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DOES THE SPILLOVER INDEX RESPOND SIGNIFICANTLY TO SYSTEMIC SHOCKS? A BOOTSTRAP-BASED PROBABILISTIC ANALYSIS

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Does the Spillover Index Respond Significantly to Systemic Shocks? A Bootstrap-Based Probabilistic Analysis

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Abstract:
The spillover index developed by Diebold and Yilmaz (Economic Journal, 2009, vol. 119, pp. 158-171) is widely used to measure connectedness in economic and financial networks. Abrupt increases in the spillover index are typically thought to result from systemic events, but evidence of the statistical significance of this relationship is largely absent from the literature. We develop a newbootstrap-based technique to evaluate the probability that the value of the spillover index changes over an arbitrary time period following an exogenously defined event. We apply our framework to the original dataset studied by Diebold and Yilmaz and obtain qualified support for the notion that the spillover index increases in a timely and statistically significant manner in the wake of systemic shocks.

JEL: C32; C58; G15
Keywords: Spillover index; systemic events; bootstrap-after-bootstrap procedure

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1 Introduction

The framework for network analysis put forth by Diebold and Yilmaz (2009) and refined by Diebold and Yilmaz (2012, 2014) represents one of the most important additions to the financial economist's toolbox in recent years. The authors' key insight is that a decomposition of the forecast error variances obtained from a vector autoregression (VAR) can be interpreted as a weighted directed network. The connectedness of the network is summarised by the *spillover index*, which measures the proportion of the total forecast error variance at a given forecast horizon that can be attributed to bilateral spillovers. The spillover index is typically evaluated over rolling samples to capture time-variation. Abrupt increases in the spillover index are evidence of increased connectedness, which is usually attributed to major economic, financial or political events. However, in the absence of an established method to characterise the density of the spillover index, such inference is chiefly based on visual inspection of point estimates of the spillover index, as opposed to a formal statistical analysis of the hypothesis that a change in the spillover index coincides with a given event. We address this issue by developing an inferential framework based on a non-parametric bootstrap-after-bootstrap procedure. We demonstrate our technique by replicating the empirical analysis of Diebold and Yilmaz (2009) to test whether the spillover index increases significantly in response to the list of adverse events that feature in the authors' narrative. Our results lend qualified support for the notion that the spillover index responds to exogenous events.

Interest in the analysis of economic and financial networks and the implications of network structure for the propagation of shocks has grown rapidly since the global financial crisis, when concerns over financial contagion and the possibility of cascading bank failures drew fresh attention to the risks of adverse spillover effects. The Diebold-Yilmaz technique is one of a number of frameworks for network analysis that have been proposed over this period. Alternative methods include the Granger-causal approach adopted by Billio, Getmansky, Lo and Pelizzon (2012), the impulse response analysis of Alter and Beyer (2014) and the decomposition of out-of-sample forecast errors advocated by Buse and Schienle (2019). The Diebold-Yilmaz technique has emerged as the most widely adopted of these methods, perhaps due to its relative ease of implementation and interpretation. The literature that applies the Diebold-Yilmaz technique can be grouped into four broad strands. The first strand focuses on spillovers among financial markets of the same type, such as the markets for equity (e.g. Engle, Gallo and Velucchi, 2012; Tsai, 2014; Baruník, Kočenda and Vácha, 2016; Yarovaya, Brzeszczyński and Lau, 2016), foreign exchange (e.g. McMillan and Speight, 2010; Bubák, Kočenda and Žikeš, 2011; Antonakakis, 2012; Greenwood-Nimmo, Nguyen and Rafferty, 2016; Baruník, Kočenda and Vácha, 2017; Greenwood-Nimmo, Nguyen and Shin, 2019b; Kočenda and Moravcová, 2019) and credit derivatives (e.g. Claeys and Vašíček, 2012; Alter and Beyer, 2014; Greenwood-Nimmo, Huang and Nguyen, 2019a; Ando, Greenwood-Nimmo and Shin, in press). The second strand considers spillovers between combinations of different types of financial markets. For example, Cronin (2014) studies the interactions between the money and asset markets, while Grobys (2015) and Do, Brooks and Treepongkaruna (2015) focus on interactions between the foreign exchange and stock markets. Substantial directional spillovers are identified between the foreign exchange and stock markets in both developed and emerging markets by Andreou, Matsi and Savvides (2013), Kumar (2013) and Do, Brooks, Treepongkaruna and Wu (2016) and in specific countries or regions, including the U.S. (Ito and Yamada, 2015), Japan (Jayasinghe and Tsui, 2008), China (Zhao, 2010), the Middle East and North Africa (Arfaoui and Ben Rejeb, 2015). The third strand focuses on more complex interactions and volatility spillovers between various combinations of the foreign exchange, equity, bond and commodity markets (Clements, Hurn and Volkov, 2015; Salisu and Mobolaji, 2013; Baruník and Kočenda, 2019; Duncan and Kabundi, 2013; Aboura and Chevallier, 2014), with a notable subset of papers focusing on spillovers to and from the oil market (e.g. Reboredo, 2014; Kang, Ratti and Yoon, 2014; Zhang and Wang, 2014; Baruník, Kočenda and Vácha, 2015). The final strand of literature considers macroeconomic linkages among countries and is well represented by Diebold and Yilmaz (2015) and Greenwood-Nimmo, Nguyen and Shin (2021).

In addition to applications of the Diebold-Yilmaz technique,a related literature focuses on refinements and extensions of the method itself. For example, Klößner and Wagner (2014) provide a method to explore all variable orderings in the construction of orthogonalised spillover indices, Baruník et al. (2016) suggest a methodology to quantify asymmetries in connectedness that arise due to positive and negative shocks, Baruník and Křehlík (2018) propose a framework for measuring connectedness that arises due to heterogeneous frequency responses to shocks and Ando et al. (in press) develop a method to characterise connectedness based on quantile regression.

Despite the significant effort that has been invested in applications and extensions of the Diebold-Yilmaz framework, none of the articles surveyed above has provided formal statistical evidence that connects changes in spillover activity with specific events. Nonetheless, progress is being made in this direction. For example, Greenwood-Nimmo et al. (2016) examine the extent to which large changes in the spillover index occur in conjunction with large changes to the federal funds rate, the TED spread and the VIX, although the analysis is based on coincidences in the timing of high/low values of these variables and does not invoke any formal statistical test. Meanwhile, Greenwood-Nimmo et al. (2019b) provide bootstrap intervals to accompany their spillover statistics, thereby providing a basis for inference. However, because the authors study a short sample of 82 trading days of foreign exchange data, they restrict their attention to full-sample analysis and they do not consider time-variation in the intensity of bilateral spillovers. More recently, Greenwood-Nimmo and Tarassow (in press) develop a bootstrap-based technique to conduct probabilistic analysis of spillover scenarios, defined through the application of inequality constraints to one or more of the edges in the estimated network. Because they focus on spillover scenarios defined at the disaggregate level, the authors do not investigate the statistical significance of changes in aggregate connectedness measured via the spillover index.

The importance of testing whether statistically significant changes in spillover activity coincide with systemic events is easily understood. The concept of financial market connectedness is of fundamental importance in asset pricing (Billio et al., 2012), portfolio allocation (Fengler and Gisler, 2015), risk management (Aboura and Chevallier, 2014) and for the development of options and hedging strategies (Jayasinghe and Tsui, 2008; James, Marsh and Sarno, 2012).[1] As a consequence, the spillover index is widely used to quantify changes in financial market connectedness, yet the degree to which these estimated changes reflect systemic conditions has yet to be formally evaluated. If the spillover index is to provide a reliable gauge of variations in financial market connectedness, then it should consistently adjust in a timely manner to systemic events. To date, the literature is silent on whether this is so.

Our goal in this paper is to develop a robust framework to test the statistical significance of changes in the spillover index. To do so, we propose a non-parametric bootstrap-after-bootstrap procedure that can be used to characterise the empirical distribution of the spillover index in order to form a foundation for statistical inference. Our technique displays several similarities to the bootstrap-after-bootstrap procedure developed by Kilian (1998) for the construction of bias-corrected small-sample confidence intervals for impulse response functions. Our use of bootstrap inference confers an important practical benefit relative to the use of asymptotic approximations, as its use is not limited to large samples.[2] Reliance on asymptotic inference may be inappropriate in cases where the spillover index is computed on a rolling-sample basis, as the length of the rolling samples will often be too short to justify a large-sample approximation in practice.

To demonstrate the utility of our framework, we revisit the analysis of global equity market connectedness conducted by Diebold and Yilmaz (2009) using the authors' original dataset, which covers 19 markets between January 1992 and November 2007. We begin with a full replication of the authors' results using both the orthogonalised spillover index employed by the authors as well as their more recent generalised spillover index (Diebold and Yilmaz, 2012, 2014). In practice, we find that the dynamics of the orthogonalised and generalised spillover indices are very similar. The main difference between the two is a level shift that arises because, unlike the orthogonalised spillover index, the generalised spillover index allows for the contemporaneous correlation among the reduced form

[1] Throughout this paper, we will use the terms 'connectedness' and 'spillovers' interchangeably, following the precedent established in the existing literature.

[2] It is worth noting that characterising the asymptotic distribution of the spillover index would be a challenging undertaking, given that it is defined as the ratio of two sets of aggregated forecast error variance decompositions, each of which takes a quadratic form in its own right.

disturbances in the VAR model, as documented by Diebold and Yilmaz (2014).

Next, we turn our attention to Diebold and Yilmaz's interpretation of changes in spillover activity. They observe that return spillovers display a gradual upward drift over their sample period, while volatility spillovers exhibit distinct bursts. This leads to the contention that, over their sample period, "many well-known events produced large volatility spillovers, whereas, with the possible exception of the recent subprime episode...*none* produced return spillovers" (p. 167). Given that Diebold and Yilmaz focus on events associated with changes in the volatility spillover index, we proceed in the same manner and test whether the volatility spillover index increases in a statistically significant manner for each of the events that they consider.

We use our bootstrap-after-bootstrap procedure to characterise the empirical density of the volatility spillover index on a rolling-sample basis. Diebold and Yilmaz (2009) compute spillover indices based on both daily and weekly data. Our technique can be applied at either frequency but we limit our attention to the daily dataset, because its higher sampling frequency allows the event dates to be identified with greater precision. Having obtained the empirical density of the spillover index in each rolling sample, it is straightforward to compute the probability that the volatility spillover index increases over a given event window. To define the relevant events, we first compile a list of events referenced by Diebold and Yilmaz (2009, Figure 3, p. 168) in their analysis of daily volatility spillovers. Diebold and Yilmaz (2009) do not provide precise dates for many of these events, so we analyse media coverage from the time of each event to precisely identify their timing. We then test the hypothesis that the daily volatility spillover index increases over each event window.

We measure the intensity of volatility spillovers prevailing before each event using the volatility spillover index estimated in the rolling sample ending immediately prior to the event date. We then compute the probability that the volatility spillover index increases over each of the following four windows relative to the day of each event: 0 days after the event (i.e. contemporaneously), 1 day after the event, 5 days (1 week) after the event and 22 days (1 month) after the event. Our results lend qualified support to the notion that the volatility spillover index increases significantly at the time of the events identified by Diebold and Yilmaz (2009). For 15 out of 19 events, using the same orthogonalised spillover index used by Diebold and Yilmaz (2009), we find a probability of 90% or more that the spillover index increases over at least one of these windows. However, we only find evidence of a contemporaneous increase in the spillover index for 6 events, which indicates that the spillover index may often react to systemic events with a lag. This suggests that the spillover index may be best suited to ex-post analysis, rather than for use as a contemporaneous or leading indicator.

The remainder of this paper is organised as follows. In Section 2, we summarise the connectedness framework developed by Diebold and Yilmaz (2009, 2012, 2014) and outline the bootstrap-after-bootstrap procedure that we devise to conduct statistical inference on the spillover index. In Section 3, we review the dataset used by Diebold and Yilmaz (2009), which the authors kindly shared with us. In Section 4, we present our replication of Diebold and Yilmaz (2009) and the results of our probabilistic analysis. In Section 5, we evaluate the sensitivity of our results to alternative definitions of the event window and to the use of different forecast horizons in the computation of the orthogonalised and generalised forecast error variance decompositions. We conclude in Section 6.

2 Empirical Methodology

2.1 The Spillover Index

The connectedness framework developed by Diebold and Yilmaz (2009) is based on a pth-order reduced form VAR model of the following form:

$$\boldsymbol{x}_t = \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{x}_{t-j} + \boldsymbol{u}_t, \tag{1}$$

for time periods $t = 1, \ldots, T$, where $\boldsymbol{x}_t$ is an $m \times 1$ vector of endogenous variables, $\boldsymbol{A}_j$, $j = 1, \ldots, p$ is the jth $m \times m$ autoregressive parameter matrix and $\boldsymbol{u}_t$ is an $m \times 1$ vector of mean-zero and serially uncorrelated disturbances with $m \times m$ positive-definite covariance matrix, $\boldsymbol{\Sigma}$. In (1), we omit deterministic terms for simplicity; their inclusion does not materially affect the discussion that follows.

The VAR(p) model (1) can be written as an infinite-order vector moving average (VMA(∞)) process, as follows:

$$\boldsymbol{x}_t = \sum_{\ell=0}^{\infty} \boldsymbol{G}_\ell \boldsymbol{u}_{t-\ell}, \tag{2}$$

where the ℓth $m \times m$ VMA parameter matrix is obtained recursively from the parameters of the VAR model as $\boldsymbol{G}_\ell = \boldsymbol{A}_1 \boldsymbol{G}_{\ell-1} + \boldsymbol{G}_2 \boldsymbol{G}_{\ell-2} + \ldots$ for $\ell = 1, 2, \ldots$, with $\boldsymbol{G}_0 = \boldsymbol{I}_m$ and $\boldsymbol{G}_\ell = \boldsymbol{0}_m$ for $\ell < 0$, where $\boldsymbol{I}_m$ and $\boldsymbol{0}_m$ denote the $m \times m$ identity and zero matrices, respectively. With the VMA parameter matrices defined in this way, the h-steps-ahead orthogonalised forecast error variance decomposition (OVD) for the i-th variable can be obtained as follows:

$$\theta_{i \leftarrow j}^{(h)} = \frac{\sum_{\ell=0}^{h} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{P} \boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{h} \boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \boldsymbol{e}_i}, \tag{3}$$

for $i, j = 1, \ldots, m$, where $\boldsymbol{e}_i$ is an $m \times 1$ selection vector, every element of which is equal to zero apart from the i-th element, which is set to unity, and where $\boldsymbol{P}$ is the $m \times m$ lower-triangular Cholesky factor of the residual covariance matrix, $\boldsymbol{\Sigma}$.

