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Detecting Statistically Significant Changes in Connectedness: A Bootstrap-Based Technique

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Abstract

Connectedness quantifies the extent of interlinkages within economies or markets based on a network approach. Connectedness is measured by the Diebold-Yilmaz spillover index, and abrupt increases in this measure are thought to result from major events. However, formal statistical evidence of events causing such increases is scant. We develop a bootstrap-based technique to evaluate the probability that the value of the spillover index changes at a statistically significant level following an exogenously defined event. We further show how our procedure can detect the dates of unknown events endogenously. The results of a simulation exercise support the effectiveness of our method. We revisit the original dataset from Diebold and Yilmaz's seminal work and obtain statistical support that the spillover index increases quickly in the wake of adverse shocks. Our methodology accounts for small sample bias and is robust with respect to modifications of the pre-event period and forecast horizon.

Keywords

connectedness, spillover index, adverse shocks, impactful events, financial contagion, bootstrap-after-bootstrap procedure

JEL Classification

C32, C58, G15

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Detecting Statistically Significant Changes in Connectedness: A Bootstrap-based Technique*

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Abstract

Connectedness quantifies the extent of interlinkages within economies or markets based on a network approach. Connectedness is measured by the Diebold-Yilmaz spillover index, and abrupt increases in this measure are thought to result from major events. However, formal statistical evidence of events causing such increases is scant. We develop a bootstrap-based technique to evaluate the probability that the value of the spillover index changes at a statistically significant level following an exogenously defined event. We further show how our procedure can detect the dates of unknown events endogenously. The results of a simulation exercise support the effectiveness of our method. We revisit the original dataset from Diebold and Yilmaz's seminal work and obtain statistical support that the spillover index increases quickly in the wake of adverse shocks. Our methodology accounts for small sample bias and is robust with respect to modifications of the pre-event period and forecast horizon.

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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) is one of the most important additions to the financial economist's toolbox of recent years. The authors' key insight is that a decomposition of the forecast error variances obtained from a vector autoregression (VAR) forms 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. Abrupt increases in the spillover index from one sample to another signify 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, as opposed to a statistical analysis of the hypothesis that a change in the spillover index coincides with a given event. This opens applications of the Diebold-Yilmaz technique to the criticism that their interpretation is nuanced or conjectural and provides motivation for developing a formal analytical approach. We address this issue by developing a probabilistic framework based on a non-parametric bootstrap-after-bootstrap procedure. We demonstrate our approach by replicating the empirical analysis of Diebold and Yilmaz (2009) to test whether the spillover index increases with high probability in response to the adverse events presented in the authors' narrative. Our results lend statistically qualified support to the notion that the spillover index responds to adverse 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. With respect to the above, the Diebold-Yilmaz technique is the leading network technique based on the forecast error variances, and in this respect, it differs from other frameworks for network analysis that have been proposed over this period. Alternative methods include the Granger-causal approach adopted by Billio et al. (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). Among those, the Diebold-Yilmaz approach is the only forecast-based technique, and perhaps this is also a reason why it has emerged as the most widely adopted of these methods. In addition, the technique offers relative ease of implementation and interpretation.

The literature that applies the Diebold-Yilmaz technique is voluminous and 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, foreign exchange, credit derivatives, or cryptocurrencies.[1] The second

[1]E.g., Bubák et al. (2011), Antonakakis (2012), Engle et al. (2012), Alter and Beyer (2014), Tsai (2014), Baruník

strand considers spillovers between combinations of different types of financial markets.[2] The third strand focuses on more complex interactions and volatility spillovers between various combinations of the foreign exchange, equity, bond, commodity, and crypto markets[3], with a notable subset of papers focusing on spillovers to and from the oil market.[4] The final strand considers macroeconomic linkages among countries and is well represented by Diebold and Yilmaz (2015) and Greenwood-Nimmo et al. (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. (2022) develop a method to characterise connectedness based on quantile regression.

None of the articles surveyed above has provided formal statistical evidence that connects changes in spillover activity with specific events, but progress is being made in this direction. In an early and innovative contribution, Claeys and Vašíček (2014) apply the Diebold-Yilmaz framework to a factor-augmented VAR model covering 16 European sovereign bond markets and test for structural breaks in the regression coefficients following Qu and Perron (2007). Evidence of structural breaks is indicative of contagion. Greenwood-Nimmo et al. (2016) examine the extent to which large changes in foreign exchange market spillovers 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. More recently, Greenwood-Nimmo et al. (2023) use the Diebold-Yilmaz method to study connectedness in the sovereign CDS market. They use kernel density estimation to characterise the density of the bilateral spillover effects over rolling samples and show that summary statistics capturing changes in the shape of the spillover density are associated with published indicators of systemic stress in a statistically significant way.

Two papers have used bootstrap methods. First, Greenwood-Nimmo et al. (2019) 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 (2022) develop a bootstrap-based

et al. (2016), Greenwood-Nimmo et al. (2016), Baruník et al. (2017), Greenwood-Nimmo et al. (2019), Kočenda and Moravcová (2019), Ji et al. (2019), Ando et al. (2022) and Mo et al. (2023).

[2]For example, money and asset markets (Cronin, 2014), foreign exchange and stock markets (Grobys, 2015; Do et al., 2015, 2016), financial technology and decentralized finance markets (Gunay et al., 2023).

[3]E.g., Salisu and Mobolaji (2013), Clements et al. (2015), Aboura and Chevallier (2014), Baruník and Kočenda (2019), Chen et al. (2022), Caporale et al. (2023) and Kyriazis et al. (2023).

[4]E.g., Reboredo (2014), Kang et al. (2014), Zhang and Wang (2014), Baruník et al. (2015), Wei et al. (2022), and Kočenda and Moravcová (2024).

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 consider changes in aggregate connectedness measured via the spillover index, which is the issue that we address in this paper.

Our goal in this paper is to develop a simple and robust framework for the probabilistic analysis 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 to form a foundation for statistical inference. Our technique displays several similarities to the bootstrap-after-bootstrap procedure developed by Kilian (1998) for constructing bias-corrected small-sample confidence intervals for impulse response functions. Our use of bootstrap inference confers an important practical benefit relative to asymptotic approximations, as its use is not limited to large samples.[5] 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 using a large-sample approximation. We perform a simulation exercise to assess the effectiveness of our method in complementing our non-parametric bootstrap-after-bootstrap procedure. In the simulation, we account for temporary and permanent shifts in the spillover index, and our procedure accurately identifies both types of change. Overall, the simulation exercise strongly supports the credibility of our method in identifying statistically significant changes in the Spillover Index.

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. Our use of the authors' seminal dataset conveys several benefits, most notably that it allows us to study the reaction of a spillover index obtained from an existing model that is not of our making to a list of events that are not of our choosing. This prevents any subconscious bias that may arise from our model specification or our selection of events and provides perfect comparability against one of the most highly cited papers in the field.

We begin with a full replication of the results in Diebold and Yilmaz (2009) 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 the generalised spillover index allows for the contemporaneous correlation among

[5] While the asymptotic theory has been developed for forecast error variance decompositions (see Lütkepohl, 1990), we are not aware of any comparable results for the spillover index. Efforts to adapt the existing asymptotic results to obtain an asymptotic distribution for the spillover index would be complicated by the fact that the latter is defined as the ratio of two sets of aggregated forecast error variance decompositions. A further complication arises in the generalised set-up of Diebold and Yilmaz (2014), where an additional row-sum normalisation step is required. Buse et al. (2022) follow Lütkepohl (2000)'s bootstrap procedure for impulse response functions in VAR and provide confidence interval for connectedness measures. However, the approach does not address the small sample bias issue as highlighted in Kilian (1998).

the reduced form disturbances, unlike its orthogonalised counterpart (see 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" (Diebold and Yilmaz, 2009, 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 evaluate the statistical evidence in support of the claim that the volatility spillover index increases 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 empirical 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 measure the intensity of volatility spillovers prevailing before each event using the volatility spillover index estimated in the rolling sample ending immediately before 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 statistically qualified support to the notion that the volatility spillover index increases 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 the 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 probabilistic analysis on the spillover index. Further, we provide simulation evidence that enhances our method's credibility and a brief outline of how to conduct our procedure to detect the dates of unknown events endogenously. 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 Diebold and Yilmaz (2009) connectedness framework starts with a pth-order reduced form VAR:

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

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, $\boldsymbol{\Sigma}$.[6] Let $\boldsymbol{G}_\ell$, $\ell = 0, \ldots, \infty$, denote ℓth $m \times m$ parameter matrix of the vector moving average represetation of (1). The h-steps-ahead orthogonalised forecast error variance decomposition (OVD) for the i-th variable is given by:

$$\theta_{i \leftarrow j}^{(h)} = \frac{\sum_{\ell=0}^{h} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{P} \boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{h} \boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \boldsymbol{e}_i}, \qquad i, j = 1, \ldots, m, \tag{2}$$

where $\boldsymbol{e}_i$ is an $m \times 1$ selection vector with 1 in the ith position and zeroes elsewhere and $\boldsymbol{P}$ is the lower-triangular Cholesky factor of $\boldsymbol{\Sigma}$.

