility spillovers are largely driven by spillovers from other currencies. After including the effect of shocks the results suggest that the additional noise in the process would produce lower estimates for the spillover index during benign periods and higher values during periods of crisis. In addition, the results suggest that the variance of day-to-day noise during benign periods is largely influenced by domestic shocks to each of the respective currencies. However, if the foreign exchange market is suffering from some form of severe financial stress, then these global shocks would cause the measure for spillovers in observed volatility to spike.

This information may assist those who are involved in risk management and option pricing, since it would imply that when forecasting long-term currency risk, one should place more emphasis on global events (rather than domestic country specific shocks). In the short term, however, country specific shocks to the respective economy may be more important. The exception to this general rule occurs during a period of a global financial crisis where global shocks are more important, and their effect is more severe and acute. While it is beyond the scope of this study to investigate the implications of these findings for forecasting currency returns and volatility, we see scope for possible improvements to made in terms of the confidence interval of the forecasts by changing the assumed impact

⁴³ This may also be due to an intervention by the central bank over this periods of time to protect the value of the domestic currency during a period of crisis, where they may have sought to dampen the extent of the shock (which resulted in a larger eventual deviation in the trend).

⁴⁴ In the SNB's latest Quarterly Bulletin, it is confirmed that "The Swiss National Bank (SNB) will continue to enforce the minimum exchange rate of CHF 1.20 per euro with the utmost determination" (SNB, 2011). It is worth noting that our data set ends just two months after the announcement of this ceiling, and during these two months, limited interventions would have been required of the SNB as the CHF was significantly stronger than the ceiling. This moderate intervention by the central bank has thus had little influence over the spillover index. Such behaviour may change, as the SNB has been forced to support the external value of its currency (since November 2011), which may result in a reduction of the spillover index for this currency.

of shocks to other currencies in accordance with the spillover index (when working with large forecasting models).⁴⁵

The findings are also of interest to those who are concerned with hedging against the volatility risk that is related to a particular market segment. For example, if you are looking to invest in an asset of a particular country that incurs a large spillover from another country, then you could hedge your currency risk by choosing to short either of these two currencies (depending on availability, transaction costs, liquidity, etc.). In addition, if you are looking to purchase a number of assets from a particular region, then rather than short each one of these currencies (which may result in relatively high transaction costs), you could elect to short the currency that has the highest spillover from the region. Of course, such a strategy would be more suited to long-term investment strategies, as short-term volatility is largely driven by country specific shocks (during the greater portion of our sample). Furthermore, information regarding an unexpected reduction in the spillover index, as occurred for the Swiss franc in 2011 and the South African rand in 2001-2002, may also be of interest to financial agents as it may indicate a sharp change in country specific factors.

6. CONCLUDING REMARKS

This paper has provided a rigorous investigation of spillover effects in the foreign exchange market, with a special focus on emerging market currencies and the South African rand. The framework was based upon that of Diebold and Yilmaz (2009), who consider the effects of spillovers in developed world equity markets. In many ways our initial results are very similar to those found in the existing literature, in that return spillovers are characterised by a positive and smooth trend (which does not react strongly to financial events). In addition, the spillover index for volatility (as measured by squared returns), displays more abrupt changes in response to global financial events, such as the bursting dot-com bubble of 2001 and the financial crisis of 2008. It is interesting to note the spillover index for short-term observed volatility appears to respond in a non-linear fashion to high-volatility events. A topic for future research may be whether there is a threshold of global risk or uncertainty (as measured by expectations driven indices such as the VIX) at which volatility spillovers will abruptly spike to a higher level.

To gain deeper understanding of the volatility spillovers, we estimated an index on the underlying trend in volatility after removing the effect of stochastic shocks with the aid of a stochastic volatility model that employs the particle filter of Liu and West (2001). It is argued that the high noise-to-signal ratio of squared returns makes this proxy more conducive to an estimate of short-term variability, while the stochastic volatility estimate reflects the long-term underlying volatility process. The estimates of the stochastic volatility model were then used to create a spillover index for latent underlying volatility.