The value of $\theta_{i \leftarrow j}^{(h)}$ is bounded between zero and one and captures the proportion of the h-steps-ahead forecast error variance of variable i that can be attributed to orthogonal shocks to variable j. By virtue of the orthogonalisation introduced via the Cholesky factor, $\boldsymbol{P}$, the OVD has the properties that $\sum_{j=1}^{m} \theta_{i\leftarrow j}^{(h)} = 1$ and $\sum_{i=1}^{m}\sum_{j=1}^{m} \theta_{i\leftarrow j}^{(h)} = m$. However, the OVD is sensitive to the ordering of the endogenous variables in the system. To achieve order-invariance, in a subsequent paper, Diebold and Yilmaz (2014) adopt the generalised forecast error variance decomposition (GVD) of Pesaran and Shin (1998). The GVD for the i-th variable can be obtained as follows:

$$\check{\vartheta}_{i\leftarrow j}^{(h)} = \frac{\sigma_{jj}^{-1}\sum_{\ell=0}^{h}\left(\boldsymbol{e}_i'\boldsymbol{G}_\ell\boldsymbol{\Sigma}\boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{h}\boldsymbol{e}_i'\boldsymbol{G}_\ell\boldsymbol{\Sigma}\boldsymbol{G}_\ell'\boldsymbol{e}_i}, \tag{4}$$

where σ_{jj} is the jth diagonal element of $\boldsymbol{\Sigma}$. By analogy to the orthogonalised case, $\check{\vartheta}_{i\leftarrow j}^{(h)}$ expresses the proportion of the h-steps-ahead forecast error variance of variable i that can be attributed to reduced form disturbances in the equation for variable j. However, it will generally be the case that $\sum_{j=1}^{m}\check{\vartheta}_{i\leftarrow j}^{(h)} > 1$ due to the cross-sectional correlation between the reduced-form residuals. Consequently, Diebold and Yilmaz (2014) apply the following row-sum normalisation to the GVD:

$$\vartheta_{i\leftarrow j}^{(h)} = \check{\vartheta}_{i\leftarrow j}^{(h)} \bigg/ \sum_{j=1}^{m}\check{\vartheta}_{i\leftarrow j}^{(h)}. \tag{5}$$

Diebold and Yilmaz (2009, 2014) show that the matrix of forecast error variance decompositions, whether defined following (3) or (5), can be interpreted as a weighted directed network. The spillover index proposed by Diebold and Yilmaz (2009) measures the proportion of the h-steps-ahead forecast error variance for all m variables in the VAR model that can be attributed to the bilateral interactions (or 'spillovers') embodied in the network, as opposed to the unilateral effects (or 'loops'). To illustrate the computation of the spillover index, consider the OVD case and denote the $m \times m$ OVD matrix as $\boldsymbol{\theta} = \{\theta_{i\leftarrow j}\}_{i,j}^{m}$. The spillover index expressed as a percentage is obtained as follows:

$$\mathcal{S}_O = 100 \times \frac{\boldsymbol{\iota}'\boldsymbol{\theta}\boldsymbol{\iota} - \mathrm{trace}(\boldsymbol{\theta})}{\boldsymbol{\iota}'\boldsymbol{\theta}\boldsymbol{\iota}}\%, \tag{6}$$

where $\boldsymbol{\iota}$ is an $m \times 1$ vector of ones. The subscript 'O' indicates that $\mathcal{S}_O$ is obtained from the OVD. To avoid confusion, we will henceforth refer to $\mathcal{S}_O$ in the text as the 'orthogonalised spillover index'. The 'generalised spillover index' based on the GVD, $\mathcal{S}_G$, is defined analogously by replacing the matrix of OVDs, $\boldsymbol{\theta}$, with the matrix of GVDs, $\boldsymbol{\vartheta} = \{\vartheta_{i\leftarrow j}\}_{i,j}^{m}$, in (6).

2.2 Statistical Inference on the Spillover Indices

If the VAR(p) model (1) is estimated over rolling-samples of length w indexed by $r = 1, \ldots, R$, then one obtains R rolling sample estimates of the spillover indices, $\mathcal{S}_O$ and $\mathcal{S}_G$, that can be used to evaluate time-variation in the aggregate strength of pairwise linkages between the endogenous variables in the vector $\boldsymbol{x}_t$. As noted in Section 1, in the existing literature, analysis typically proceeds chiefly on the basis of visual inspection of the rolling sample point estimates of the spillover index. However, this process does not convey any information on the statistical significance of changes in spillover activity from one rolling sample to another.

In principle, one could develop asymptotic theory for the spillover indices to form a basis for statistical inference. However, reliance on asymptotic results may be inappropriate in a rolling sample setting, as the window length, ω, is typically relatively small. Therefore, following Greenwood-Nimmo et al. (2019b) and Greenwood-Nimmo and Tarassow (in press), we propose a bootstrap-based inferential technique. Greenwood-Nimmo et al. (2019b) employ a residual bootstrap to construct empirical intervals for spillover statistics, while Greenwood-Nimmo and Tarassow (in press) use the block bootstrap routine developed by Brüggemann, Jentsch and Trenkler (2016) to conduct probabilistic analysis of spillover scenarios. However, neither of these studies addresses the issue that attempts to evaluate the empirical distributions of impulse response functions and forecast error variance decompositions obtained from VAR models using common bootstrapping techniques may be subject to bias (e.g. Kilian, 1998). Therefore, we employ a bootstrap-after-bootstrap procedure, where bootstrapping is performed twice. In the first step, one estimates the magnitude of the bias. In the second step, one uses the estimate of the bias from the first step to generate bias-corrected bootstrap estimates.

To illustrate how our procedure is implemented, we will limit our attention to the case of the orthogonalised spillover index. The discussion is easily modified for the generalised case. For a given lag order, p, and window length, ω, our algorithm proceeds as follows:

1. For the first rolling sample, estimate (1) by OLS and save the estimated parameter matrices, $\widehat{\boldsymbol{A}}_j$, $j = 1, \ldots, p$, the residuals, $\widehat{\boldsymbol{u}}_t$ and the estimated orthogonalised spillover index, $\widehat{\mathcal{S}_O}$.

2. Obtain B bootstrap samples of $\boldsymbol{x}_t$, denoted $\boldsymbol{x}_t^{(b)}$, as follows:

$$\boldsymbol{x}_t^{(b)} = \sum_{j=1}^{p} \widehat{\boldsymbol{A}}_j \boldsymbol{x}_{t-j}^{(b)} + \boldsymbol{u}_t^{(b)}, \tag{7}$$

   where the p initial values of $\boldsymbol{x}_t^{(b)}$ are taken as given and where $\boldsymbol{u}_t^{(b)}$ can be obtained either non-parametrically by resampling with replacement from the VAR residuals, $\widehat{\boldsymbol{u}}_t$, or parametrically by drawing from an appropriate multivariate distribution.

3. Having obtained the set of B bootstrap samples, $\boldsymbol{x}_t^{(b)}$, re-estimate the VAR model (1) B times to obtain new parameter estimates, $\widehat{\boldsymbol{A}}_j^{(b)}$, $j = 1, \ldots, p$, new estimates of the residual covariance

matrix, $\widehat{\boldsymbol{\Sigma}}^{(b)}$, and new estimates of the orthogonalised spillover index, $\widehat{\mathcal{S}}_O^{(b)}$, $b = 1, \ldots, B$.[3]

4. Estimate the magnitude of the bias in the bootstrap estimates of the orthogonalised spillover index as $\widehat{\Upsilon}_O = B^{-1} \sum_{b=1}^{B} \widehat{\mathcal{S}}_O^{(b)} - \widehat{\mathcal{S}}_O$.

5. Discard all of the output from steps 2 to 4 except for $\widehat{\Upsilon}_O$. Repeat steps 2 to 4 to obtain B new bootstrap estimates of the orthogonalised spillover index, $\widehat{\mathcal{S}}_O^{(b)}$, each time subtracting the estimated bias, $\widehat{\Upsilon}_O$.

6. Repeat steps 1-5 for all of the remaining rolling samples to obtain the bias-corrected empirical distribution of the orthogonalised spillover index for each rolling sample.

Statistical inference can proceed on the basis of the empirical distributions obtained in step 6. Continuing with the case of the orthogonalised spillover index for illustrative purposes, suppose that an adverse event affects the final observation in rolling sample r_e. For some non-negative integer, $j \geq 0$, the probability that the orthogonalised spillover index obtained in rolling sample $r_e + j$ exceeds the mean of the orthogonalised spillover index evaluated across bootstrap samples in rolling sample $r_e - 1$, denoted $\overline{\mathcal{S}}_{O,r_e-1} = B^{-1} \sum_{b=1}^{B} \widehat{\mathcal{S}}_{O,r_e-1}^{(b)}$, is computed as follows:

$$\Pr\left(\mathcal{S}_{O,r_e+j} > \overline{\mathcal{S}}_{O,r_e-1}\right) = B^{-1} \sum_{b=1}^{B} \mathbb{I}\left\{\left(\widehat{\mathcal{S}}_{O,r_e+j}^{(b)} - \overline{\mathcal{S}}_{O,r_e-1}\right) > 0\right\}, \tag{8}$$

where $\mathbb{I}\{\cdot\}$ is a Heaviside function taking the value 1 if the condition in braces is satisfied and 0 otherwise. It is straightforward to modify this procedure to compute probabilities based on alternative pre-event and post-event time periods (e.g. using the average value of the spillover index over a specified pre/post-event time period instead of its value on a single pre/post-event day) and/or based on the generalised spillover index instead of the orthogonalised spillover index.

3 Dataset

Our empirical analysis is based on the original dataset constructed by Diebold and Yilmaz (2009), which the authors kindly shared with us. In this section, we offer a brief overview of the construction of the dataset. For detailed descriptive statistics, see Tables 1 and 2 in Diebold and Yilmaz (2009).

The dataset is constructed from daily nominal index values for 19 global stock markets over the period January 1992 to November 2007, which the authors obtain from Thomson Datastream and Global Financial Data. In total, there are 7 developed markets (the US, the UK, France, Germany,

[3] For each bootstrap sample, the eigenvalue stability condition for the VAR model is tested. If a bootstrap sample yields an unstable model, then it is discarded and a new bootstrap sample drawn.

Hong Kong, Japan and Australia) and 12 emerging markets (Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico and Turkey). Diebold and Yilmaz (2009) begin by analysing the connectedness among these 19 markets using weekly real returns and weekly realised volatilities. The weekly real return for the ith market is computed on a Friday-to-Friday basis and is deflated using the appropriate monthly consumer price index from the IMF's *International Financial Statistics*. To obtain weekly inflation data, the authors assume that the weekly inflation rate is constant across a given month and can, hence, be approximated by $\pi_t^{\frac{1}{4}}$, where π_t is the monthly inflation rate. Consequently, the weekly real return for the ith market, r_{it}, is given by:

$$r_{it} = \frac{1 + q_{it}}{1 + \pi_{it}} - 1, \tag{9}$$

where q_{it} is the weekly nominal log-return for market i.

To construct a corresponding weekly realised volatility series, Diebold and Yilmaz (2009) employ the range-based volatility estimator of Garman and Klass (1980) and Alizadeh, Brandt and Diebold (2002). Under the assumption that volatility is fixed within weeks but variable between weeks, the realised variance for the ith market in period t, σ_{it}^2, is estimated as follows:

$$\begin{aligned} \widehat{\sigma}_{it}^2 &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &- 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2, \end{aligned} \tag{10}$$

where H_{it}, L_{it}, O_{it} and C_{it} denote the Monday–Friday high, low, open and close prices for the ith market, all expressed as natural logarithms. For both weekly returns and volatilities, the authors obtain a sample of $T = 829$ weeks.

Finally, the authors move to a higher-frequency setting, working with daily range-based realised volatility estimates. In this case, the sample size is $T = 2,823$ days. Our probabilistic event analysis will make use of this daily dataset, as it possible to identify the timing of events with greater accuracy when using daily data than weekly data.

4 Empirical Analysis

4.1 Replication of Diebold and Yilmaz (2009)

Before we proceed with our probabilistic analysis, it is first necessary to replicate the analysis of Diebold and Yilmaz (2009). To conserve space, we only present replication results for Figure 3 in their paper in the main text, which reports the rolling-sample spillover index estimated using daily realised volatility data at the 2-days-ahead and 10-days-ahead forecast horizons. As mentioned above, the results contained in this figure will be central to our probabilistic analysis. A full replication of all of the results reported by Diebold and Yilmaz (2009) using both the orthogonalised and generalised spillover indices may be found in Appendix A.

Our replication of Figure 3 in Diebold and Yilmaz (2009) is reported in Figure 1. First, consider the results obtained from the OVD method, which are directly comparable to those presented by the authors. For both the 2-days-ahead and 10-days-ahead forecast horizons, we are able to replicate the dynamics obtained by the authors subject to a minor level shift. We are able to eliminate computational error as the source of this discrepancy, because our computational routine delivers a perfect elementwise replication of the results presented by Diebold and Yilmaz (2009) using weekly data (see Appendix A). Consequently, we conclude that the level shift between our spillover indices and those presented by the authors is most likely due to a difference in the specification of our respective VAR models. The authors comprehensively document the specification of their weekly VAR models but do not provide details of the specification of the VAR models that they fit to the daily realised volatility data. In the absence of information to the contrary, we proceed under the assumption that they employ the same specification at both daily and weekly frequency.[4] Note, however, that it is the dynamics of the spillover index that play a central role in our analysis, not its level, so a minor discrepancy in levels does not pose a problem for the probabilistic analysis that follows.