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. However, the OVD is sensitive to the ordering of the endogenous variables in the system. To achieve order-invariance, Diebold and Yilmaz (2014) adopt the generalised forecast error variance decomposition (GVD) of Pesaran and Shin (1998), which is given by:

$$\check{\vartheta}_{i \leftarrow j}^{(h)} = \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^{h} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{h} \boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \boldsymbol{e}_i}, \tag{3}$$

where σ_{jj} is the jth diagonal element of $\boldsymbol{\Sigma}$. $\check{\vartheta}_{i \leftarrow j}^{(h)}$ is interpreted similarly to $\theta_{i \leftarrow j}^{(h)}$, except that is based

[6] We omit deterministic terms for simplicity; their inclusion does not materially affect the discussion that follows.

on cross-sectionally correlated disturbances, meaning that the GVDs may sum to more than 100%. Diebold and Yilmaz (2014) therefore apply the row-sum normalization $\vartheta_{i\leftarrow j}^{(h)} = \check{\vartheta}_{i\leftarrow j}^{(h)} \Big/ \sum_{j=1}^{m} \check{\vartheta}_{i\leftarrow j}^{(h)}$.

Diebold and Yilmaz (2009, 2014) show that the matrix of forecast error variance decompositions, whether obtained using the OVD or GVD, forms a weighted directed network. The spillover index proposed by Diebold and Yilmaz (2009) is defined as the sum of all off-diagonal elements of the matrix of forecast error variance decompositions expressed as a percentage of the grand sum of all of the elements of the matrix. Consequently, it measures the percentage of the h-steps-ahead forecast error variance for all m variables that can be attributed to bilateral spillovers as opposed to unilateral loops. To avoid ambiguity, we will henceforth refer to OVD-based spillover matrix from Diebold and Yilmaz (2009) as the 'orthogonalised spillover index' and its GVD-based counterpart from Diebold and Yilmaz (2014) as the 'generalised spillover index'.

2.2 Probabilistic Analysis of the Spillover Indices

If the VAR(p) model (1) is estimated over rolling samples of length w indexed by $r = 1, \dots, R$, then one obtains R rolling sample estimates of the orthogonalised and generalised spillover indices 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 based on visual inspection of the rolling sample point estimates of the spillover index. However, this process does not convey any probabilistic information on the significance of changes in spillover activity from one rolling sample to another.

In principle, one could develop an 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. (2019) and Greenwood-Nimmo and Tarassow (2022), we propose a bootstrap-based technique. Greenwood-Nimmo et al. (2019) employ a residual bootstrap to construct empirical intervals for spillover statistics, while Greenwood-Nimmo and Tarassow (2022) use a block bootstrap routine 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. The extent of the bias is discussed in detail in Section 4.1.

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, $\widehat{\mathcal{S}}$.

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

$$\boldsymbol{x}_t^{(b)} = \sum_{j=1}^{p} \widehat{\boldsymbol{A}}_j \boldsymbol{x}_{t-j}^{(b)} + \boldsymbol{u}_t^{(b)}, \tag{4}$$

   where the p initial values of $\boldsymbol{x}_t^{(b)}$ are taken as given and where $\boldsymbol{u}_t^{(b)}$ can be obtained either by resampling with replacement from the VAR residuals, $\widehat{\boldsymbol{u}}_t$, or by a parametric procedure.

3. Re-estimate (1) B times to obtain new estimates of the parameter matrices, $\widehat{\boldsymbol{A}}_j^{(b)}$, $j = 1, \ldots, p$, the residual covariance matrix, $\widehat{\boldsymbol{\Sigma}}^{(b)}$, and the orthogonalised spillover index, $\widehat{\mathcal{S}}^{(b)}$, $b = 1, \ldots, B$.[7]

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

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

6. Repeat steps 1-5 for all the remaining rolling samples to obtain the bias-corrected empirical distribution of the orthogonalised spillover index for each rolling sample. In our analysis, the number of bootstrap samples B is set to 1000 for both the bias correction (steps 2-4) and for generating the final bias-corrected distribution of the spillover indices (step 5).

In the above algorithm, we used a lag value $p = 2$, an $h = 10$-step ahead forecast horizon, and a window length $w = 200$ as in Diebold and Yilmaz (2009).[8] Probabilistic analysis can proceed on the basis of the empirical distributions obtained in step 6. 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

[7]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.

[8]The window lengths play an important role in estimating the VAR(p) model. However, in our procedure, we focus on conducting a probability event analysis based on Diebold and Yilmaz (2009) who do not consider different window lengths. We want to avoid any potential confusion between our method and the set-up in the seminal DY paper or any doubts that our findings are due to different window lengths. On the other hand, Bartušek and Kočenda (2023) performed an analysis with window lengths of 100 and 200 days and reported that the events with major impacts were identified in connectedness quantified under both rolling windows.

$\overline{\mathcal{S}}_{r_e-1} = B^{-1}\sum_{b=1}^{B}\widehat{\mathcal{S}}_{r_e-1}^{(b)}$, is computed as follows:

$$\Pr\left(\mathcal{S}_{r_e+j} > \overline{\mathcal{S}}_{r_e-1}\right) = B^{-1}\sum_{b=1}^{B}\mathbb{I}\left\{\left(\widehat{\mathcal{S}}_{r_e+j}^{(b)} - \overline{\mathcal{S}}_{r_e-1}\right) > 0\right\}, \tag{5}$$

where $\mathbb{I}\{\cdot\}$ is an indicator 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.

Finally, the rationale behind our formulation of probability (as depicted in formula (6)) accords with the common interpretation from the connectedness literature that adverse events are associated with a higher level of the Spillover Index. In essence, we compare the levels of the Spillover Index at two points in time (say, $t-1$ versus $t+i$, for $i = 0, 1, 2, \ldots$), and compute the probability that the Spillover Index at time $t+i$ is greater than its value at time $t-1$. The calculated probability for such an event (say, 90%) indicates whether there is a statistically significant change (increase) in the Spillover Index at time $t+i$. As we compare the levels of the Spillover Index at two points in time, the computation does not imply that the change is perpetual.[9]

2.3 Simulation Evidence

In this section, we demonstrate the usefulness of our method through simulation analysis. We generate m stationary time series, denoted $\mathbf{y}_t$, over T periods using VAR(1) as the data generating process (DGP). We then apply our bootstrap-after-bootstrap procedures on a rolling basis with a window length w, to calculate probability events of interest for the simulated DY Spillover Index. In the DGP, we allow the relationship among these m series to change (stronger spillover) at time $t = \tau$ with $w < \tau < T$ by changing how the innovations to these series, denoted $\mathbf{e}_t$, are drawn. We allow for two scenarios: (i) the relationship among $\mathbf{y}_t$ only changes temporarily, and (ii) the relationship among $\mathbf{y}_t$ changes permanently. To do so, we first draw two sets of innovations, $\mathbf{e}_{1t}$ and $\mathbf{e}_{2t}$ as follows:

[9] For the sake of complete exposition, we note that there are other ways of defining the probability formula, depending on the interests of users. For example, we could simply redefine the event in the probability formula (5) in an alternative way as in the formula (6) below:

$$\Pr\left(\mathcal{S}_{r_e+j} < \overline{\mathcal{S}}_{r_e-1}\right) = B^{-1}\sum_{b=1}^{B}\mathbb{I}\left\{\left(\widehat{\mathcal{S}}_{r_e+j}^{(b)} - \overline{\mathcal{S}}_{r_e-1}\right) < 0\right\}. \tag{6}$$

The modification would allow us to identify events resulting in decreases in the Spillover Index (or in spillovers in the network). Such events are useful in identifying when the network returns to a 'normal' state following adverse events (with elevated spillovers across the units with the networks). However, in our procedure, we aim to detect increases in the Spillover Index, which resonates with the events in the seminal paper of Diebold and Yilmaz (2009) and simply follows a common interest in detecting adverse events (associating with sudden and large increase in the Spillover Index) in the connectedness literature.