The spillover index for the underlying volatility process is consistently very high, around 80% for most currencies, and displays no apparent change in the trend (which is in contrast to the behaviour of spillover index for squared returns). In addition, the underlying volatility process displays only moderate reactions to the global financial crisis, much like the reaction of return spillovers. This suggests that the abrupt changes in

⁴⁵ This is due to the fact that the spillover index adds information about the sources of the forecast variance.

volatility spillovers that has repeatedly been observed in the literature (for example by Diebold and Yilmaz 2009 and Duncan and Kabundi 2011a) are generally responding to short-term stochastic exchange rate shocks and are not caused by structural changes to the respective currency's volatility process.

The spillover index for underlying volatility behaved different for the South African rand than the other currencies. In South Africa, the measure of underlying volatility spillovers behaved similarly to the spillovers in squared returns. This would suggest that the volatility spillover index responded to structural changes to the South African economy which occurred over time. It may be surprising that other emerging economies (which may have experienced similar structural changes after becoming more integrated in the global economy) did not see the same change in the underlying volatility spillover index. Thus, the reason for the unique behaviour of South Africa's underlying volatility spillover index appears to be the South Africa's specific currency crisis in 2001-2002. During this crisis, the structural underlying volatility of the rand was dominated by South African specific events, which explains the low underlying volatility spillover index during this period of time. After the crisis, the underlying volatility has gradually returned to the level shared by most other emerging and developed economies.

In addition, it is also noted that the returns and squared returns spillover indices for South Africa behave similarly to those of other major emerging markets such as the Korean Won, Mexican Peso and Brazilian Real following the onset of the global financial crisis. These emerging market currencies were all characterised by a considerable increase in return spillovers, from less than 20% in 2002 to more than 60% in 2011. The same currencies saw the spillover index for squared returns move from less than 20% prior to the global financial crisis to between 70% and 100% at the peak of the crisis.

Lastly, future research into volatility spillovers, not only in foreign exchange markets but also equities and other asset classes, should possibly incorporate a study to distinguish between spillovers in long-term underlying volatility and the effects of short-term shocks. The results of this paper provide evidence that the spillover effects of the two types of volatility are likely to behave differently over time and a study of their behaviour may provide for an interesting subject for further analysis. In addition, it would also be of interest to investigate the effects of changes to the various spillover indices, with regards to their possible impact on macroeconomic measures.

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APPENDIX A. SPILLOVERS IN RETURNS FOR SELECTED REGIONS AND COUNTRIES