— Insert Figure 1 about here —

Next, consider the spillover index obtained from the GVD method. At both the 2-days-ahead and 10-days-ahead forecast horizons, the dynamics of the generalised and orthogonalised spillover indices track one-another very closely. The level of the generalised spillover index is slightly higher than its orthogonalised counterpart, reflecting the observation by Diebold and Yilmaz (2014, p. 130) that the value of the orthogonalised spillover index provides a lower bound on the value of the generalised spillover index. The overall implication of this exercise is that the choice to use either the orthogonalised method proposed by Diebold and Yilmaz (2009) or the generalised method advanced in Diebold and Yilmaz (2012, 2014) is expected to have little bearing on the dynamics of the resulting spillover indices.

For completeness and to develop intuition for the behaviour of the empirical distribution of the daily volatility spillover indices obtained from our bootstrap-after-bootstrap procedure, Figure 2 plots the point estimates of the 10-days-ahead orthogonalised and generalised volatility spillover indices alongside their respective 90% empirical confidence intervals. The confidence intervals are typically relatively narrow in both cases, only widening appreciably during periods of elevated uncertainty, such

[4]We have sought clarification from the authors on this point on two occasions but are yet to receive a reply.

as the months following the 9/11 terror attacks and in the months leading up to the global financial crisis.

— Insert Figure 2 about here —

4.2 Probabilistic Analysis of Events

To facilitate the interpretation of their results, Diebold and Yilmaz (2009, Figure 3, p. 168) annotate time series plots of their spillover indices to show the approximate timing of a range of significant macroeconomic and financial events. However, they they do not specify the exact timing of many of these events. Consequently, a necessary precursor to our probabilistic analysis is to precisely specify their timing. In Table 1, we present a list of 19 events identified in Figure 3 of Diebold and Yilmaz (2009). For each event, we analyse contemporary media coverage in order to identify a single trading day that we will treat as the 'event date'. In many cases, this requires informed judgment – for example, the East Asian crisis spread to Hong Kong gradually, so identifying a single day for this event is not trivial. In each case, we provide a reference for each event that supports our choice of event date.

— Insert Table 1 about here —

The events identified by Diebold and Yilmaz can be broadly characterised as adverse systemic shocks that may be associated with increased spillover activity, including financial crises, currency crises, terror attacks and periods of adverse market sentiment.[5] Consequently, in Table 2, we report the estimated probability that each event is associated with an *increase* in the value of the 10-days-ahead orthogonalised/generalised spillover index on the day of impact (i.e. in the rolling sample ending on the day of the event, $r_e + 0$) and after 1, 5 and 22 trading days have passed (i.e. $r_e + 1$, $r_e + 5$ and $r_e + 22$, respectively). Specifically, the table reports the empirical probability that the value of the spillover index in rolling sample $r_e + j$, $j = \{0, 1, 5, 22\}$, exceeds the mean value of the spillover index evaluated across bootstrap samples in rolling sample $r_e - 1$. The results of sensitivity analysis with respect to the forecast horizon used in construction of the spillover index and to the definition of the pre-event period are reported in Section 5.

— Insert Table 2 about here —

Events 1 and 2 both relate to the 1997 East Asian crisis, the origins of which lie in capital flight following the de-pegging and subsequent collapse of the Thai baht in July 1997 (Bartram, Brown and Hund, 2007). Event 1 corresponds to the spread of the crisis to Hong Kong, which suffered

[5] The exceptions are the two US monetary policy interventions detailed in Table 1 (Events 9 and 13).

an abrupt crash on 17 October (Forbes and Rigobon, 2002). We find evidence of elevated spillover activity on impact, as well as a significant increase over the 5-day and 22-day horizons. Meanwhile, Event 2 relates to the continuing spread of the financial crisis within the region, which led to sharp losses across global stock markets on 27 October, before an abrupt rally. In this case, using either the orthogonalised or generalised spillover index, we observe a high probability of elevated spillovers on impact and throughout the following month. Such an increase in spillovers is consistent with evidence of contagion presented by Corsetti, Pericoli and Sbracia (2005), who observe that stock prices in Hong Kong declined until the end of November and impacted returns in several other markets. Specifically, Corsetti et al. (2005, p. 1193) "find evidence of contagion from the Hong Kong stock market to the stock markets in Singapore and the Philippines, among the emerging markets, and France, Italy and the UK, among the industrial countries."

Events 3 and 4 relate to the key events of the Russian financial crisis, which placed the ruble under intense pressure from late-May until July 13, 1998 (Event 3) when, after "two weeks of negotiations, the Russian Government, the IMF, the World Bank, and Japan agreed on a stabilization package that seemed large enough to stabilize the ruble" (Åslund, 1998, p. 325). The first stage of the Russian crisis associated with the announcement of the IMF aid package (Event 3) is not associated with any significant increase in either the orthogonalised or generalised spillover indices, a finding that is consistent with evidence that the short-term impact of IMF-related announcements does not generate significant effects in the market unless they are announcements that IMF support will not be forthcoming. For example, Brealey and Kaplanis (2004) conclude that if an IMF intervention is generally anticipated, then only bad news triggers noticeable reactions.

In the absence of a second rescue package, further deterioration of the financial position in Russia raised expectations of a currency devaluation and sovereign debt restructuring, which was announced on August 25, 1998 (Bartram et al., 2007). This is Event 4, which precedes a significant increase in both the orthogonalised and generalised spillover indices by one week. The delayed spillover effect in this case may reflect enduring hopes for a rescue package. As noted by Åslund (1999, p. 71), it may have been viewed as surprising that "the international community did not prevent the default of a country that was believed to be 'too big and too nuclear to fail' ". Furthermore, the persistence of the change in the spillover activity is consistent with evidence that the Russian default was unexpected and changed investors' perceptions about the likelihood of future official bailouts (Dell'Ariccia, Schnabel and Zettelmeyer, 2006).

The next event also relates to a currency crisis, this time in Brazil, which was triggered by the devaluation of the Brazilian real on 13 January 1999 (Event 5). Both fiscal imbalances and a difficult external environment ultimately contributed to the collapse of Brazil's moving peg (Tanner and Ramos, 2003), which led to massive capital outflows (Bartram et al., 2007). Yet despite the extent of these dislocations, we find no evidence of a statistically significant increase in spillover activity at any horizon. This may be because "the private sector was largely hedged at the moment of the crisis and was insulated from the immediate effects of the devaluation. The reason for this "prudent" behavior is that the Brazilian crisis was anticipated by market participants" (Goldfajn, 2000, p. 3).

Diebold and Yilmaz (2009) go on to identify three events linked to heightened volatility related to U.S. technology stocks. The first of these, Event 6, is labelled 'profit taking in tech stocks'. The date that we associate with this event is January 5, 2000, a day after the NASDAQ fell by approximately 5.5% and tech stocks continued to fall despite a rally in broader indices. Diebold and Yilmaz characterise this as a period where investors sought to realise substantial recent gains in the index. The generalised spillover index increases significantly on impact and on the day after the event and records an 89.6% probability of an increase at the 5-day horizon. Meanwhile, the orthogonalised spillover index shows an 85.8% probability of a contemporaneous increase followed by significant increases at the 1-day and 5-day horizons.

Diebold and Yilmaz describe Event 7 as 'increased market worries for tech stocks'. We identify the event as Friday April 14, 2000, which saw the third-largest one-day percentage fall in the history of the NASDAQ. The NASDAQ Composite index fell 9%, ending a week in which it fell by 25%. Neither the orthogonalised or generalised spillover indices respond to this event contemporaneously but both increase significantly on the following trading day (Monday, April 17) and remain elevated over the following month. The effect of this event on the spillover index may have been amplified as a result of its timing. Monday, April 17, 2000 was the due date to pay taxes on gains realized in the previous year. Consequently, many investors may have liquidated their positions both in response to price falls and also in an effort to optimise their tax obligations.

Finally, Event 8 occurs on 3 January, 2001, when US stock markets recorded substantial gains following a 50 bp interest rate cut by the Fed, with the NASDAQ recording its largest single-day percentage gain in history, at 14.17%. Cochrane and Piazzesi (2002) classify this rate cut as unanticipated (p. 91) and note that, in response, "the one and three-year rates fell 70 bp, and the five-year rate fell about 50 bp. The natural interpretation is that the cut signaled a change of direction; in the place of further tightening, there would be further rate cuts". In response to this change of the Fed's stance, the orthogonalised and generalised spillover indices record a contemporaneous jump with high probability but show no significant increase at longer horizons, indicating that global equity markets rapidly impounded news of the Fed's policy decision.

The next event discussed in Diebold and Yilmaz (2009) also relates to US monetary policy. On March 20, 2001 the Fed reduced the funds rate by 50 bps, from 5.5% to 5.0% (Event 9). Cochrane and Piazzesi (2002) show that market participants expected a rate cut on this occasion but that the expected cut was larger than the actual cut enacted by the Fed, resulting in a contractionary monetary shock. In this case, neither spillover index increases on the day of the rate cut but both subsequently increase significantly over the following month (albeit marginally insignificantly at the 22-day horizon in the GVD-based case). This suggests that the market response to monetary policy interventions that are unanticipated (e.g. Event 8) may be more rapid than in the case of (partially) anticipated policy interventions (e.g. Event 9).

Event 10 corresponds to the 9/11 terror attacks, which precipitated a halt in trading on the New York stock exchange followed by intense volatility thereafter. In response to this period of turmoil in the financial markets, both the orthogonalised and generalised spillover indices jump and remain elevated throughout the following month. This is consistent with the findings of Straetmans, Verschoor and Wolff (2008), who document a lasting impact of 9/11 on the financial markets, including a statistically and economically significant impact on volatility and co-movement measures. The sustained increase in connectedness that we observe at this time suggests a reduction in the potential to manage risk through international diversification.

The US stock market crash of 2002 is the focus of Event 11, which we date to 19 July, 2002. Between 19 and 23 July, 2002, the Dow Jones industrial average recorded a substantial decline to its lowest level in four years. Both spillover indices increase significantly on the following business day and remain elevated over the next month with high probability. The delayed response in this case may be due to a weekend effect, as the event day (19 July, 2002) is a Friday. The long-lasting effect of the 2002 crash on stock market connectedness may be related to an ongoing slide in a consumer confidence lasting until the end of 2002, as reflected in the OECD consumer confidence index.[6] Using a multivariate logit model, Zouaoui, Nouyrigat and Beer (2011) document a strong link between consumer confidence and stock market crashes in a number of countries, including the US; a sharp decline in both consumer confidence index and the S&P 500 Index is found in 2002 (p. 730; Fig. 1, panel B).

Events 12a and 12b correspond to two bomb attacks in Turkey over a five day interval in November 2003. The first attack targeted two Jewish synagogues (Event 12a on November 15), while the second targeted the British Consulate and HSBC Bank (Event 12b on November 20).[7] The evidence for a statistically significant increase in either spillover index at this time is weak. Using the orthogonalised spillover index, we find a 90.9% probability of an increase in the spillover index five days after the first attack. This timing is notable, because it precisely coincides with the second bombing (Event

[6]Data on the consumer confidence index may be accessed via `https://data.oecd.org/leadind/consumer-confidence-index-cci.htm`.

[7]In Figure 3 of Diebold and Yilmaz (2009), only one explosion in Istanbul is identified. However, as two explosions occurred in a short period of time, we consider both events separately.

12b). We find no other evidence of a statistically significant response of either spillover index to either bombing. This is consistent with the literature, which indicates that the impacts of the terror attacks on Turkish financial markets were isolated to the event days (Markoulis and Katsikides, 2020) and that "the rebound of the Stock Exchange was very quick despite the severity of the events" (Christofis, Kollias, Papadamou and Stagiannis, 2010, p. 12). The Istanbul Stock Exchange was closed for six trading days following the November 20 attack and re-opened on December 1, but the closure "proved enough for the indices and the investors to recover in a single trading day" (Christofis et al., 2010, p. 11). Our findings are also in line with Aksoy and Demiralay (2019), who show that, between 1988 and 2015, financial markets in Turkey quickly absorbed the impact of terror attacks.

Event 13 corresponds to another reversal in US monetary policy, this time the switch from an accommodative regime to a contractionary regime on 30 June, 2004. Having kept the federal funds rate at 1% for a year, the Federal Open Market Committee (FOMC) elected to raise it by 25 bps in a move that was widely anticipated by market participants.[8] Anticipated monetary policy interventions typically have little impact on the markets because they are priced ex ante. Our finding that neither spillover index increases in the short term following the policy announcement is consistent with this phenomenon. Interestingly, we estimate that there is approximately a 90% probability of an increase in both spillover indices after one month. One plausible explanation of this phenomenon is suggested by Poole (2005), who notes that, on the day of the rate hike, the yield on the October 2004 funds futures contract *declined* by 8 bps and that "the market reaction might suggest some confusion about FOMC intentions" (p. 665). This confusion may be responsible for the gradual increase in spillover activity that is observed throughout July 2004 in Figure 1.

Diebold and Yilmaz (2009, p. 166) describe Event 14 as "the dollar crisis of March 2005, associated with remarks from policy makers in several emerging and industrialised countries (South Korea, Russia, China, India and Japan) indicating that they were considering central bank reserve diversification away from the US dollar". An event of this type does not occur on a single day. We set the event date as 22 Feb 2005, which is when the Bank of Korea discussed diversifying its holdings of foreign reserves away from the dollar. To the best of our knowledge, this is the first official statement made by a central bank with the specific intention of diversification away from the dollar (Dougherty, 2005).[9] However, we find no evidence of a statistically significant increase in either the orthogonalised or generalised spillover index over any horizon.[10]

[8]The following news article from 29 June is a good example of anticipatory media coverage in the days preceding the rate hike: https://money.cnn.com/2004/06/23/pf/debt/fed_hike_effects/index.htm.

