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Volatility spillover shifts in global financial markets☆

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ABSTRACT

This paper analyzes the volatility spillovers across global financial markets using a generalized variance decomposition, and by incorporating a fast-tractable Markov regime-switching framework into the vector autoregressive (VAR) model. The new approach outperforms the classical single-regime framework, by detecting different dynamics of spillovers during periods of crisis and periods of tranquility. Moreover, the proposed estimation method has the advantage over existing procedures to converge remarkably fast when applied to a large number of variables. Empirical investigation on volatility indices of eight developed financial stock markets shows that the total and directional spillovers are more intense during turbulent periods, with frequent swings between net risk transmission and net risk reception. Conversely, during periods of tranquility, volatility spillovers are relatively moderate.

1. Introduction

The last three decades have known large perturbations in financial markets, which resulted in widespread international crises, such as the black Monday of October 1987, the U.S. born global financial crisis of 2008–2009, and the European sovereign debt crisis in late 2009, among others. Following these major events, an exuberant financial literature studied the mechanism of shock transmission across borders and came up with words, such as "*contagion*" to define the increase in cross-market linkage after a shock (Forbes and Rigobon, 2002), and "*volatility spillovers*" to define the causality in variance between markets (Engle et al., 1990). Both definitions indicate shock transmissions that cannot be explained by fundamentals, nor co-movements (Bekaert et al., 2014), and the distinction between them is tenuous and model dependent. Rigobon (2016) argues that spillovers are present during good and bad times to measure the interdependence, whereas, the contagion is more prominent during crises and measures the degree of intensification of shock propagation. In a recent study, Wegener et al. (2018) introduced the concept of *spillovers of explosive regimes* to shed light on the migration process between crises, *i.e.*, how one crisis triggers another one.

Spillovers are observed in returns and volatility, which is usually associated with risk (Diebold and Yilmaz, 2009). Understanding the volatility in financial markets is crucial to risk managers, decision makers, and hedgers, especially in the aftermath of financial crises. Consequently, studying the volatility spillovers has direct implications on designing optimal portfolios and building policies to prevent harmful shock transmission.

This paper extends the work of Diebold and Yilmaz (2012) by incorporating a Markov switching framework into the generalized vector autoregressive (VAR) model. Analyzing shifts in the volatility spillovers is of particular interest. Indeed, this approach takes into account the different volatility states – high and low – and interdependences due to economic and financial changes. Moreover, shifts in regimes are regarded as random events and unpredictable to allow better identification of the different volatility states. Application is conducted on volatility indices – Option-implied standard deviations of stock indices – of eight developed financial stock markets, namely, U.S., U.K., France, Germany, Netherlands, Switzerland, Hong Kong, and Japan.

There exist extensive literature dealing with regime-switching volatility spillovers. For instance, Billio and Pelizzon (2003) studied the spillovers using a switching beta model; Baele (2005) employed a

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simple linear model with heteroskedastic volatility, where the Markov chain is introduced in the mean equation; Psaradakis et al. (2005) used a switching bivariate VAR model to analyze changes in the Granger causality; Gallo and Otranto (2008) developed a multi-chain Markov switching model to detect spillovers; Beckmann et al. (2014) advanced a Markov switching vector error correction model (VECM) with shifts in the adjustment coefficients and the variance-covariance matrix by applying a Gibbs sampler to analyze the relationship between global liquidity and commodity prices; Nomikos and Salvador (2014) utilized a Markov bivariate BEKK model to compute the time varying correlation; and Otranto (2015) proposed a multiplicative error model with highly complicated transition probability matrix to capture the volatility spillovers. The main drawback of these studies is that they analyze spillovers on bivariate cases due to the complexity of their designs, *i.e.*, even when applied to multiple dependent variables, the transmission mechanism is still investigated for a pair of variables at a time. Recently, Leung et al. (2017) avoided the complexity of regime-switching models by incorporating a dummy variable in a simple linear regression framework to examine possible changes of volatility spillovers during crises. However, to estimate this model, crisis periods must be defined in advance, ruling out undocumented bursts that may follow major events, and we prefer the full power of unpredictable regime shift detection offered by Markov switching models.

Our motivation for a Markov switching framework is to extend the risk propagation analysis, by shedding light on the elusive dynamics of volatility spillovers among financial markets during largely documented turmoil periods, as well as undocumented side bursts that may follow these major events. Commonly, crashes in financial markets are unpredictable, as market downturns are associated with periods of high risk (Bekaert et al., 2014). Therefore, the issue of volatility spillovers across stock markets is nontrivial to investors in managing their optimal portfolio diversification and asset allocation strategies, and to decision makers in promoting financial stability.

Our study is the first to incorporate a Markov regime-switching into a vector autoregressive model to infer the multiple spillover indices. First, we employ a simple method similar to Diebold and Yilmaz (2012) to compute directional and net spillovers across markets. Second, contrary to previous researches, our model is highly tractable even for a large number of dependent variables. Third, the proposed estimation method is remarkably fast compared to existing numerical procedures. Fourth, to the best of our knowledge, this is the first study to investigate volatility spillovers based on stock market volatility indices. Previous studies constructed the market volatility from index returns through different models, such as heteroskedastic models, or range volatility estimators of Parkinson (1980) or Rogers and Satchell (1991).

The remainder of the paper is organized as follows. Section 2 develops the regime-switching vector autoregressive model, and explains the estimation procedure. Section 3 explores the concept of spillovers. Section 4 presents the data and discusses the results. Finally, Section 5 concludes the paper.