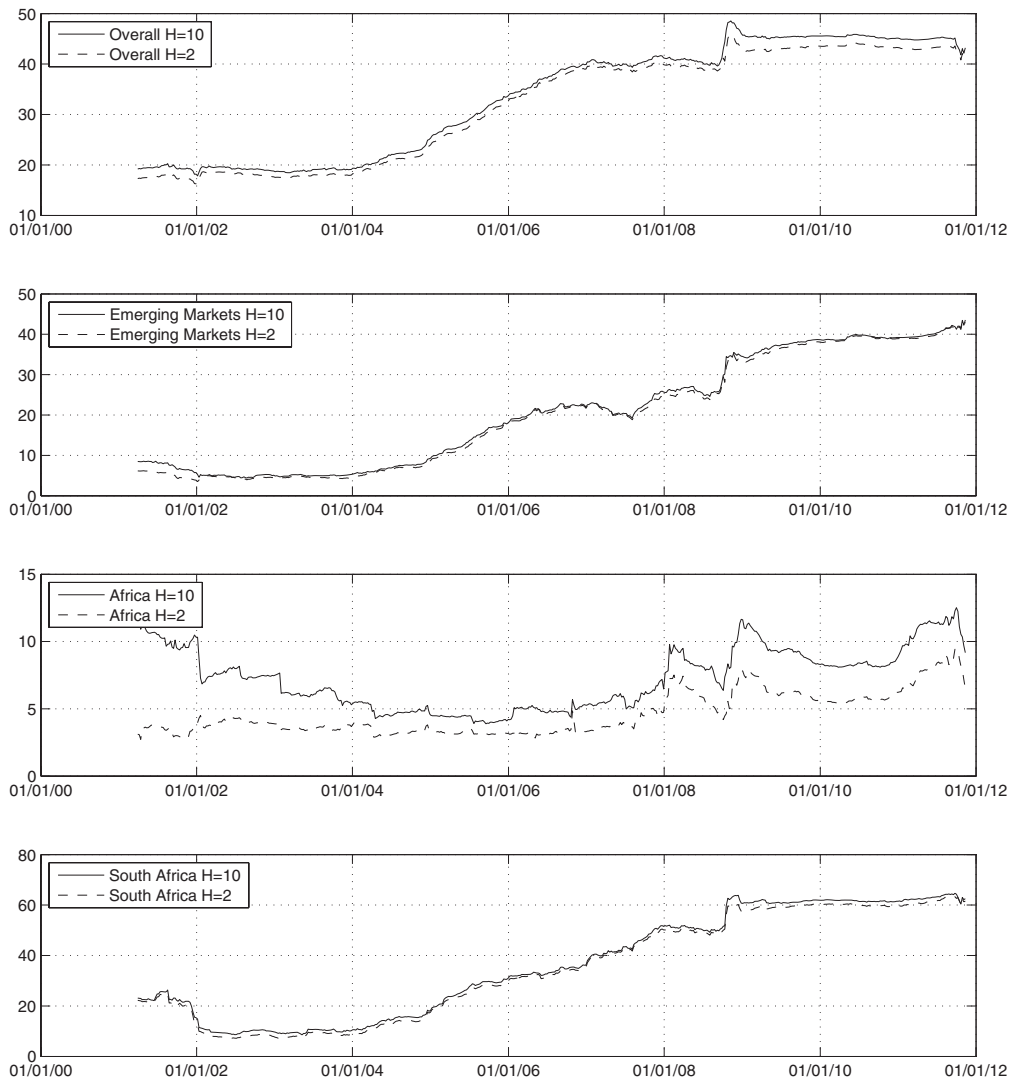


Figure A1. Spillover index for returns estimated with a 3 year (720 day) rolling window