[9]The IMF Financial Stability Report of April 2005 mentions dollar volatility with respect to global imbalances along with some diversification away from the dollar but does not describe a 'dollar crisis' per se (International Monetary Fund, 2018). Likewise, the occurrence of a 'dollar crisis' in 2005 is not discussed unambiguously in the relevant forex literature (e.g. Chinn and Frankel, 2008; Giannellis and Kouretas, 2014).

[10]To test the robustness of this finding, following the discussion in Valderrama (2005), we computed event probabilities using the alternative event date of March 16, 2005, which coincides with the discussion of diversification away from the

The 7/7 terror attacks in London are captured by Event 15. As with 9/11 in the US, the 7/7 attacks gave rise to an immediate and highly significant increase in spillover activity that is sustained over the next month. Both the 9/11 and 7/7 attacks targeted major global financial centers and had broadly similar implications for the financial markets since "both the September 11, 2001 attacks, and the London tube bombing of July 7, 2005, point to a significant negative impact on financial markets as a consequence of terrorism" (Goel, Cagle and Shawky, 2017, p. 124).

Event 16 relates to capital outflows from emerging markets. This is a difficult event to date precisely, so we make use of the documented link between equity market volatility and capital flows (e.g. Bank for International Settlements, 2006; Gourio, Siemer and Verdelhan, 2016) and set the event date according to the turning point in the VIX on 12 May, 2006. With the timing of the event specified in this way, we find that both the orthogonalised and generalised spillover indices increase significantly on the day after the event and remain elevated for the remainder of the month.

Event 17 refers to the collapse of the Thai stock index on 19 December, 2006 due to announcement of a 30% unremunerated reserve requirement by the Bank of Thailand that was intended to prevent speculation related to the sharp appreciation of the Thai baht (Sethapramote and Prukumpai, 2012). We observe a significant contemporaneous increase in the value of both spillover indices that continues over the following week before dying away.

The last two events discussed by Diebold and Yilmaz (2009) relate to the subprime mortgage crisis in the US and the early stages of the global financial crisis. The authors describe Event 18 as the 'first signs of subprime worries'. Brunnermeier (2009, p.82) notes that the "trigger for the liquidity crisis was an increase in subprime mortgage defaults, which was first noted in February 2007". Two significant events on 8 February, 2007 instigated a marked widening of the spread on non-investment grade residential mortgage collateralised debt obligations over the following two days. The first was the collapse of the share price of New Century Financial Corporation, the third largest subprime lender in the US, from \$30.16 on 7 February to \$19.24 on 8 February. The second was the announcement by HSBC Finance that its allowance for losses on subprime mortgages would exceed expectations by 20%. Neither the orthogonalised or generalised spillover indices increase significantly on 8 February, 2007 or over the following two weeks. However, we do observe a significant increase in the orthogonalised spillover index after one month, which suggests a role for a different, later event. In practice, we find that both spillover indices increase significantly after remarks by Alan Greenspan on 26 February, 2007, in which he warned of a forthcoming US recession. However, in his remarks, Greenspan downplayed the role of the housing contraction, noting that "[w]e are now well into the

dollar in Japan (Koizumi, 2005). This alternate dating strategy reveals a short-lived statistically significant increase in spillover activity. This may suggest that announcements regarding foreign reserves coming from the Bank of Japan attract greater attention than similar announcements from the Bank of Korea, perhaps reflecting its larger holdings of US debt.

contraction period and so far we have not had any major, significant spillover effects on the American economy from the contraction in housing".[11] This suggests that the increase in spillover activity noted by Diebold and Yilmaz (2009) in early-2007 may have been driven by fears of a recession more than by concern over the subprime mortgage market per se.

Lastly, Event 18 refers to the 'global financial market turmoil' observed in summer 2007. The consensus in the literature on the subprime crisis is that the crisis broke in mid-2007 (e.g. Caballero, Farhi and Gourinchas, 2008; Brunnermeier, 2009; Phillips and Yu, 2011; Eichengreen, Mody, Nedeljkovic and Sarno, 2012). In the subsequent connectedness literature that has adopted the framework of Diebold and Yilmaz (2009, 2012, 2014), the first substantial increase in US stock market connectedness is typically detected in mid-August 2007 (e.g. Baruník et al., 2016). On 9 August, 2007, BNP Paribas halted withdrawals from three hedge funds due to "a complete evaporation of liquidity in certain market segments of the US securitisation market" (Davies and Green, 2010, p. 1). At the same time, central banks around the world intervened in the money markets to mitigate liquidity pressures faced by banks in the interbank market. We find evidence of a significant increase in spillover activity only at the one-month horizon. However, this finding should be treated with caution, as the VAR model is unstable over a block of three trading days from 16 August 2007 to 20 August 2007, inclusive.[12] Over this period, the estimated spillover index jumps from 68.38% on 15 August to 77.64% on 21 August. This is consistent with a large jump in global stock market connectedness over this period, but this behaviour cannot be captured by the model.

5 Sensitivity Analysis

The first robustness test that we perform focuses on the pre-event comparison period used in the construction of our empirical probabilities. Recall that the results presented above are obtained using the trading day immediately prior to a given event as the comparison period, as shown in (8). To account for the possibility that conditions on the day prior to an event may not always be representative of pre-event conditions (e.g. due to outlying observations in the data or to the leakage of information prior to an event), in Table 3, we repeat our analysis using the average spillover in the week prior to a given event as the comparison instead of the day prior to the event. In practice, this change barely

[11] For media coverage of Greenspan's remarks, see http://www.nbcnews.com/id/17343814/ns/business-stocks_and_economy/t/greenspan-warns-us-recession-risk/#.XD7EM1wza70.

[12] This unstable period manifests as a gap in the plot of the spillover index reported by Diebold and Yilmaz (2009). While it may be possible to modify the specification of the VAR model or the method used to estimate the VAR parameters in order to obtain stable solves over this period, we do not pursue this option as it would represent a departure from the results reported by Diebold and Yilmaz (2009). Instead, in rolling samples where unstable solves prevent us from estimating the spillover index, we assume that it remains unchanged from the last available estimate (i.e. the estimate obtained from the previous stable rolling sample). This can be thought of as treating the spillover index as a random walk for the purpose of filling missing observations.

affects our results. For all but three events, the pattern of significance among OVDs and GVDs and across horizons is unchanged. Of the remaining three events, we find one fewer significant changes for event (down from 6 to 5), one more significant change for event 12b (up from 0 to 1) and three more significant changes for event 6 (up from 4 to 7). In each of these cases, the probability recorded in Table 3 exceeds that in Table 2, which suggests that the 5-day average of the spillover index is lower than the spillover index on the day prior to each of these three events.

Next, following Diebold and Yilmaz (2009), we replicate the analysis in Table 2 having changed the forecast horizon used to compute the spillover statistics from 10-days-ahead to 2-days-ahead. The results are reported in Table 4. While Diebold and Yilmaz show that this change has little visible effect on a graph of the spillover index, it has a considerably larger effect on our estimated probabilities, with at least some change in significance visible in more than half of the events under consideration. In general, when working at the 2-days-ahead horizon, there is less evidence of significant increases in spillover activity. This is an interesting finding, which likely reflects the fact that both the OVDs and GVDs tend to have converged to their long-run values within 10-days but not within 2-days. The greater stability of the OVDs and GVDs at longer horizons is reflected in less dispersion of the bootstrap spillover indices and this allows for greater precision in the estimation of the empirical probabilities.

Our final robustness test combines the use of the 5-day average pre-event comparison period with the 2-days-ahead forecast horizon. The results are reported in Table 5 and are similar to those in Table 4. This is not surprising, given that switching the forecast horizon to 2-days-ahead had a much larger impact on the estimated probabilities than switching the definition of the comparison period.

The primary implication of our sensitivity tests is that our results are largely robust to changes in the definition of the comparison period. This is an important finding, because the choice of comparison period is a new aspect of the analysis for which no precedent is available in the connectedness literature. A secondary implication of our robustness tests is that the selection of forecast horizon for use in applications of the Diebold and Yilmaz (2009) method should be guided, at least in part, by the degree of persistence in the data, as this will affect the time taken for OVDs/GVDs to converge to their long-run values.

6 Concluding Remarks

The spillover index developed by Diebold and Yilmaz (2009, 2012, 2014) has been widely used to analyse and quantify changes in financial market connectedness. Yet despite its popularity, formal statistical evidence of its response to exogenous systemic events is absent from the literature. We address this issue by developing a non-parametric bootstrap-after-bootstrap framework that supports formal statistical inference on the spillover index.

We apply our technique to the same dataset used in the seminal analysis of Diebold and Yilmaz (2009). Our results lend qualified support to the notion that the spillover index increases in a statistically significant manner in the wake of systemic shocks. Specifically, for 15 of the 19 events discussed by Diebold and Yilmaz, we find a probability of 90% or more that the either the orthogonalised or generalised spillover index increases contemporaneously or with a delay of 1-day, 5-days or 22-days. However, we only find evidence of a contemporaneous increase in the spillover index for 6 events, which indicates that the spillover index may often react to systemic events with a lag.

Our bootstrap-after-bootstrap technique represents a useful addition to the connectedness literature. We have shown how it can be used to construct confidence intervals for the spillover index (and other related statistics) and to formally analyse the impact of systemic events on financial market connectedness. In addition, by enriching the statistical foundations of the connectedness framework of Diebold and Yilmaz (2009, 2012, 2014), our technique provides new opportunities for its use in asset pricing, portfolio allocation, risk management and for the development of options and hedging strategies.

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Event	Event Description	Date	Supporting Reference
1	East Asian crisis spreads to Hong Kong	10/17/1997	Forbes and Rigobon (2002)
2	East Asian crisis spreads to other countries	10/27/1997	https://money.cnn.com/1997/10/27/markets/marketwrap/
3	Russian crisis I	07/13/1998	https://www.chicagotribune.com/news/ct-xpm-1998-07-14-9807140121-story.html
4	Russian crisis II	08/25/1998	https://money.cnn.com/1998/08/25/economy/russia_debt/
5	Brazilian crisis	01/13/1999	https://money.cnn.com/1999/01/13/worldbiz/brazil_wrapup/
6	Profit taking in tech stocks	01/05/2000	http://edition.cnn.com/TRANSCRIPTS/0001/05/tod.03.html
7	Increased market worries for tech stocks	04/14/2000	https://money.cnn.com/2000/04/14/markets/markets_newyork/
8	Nasdaq & DJIA soar amid continued concerns over tech stocks but recover	01/03/2001	https://money.cnn.com/2001/01/03/markets/markets_newyork/
9	Markets fall before and after the Fed rate cut	03/20/2001	https://www.federalreserve.gov/fomc/minutes/20010320.htm
10	9/11 terrorist attacks	09/11/2001	https://www.washingtonpost.com/opinions/september-11-2001/2011/09/09/gIQApSwuFK_story.html
11	Global markets chasing US stocks lower	07/19/2002	https://money.cnn.com/2002/07/19/markets/markets_newyork/
12a	Bomb explosions in Istanbul	11/15/2003	https://www.independent.co.uk/news/world/europe/istanbul-attacks-a-timeline-of-recent-bombings-in-turkeys-largest-city-a6807376.html
12b	Bomb explosions in Istanbul	11/20/2003	See above
13	Reversal in Fed interest rate policy stance	06/30/2004	https://www.federalreserve.gov/monetarypolicy/files/FOMC20040630meeting.pdf
14	Dollar crisis	02/22/2005	https://www.nytimes.com/2005/02/23/business/worldbusiness/dollar-plunges-on-proposal-by-korea-bank-to.html
15	London terror attack	07/07/2005	https://www.theguardian.com/uk/2005/jul/08/terrorism.july74
16	Capital outflows from EMs	05/12/2006	Based on the turning point in the VIX. Supporting discussion in https://www.bis.org/publ/arpdf/ar2006e3.pdf.
17	Thai market plunges 15%	12/19/2006	http://www.nbcnews.com/id/16279821/ns/business-world_business/t/thai-investment-rules-lifted-after-market-rout/#.XD63p1wza71
18	First signs of subprime worries	02/08/2007	https://www.reuters.com/article/us-crunch-timeline-idUSL155564520080805
19	Global financial market turmoil	08/09/2007	See above

NOTES: In Figure 3 of Diebold and Yilmaz (2009), only one bombing in Istanbul is identified. However, as two attacks occurred in a short period of time, we consider both events.

Table 1: Timing and Description of Events, including Supporting References

Event	Event Description	$r_e + 0$		$r_e + 1$		$r_e + 5$		$r_e + 22$	
		OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	East Asian crisis spreads to Hong Kong	95.2	97.1	78.7	84.9	100.0	100.0	100.0	100.0
2	East Asian crisis spreads to other countries	95.1	90.3	94.7	90.4	100.0	100.0	100.0	99.9
3	Russian crisis I	50.7	52.0	51.4	50.6	69.3	62.4	0.0	1.1
4	Russian crisis II	31.1	29.1	33.2	31.5	100.0	100.0	100.0	100.0
5	Brazilian crisis	54.4	55.6	55.1	51.5	9.8	15.8	3.6	10.6
6	Profit taking in tech stocks	85.8	92.4	99.8	99.9	90.1	89.6	74.1	76.0
7	Increased market worries for tech stocks	59.5	53.7	100.0	100.0	99.5	99.3	98.7	99.8
8	NASDAQ and DJIA soar amid continued worries	100.0	100.0	0.0	0.1	0.0	0.1	0.2	0.6
9	Markets fall before and after the Fed rate cut	54.1	50.9	95.4	95.9	96.2	94.0	93.8	85.7
10	9/11 terrorist attacks	98.8	99.2	100.0	100.0	100.0	100.0	100.0	100.0
11	Global markets chasing US stocks lower	61.7	52.2	99.5	92.5	100.0	100.0	98.2	99.9
12a	Bomb explosions in Istanbul	41.0	41.0	47.5	46.1	90.9	77.3	70.7	37.8
12b	Bomb explosions in Istanbul	48.2	46.8	86.1	76.9	62.2	53.4	0.0	0.1
13	Reversal in Fed interest rate policy stance	44.3	46.5	52.7	58.2	43.3	49.4	90.5	90.9
14	Dollar crisis	34.8	28.1	34.1	26.0	40.7	30.4	18.0	2.4
15	London terror attack	100.0	100.0	100.0	100.0	98.8	89.5	97.9	91.8
16	Capital outflows from EMs	46.4	44.3	96.5	97.5	100.0	100.0	100.0	100.0
17	Thai market plunges 15%	100.0	100.0	100.0	100.0	64.2	44.8	29.0	33.6
18	First signs of subprime worries	53.3	51.7	51.5	51.4	56.0	56.2	98.7	82.4
19	Global financial market turmoil	50.8	48.3	67.6	57.3	52.7	47.7	100.0	100.0

NOTES: For each listed event, the table reports the empirical probability that the value of the DY spillover index in rolling sample $r_e + j$, $j = 0, 1, 5, 22$, exceeds the mean of the DY spillover index evaluated across bootstrap samples in rolling sample $r_e - 1$, where r_e denotes the rolling sample ending on the event date. Results under the headings 'OVD' and 'GVD' are obtained using the orthogonalised and generalised forecast error variance decompositions, respectively. The results are based on 1,000 bootstrap-after-bootstrap replications. Specifically, for each rolling sample, we generate an initial 1,000 non-parametric bootstrap replications to estimate the sign and magnitude of the bias in the estimation of the orthogonalised and generalised spillover indices. Given the estimated bias, we then generate another 1,000 non-parametric bootstrap replications to construct the bias-corrected distribution of the orthogonalised and generalised spillover indices. Probabilities of 90% or greater are printed in black, while probabilities lower than 90% are printed in grey.

