Economic Modelling 31 (2013) 566–573

Contents lists available at SciVerse ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Domestic and foreign sources of volatility spillover to South African asset classes☆

Andrew S. Duncan *, Alain Kabundi

Department of Economics and Econometrics, University of Johannesburg, Auckland Park, 2006, Johannesburg, South Africa

ARTICLE INFO

Article history:
Accepted 11 November 2012

JEL classification:
G01
G1
F3

Keywords:
Asset market linkages
Financial crises
Generalised variance decompositions
Small open economies
Volatility spillovers

ABSTRACT

The paper characterises domestic and foreign sources of volatility transmission for South African (SA) bonds, commodities, currencies, and equities. We introduce a small-open-economy extension of the volatility spillover model proposed by Diebold and Yilmaz (2012). Based on generalised variance decompositions (Pesaran and Shin, 1998) of a vector autoregressive model, this approach combines bidirectional spillovers exchanged by domestic assets with volatility injections imported from shocks to the global financial system. The analysis relates to a sample of daily observations ranging from October 1996 to June 2010. The estimated spillover levels are time-varying, and increase during domestic and foreign crises. Average domestic spillovers of 38% exceed average foreign spillovers of 4.7%, and maximum domestic spillovers estimated for the United States for a similar sample period (Diebold and Yilmaz, 2012). These findings suggest a high degree of systemic risk in SA and, furthermore, that this risk is predominantly related to country-specific factors. Commodity and equity shocks are identified as the primary sources of spillovers to other asset classes.

1. Introduction

This paper studies volatility transmission as it relates to representatives of four South African (SA) asset classes, namely bonds, commodities, currencies, and equities. The objective is to empirically characterise domestic and foreign sources of volatility spillover. A volatility spillover is the share of future variability in one asset's returns that is expected to result from volatility surprises in another asset. The study is motivated by a large literature that documents synchronisation of cross-market volatilities, both internationally and across different asset classes (see, for example, Duncan and Kabundi, 2011a; Dungey and Martin, 2007; Morana and Beltratti, 2008).

Volatility spillovers are computed using a small-open-economy (SOE) extension of the method proposed by Diebold and Yilmaz (2012). In this method, spillovers are derived from generalised variance decompositions (GVDs; Pesaran and Shin, 1998) of a vector autoregressive (VAR) model. GVDs are invariant to variable ordering, thus facilitating bidirectional shock transmission in the VAR. This precludes the imposition of *a priori* restrictions on the causality of domestic spillovers. The bidirectional property is an important feature of the model, since theories of cross-market connections between asset markets are still in their infancy.[1]

A novel contribution of the paper is to introduce foreign sources of volatility spillover to domestic assets. However, spillovers are not permitted to flow in the opposite direction. This restriction reflects the idea that, whilst SOEs such as SA may be highly sensitive to international events, financial shocks originating in these economies are idiosyncratic to the global financial system. For simplicity, we consider only one source of foreign volatility transmission, namely the Chicago Board Exchange Market Volatility Index (VIX).[2] The VIX – popularly referred to as the "fear index" – measures the option cost of insuring against downside risk in the United States (US) S&P 500 index, the world's largest equity market.

The results are based on a sample of daily observations ranging from October 1996 to June 2010. Time-varying spillover estimates are obtained from 200-period (40 weeks) rolling window regressions. On average, domestic spillovers account for 38% of system-wide volatility. Spillover magnitudes range between 15.9 and 75%, indicating the importance of structural breaks in volatility transmission. Peaks in spillover levels are correlated with the timing of recurring crises in the domestic currency market and in the global financial system. In particular, domestic spillovers in excess of 70% are recorded during the

☆ The authors gratefully acknowledge financial support from the Economic Research Southern Africa (ERSA). We have benefitted from the comments and suggestions of an anonymous referee. We also received useful feedback from Shakill Hassan and Nicola Viegi. The usual disclaimer applies.

* Corresponding author.
E-mail addresses: andrewd@uj.ac.za (A.S. Duncan), akabundi@uj.ac.za (A. Kabundi).