APPENDIX B. SPILLOVERS IN VOLATILITY FOR SELECTED REGIONS AND COUNTRIES

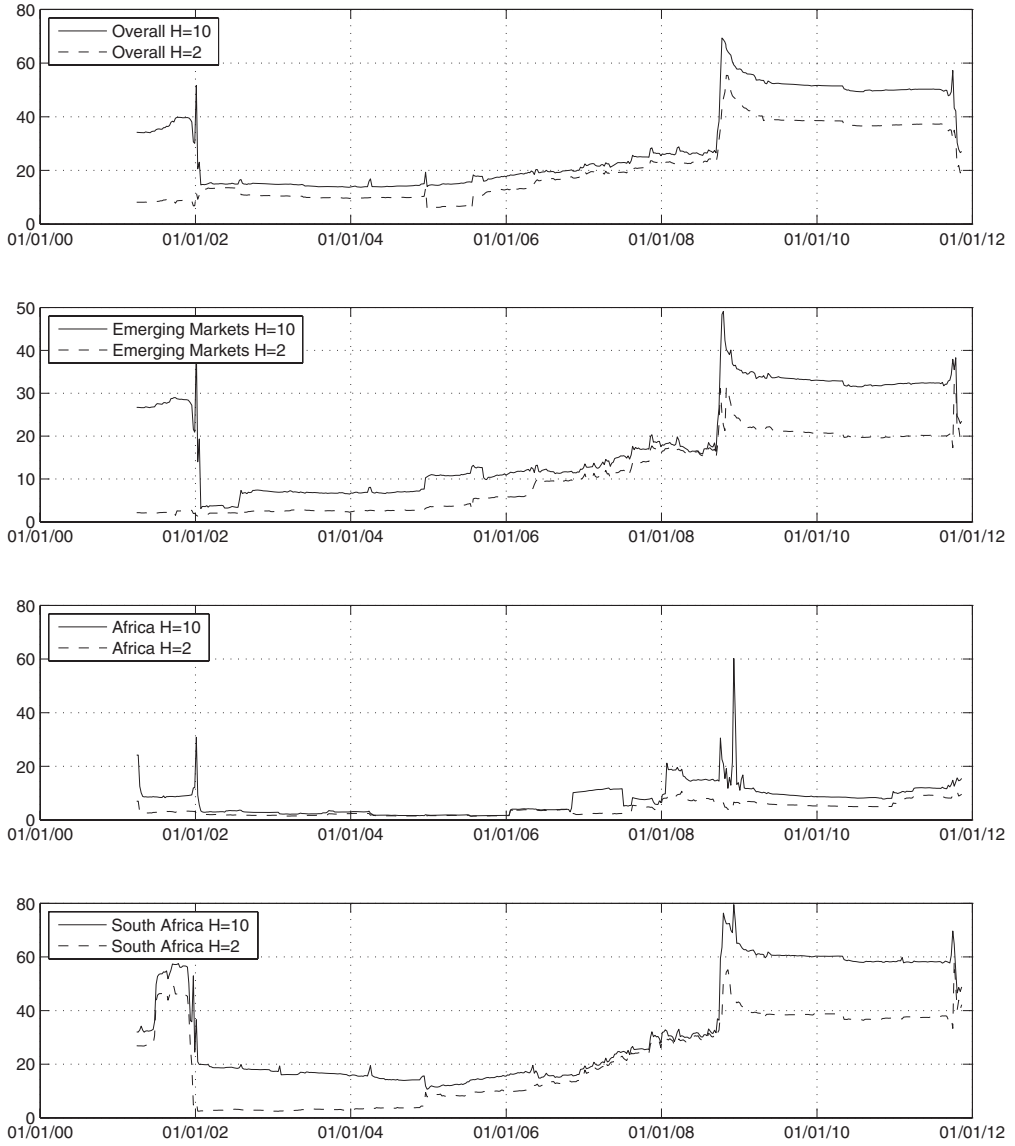


Figure B2. Spillover index for volatility estimated with 3 year (720 day) rolling window