Table 2: Empirical Probability of an Increase in Spillover Activity after Selected Events, in Percent

Event	Event Description	$r_e + 0$		$r_e + 1$		$r_e + 5$		$r_e + 22$	
		OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	East Asian crisis spreads to Hong Kong	94.4	97.1	75.9	84.1	100.0	100.0	100.0	100.0
2	East Asian crisis spreads to other countries	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
3	Russian crisis I	52.6	52.3	52.3	50.7	70.4	62.7	0.0	1.1
4	Russian crisis II	46.8	37.4	50.0	39.7	100.0	100.0	100.0	100.0
5	Brazilian crisis	36.0	50.9	34.7	47.3	3.9	13.7	0.9	8.5
6	Profit taking in tech stocks	97.1	97.0	100.0	100.0	98.1	95.8	92.7	87.6
7	Increased market worries for tech stocks	68.9	63.4	100.0	100.0	99.8	99.7	99.6	99.8
8	NASDAQ and DJIA soar amid continued worries	100.0	100.0	0.0	0.1	0.0	0.1	0.1	0.6
9	Markets fall before and after the Fed rate cut	56.2	47.3	95.5	95.3	96.6	93.0	94.1	83.7
10	9/11 terrorist attacks	98.7	99.6	100.0	100.0	100.0	100.0	100.0	100.0
11	Global markets chasing US stocks lower	48.6	13.9	98.8	63.0	100.0	99.6	97.0	96.3
12a	Bomb explosions in Istanbul	48.6	47.4	53.7	53.1	94.0	80.9	76.0	43.9
12b	Bomb explosions in Istanbul	56.4	49.1	91.6	78.7	69.0	56.4	0.0	0.1
13	Reversal in Fed interest rate policy stance	46.9	49.8	54.6	62.9	44.9	52.3	91.6	92.3
14	Dollar crisis	2.6	1.2	3.1	1.7	3.5	2.5	0.8	0.0
15	London terror attack	100.0	100.0	100.0	100.0	98.2	89.1	97.1	90.9
16	Capital outflows from EMs	37.9	48.5	95.0	97.8	100.0	100.0	100.0	100.0
17	Thai market plunges 15%	100.0	100.0	100.0	100.0	66.2	47.3	30.6	36.8
18	First signs of subprime worries	57.7	52.5	56.1	52.6	59.5	56.6	99.1	82.9
19	Global financial market turmoil	39.0	43.1	55.8	49.6	40.3	41.4	100.0	100.0

NOTES: For each listed event, the table reports the empirical probability that the value of the DY spillover index in rolling sample $r_e + j$, $j = 0, 1, 5, 22$, exceeds the mean of the DY spillover index evaluated across bootstrap samples in rolling samples $r_e - 5, \ldots, r_e - 1$, where r_e denotes the rolling sample ending on the event date. Results under the headings 'OVD' and 'GVD' are obtained using the orthogonalised and generalised forecast error variance decompositions, respectively. The results are based on 1,000 bootstrap-after-bootstrap replications. Specifically, for each rolling sample, we generate an initial 1,000 non-parametric bootstrap replications to estimate the sign and magnitude of the bias in the estimation of the orthogonalised and generalised spillover indices. Given the estimated bias, we then generate another 1,000 non-parametric bootstrap replications to construct the bias-corrected distribution of the orthogonalised and generalised spillover indices. Probabilities of 90% or greater are printed in black, while probabilities lower than 90% are printed in grey.

Table 3: Robustness of the Empirical Probabilities to the use of the 5-day Average as the Pre-Event Comparison

Event	Event Description	$r_e + 0$		$r_e + 1$		$r_e + 5$		$r_e + 22$	
		OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	East Asian crisis spreads to Hong Kong	85.1	85.5	80.0	78.7	100.0	100.0	100.0	100.0
2	East Asian crisis spreads to other countries	62.8	44.4	59.5	39.8	100.0	100.0	100.0	100.0
3	Russian crisis I	50.7	50.6	51.2	51.7	68.7	62.8	0.0	0.0
4	Russian crisis II	61.7	58.9	60.2	59.7	100.0	100.0	100.0	99.5
5	Brazilian crisis	60.4	58.6	61.4	52.6	22.8	22.7	11.4	15.2
6	Profit taking in tech stocks	64.6	74.9	78.1	83.3	84.5	84.6	46.1	63.2
7	Increased market worries for tech stocks	58.5	53.1	100.0	100.0	99.5	99.7	99.4	99.3
8	NASDAQ and DJIA soar amid continued worries	47.8	45.3	45.8	45.3	36.0	44.6	0.0	0.0
9	Markets fall before and after the Fed rate cut	51.9	48.0	67.2	64.7	96.0	92.1	89.5	78.1
10	9/11 terrorist attacks	86.4	91.3	99.6	99.4	100.0	100.0	100.0	100.0
11	Global markets chasing US stocks lower	47.7	42.3	62.9	45.5	99.3	96.8	89.1	97.0
12a	Bomb explosions in Istanbul	44.8	46.7	43.8	48.0	46.8	38.2	41.8	25.6
12b	Bomb explosions in Istanbul	41.1	40.4	45.1	39.2	32.3	25.1	0.0	0.3
13	Reversal in Fed interest rate policy stance	45.8	49.1	62.4	64.1	53.3	55.3	93.3	92.1
14	Dollar crisis	33.3	31.9	33.2	32.9	39.2	34.7	51.1	7.7
15	London terror attack	100.0	99.6	99.4	87.5	99.3	89.5	98.1	84.7
16	Capital outflows from EMs	48.2	45.7	89.6	89.9	99.9	99.4	100.0	100.0
17	Thai market plunges 15%	100.0	95.0	79.1	56.1	75.5	54.7	55.1	48.7
18	First signs of subprime worries	47.7	48.5	49.3	50.3	52.7	54.9	91.9	78.5
19	Global financial market turmoil	42.2	46.3	46.6	48.9	39.1	41.9	100.0	100.0

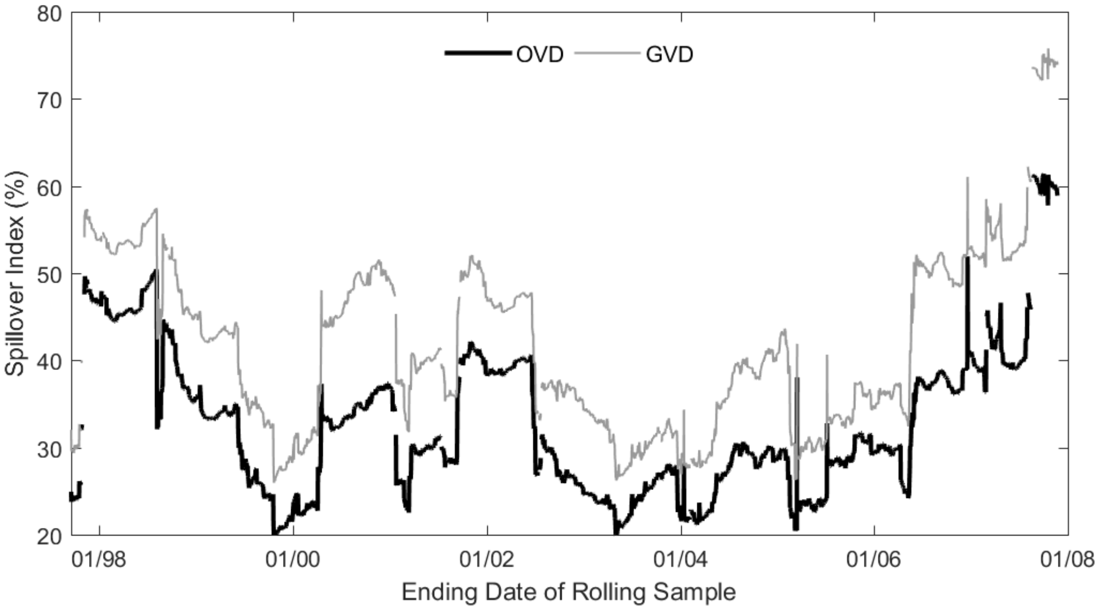
NOTES: For each listed event, the table reports the empirical probability that the value of the DY spillover index in rolling sample $r_e + j$, $j = 0, 1, 5, 22$, exceeds the mean of the DY spillover index evaluated across bootstrap samples in rolling samples $r_e - 5, \dots, r_e - 1$, where r_e denotes the rolling sample ending on the event date. Results under the headings 'OVD' and 'GVD' are obtained using the orthogonalised and generalised forecast error variance decompositions, respectively. The results are based on 1,000 bootstrap-after-bootstrap replications. Specifically, for each rolling sample, we generate an initial 1,000 non-parametric bootstrap replications to estimate the sign and magnitude of the bias in the estimation of the orthogonalised and generalised spillover indices. Given the estimated bias, we then generate another 1,000 non-parametric bootstrap replications to construct the bias-corrected distribution of the orthogonalised and generalised spillover indices. Probabilities of 90% or greater are printed in black, while probabilities lower than 90% are printed in grey.

Table 4: Robustness of the Empirical Probabilities to the use of the 2-day Forecast Horizon

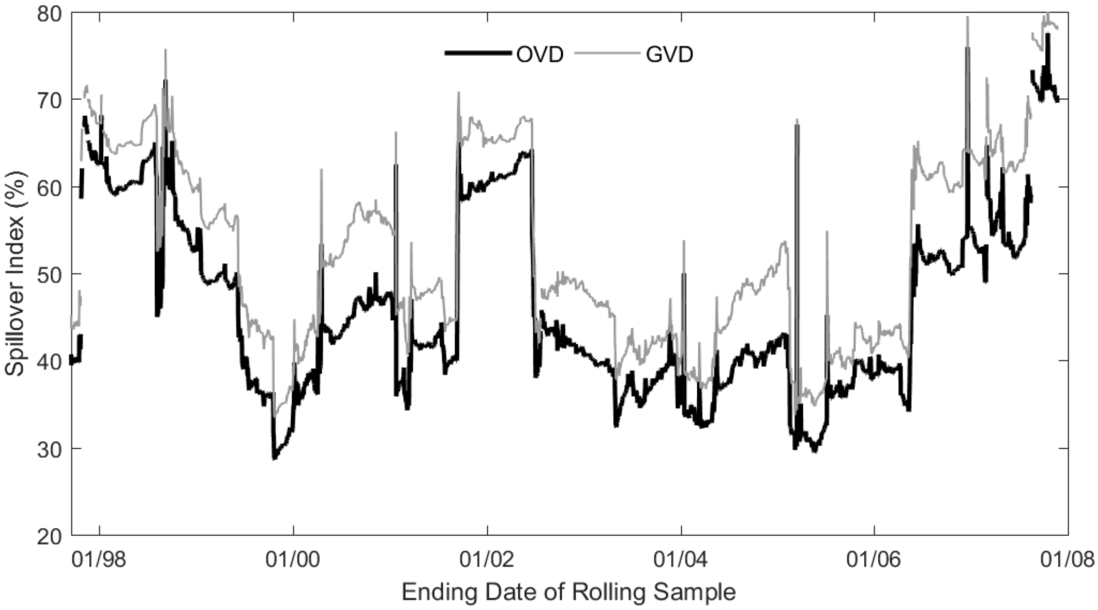
Event	Event Description	$r_e + 0$		$r_e + 1$		$r_e + 5$		$r_e + 22$	
		OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	East Asian crisis spreads to Hong Kong	84.0	84.3	78.9	77.3	100.0	100.0	100.0	100.0
2	East Asian crisis spreads to other countries	100.0	100.0	99.9	99.6	100.0	100.0	100.0	100.0
3	Russian crisis I	54.3	52.8	54.9	53.8	71.2	64.8	0.0	0.0
4	Russian crisis II	86.1	70.8	87.3	71.8	100.0	100.0	100.0	99.9
5	Brazilian crisis	60.9	60.8	62.4	55.3	23.1	24.3	11.5	16.2
6	Profit taking in tech stocks	69.5	72.6	81.3	80.6	88.0	82.3	51.6	60.0
7	Increased market worries for tech stocks	62.7	59.3	100.0	100.0	99.6	99.8	99.5	99.7
8	NASDAQ and DJIA soar amid continued worries	45.6	41.5	44.9	40.3	35.3	40.6	0.0	0.0
9	Markets fall before and after the Fed rate cut	62.6	58.8	76.8	72.5	98.2	95.9	94.6	83.7
10	9/11 terrorist attacks	88.9	94.5	99.7	99.6	100.0	100.0	100.0	100.0
11	Global markets chasing US stocks lower	53.3	33.2	68.0	37.4	99.5	94.8	91.4	95.1
12a	Bomb explosions in Istanbul	54.9	56.2	55.7	57.3	58.2	47.8	51.5	34.3
12b	Bomb explosions in Istanbul	43.4	39.5	49.1	38.7	35.2	23.9	0.0	0.3
13	Reversal in Fed interest rate policy stance	49.6	51.1	66.0	66.0	57.4	58.3	94.5	93.2
14	Dollar crisis	11.4	7.3	10.9	7.1	13.5	8.8	14.0	0.3
15	London terror attack	100.0	99.7	99.4	88.5	99.3	91.0	98.1	86.9
16	Capital outflows from EMs	52.0	53.3	90.4	91.8	99.9	99.5	100.0	100.0
17	Thai market plunges 15%	100.0	95.1	79.2	56.9	75.9	55.6	55.5	49.5
18	First signs of subprime worries	49.4	48.4	51.5	50.0	55.0	54.7	92.9	78.5
19	Global financial market turmoil	41.6	48.5	46.1	50.8	38.0	44.8	100.0	100.0

NOTES: For each listed event, the table reports the empirical probability that the value of the DY spillover index in rolling sample $r_e + j$, $j = 0, 1, 5, 22$, exceeds the mean of the DY spillover index evaluated across bootstrap samples in rolling samples $r_e - 5, \ldots, r_e - 1$, where r_e denotes the rolling sample ending on the event date. Results under the headings 'OVD' and 'GVD' are obtained using the orthogonalised and generalised forecast error variance decompositions, respectively. The results are based on 1,000 bootstrap-after-bootstrap replications. Specifically, for each rolling sample, we generate an initial 1,000 non-parametric bootstrap replications to estimate the sign and magnitude of the bias in the estimation of the orthogonalised and generalised spillover indices. Given the estimated bias, we then generate another 1,000 non-parametric bootstrap replications to construct the bias-corrected distribution of the orthogonalised and generalised spillover indices. Probabilities of 90% or greater are printed in black, while probabilities lower than 90% are printed in grey.