[1] Allen and Gale (2000), Battiston et al. (2012, forthcoming), Blume et al. (2011), and others, use network theory to describe financial connectivity, particularly between banks. Refer to Allen and Babus (2009) for a survey of this literature. However, these models have yet to be applied to explain domestic or international linkages across asset classes.

[2] We thank an anonymous referee for this suggestion.

0264-9993/$ – see front matter
http://dx.doi.org/10.1016/j.econmod.2012.11.016

Asian crisis of 1997–8, during the 1998 SA currency crisis, and prior to the US dot-com crisis in 2000. Magnitudes of SA spillovers are much larger than those of corresponding spillovers estimated for US asset classes using the same approach (Diebold and Yilmaz, 2012). This indicates, that relative to the US benchmark, there is a high degree of cross-market volatility dependence in SA.

Commodity and equity markets are identified as the primary origins for spillovers to other asset classes. As a net receiver of spillovers on 91.8% of trading days, the bond market plays a passive role in volatility transmission. The same conclusion generally applies to the currency market. However, in the period following the 2001 currency crisis up until the end of 2005, currency shocks temporarily dominate domestic volatility transmission.

With an average value of only 4.7%, foreign spillovers are relatively small in magnitude. Nevertheless, up to 20.9% of SA volatility is imported during the Asian crisis. Other peaks in foreign spillovers are measured following the September 2001 terrorist attack and during the 2007–8 subprime crisis. The maximum foreign spillover of 29.7% occurs on 7 May 2010, the day following the "flash-crash" in US equities (Easley et al., 2011).

The paper is one of only a few studies to model volatility spillovers across both national and asset class dimensions. In this respect, Dungey and Martin (2007) represent an important precursor to our analysis. These authors 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.[3] Dungey and Martin (2007) focus on interactions between currency and equity markets located in countries affected (directly or indirectly) by the Asian crisis. Variance decompositions of the modelled factors indicate an important role for bidirectional contagion and spillovers in most countries, especially in the post-crisis period.[4]

Fleming et al. (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.[5] 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, the authors estimate their model for US futures markets in a sample period ranging from January 1983 to August 1995. Their results suggest strong comovements of volatility across all three asset classes. They find that market linkages are time-varying. In particular, correlations between realised volatility in different asset classes increase following the 1987 stock market crash.

The class of spillover indices that we describe above is originally developed by Diebold and Yilmaz (2009, 2012). In the first paper, the authors use variance decompositions from a Cholesky-restricted VAR to measure unidirectional returns and volatility spillovers between 1992 and 2007 for a panel of seven developed and twelve emerging markets. The results indicate, that whilst returns spillovers increase smoothly over time, the level of volatility spillover is characterised by substantial instability. Local maxima in volatility spillovers coincide with periods of global financial crisis. In the second paper, bidirectional spillovers are introduced to study domestic volatility transmission across US bonds, commodities, currencies, and equities between 1999 and 2010. Once again, spillover magnitudes fluctuate through time, reaching a maximum of roughly 32% during the subprime crises.

The rest of the paper is structured as follows. Section 2 outlines the methodology used in constructing domestic and foreign volatility spillover indices. Details of the data set are provided in Section 3. The results are summarised in Section 4. The implications of our findings are discussed in Section 5. Section 6 concludes.

2. Methodology

Let $\mathbf{x}_t=(\mathbf{y}_t,\mathbf{z}_t)'$, where $\mathbf{y}_t=(y_{1t},y_{2t},\ldots,y_{mt})$ is a vector of volatilities in m domestic asset classes, and $\mathbf{z}_t=(z_{m+1},z_{m+2},\ldots,z_n)$ is a vector of n–m foreign volatility sources $(1\leq m\leq n)$. Consider the VAR(p) model given by