APPENDIX C. ALTERNATIVE CHOLESKY ORDERING

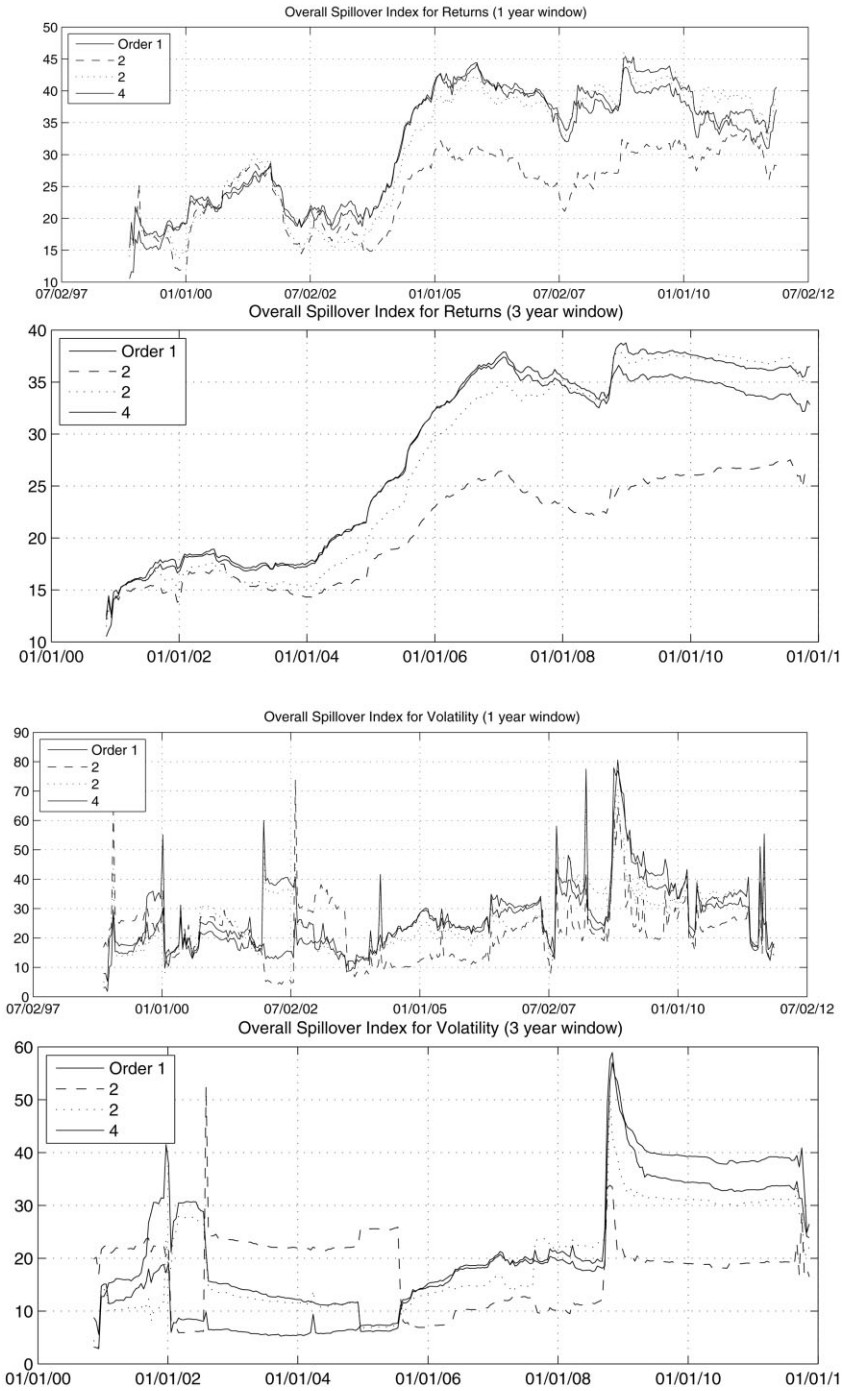


Figure C3. Alternative Cholesky Orderings. Estimated with 1 year (top) and 3 year (bottom) rolling windows

APPENDIX D. ESTIMATES OF STOCHASTIC VOLATILITY IN THE ZAR

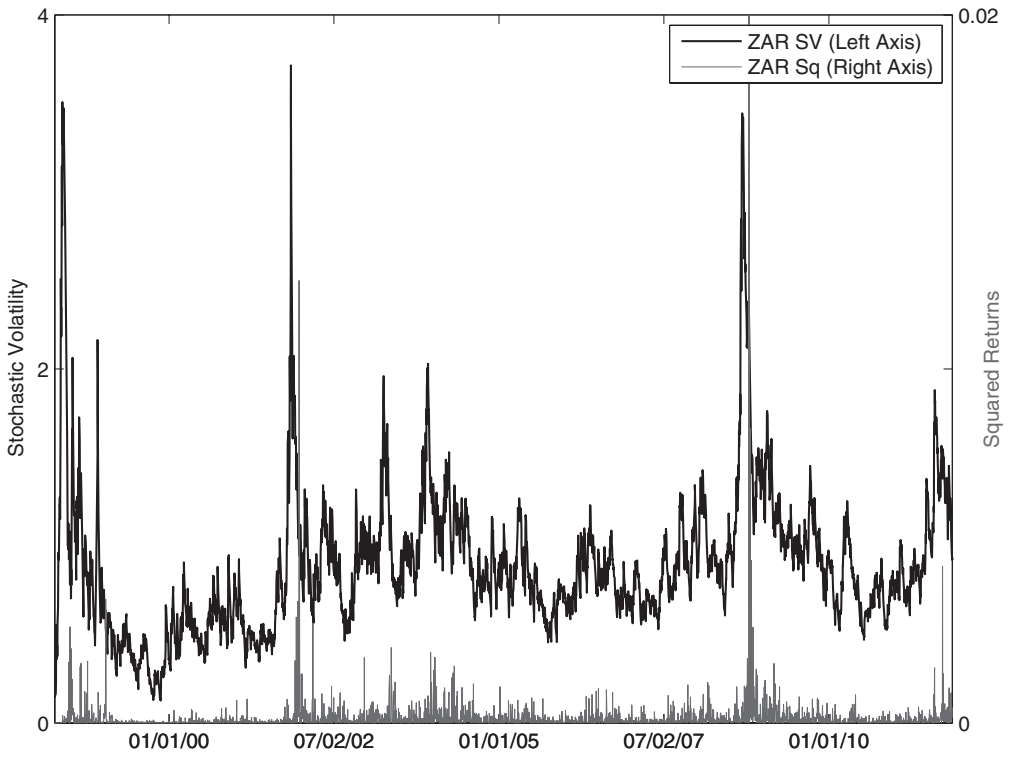


Figure D4. Stochastic volatility (black line, left axis) and squared returns (grey line, right axis)