Table 5: Robustness of the Empirical Probabilities to the use of the 2-day Forecast Horizon and the 5-day Average as the Pre-Event Comparison

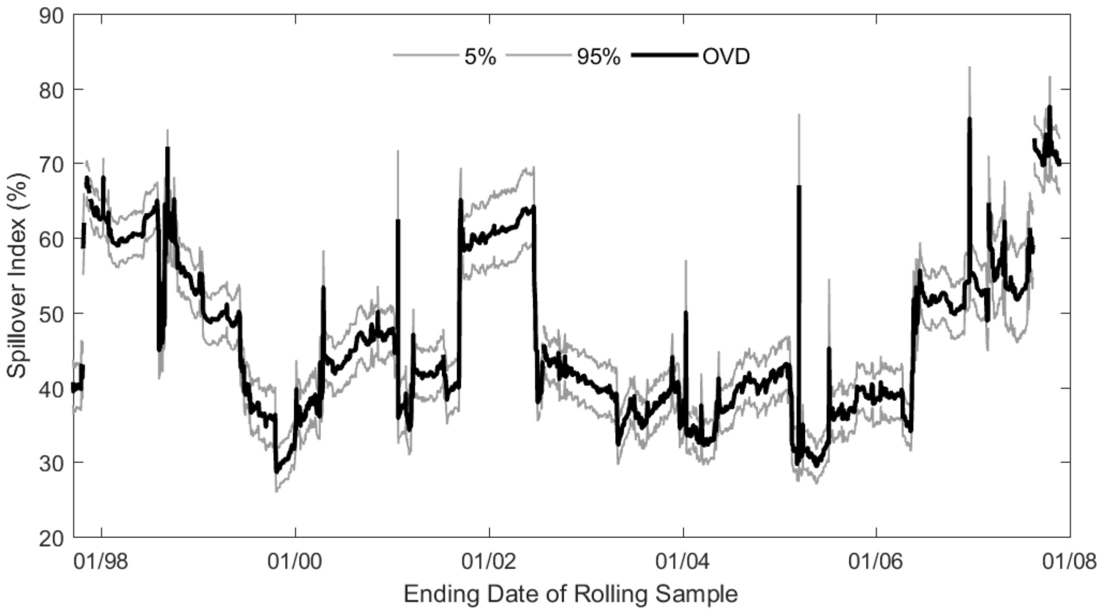


(a) Daily Volatility Spillover Index, 2-days-ahead

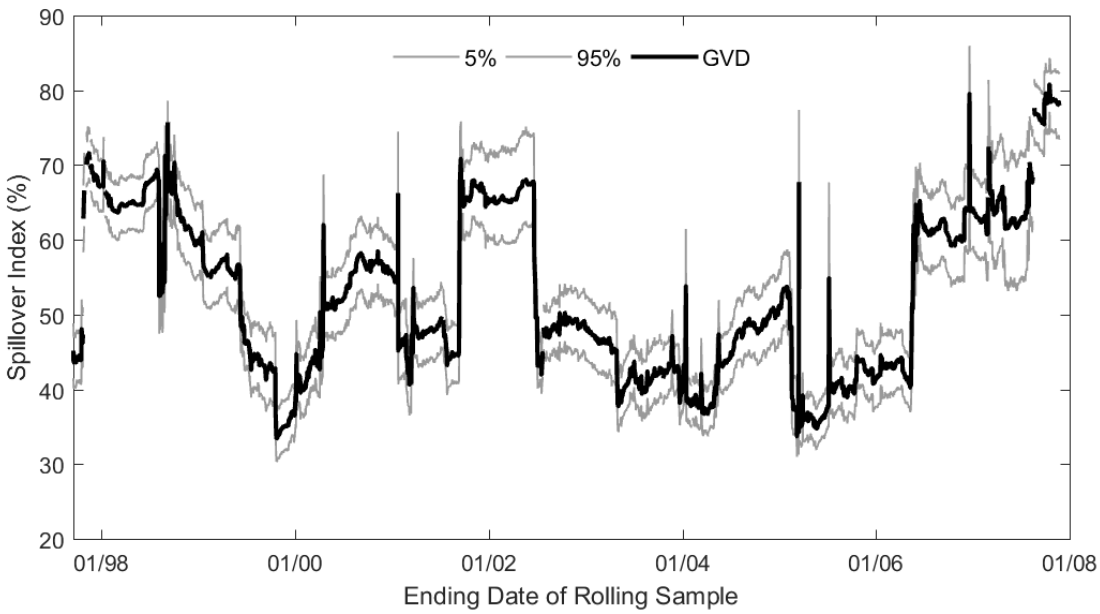


(b) Daily Volatility Spillover Index, 10-days-ahead

Figure 1: Replication of Figure 3 from Diebold and Yilmaz (2009)



(a) OVD-based Daily Volatility Spillover Index, 10-days-ahead



(b) GVD-based Daily Volatility Spillover Index, 10-days-ahead

NOTES: The heavy black line in each panel of the figure reports the point estimate of the 10-days-ahead volatility spillover index, while the gray lines report the fifth and ninety-fifth percentiles of the empirical distribution of the spillover index obtained from our bootstrap-after-bootstrap procedure.

Figure 2: Evolution of the Empirical Distribution of the 10-days-ahead Volatility Spillover Index

Appendix A: Replication of Diebold and Yilmaz (2009)

This Appendix provides a complete replication of the estimation results presented by Diebold and Yilmaz (2009), using both the spillover measures obtained from the OVD (following the method developed by Diebold and Yilmaz, 2009) and the GVD (following the method developed by Diebold and Yilmaz, 2012). Note that Tables 1 and 2 in Diebold and Yilmaz (2009) contain descriptive statistics, which we do not reproduce here.

Replication of Tables 3 and 4

Table A.1 perfectly replicates the full-sample 10-weeks-ahead spillover table for returns reported in Table 3 of Diebold and Yilmaz (2009). Table A.2 reports the corresponding results obtained using the GVD method. The magnitude of the off-diagonal elements of the spillover table obtained using the GVD are larger than those obtained from the OVD, and the values of the prime diagonal are smaller. This effect arises because the GVD allows for contemporaneous correlations among the disturbances in the VAR model, unlike the OVD, where contemporaneous correlations are removed through the use of Cholesky factorisation. Nonetheless, the relative magnitudes observed in the cross-section of bilateral spillovers are similar in both cases.

Table A.3 perfectly replicates the full-sample 10-weeks-ahead volatility spillover table reported in Table 4 of Diebold and Yilmaz (2009). Table A.4 contains corresponding results obtained using the GVD framework. As in the case of return spillovers, the GVD results in larger estimated bilateral spillover effects in the off-diagonal positions and weaker own effects on the prime diagonal.

Replication of Figure 1

Figure 1 in Diebold and Yilmaz (2009) reports the rolling sample return and volatility spillover indices obtained from a VAR(2) specification with the rolling sample size set to 200 weeks and the forecast horizon set to 10 weeks. Figure A.1 presents our replication of Figure 1 from Diebold and Yilmaz (2009), using both the OVD and GVD approaches. As expected, the GVD procedure produces a larger value for both the return and volatility spillover indices in every rolling sample. However, the dynamic pattern is very similar in both cases, with the spillover indices obtained from the OVD and GVD sharing approximately the same trends, turning points and spikes.

Replication of Figure 2

Figure 2 in Diebold and Yilmaz (2009) evaluates the sensitivity of the weekly volatility spillover index to a reduction of the forecast horizon from 10 weeks to 2 weeks. Figure A.2 presents our replication

	US	UK	FRA	GER	HKG	JPN	AUS	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR
US	93.6	1.6	1.5	0.0	0.3	0.2	0.1	0.1	0.2	0.3	0.2	0.2	0.3	0.2	0.1	0.1	0.0	0.5	0.3
UK	40.3	55.7	0.7	0.4	0.1	0.5	0.1	0.2	0.2	0.3	0.2	0.0	0.1	0.1	0.1	0.1	0.0	0.4	0.5
FRA	38.3	21.7	37.2	0.1	0.0	0.2	0.3	0.3	0.3	0.2	0.2	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.3
GER	40.8	15.9	13.0	27.6	0.1	0.1	0.3	0.4	0.6	0.1	0.3	0.3	0.0	0.2	0.0	0.1	0.0	0.1	0.1
HKG	15.3	8.7	1.7	1.4	69.9	0.3	0.0	0.1	0.0	0.3	0.1	0.0	0.2	0.9	0.3	0.0	0.1	0.3	0.4
JPN	12.1	3.1	1.8	0.9	2.3	77.7	0.2	0.3	0.3	0.1	0.2	0.3	0.3	0.1	0.1	0.0	0.0	0.1	0.1
AUS	23.2	6.0	1.3	0.2	6.4	2.3	56.8	0.1	0.4	0.2	0.2	0.2	0.4	0.5	0.1	0.3	0.1	0.6	0.7
IDN	6.0	1.6	1.2	0.7	6.4	1.6	0.4	77.0	0.7	0.4	0.1	0.9	0.2	1.0	0.7	0.1	0.3	0.1	0.4
KOR	8.3	2.6	1.3	0.7	5.6	3.7	1.0	1.2	72.8	0.0	0.0	0.1	0.1	1.3	0.2	0.2	0.1	0.1	0.7
MYS	4.1	2.2	0.6	1.3	10.5	1.5	0.4	6.6	0.5	69.2	0.1	0.1	0.2	1.1	0.1	0.6	0.4	0.2	0.3
PHL	11.1	1.6	0.3	0.2	8.1	0.4	0.9	7.2	0.1	2.9	62.9	0.3	0.4	1.5	1.6	0.1	0.0	0.1	0.2
SGP	16.8	4.8	0.6	0.9	18.5	1.3	0.4	3.2	1.6	3.6	1.7	43.1	0.3	1.1	0.8	0.5	0.1	0.3	0.4
TAI	6.4	1.3	1.2	1.8	5.3	2.8	0.4	0.4	2.0	1.0	1.0	0.9	73.6	0.4	0.8	0.3	0.1	0.3	0.0
THA	6.3	2.4	1.0	0.7	7.8	0.2	0.8	7.6	4.6	4.0	2.3	2.2	0.3	58.2	0.5	0.2	0.1	0.4	0.3
ARG	11.9	2.1	1.6	0.1	1.3	0.8	1.3	0.4	0.4	0.6	0.4	0.6	1.1	0.2	75.3	0.1	0.1	1.4	0.3
BRA	14.1	1.3	1.0	0.7	1.3	1.4	1.6	0.5	0.5	0.7	1.0	0.8	0.1	0.7	7.1	65.8	0.1	0.6	0.7
CHL	11.8	1.1	1.0	0.0	3.2	0.6	1.4	2.3	0.3	0.3	0.1	0.9	0.3	0.8	2.9	4.0	65.8	2.7	0.4
MEX	22.2	3.5	1.2	0.4	3.0	0.3	1.2	0.2	0.3	0.9	1.0	0.1	0.3	0.5	5.4	1.6	0.3	56.9	0.6
TUR	3.0	2.5	0.2	0.7	0.6	0.9	0.6	0.1	0.6	0.3	0.6	0.1	0.9	0.8	0.5	1.1	0.6	0.2	85.8

NOTES: Markets are abbreviated as follows: US–United States; UK–United Kingdom; FRA–France; GER–Germany; HKG–Hong Kong; JPN–Japan; AUS–Australia; IDN–Indonesia; KOR–Korea; MYS–Malaysia; PHL–Philippines; SGP–Singapore; TAI–Thailand; ARG–Argentina; BRA–Brazil; CHL–Chile; MEX–Mexico; and TUR–Turkey. The order in which the markets are listed corresponds to the order of the variables in the VAR model. Results are obtained from a VAR(2) model using a forecast horizon of 10 weeks.