- For $t = 1, ..., \tau - 1$, $\mathbf{e}_{1t}$ and $\mathbf{e}_{2t}$ are drawn similarly from $MN(\mathbf{0}, \mathbf{\Sigma})$ where $\mathbf{\Sigma}$ is diagonal and its diagonal element σ_{jj} (variance of innovation j) is drawn as $\sigma_{jj} \sim U(0, a)$ for $j \in \{1, ..., m\}$. As such, innovations in $\mathbf{e}_{1t}$ and $\mathbf{e}_{2t}$ are set to be strictly uncorrelated.

- For $t = \tau, \tau + 1, ..., T$:

  (i) In Scenario 1, we only allow the innovations in $\mathbf{e}_{1t}$ to be strongly correlated for one day, $t = \tau$, with $\mathbf{e}_{1\tau} \sim MN(\mathbf{0}, \tilde{\mathbf{\Sigma}})$ where $\tilde{\mathbf{\Sigma}} = \mathbf{CC}'$ is non-diagonal and the $(i,j)^{th}$ element of $\mathbf{C}$ is drawn as $c_{ij} \sim U(-b \times a, b \times a)$ for $i, j \in \{1, ..., m\}$. For $t = \tau + 1, ..., T$, $\mathbf{e}_{1t}$ are again drawn from $MN(\mathbf{0}, \mathbf{\Sigma})$.

  (ii) In Scenario 2, $\mathbf{e}_{2t} \sim MN(\mathbf{0}, \tilde{\mathbf{\Sigma}})$ for $t = \tau, \tau + 1, ..., T$.

With $\mathbf{e}_{1t}$ and $\mathbf{e}_{2t}$, we then generate two sets of stationary data, $\mathbf{y}_{1t}$ and $\mathbf{y}_{2t}$, as follows:

$$\mathbf{y}_{lt} = \mathbf{B}\mathbf{y}_{l,t-1} + \mathbf{e}_{lt}, \text{ for } l \in \{1, 2\}. \tag{7}$$

We follow Greenwood-Nimmo et al. (2023) and draw $\mathbf{B} \sim MN(\mathbf{0}, \mathbf{\Omega}_B)$ where $\mathbf{\Omega}_B = \tilde{\mathbf{B}}\tilde{\mathbf{B}}'$ and the $(i,j)^{th}$ element of $\tilde{\mathbf{B}}$ is drawn as $\omega_{\tilde{B},ij} \sim U(-1/2m, 1/2m)$ for $i, j \in \{1, 2, ..., m\}$. $\mathbf{B}$ is fixed to stay the same throughout the sample period. At time $t = 1$, we set $\mathbf{y}_{l1} = \mathbf{e}_{l1}$ for $l \in \{1, 2\}$. Based on this setup, the weak dependency among the data in $\mathbf{y}_{1t}$ and in $\mathbf{y}_{2t}$ for $t = 1, ..., \tau - 1$ is purely driven by the autoregressive parameters in $\mathbf{B}$. For $\mathbf{y}_{1t}$, the dependency among m series in $\mathbf{y}_{1t}$ is changed temporarily due to correlated innovations at $t = \tau$ only. For $\mathbf{y}_{2t}$, the dependency among among m series in $\mathbf{y}_{1t}$ is changed permanently due to correlated innovations at $t = \tau$ and onwards.

In our simulation analysis, we set $T = 600, m = 19, w = 200, \tau = 301, a = 0.1, b = 5$. The values of m and w are set to be similar to those in Diebold and Yilmaz (2009). τ can be set anywhere between (w, T). The value of b ($b > 0$) dictates how big the upward/downward shift in the DY Spillover Index is at $t = \tau$ and onwards. With the simulated $\mathbf{y}_{1t}$ and $\mathbf{y}_{2t}$, we estimate two VAR(1) models, one for each simulated dataset, on a rolling basis and compute the respective GVD-based 10-day-ahead spillover indexes. Figure 1 plots the spillover indices for the two simulated datasets. The figure shows the sharp increases in the spillover indexes at the rolling sample $r = \tau - w = 101$. By construction, the spillover index computed from $\mathbf{y}_{2t}$ in Panel (b) shows a permanent shift in the relationship among m data series. Meanwhile, the spillover index computed from $\mathbf{y}_{1t}$ in Panel (a) only shows a sharp increase at the rolling sample ending on day $t = \tau$, and displays a partial reversal on the following day. The spillover index in Panel (a) subsequently returns to its 'pre-event' level once the rolling window no longer covers the observation at day $t = \tau$.

— Insert Figure 1 and Table 1 about here —

Based on the simulated $\mathbf{y}_{1t}$ and $\mathbf{y}_{2t}$ and the two estimated VAR(1) models from these two simulated datasets, we follow our bootstrap-after-bootstrap procedure and generate 1000 bootstrapped GVD-based spillover indices from each VAR(1) model for probabilistic analysis. With the simulated spillover indices, we compute the following probabilities:

$$Prob(\Delta\mathcal{S}_{t+i} > 0),\ \text{where}\ \Delta\mathcal{S}_{t+i} = 100 \times (\frac{\mathcal{S}_{t+i} - \overline{\mathcal{S}}_{t-1}}{\overline{\mathcal{S}}_{t-1}}),\ i \in \{0, 1, 5, 22\}. \tag{8}$$

$\mathcal{S}_{t+i}$ is the bootstrapped DY spillover index computed on the rolling sample ending on day $t+i$ and $\overline{\mathcal{S}}_{t-1}$ is the mean of the spillover index evaluated across bootstrap samples in the rolling window ending on day $t-1$. Table 1 provides the probabilities for the above defined events around the event date $t \in [\tau-2, \tau+2]$. Probabilities smaller than 90% are in gray while those greater than or equal to 90% are in black.

In sum, the results show that whether the shift in the spillover index is temporary or permanent, our proposed method is able to detect such changes in the data or the relationship among the data series in the model. Overall, the simulation exercise strongly supports the credibility of our method in identifying statistically significant changes in the Spillover Index.

2.4 Endogenous Detection of Unknown Events

Instead of testing the statistical significance of the spillover index in response to an exogenous event, our methodology can be easily adapted to endogenously detect unknown events, ex-ante, that result in significant changes in the spillover index. Therefore, our method is not constrained to test for significant changes in the spillover index given a set of known events, but can also be used for monitoring purposes.

Our procedure can be implemented in a way to test for statistically significant changes in the spillover intensity in each new rolling sample compared to one or more previous rolling samples. Specifically, one can use our procedure to calculate the following probabilities on a rolling basis:

$$Prob\left(100 \times \left[\frac{\mathcal{S}_{t+i} - \overline{\mathcal{S}}_{t-j}}{\overline{\mathcal{S}}_{t-j}}\right] > \alpha\right),\ i \in \{0, 1, ...\},\ j \in \{1, 2, ..\}, \tag{9}$$

where $\mathcal{S}_{t+i}$ is the bootstrapped DY spillover index computed on the rolling sample ending on day $t+i$ and $\overline{\mathcal{S}}_{t-j}$ is the mean of the spillover index evaluated across bootstrap samples in the rolling window ending on day $t-j$. $\overline{\mathcal{S}}_{t-j}$ is the reference point.

An example of how to detect unknown events with large changes in the spillover index is to set $j = 1$, $i \in \{0, 1, 5, 10, 22\}$ and $\alpha = 5\%$. The value of α indicates the magnitude of the change in the spillover index (or how large the shock is). Whenever the probability at time $t+i$ with $i = 0$ is greater than or equal to 90%, day t is identified as a statistically significant event resulting in a change of 5% or greater in the spillover index. By setting $i \in \{1, 5, 10, 22\}$, we can draw statistical inferences of the event's impact on connectedness occurring 1, 5, 10, and 22 days after the event took place, which corresponds to the length from one day to one business month.

Finally, simply reversing the inequality and changing the value of α to 0 or negative would allow us to identify events resulting in decreased spillovers in the network. Nevertheless, the economic significance of such an analysis is minor, and for that, in our procedure, we focus on spillover increases. Hence, we concentrate on events prompting a rise in the overall connectedness as in Diebold and Yilmaz (2009) and subsequent connectedness literature.

The above steps describe how it is feasible to detect endogenously the events associated with notable increases in connectedness. In this manner, our methodology has been recently employed to detect global shocks leading to statistically significant increases in connectedness in a forex market (Albrecht and Kočenda, 2024b), commodities (Albrecht et al., 2023; Bartušek and Kočenda, 2023), and cryptocurrencies (Albrecht and Kočenda, 2024a).