APPENDIX E. THE EFFECTS OF VOLATILITY SHOCKS AND CHANGES TO THE STOCHASTIC TREND

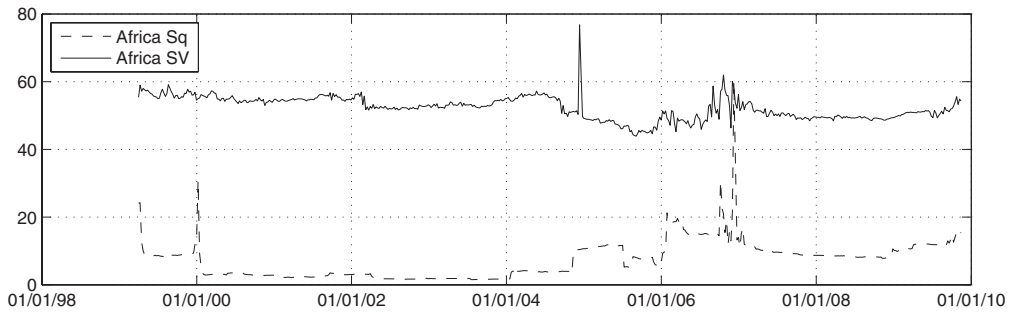
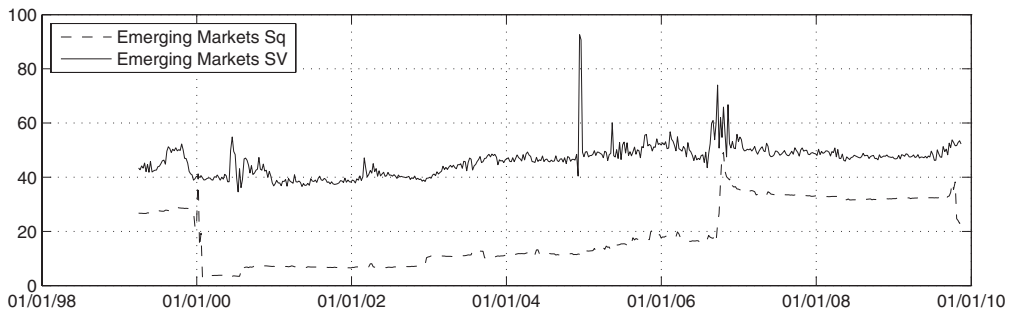
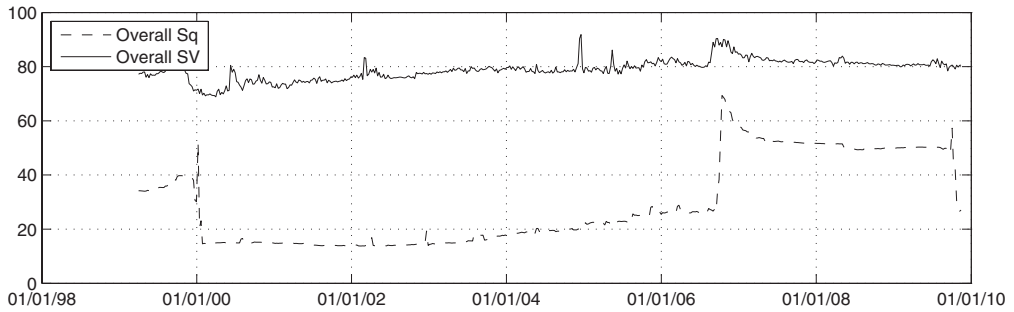


Figure E5. Overall, Emerging Market and Africa spillover index for volatility, based on stochastic volatility estimates (SV) and squared returns (Sq)