Table A.1: Full-Sample Spillover Table for Weekly Returns based on the OVD

	US	UK	FRA	GER	HKG	JPN	AUS	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR
US	25.5	10.7	10.1	10.8	3.9	3.0	5.9	1.2	2.1	1.0	2.3	4.4	1.2	1.4	3.0	3.6	3.1	6.1	0.6
UK	10.0	23.7	14.0	12.6	5.5	3.0	5.6	0.9	2.1	1.2	1.9	4.2	1.1	1.7	2.6	2.1	2.1	4.5	1.2
FRA	9.3	13.8	23.4	15.9	4.4	3.4	4.9	1.1	2.2	1.0	1.5	3.6	1.3	1.4	3.0	2.2	2.3	4.5	0.9
GER	9.8	12.3	15.8	23.1	4.9	3.0	4.8	1.4	2.3	1.3	1.7	4.0	1.8	1.6	2.4	2.4	2.1	4.4	0.9
HKG	4.3	6.4	5.3	5.8	26.4	2.5	6.2	3.1	3.8	4.0	4.2	10.1	3.0	4.2	1.9	1.9	2.5	4.0	0.4
JPN	5.0	5.3	6.0	5.6	3.7	38.9	6.0	2.5	4.5	2.0	1.2	4.6	3.2	1.3	1.6	3.0	1.4	3.0	0.8
AUS	7.1	7.4	6.6	6.3	6.5	4.3	27.6	1.6	3.3	2.1	3.0	4.6	1.6	2.5	2.8	3.3	3.1	5.1	1.2
IDN	2.5	2.6	1.9	2.6	5.0	2.6	2.6	37.6	3.3	6.1	6.9	7.4	1.6	7.1	1.8	2.1	3.4	2.5	0.7
KOR	3.4	3.7	3.6	3.9	5.5	4.4	4.7	2.9	38.4	2.0	1.6	6.3	3.6	6.1	1.8	1.9	1.9	3.0	1.3
MYS	1.7	2.4	1.7	2.6	7.0	2.1	3.1	6.5	2.6	38.4	5.6	9.6	2.5	7.1	1.6	0.5	2.1	2.7	0.2
PHL	4.0	3.5	2.5	2.9	6.1	1.5	4.1	5.9	1.8	5.3	32.5	8.4	2.7	6.8	3.1	1.7	2.3	4.1	0.7
SGP	4.7	5.1	4.1	4.6	9.7	3.0	4.3	4.4	4.2	6.0	5.7	24.7	3.3	6.0	2.6	1.3	2.4	3.4	0.6
TAI	3.0	3.0	3.4	4.5	5.5	3.6	2.5	1.6	4.2	2.9	3.1	6.3	44.0	2.9	2.0	1.2	1.8	3.5	0.9
THA	2.4	2.9	2.1	2.7	5.6	1.3	3.3	6.1	5.6	6.2	5.9	8.1	2.2	35.4	1.9	1.8	2.4	3.0	1.1
ARG	4.8	4.5	4.9	4.0	2.9	1.9	4.2	1.1	2.0	1.6	2.0	3.8	1.9	1.7	38.1	6.9	4.2	8.6	0.9
BRA	5.9	3.8	4.2	4.2	3.1	3.0	5.1	1.7	1.9	0.8	1.8	1.9	1.0	1.9	7.0	38.1	6.0	7.2	1.4
CHL	4.8	3.6	3.6	3.3	4.1	1.7	4.5	3.1	2.1	2.1	2.3	4.2	1.7	2.9	4.3	6.4	37.3	6.5	1.5
MEX	7.1	6.0	5.9	5.8	4.7	2.2	5.3	1.4	2.3	2.1	2.9	4.0	1.9	2.1	6.3	5.2	3.6	30.5	0.6
TUR	2.1	3.6	2.7	3.3	1.6	1.5	2.4	0.6	1.9	0.5	1.3	1.7	1.9	1.7	1.7	2.6	2.1	1.3	65.5

NOTES: Markets are abbreviated as follows: US–United States; UK–United Kingdom; FRA–France; GER–Germany; HKG–Hong Kong; JPN–Japan; AUS–Australia; IDN–Indonesia; KOR–Korea; MYS–Malaysia; PHL–Philippines; SGP–Singapore; TAI–Thailand; ARG–Argentina; BRA–Brazil; CHL–Chile; MEX–Mexico; and TUR–Turkey. Results are obtained from a VAR(2) model using the order-invariant GVD with a forecast horizon of 10 weeks.

Table A.2: Full-Sample Spillover Table for Weekly Returns based on the GVD

	US	UK	FRA	GER	HKG	JPN	AUS	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR
US	63.6	14.9	4.0	1.9	4.8	0.2	1.8	0.3	1.6	0.9	0.4	2.6	0.4	0.1	0.1	0.1	0.1	0.2	2.0
UK	22.9	54.3	5.0	1.3	7.4	0.5	2.1	0.3	1.1	0.8	0.1	2.4	0.2	0.2	0.4	0.2	0.1	0.1	0.7
FRA	23.9	32.8	27.2	0.2	5.3	0.2	2.9	0.4	0.3	1.2	0.4	2.4	0.2	0.3	0.6	0.3	0.1	0.1	0.9
GER	26.9	29.5	13.6	13.6	4.7	0.2	4.0	0.2	0.3	1.4	0.8	2.1	0.2	0.4	0.6	0.3	0.1	0.2	1.0
HKG	2.0	0.5	0.7	0.0	87.6	0.1	0.1	0.4	1.4	0.5	1.5	3.4	0.6	0.4	0.0	0.1	0.0	0.1	0.3
JPN	2.7	3.3	0.4	0.7	1.6	82.7	0.2	0.1	0.9	1.1	0.2	1.6	0.3	0.0	0.6	0.3	0.3	0.2	2.8
AUS	8.9	2.2	0.3	0.6	43.9	0.2	34.7	1.2	1.7	1.3	0.2	2.8	0.1	1.0	0.1	0.2	0.2	0.3	0.1
IDN	2.8	0.9	0.3	1.0	6.1	0.3	0.6	71.1	7.0	2.3	2.5	2.9	0.7	0.0	0.0	0.3	0.2	0.2	0.9
KOR	2.5	0.6	0.4	0.4	9.1	1.0	1.0	10.3	67.3	1.4	0.9	2.6	0.8	0.2	0.1	0.1	0.2	0.3	0.9
MYS	1.3	0.6	0.3	0.6	7.2	1.0	0.9	0.9	1.7	70.6	3.1	6.1	0.3	0.5	0.9	0.6	0.1	1.5	1.9
PHL	2.1	0.3	0.3	0.4	8.9	0.3	0.4	8.8	3.0	6.1	66.6	1.5	0.2	0.2	0.2	0.2	0.1	0.2	0.3
SGP	12.5	4.1	0.6	0.1	12.2	0.8	0.9	7.6	7.3	2.9	1.5	45.7	0.5	0.1	0.7	0.7	0.0	0.7	1.2
TAI	8.5	0.4	0.4	0.2	2.8	0.7	1.3	0.5	9.5	0.7	1.7	0.6	68.9	0.2	0.4	0.8	0.2	0.7	1.3
THA	0.5	0.7	0.4	0.3	9.0	0.2	0.3	3.6	2.9	0.4	0.8	5.3	0.2	73.8	0.1	0.5	0.1	0.7	0.2
ARG	3.5	1.5	1.6	0.4	2.7	0.5	1.2	0.3	0.1	2.1	0.2	0.8	0.4	0.3	80.9	0.9	0.8	0.6	1.0
BRA	4.5	2.3	1.5	0.3	12.6	0.4	3.3	1.0	0.3	10.0	0.7	3.5	0.5	0.3	11.6	45.1	0.3	0.9	0.8
CHL	3.5	0.7	0.7	0.3	2.7	0.1	3.6	1.1	0.2	1.8	0.3	1.8	0.3	0.4	3.6	5.0	73.7	0.2	0.1
MEX	6.5	1.3	0.7	0.3	25.0	0.2	4.8	0.3	0.5	2.4	0.3	2.1	0.2	0.5	6.3	3.0	0.3	44.0	1.1
TUR	2.8	1.7	0.8	0.7	3.9	0.3	1.2	0.3	1.2	2.7	0.5	1.0	4.0	0.1	0.7	0.3	0.2	1.1	76.7

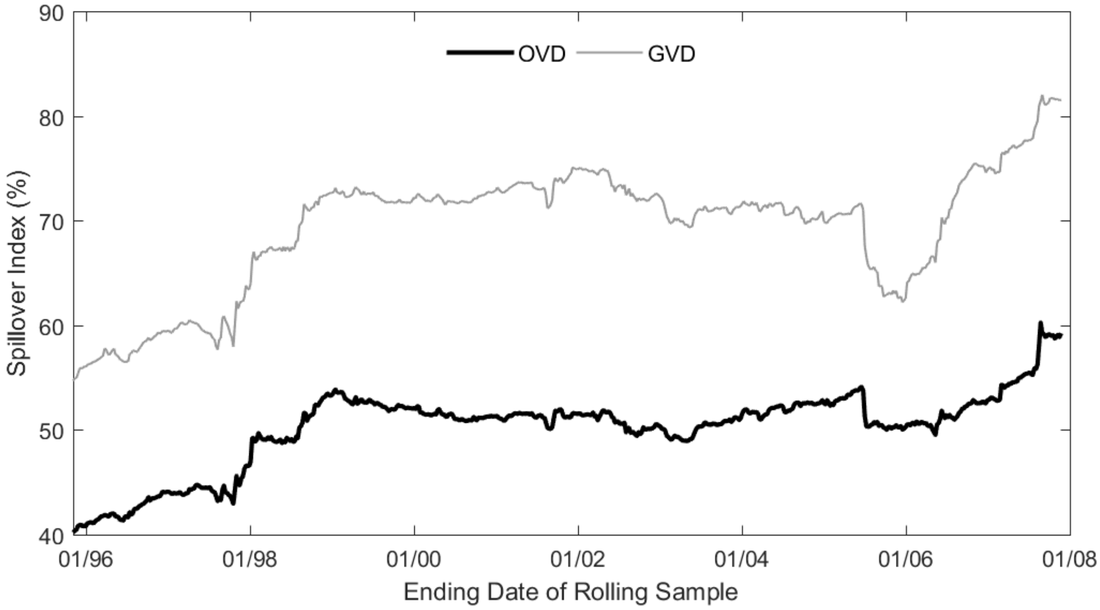
NOTES: Markets are abbreviated as follows: US–United States; UK–United Kingdom; FRA–France; GER–Germany; HKG–Hong Kong; JPN–Japan; AUS–Australia; IDN–Indonesia; KOR–Korea; MYS–Malaysia; PHL–Philippines; SGP–Singapore; TAI–Thailand; ARG–Argentina; BRA–Brazil; CHL–Chile; MEX–Mexico; and TUR–Turkey. The order in which the markets are listed corresponds to the order of the variables in the VAR model. Results are obtained from a VAR(2) model using a forecast horizon of 10 weeks.

Table A.3: Full-Sample Spillover Table for Weekly Volatility, obtained from the OVD

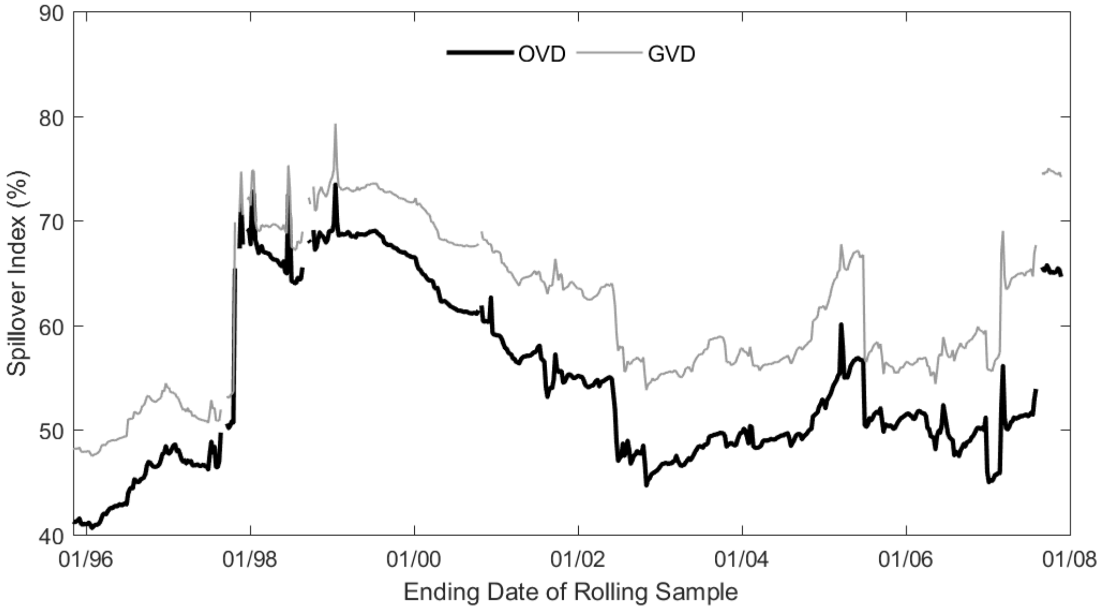
	US	UK	FRA	GER	HKG	JPN	AUS	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR
US	27.3	16.9	17.5	14.0	3.8	1.0	3.3	0.3	1.5	0.3	0.9	1.3	2.6	0.1	1.6	1.3	0.8	3.2	2.2
UK	9.1	30.5	21.7	15.8	4.5	1.7	3.3	0.4	1.1	0.4	0.5	1.7	1.7	0.3	1.9	1.5	0.6	2.0	1.4
FRA	9.0	20.5	30.1	20.5	3.5	1.2	1.8	0.3	0.6	0.3	0.5	1.3	1.5	0.3	2.3	2.3	0.3	2.2	1.7
GER	10.2	19.9	24.2	27.3	3.1	1.2	1.3	0.3	0.7	0.4	0.6	1.2	1.4	0.3	2.1	1.9	0.2	1.9	1.9
HKG	1.2	0.9	1.4	1.2	53.9	0.8	6.2	2.5	4.5	2.8	8.3	5.5	3.6	2.1	0.4	1.9	0.2	2.2	0.4
JPN	2.0	4.2	3.6	3.6	2.0	66.2	1.5	0.4	1.9	2.7	0.3	1.2	1.8	0.4	2.0	2.0	0.1	1.3	2.8
AUS	5.5	4.5	3.3	2.5	29.3	0.7	31.6	0.8	1.6	0.8	3.0	2.6	1.1	0.1	1.2	2.3	2.3	6.0	1.0
IDN	1.8	1.6	1.2	1.9	4.9	0.5	1.8	50.7	6.8	3.7	10.4	7.6	0.9	2.0	0.3	1.2	0.9	0.8	1.1
KOR	1.6	1.3	1.2	1.4	6.9	1.4	1.4	9.0	50.0	2.1	2.8	7.1	9.2	2.5	0.2	0.3	0.0	0.7	0.9
MYS	1.0	0.9	0.5	0.8	6.0	1.2	2.7	1.4	2.4	61.6	3.9	1.6	1.2	0.9	2.3	5.7	0.4	3.2	2.1
PHL	1.4	0.7	0.8	1.1	6.7	0.2	1.4	8.5	2.4	5.8	57.7	5.6	0.9	1.8	0.7	2.1	0.8	1.0	0.5
SGP	5.1	5.0	4.5	4.3	6.6	1.4	3.5	5.7	5.6	2.9	3.3	31.6	3.9	4.6	2.3	3.6	1.8	2.9	1.5
TAI	5.8	2.5	3.1	3.0	2.9	1.2	0.6	0.4	9.2	0.5	1.5	3.5	61.1	0.7	0.9	0.2	0.3	1.2	1.5
THA	0.3	0.4	0.5	0.4	6.8	0.5	0.3	4.1	3.8	1.1	3.5	9.3	1.5	65.1	0.2	0.9	0.1	0.8	0.2
ARG	2.1	2.4	3.6	3.1	2.2	0.9	2.6	0.3	0.4	2.0	0.2	1.5	0.9	0.3	54.7	8.3	1.9	10.5	2.1
BRA	2.3	2.8	3.1	3.0	7.8	0.9	6.0	1.2	0.5	7.9	2.2	2.5	0.8	0.6	10.2	34.7	3.4	8.7	1.3
CHL	2.3	1.8	1.1	0.8	2.2	0.1	4.8	1.6	0.1	1.8	1.1	3.4	0.1	0.1	4.4	7.3	61.1	5.2	0.7
MEX	3.6	2.9	3.3	3.0	15.0	0.3	7.3	0.3	0.9	1.9	1.9	1.4	1.0	0.2	6.4	7.1	2.5	38.8	2.1
TUR	2.1	2.8	3.3	3.9	3.7	0.4	2.1	0.9	2.0	2.9	1.0	1.4	4.9	0.3	1.6	1.7	0.7	3.2	61.4