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 Refinitiv Datastream and Global Financial Data. In total, there are 7 developed markets (the US, the UK, France, Germany, 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:

$$r_{it} = \frac{1 + q_{it}}{1 + \pi_{it}} - 1, \tag{10}$$

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 et al. (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:

$$\begin{aligned} \widehat{\sigma}_{it}^2 &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &- 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2, \end{aligned} \tag{11}$$

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 is 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 2. For replication, we use the same values as in Diebold and Yilmaz (2009): a lag value of 2, a 10-step ahead forecast, and a window of 200 days. 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.[10] 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 2 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 3 plots the point estimates of the 10-days-ahead orthogonalised and generalised volatility spillover indices alongside their respective 90% empirical confidence intervals. The intervals are typically relatively narrow in both cases, only widening appreciably during periods of elevated uncertainty, such as the months following the 9/11 terror attacks and in the months leading up to the global financial crisis.

— Insert Figure 3 about here —

Before moving to the probabilistic analysis, we show the impact of the bias-correction procedure. Figure 4 provides the extent of the bias for the daily volatility spillover index in the GVD-based network. The bias-corrected bootstrap mean estimate of the DY spillover index is shown by the pale gray shading, the bias component is shown by the dark-gray shading and the point estimate of the DY spillover-index is plotted as a red line. The bias-corrected bootstrap mean value tracks the point estimate closely, which one would expect given the design of the procedure.

— Insert Figure 4 about here —

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

The bias component is positive in all rolling samples, indicating that a naive single-step bootstrap procedure would result in a bootstrap distribution for the DY spillover index that is centered at the wrong value (specifically, one that is centered too high). This is precisely what we expect to see, given that the FEVD is proportional to the square of the impulse response function (IRF). Therefore, the bias term that would be encountered in bootstrapping the IRF (which is discussed extensively in Kilian (1998)) gets squared when one bootstraps an FEVD, resulting in a positive bias in all rolling samples. Figure 4 also shows that in volatile times when the value of the DY spillover index increases, the magnitude of the bias term relative to the value of the DY spillover index falls. We conjecture that this can be interpreted in signal-to-noise terms – when the connectedness of the system increases, the signal is stronger, the DY spillover index gets larger and the bias associated with its estimation gets smaller.

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 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 2, 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'. We provide references that support our choice of each event date, and discuss the relevant factors associated with adverse shocks.

— Insert Table 2 about here —

The events identified by Diebold and Yilmaz can be broadly characterised as adverse shocks that may be associated with increased spillover activity, including financial crises, currency crises, terror attacks and periods of adverse market sentiment.[11] Consequently, in Table 3, 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.

[11] The exceptions are the two US monetary policy interventions detailed in Table 2 (Events 9 and 13).

— Insert Table 3 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 et al., 2007). Event 1 corresponds to the spread of the crisis to Hong Kong, which suffered an abrupt crash on 17 October 1997 (Forbes and Rigobon, 2002). 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 1997 (Corsetti et al., 2005). For both of these unanticipated events, using either the orthogonalised or generalised spillover index, we observe a high probability of elevated spillovers on impact and throughout the following month.

During the Russian financial crisis (Events 3 and 4), the local currency came under intense pressure from late May until 13 July 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). Our results indicate a low probability that the first stage of the Russian crisis associated with the announcement of the IMF aid package (Event 3) leads to an increase in either the orthogonalised or generalised spillover indices. The finding is consistent with evidence that IMF interventions, and their announcements, are generally anticipated and only bad news triggers noticeable reactions (Brealey and Kaplanis, 2004). 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 25 August 1998 (Bartram et al., 2007). This is Event 4, which precedes an 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. 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 et al., 2006).

Event 5 relates to a currency crisis in Brazil, which was triggered by the devaluation of the Brazilian real (13 January 1999) due to fiscal imbalances and a challenging external environment that led to massive capital outflows (Tanner and Ramos, 2003; Bartram et al., 2007). Despite the extent of these dislocations, the empirical probability of an increase in spillover activity is only roughly 50 percent in the short term and drops close to zero percent after one week. This reflects the fact that "the private sector was largely hedged at the moment of the crisis" as "the Brazilian crisis was anticipated by market participants" (Goldfajn, 2000, p. 3).

Diebold and Yilmaz (2009) identify three events linked to heightened volatility related to U.S. technology stocks. The first of these, Event 6, is labeled 'profit-taking in tech stocks.' The date that we associate with this event is 5 January 2000, a day after the NASDAQ fell by approximately 5.5

percent and tech stocks continued to fall despite a rally in broader indices. The event is associated with a statistically significant probability of an increase in both the generalised and orthogonalised spillover indices with varying persistence.

Event 7 is described by Diebold and Yilmaz (2009) as 'increased market worries for tech stocks'. We identify the event as Friday, 14 April 2000, which saw the third-largest one-day percentage fall in the history of the NASDAQ, with the Composite index falling by 9 percent to end a week in which it fell by 25 percent. Neither the orthogonalised or generalised spillover indices respond to this event contemporaneously but both increase with high probability on the following trading day (Monday, 17 April) and remain elevated over the following month.[12]

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 percent. Cochrane and Piazzesi (2002, p. 91) classify this rate cut as unanticipated and note that "the cut signaled a change of direction" implying potential "further rate cuts". In response, the orthogonalised and generalised spillover indices record a contemporaneous jump with high probability but show no evidence of an increase at longer horizons, indicating that global equity markets rapidly impounded news of the Fed's policy decision.

Event 9 also relates to US monetary policy—on 20 March 2001, the Fed reduced the funds rate by 50 bps, from 5.5 percent to 5.0 percent. Cochrane and Piazzesi (2002) show that market participants expected a deeper cut than the Fed undertook, resulting in a contractionary monetary shock. In this case, there is little evidence that either spillover index increases on the day of the rate cut but both indices subsequently increase with high probability over the following month.

Event 10 corresponds to the 9/11 terror attacks on 11 September 2001. In response to the resulting period of turmoil in the financial markets, both the orthogonalised and generalised spillover indices jump and remain elevated throughout the following month, with a probability close to 100 percent at all horizons. This is consistent with the findings of Straetmans et al. (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 US stock market crash of 2002 is the focus of Event 11, which we date to 19 July 2002. Both spillover indices increase with a high probability on the following business day and remain elevated over the next month.[13] The long-lasting effect of the 2002 crash on stock market connectedness may be related to an ongoing slide in consumer confidence lasting until the end of 2002, as reflected in the

[12] The effect of this event on the spillover index may have been amplified as a result of its timing. Monday, 17 April, 2000 was the due date to pay taxes on gains realised 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.

[13] Between 19 and 23 July 2002, the Dow Jones industrial average recorded a substantial decline to its lowest level in four years. The delayed response in this case may be due to a weekend effect, as the event day (19 July 2002) is a Friday. The absolute 2002 low was reached on 9 October.

OECD consumer confidence index.[14]

Events 12a and 12b correspond to two bomb attacks in Turkey over a five day interval in November 2003. The first attack targeted two synagogues (Event 12a on November 15), while the second targeted the British Consulate and HSBC Bank (Event 12b on 20 November).[15] The evidence for an 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 12b). There are no other horizons where we find a probability of 90 percent or greater than either spillover index increases. Findings from our procedure are consistent with the literature indicating 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 market was very quick (Christofis et al., 2010).[16]

Event 13 corresponds to another reversal in US monetary policy - the switch from an accommodative regime to a contractionary regime on 30 June 2004. Having kept the federal funds rate at 1 percent 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.[17] Application of our procedure shows a very low probability that either spillover index increases in the short term following the policy announcement. This result is consistent with the fact that anticipated monetary policy interventions typically have little impact on the markets because they are priced ex-ante.[18]

Diebold and Yilmaz (2009, p. 166) describe Event 14 as "the dollar crisis of March 2005, associated with remarks from policymakers 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 February 2005, when the Bank of Korea shook financial markets when officials discussed diversifying its holdings of foreign reserves away from the dollar (Click, 2006). To the best of our knowledge, this is the first official statement made by a major central bank with the specific intention of diversification

[14] Zouaoui et al. (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).

[15] 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.

[16] 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).

[17] 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`.

[18] 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 2.

away from the dollar (Dougherty, 2005).[19] However, we find little evidence of an increase in either the orthogonalised or generalised spillover index over any horizon.[20]

The 7/7 terror attacks in London are captured by Event 15. As with 9/11 in the US, we find very strong evidence that the 7/7 attacks gave rise to an immediate increase in spillover activity that was 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 et al., 2017, p. 124).