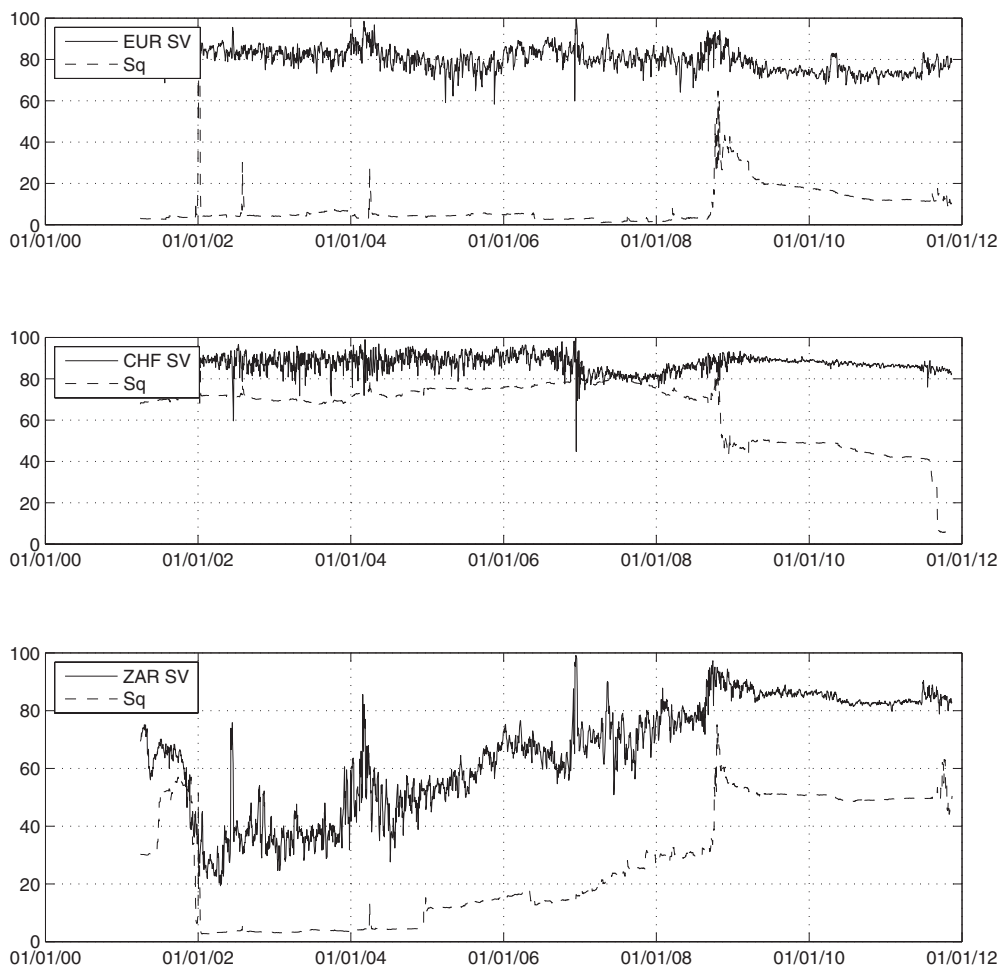


Figure E6. Individual spillover index for volatility, based on stochastic volatility estimates (SV) and squared returns (Sq)

Table E2. Summary Statistics of the Exchange Rate Data (measured in returns)

	EUR	JPY	GBP	AUD	CHF	CAD	KRW	MXN	INR	BRL	EGP	MUR	KES	NGN	ZAR
mean	0	-0.01	0	-0.01	-0.01	-0.01	-0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.01
stan. dev.	0.66	0.71	0.58	0.89	0.72	0.58	0.8	0.69	0.36	1.14	0.43	0.61	0.54	1.02	1.15
skewness	0.04	-0.37	-0.31	0.49	0.42	0.17	-0.65	0.85	0.06	0.47	14.73	0.69	0.18	-0.55	0.87
kurtosis	4.28	9.49	5.6	16.76	11.77	6.33	33.85	18.85	13.29	16.61	500.48	28.94	17.69	54.55	19.83