NOTES: Markets are abbreviated as follows: US–United States; UK–United Kingdom; FRA–France; GER–Germany; HKG–Hong Kong; JPN–Japan; AUS–Australia; IDN–Indonesia; KOR–Korea; MYS–Malaysia; PHL–Philippines; SGP–Singapore; TAI–Thailand; ARG–Argentina; BRA–Brazil; CHL–Chile; MEX–Mexico; and TUR–Turkey. Results are obtained from a VAR(2) model using the order-invariant GVD with a forecast horizon of 10 weeks.

Table A.4: Full-Sample Spillover Table for Weekly Volatility, obtained from the GVD



(a) Weekly return spillovers, 10-weeks-ahead



(b) Weekly volatility spillovers, 10-weeks-ahead

Figure A.1: Replication of Figure 1 from Diebold and Yilmaz (2009)

of this exercise, using both the OVD and GVD methods. As before, the GVD methods results in a higher spillover index, although the difference is less pronounced in this case, because the use of a shorter forecast horizon results in the use of smaller powers in the computation of the GVD. The choice of OVD or GVD does not affect the dynamics of the volatility spillover index appreciably.

Replication of Figure 3

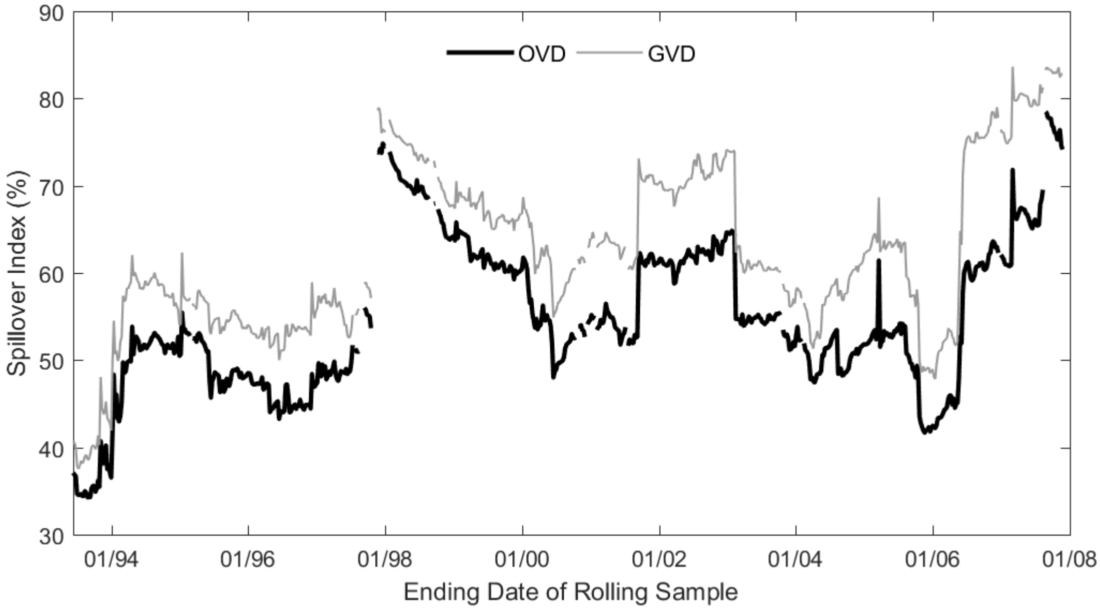
For our replication of Figure 3 from Diebold and Yilmaz (2009), please see Figure 1 in the main text.

Replication of Figure 4

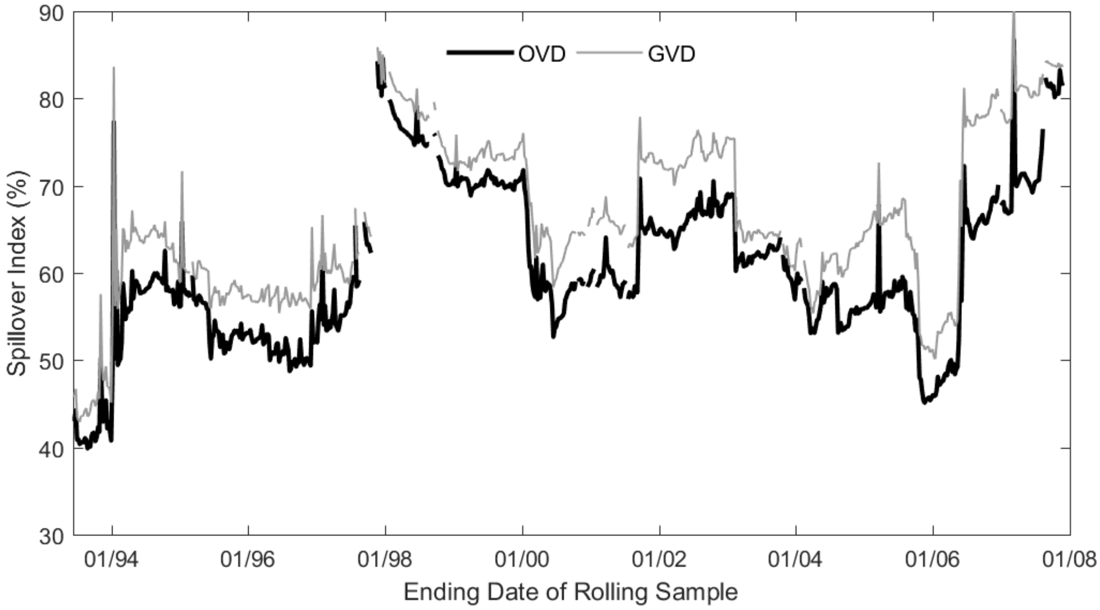
Figure 4 in Diebold and Yilmaz (2009) evaluates the robustness of the volatility spillover index to alternative orderings of the variables entering the VAR model. For this exercise, the authors use a rolling sample of 200 weeks and conduct two different exercises. First, the authors simply consider 18 different orderings obtained by rotating the variables in the VAR model by sequentially moving the market at the top of the order (initially the US, then the UK etc.) to last place and continuing until the market that was initially ordered last (Turkey) is ordered first. This is a perfectly replicable exercise and Figure A.3(a) reveals that we obtain a perfect replication using the OVD method. Note that we exclude rolling samples in which the maximum eigenvalue of the VAR companion matrix is equal to or greater than 1.

The second exercise that Diebold and Yilmaz (2009) conduct is based on 50 random orderings. This exercise is not perfectly replicable without knowledge of the random number sequence used by the authors. Nonetheless, our analysis of 50 random re-orderings of the markets in Figure A.3(b) using the OVD method yields results that closely resemble those in Figure 4(b) of Diebold and Yilmaz (2009).

Note that we do not present a replication of Figure 4 from Diebold and Yilmaz (2009) based on the GVD method, because it is invariant to the ordering of the variables in the VAR model and would, therefore, display perfect robustness in both of the exercises undertaken here.

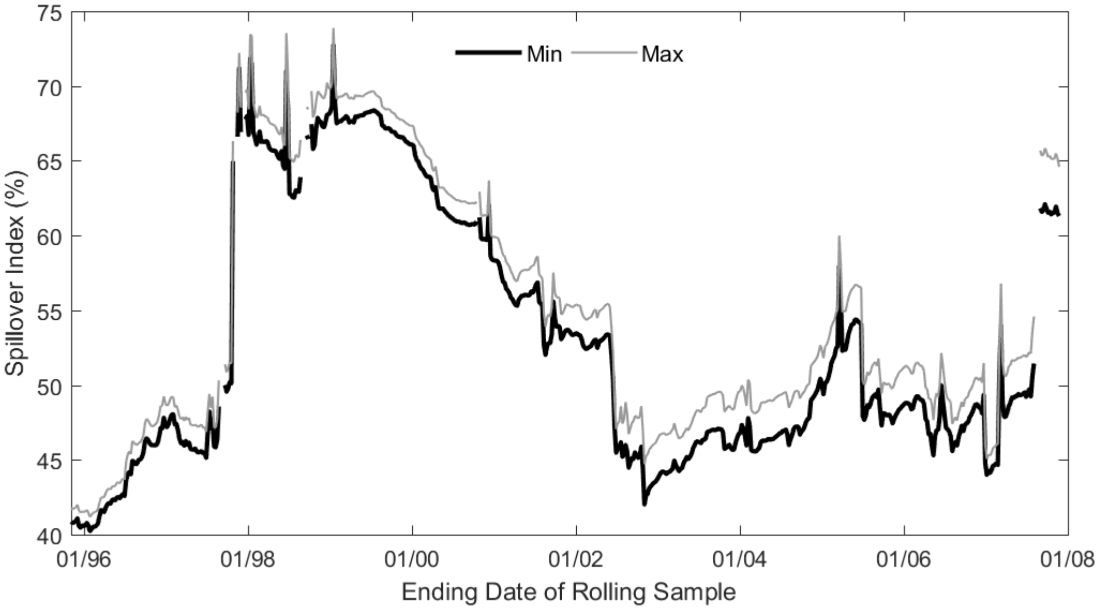


(a) Weekly volatility spillover index, 2-weeks-ahead

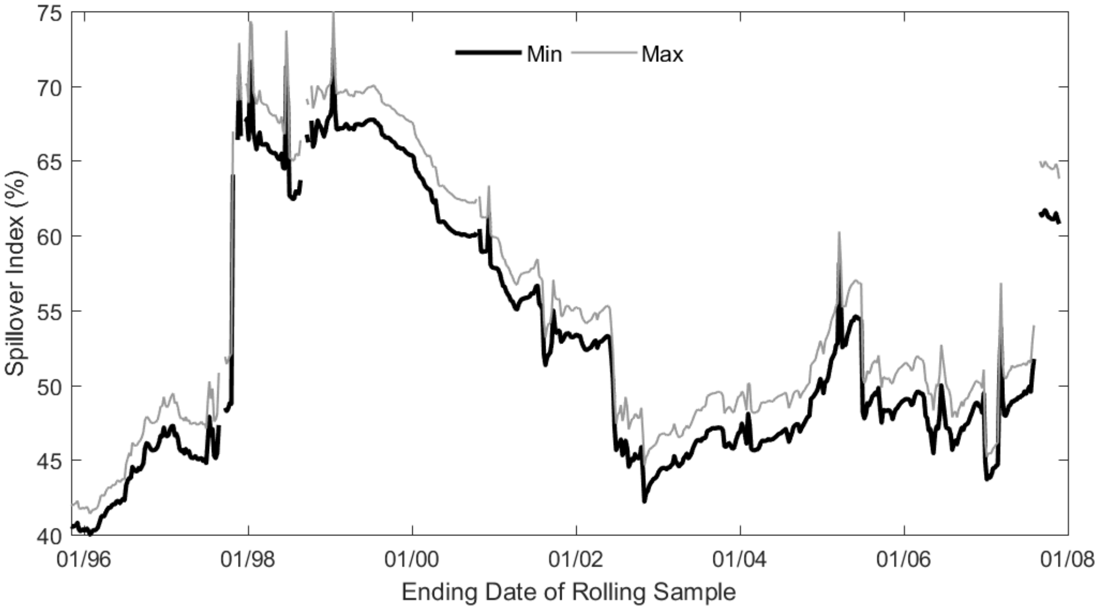


(b) Weekly volatility spillover index, 10-weeks-ahead

Figure A.2: Replication of Figure 2 from Diebold and Yilmaz (2009)



(a) Robustness of the weekly volatility spillover index evaluated over 18 rotated orderings



(b) Robustness of the weekly volatility spillover index evaluated over 50 random orderings

Figure A.3: Replication of Figure 4 from Diebold and Yilmaz (2009)

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