Event 16 relates to capital outflows from emerging markets documented via the link between equity market volatility and capital flows (e.g. Bank for International Settlements, 2006; Ahmed and Zlate, 2014). The event date (12 May 2006) marks the turning point in the VIX dynamics, and we find a high probability that both the orthogonalised and generalised spillover indices increase 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 the announcement of a 30 percent 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). Our results provide strong evidence of a contemporaneous increase in the value of both spillover indices that continues into the following day 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; both events deserve some discussion. 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 substantial widening of the spread on non-investment grade residential mortgage collateralised debt obligations over the following two days: (i) the collapse of the share price of New Century Financial Corporation, the third largest subprime lender in the US and (ii) the announcement by HSBC Finance that its allowance for losses on subprime mortgages would exceed expectations by 20 percent. We find little evidence that either the orthogonalised or generalised spillover indices increase on 8 February 2007 or over the

[19] 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).

[20] To test the robustness of this finding, following the discussion in Valderrama (2005), we computed event probabilities using the alternative event date of 16 March 2005, which coincides with the discussion of diversification away from the dollar by representatives of three large economies (Japan, India, Ukraine) in their accounts spaced within a single week (Eichengreen and Frankel, 2005). This alternate dating strategy reveals a high probability of a short-lived increase in spillover activity. This may suggest that announcements regarding foreign reserves coming from (the Bank of) Japan (and other large countries) attract greater attention than similar announcements from the Bank of Korea, perhaps reflecting their larger holdings of US debt.

following two weeks. However, there is a 98.7 percent probability that the orthogonalised spillover index increases after one month, which suggests a role for a different, later event.[21]

Lastly, Event 19 refers to the 'global financial market turmoil' observed in the summer of 2007 that aligns with the first substantial increase in US stock market connectedness, 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). We find a high probability of an 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.[22] Over this period, the estimated spillover index jumps from 68.38 percent on 15 August to 77.64 percent 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.

In sum, this exercise has three key implications. First, our results suggest that unanticipated adverse shocks may often be associated with a high probability of increased connectedness. By contrast, spillover intensity does not appear to vary systematically in relation to anticipated events, which are typically priced by financial market participants ex-ante. This is a natural finding that is well illustrated by a comparison of Events 8 and 9, which reflect unanticipated and (partially) anticipated monetary policy changes, respectively. Second, in the absence of a formal method to test for changes in spillover activity, several events that have been identified as drivers of heightened connectedness in existing studies may, in fact, not coincide with any significant increase in spillover intensity. Third, events that are thought to be associated with elevated connectedness may sometimes be misidentified, partly due to the common practice of studying point estimates of the spillover index without supporting information on its distribution. Our method offers researchers a systematic framework to analyse changes in spillover intensity that can alleviate these last two issues.

[21] In practice, we find that both spillover indices appear to increase 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 contraction period and so far we have not had any major, significant spillover effects on the American economy from the contraction in housing". 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. 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`.

[22] 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 in missing observations.

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 (5). 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 4, 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 affects our results. To simplify comparisons between our baseline results and the results of our sensitivity tests, we refer to estimated probabilities of 90 percent or more as evidence of a 'significant' change in spillover activity. 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 change for event 11 (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 4 exceeds that in Table 3, 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 3 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 5. 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 6 and are similar to those in Table 5. 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 adverse events is absent from the literature. We address this issue by developing a non-parametric bootstrap-after-bootstrap framework that supports formal probabilistic analysis of changes in 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 adverse shocks. Specifically, for 15 of the 19 events discussed by Diebold and Yilmaz, we find a probability of 90% or more that either the orthogonalised or generalised spillover index increases contemporaneously or with a delay of 1-day, 5-days, or 22-days. However, we find a 90 percent or greater probability of a contemporaneous increase in the spillover index for only 6 events, which indicates that the spillover index may often react to the events with a lag.

Our bootstrap-after-bootstrap technique accounts for small sample bias and represents a useful addition to the connectedness literature. Our procedure can be easily adapted to endogenously detect significant changes in the spillover index that are linked to ex-ante unknown events, and it can be used for monitoring purposes. 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 important 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 the development of options and hedging strategies.

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Panel A: Temporary Shift ($\mathbf{y}_{1t}$)

	Prob($\Delta\mathcal{S}_t > 0$)	Prob($\Delta\mathcal{S}_{t+1} > 0$)	Prob($\Delta\mathcal{S}_{t+5} > 0$)	Prob($\Delta\mathcal{S}_{t+10} > 0$)	Prob($\Delta\mathcal{S}_{t+22} > 0$)
$\tau - 2$	38.8	28.3	78.7	80.7	85.7
$\tau - 1$	38	90.7	82.7	84.6	88
τ	93	86.8	86.1	89.1	91.3
$\tau + 1$	22.7	22.9	24.3	21.8	26.1
$\tau + 2$	35.1	38.9	43.7	40	42.8

Panel B: Permanent Shift ($\mathbf{y}_{2t}$)

	Prob($\Delta\mathcal{S}_t > 0$)	Prob($\Delta\mathcal{S}_{t+1} > 0$)	Prob($\Delta\mathcal{S}_{t+5} > 0$)	Prob($\Delta\mathcal{S}_{t+10} > 0$)	Prob($\Delta\mathcal{S}_{t+22} > 0$)
$\tau - 2$	38.8	28.3	100	100	100
$\tau - 1$	38	90.7	100	100	100
τ	93	99.6	100	100	100
$\tau + 1$	68.1	78.1	100	100	100
$\tau + 2$	54.2	68	100	100	100

NOTES: $\Delta\mathcal{S}_{t+i} = 100 \times (\mathcal{S}_{t+i} - \overline{\mathcal{S}}_{t-1})/\overline{\mathcal{S}}_{t-1}$ for $i \in \{0, 1, 5, 22\}$; $\mathcal{S}_{t+i}$ is the bootstrapped DY spillover index computed on the rolling sample ending on day $t + 1$; $\overline{\mathcal{S}}_{t-1}$ is the mean of the spillover index evaluated across bootstrap samples in rolling window ending on day $t - 1$.

Table 1: Simulation Results for Probability Event Analysis

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 2: 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 3: 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 $r_e - 5, \dots, r_e - 1$, 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 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

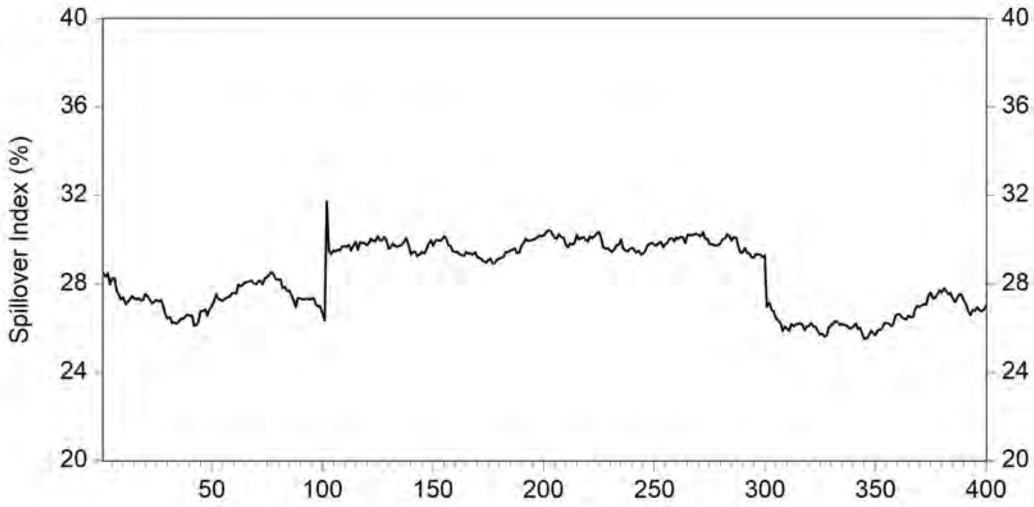
NOTES: For each listed event, the table reports the empirical probability that the value of the DY spillover index in rolling sample r_e+j, $j=0,1,5,22$, exceeds the mean of the DY spillover index evaluated across bootstrap samples in rolling samples $r_e-5,\dots,r_e-1$, where r_e denotes the rolling 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 5: Robustness of the Empirical Probabilities to the use of the 2-day Forecast Horizon