2. The model

2.1. Regime-switching vector autoregressive

Diebold and Yilmaz (2009, 2012) state that the multivariate VAR model can be employed as a simple framework to measure volatility spillovers across different markets. We extend the generalized approach of Diebold and Yilmaz (2012), where the variable ordering has no influence on the spillover index, by allowing a Markov regime-switching. Consider a K-state Markov switching VAR model (MS-VAR) in eq. (1).

$$\boldsymbol{y}_t \mid s_t = \boldsymbol{\nu}_k + \sum_{i=1}^{p} \boldsymbol{\Phi}_{k,i}\boldsymbol{y}_{t-i} + \boldsymbol{u}_{s_t,t} \tag{1}$$

where $\boldsymbol{y}_t$ is a n-dimensional random vector of observations in $\mathbb{R}^n$, such that $\boldsymbol{y}_t = (y_{1,t}, \dots, y_{n,t})'$ for $t = 1, \dots, T$. $\boldsymbol{\nu}_k$ is a $(n \times 1)$ regime-dependent vector of intercepts; $\{\boldsymbol{\Phi}_{k,i}\}_{i=1}^{p}$ are $(n \times n)$ state-dependent matrices ($\boldsymbol{\Phi}_{k,p} \neq \mathbf{0}$, where $\mathbf{0}$ denotes the n-by-n null matrix); and $\boldsymbol{u}_{s_t,t}$ is a vector of residuals.

To allow for different variances in each regime, we set $\boldsymbol{u}_{s_t,t} = \boldsymbol{\Sigma}_k\, \boldsymbol{\varepsilon}_t$, with ϵ_t is a stationary and ergodic sequence of zero-mean independently and identically distributed (*i.i.d.*) white noise process assumed to be multivariate normal, *i.e.*, $\varepsilon_t \overset{i.i.d.}{\sim} \mathcal{N}(\mathbf{0}_n, \mathbf{I}_n)$, where $\mathbf{I}_n$ is the $(n \times n)$ identity matrix, and $\mathbf{0}_n$ is a $(n \times 1)$ vector of zeros. $\boldsymbol{\Sigma}_k$ represents a lower triangular $(n \times n)$ regime-dependent Cholesky factorization of the symmetric variance-covariance matrix denoted $\boldsymbol{\Omega}_k$. In other words, $\boldsymbol{\Omega}_k = \boldsymbol{\Sigma}_k \boldsymbol{\Sigma}_k'$. Hence, we have:

$$\boldsymbol{y}_t \mid s_t \sim \mathcal{N}(\boldsymbol{\nu}_k, \boldsymbol{\Omega}_k) \tag{2}$$

Each regime $k = \{1, \dots, K\}$ is characterized by its own intercept vector $\boldsymbol{\nu}_k$, autoregressive matrices $\{\boldsymbol{\Phi}_{k,i}\}_{i=1}^{p}$ and variance-covariance matrix $\boldsymbol{\Omega}_k$. This model is based on the assumption of varying intercepts according to the state of market, controlled by the state variable $\{s_t\}$. The autoregressive parameter matrices control the intensity of spillovers among variables, depending on the regime. The Markov switching heteroskedastic variance-covariance matrix is exploited to identify structural shocks in the errors (Herwartz and Lütkepohl, 2014).

The state variable $\{s_t\}$ evolves according to a discrete, homogeneous, irreducible and ergodic first-order Markov chain with a transition probability matrix $\mathbf{P}$, *i.e.*, for K regimes $s_t = \{1, \dots, K\}$.[1] Each element of $\mathbf{P}$ denotes the probability of being in regime j at time t, knowing that at time $t-1$ the regime was i. It is expressed in eq. (3).

$$\mathbf{P} = \begin{pmatrix} p_{1,1} & \cdots & p_{1,K} \\ \vdots & \ddots & \vdots \\ p_{K,1} & \cdots & p_{K,K} \end{pmatrix} \qquad p_{i,j} = \Pr(s_t = j \mid s_{t-1} = i) \tag{3}$$

where each column of $\mathbf{P}$ sums up to one, $\sum_{i=1}^{K} p_{i,j} = 1$. In case of two regimes, the transition matrix becomes:

$$\mathbf{P} = \begin{pmatrix} p & 1-q \\ 1-p & q \end{pmatrix}$$

The ergodic or unconditional probability $\boldsymbol{\pi}$ is the eigenvector of $\mathbf{P}$ corresponding to the unit eigenvalue normalized by its sum. It satisfies $\mathbf{P}\,\boldsymbol{\pi} = \boldsymbol{\pi}$, and $\mathbf{1}_K'\boldsymbol{\pi} = 1$, where $\mathbf{1}_K$ is a $(K \times 1)$ column vector of ones (Hamilton, 1994, p. 684). Formally,

$$\boldsymbol{\pi} = \left(\mathbf{A}'\mathbf{A}\right)^{-1}\mathbf{A}' \begin{bmatrix} \mathbf{0}_K \\ 1 \end{bmatrix} \tag{4}$$

where $\mathbf{0}_K$ is a $(K \times 1)$ column vector of zeros, and

$$\underset{(K+1)\times K}{\mathbf{A}} = \begin{bmatrix} \mathbf{I}_K - \mathbf{P} \\ \mathbf{1}_K' \end{bmatrix}$$

In other words, $\boldsymbol{\pi}$ is the $(K+1)$th column of $\left(\mathbf{A}'\mathbf{A}\right)^{-1}\mathbf{A}'$. In the special case of two regimes, the unconditional probabilities are expressed as follows:

$$\begin{cases} \pi_1 &= \dfrac{1-q}{2-p-q} \\ \pi_2 &= \dfrac{1-p}{2-p-q} \end{cases}$$

[1] These properties are crucial to refrain the chain from being stuck in one state. Ergodicity implies that each state is aperiodic and recurrent.