$$\mathbf{x}_t=\sum_{k=1}^{p}\Phi_k\mathbf{x}_{t-k}+\epsilon_t, \tag{1}$$

where, for $k=1,\ldots,p$, Φ_k is a coefficient matrix and $\epsilon_t=(\epsilon_t^d,\epsilon_t^f)'$ is a vector of mean-zero error terms. The error vectors, $\epsilon_t^d=(\varepsilon_{1t}^d,\varepsilon_{2t}^d\ldots,\varepsilon_{mt}^d)$ and $\epsilon_t^f=(\varepsilon_{m+1t}^f,\varepsilon_{m+2t}^f\ldots,\varepsilon_{nt}^f)$, collect the innovations associated with $\mathbf{y}_t$ and $\mathbf{z}_t$, respectively. We assume that ϵ_t has a multivariate normal distribution, with ϵ_t independent of $\epsilon_s(s\neq t)$, and with nonsingular covariance matrix $\Sigma_\epsilon=E_{t-1}(\epsilon_t\epsilon_t')=\{\sigma_{ij}\}$.

In the case of domestic assets, our intention is to measure bidirectional volatility spillovers, as well as spillovers received from foreign sources. In contrast, we assume that foreign volatilities are independent of each other and that they are unaffected by spillovers from shocks to domestic assets. Thus, we impose the following restriction on the form of each Φ_k:

$$\Phi=\begin{bmatrix}\phi_{1,1}^d & \cdots & \phi_{1,m}^d & \phi_{1,m+1}^f & \phi_{1,m+2}^f & \phi_{1,m+3}^f & \cdots & \phi_{1,n}^f\\ \vdots & & & & & & & \vdots\\ \phi_{m,1}^d & \cdots & \phi_{m,m}^d & \phi_{m,m+1}^f & \phi_{m,m+2}^f & \phi_{m,m+3}^f & \cdots & \phi_{m,n}^f\\ 0 & \cdots & 0 & \phi_{m+1,m+1}^f & 0 & 0 & \cdots & 0\\ 0 & \cdots & 0 & 0 & \phi_{m+2,m+2}^f & 0 & \cdots & 0\\ 0 & \cdots & 0 & 0 & 0 & \ddots & \cdots & 0\\ \vdots & & & & & & & \vdots\\ 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & \phi_{n,n}^f\end{bmatrix},$$

where k is suppressed for notational convenience.

Under covariance stationarity, Eq. (1) has an infinite moving average representation:

$$\mathbf{x}_t=\sum_{k=0}^{\infty}A_k\epsilon_{t-k}. \tag{2}$$

By setting $A_k=0$ for $k<0$ and $A_0=I_n$ (where I_n is the n-dimensional identity matrix), we establish coefficient matrix $A_k=\Phi_1A_{k-1}+\Phi_2A_{k-2}+\cdots\Phi_pA_{k-p}$ recursively for $k=1,2,\ldots$.

Pesaran and Shin (1998) define the h-step-ahead *generalised* forecast-error variance decomposition (GVD) for variable i as follows:

$$\theta_{ij}^h=\frac{\sigma_{ii}^{-1}\sum_{\ell=0}^{h}\left(\mathbf{e}_i'A_\ell\Sigma_\epsilon\mathbf{e}_j\right)^2}{\sum_{\ell=0}^{h}\mathbf{e}_i'A_\ell\Sigma_\epsilon A_\ell'\mathbf{e}_i}, \tag{3}$$

where $\mathbf{e}_i$ denotes the ith column of I_n. In the sequel, we suppress the h in θ_{ij}^h for notational convenience. A special property of the GVD is that θ_{ij} is invariant to the ordering of variables i and j in the VAR.[6]

Volatility spillover indices are constructed using GVDs as inputs. In this context, θ_{ij} measures the expected magnitude (in absolute terms) of h-horizon future volatility in asset i which is attributable to period-t volatility in asset j.

[3] 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.

[4] Also refer to Dungey et al. (2010), who use Dungey and Martin's (2007) framework to study similarities between several recent financial crises.

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

[6] Pesaran and Shin (1998) show that if Σ_ϵ is nondiagonal, then generalised impulse responses and GVDs coincide with their Cholesky-restricted analogues only if j is the first variable included in the VAR.