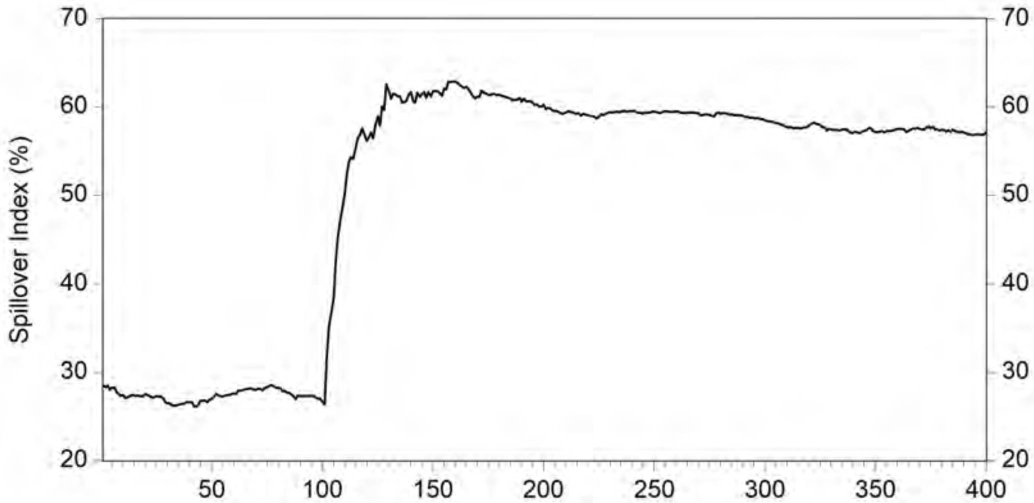
Event	Event Description	r_e+0		r_e+1		r_e+5		r_e+22	
		OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	East Asian crisis spreads to Hong Kong	84.0	84.3	78.9	77.3	100.0	100.0	100.0	100.0
2	East Asian crisis spreads to other countries	100.0	100.0	99.9	99.6	100.0	100.0	100.0	100.0
3	Russian crisis I	54.3	52.8	54.9	53.8	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 6: Robustness of the Empirical Probabilities to the use of the 2-day Forecast Horizon and the 5-day Average as the Pre-Event Comparison

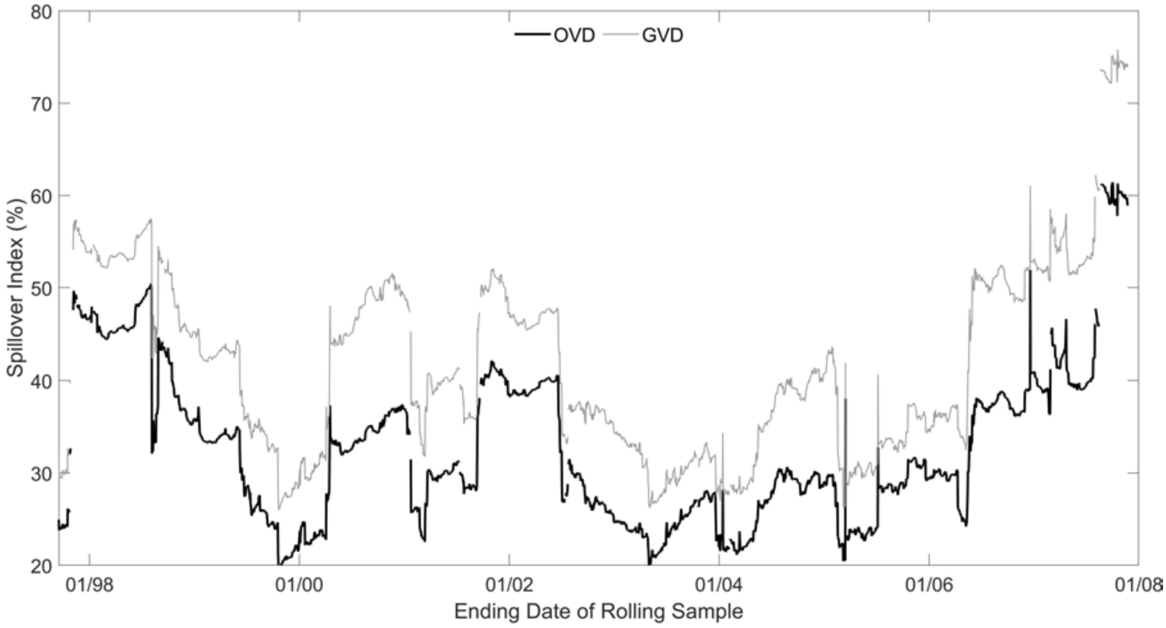


(a) Simulated GVD-based Spillover Index with Temporary Shift

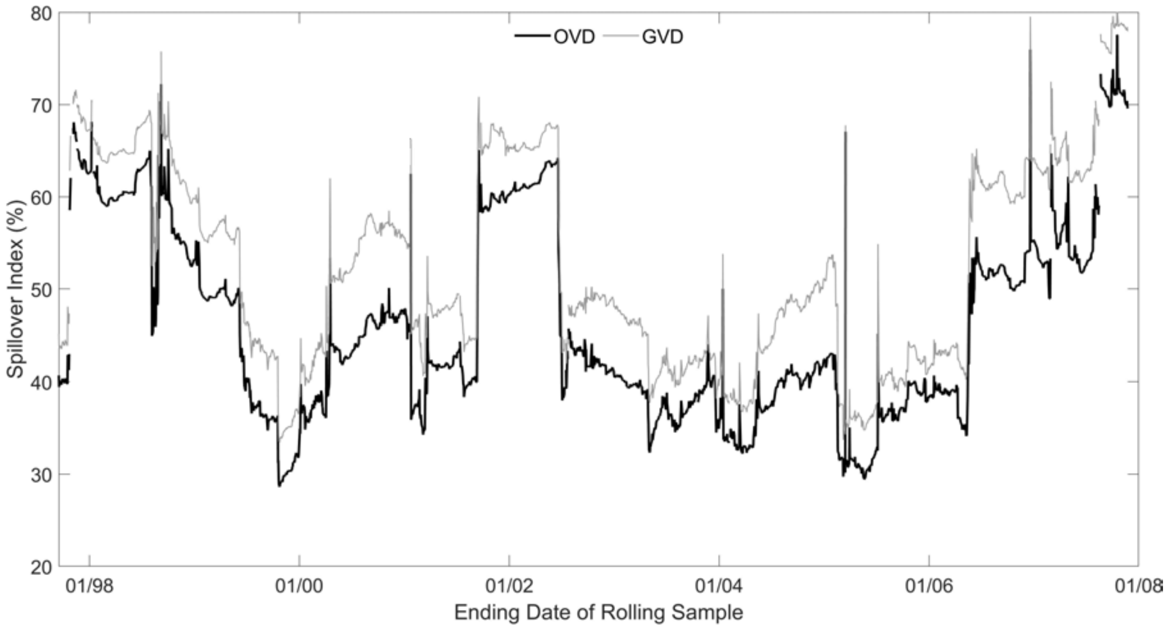


(b) Simulated GVD-based Spillover Index with Permanent Shift

Figure 1: Simulated Spillover Index

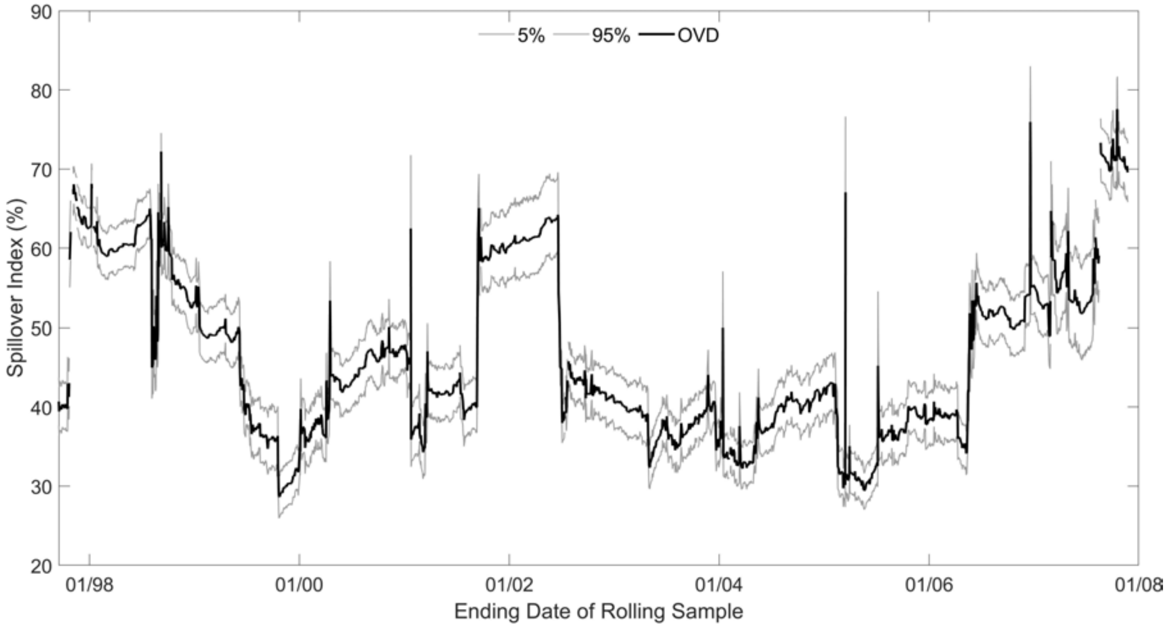


(a) Daily Volatility Spillover Index, 2-days-ahead

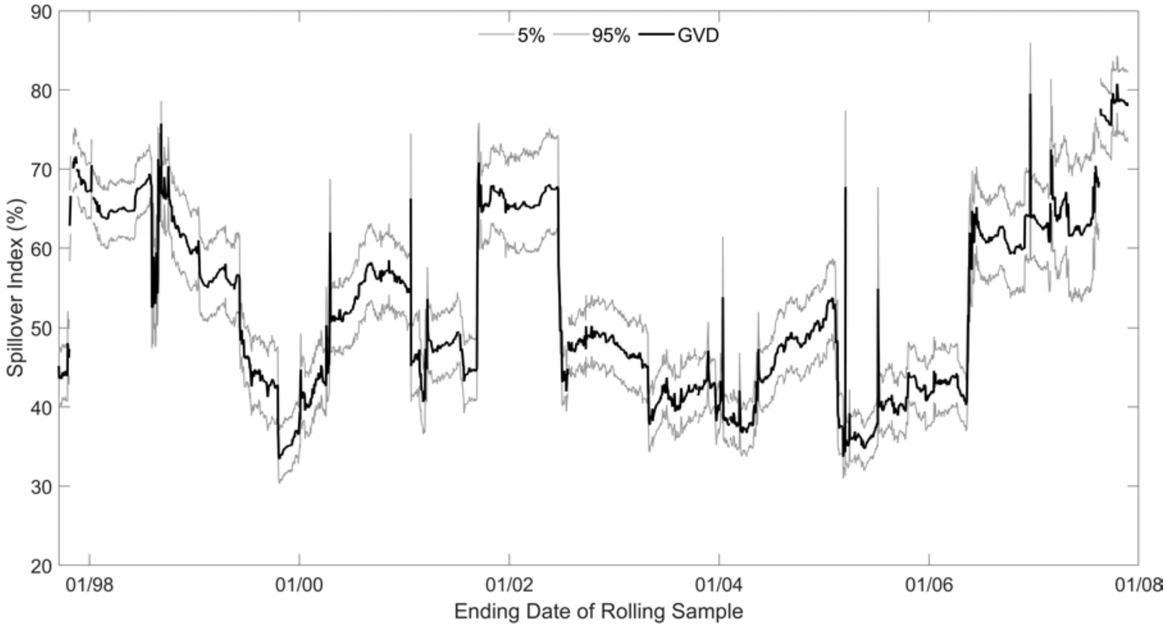


(b) Daily Volatility Spillover Index, 10-days-ahead

Figure 2: Replication of Figure 3 from Diebold and Yilmaz (2009)



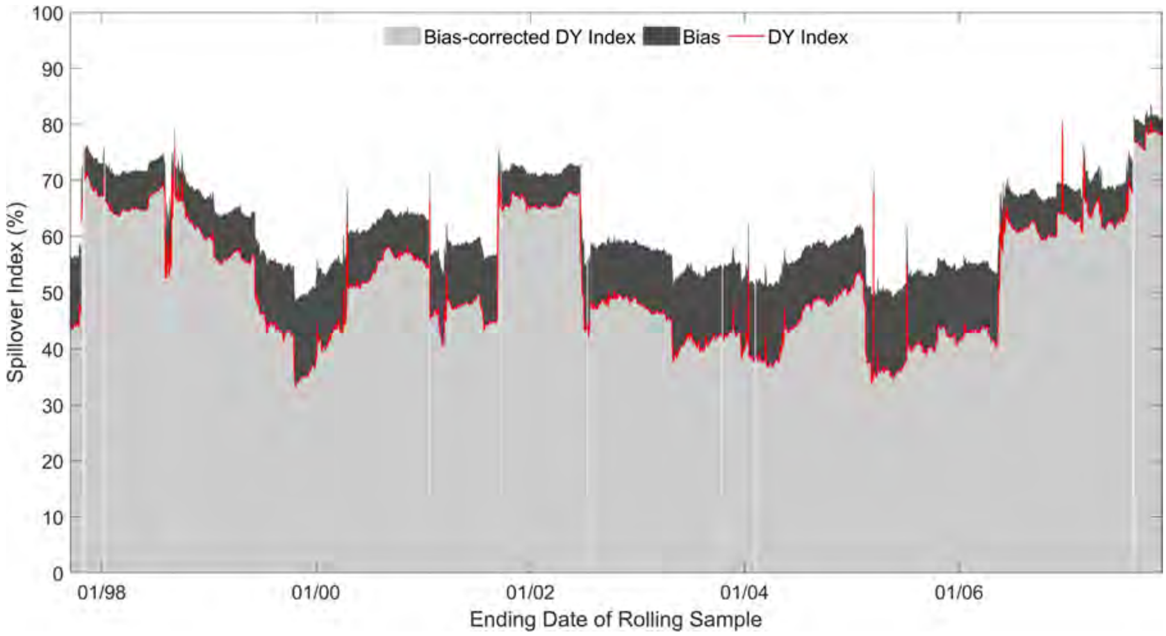
(a) OVD-based Daily Volatility Spillover Index, 10-days-ahead



(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 3: Evolution of the Empirical Distribution of the 10-days-ahead Volatility Spillover Index



NOTES: The extent of the bias is shown by the dark-shaded area.

Figure 4: Estimated Bias with GVD-based Daily Volatility Spillover Index, 10-days-ahead

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

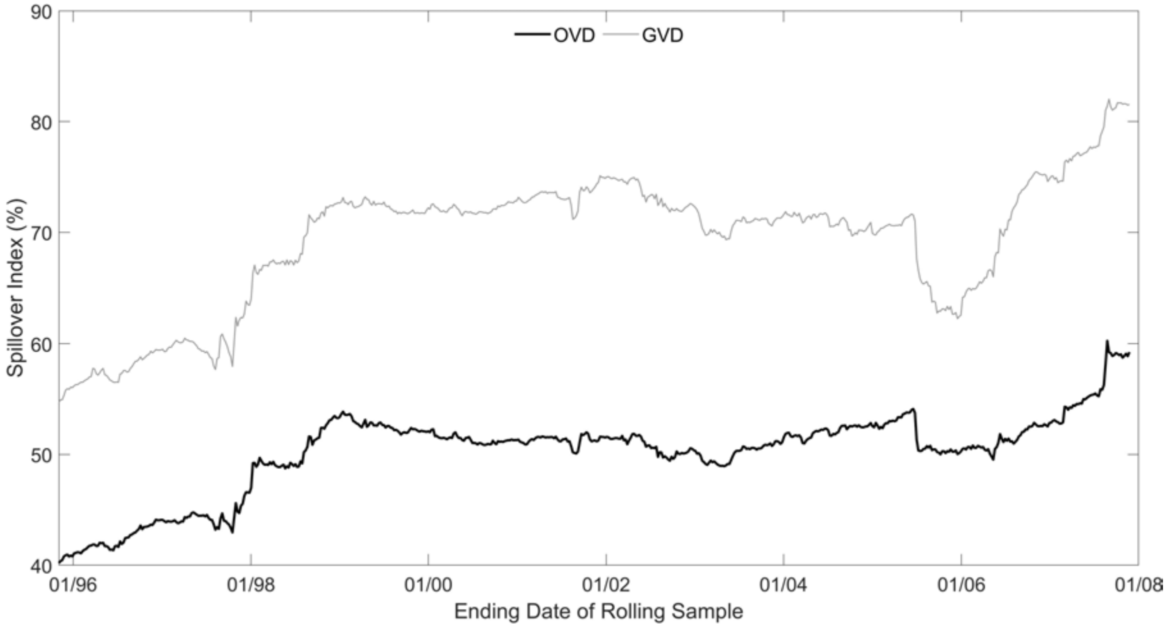
NOTES: Markets are abbreviated as follows: US–United States; UK–United Kingdom; FRA–France; GER–Germany; HKG–Hong Kong; JPN–Japan; AUS–Australia; IDN–Indonesia; KOR–Korea; MYS–Malaysia; PHL–Philippines; SGP–Singapore; TAI–Thailand; ARG–Argentina; BRA–Brazil; CHL–Chile; MEX–Mexico; and TUR–Turkey. The 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

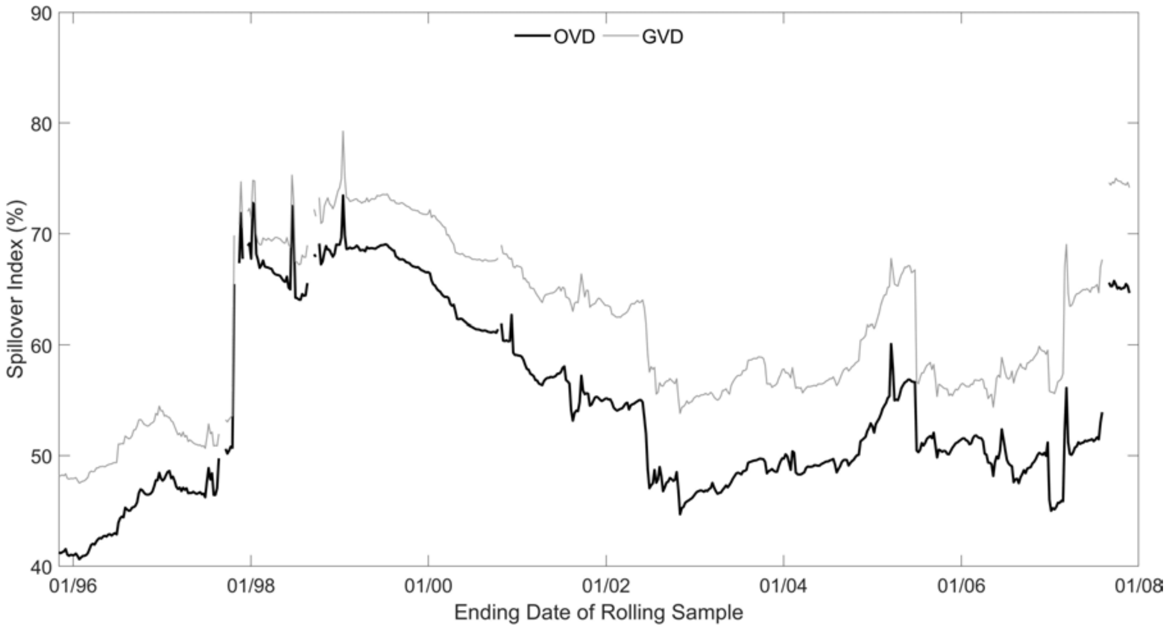
	US	UK	FRA	GER	HKG	JPN	AUS	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR
US	27.3	16.9	17.5	14.0	3.8	1.0	3.3	0.3	1.5	0.3	0.9	1.3	2.6	0.1	1.6	1.3	0.8	3.2	2.2
UK	9.1	30.5	21.7	15.8	4.5	1.7	3.3	0.4	1.1	0.4	0.5	1.7	1.7	0.3	1.9	1.5	0.6	2.0	1.4
FRA	9.0	20.5	30.1	20.5	3.5	1.2	1.8	0.3	0.6	0.3	0.5	1.3	1.5	0.3	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

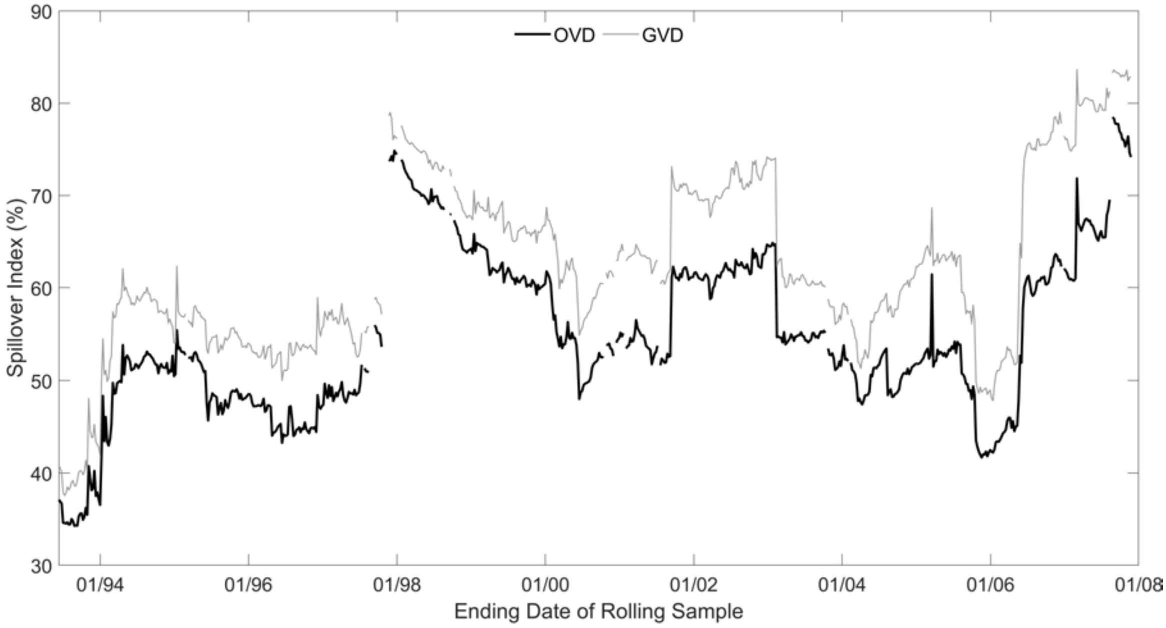
For our replication of Figure 3 from Diebold and Yilmaz (2009), please see Figure 2 in the main text.

Replication of Figure 4

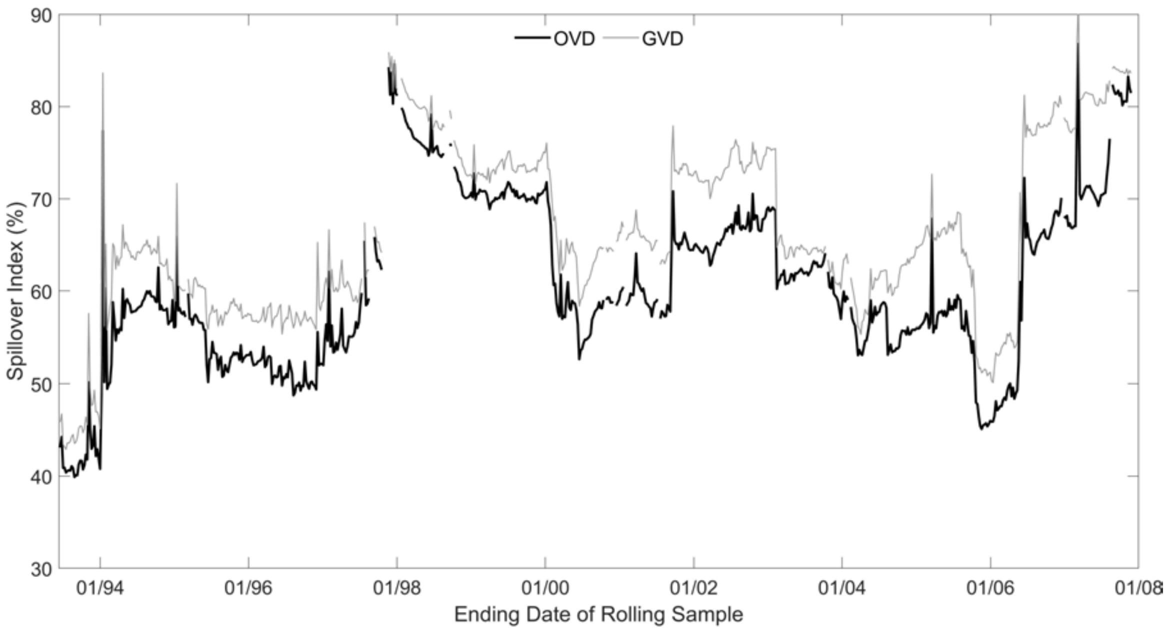
Figure 4 in Diebold and Yilmaz (2009) evaluates the robustness of the volatility spillover index to alternative orderings of the variables entering the VAR model. For this exercise, the authors use a rolling sample of 200 weeks and conduct two different exercises. First, the authors simply consider 18 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.

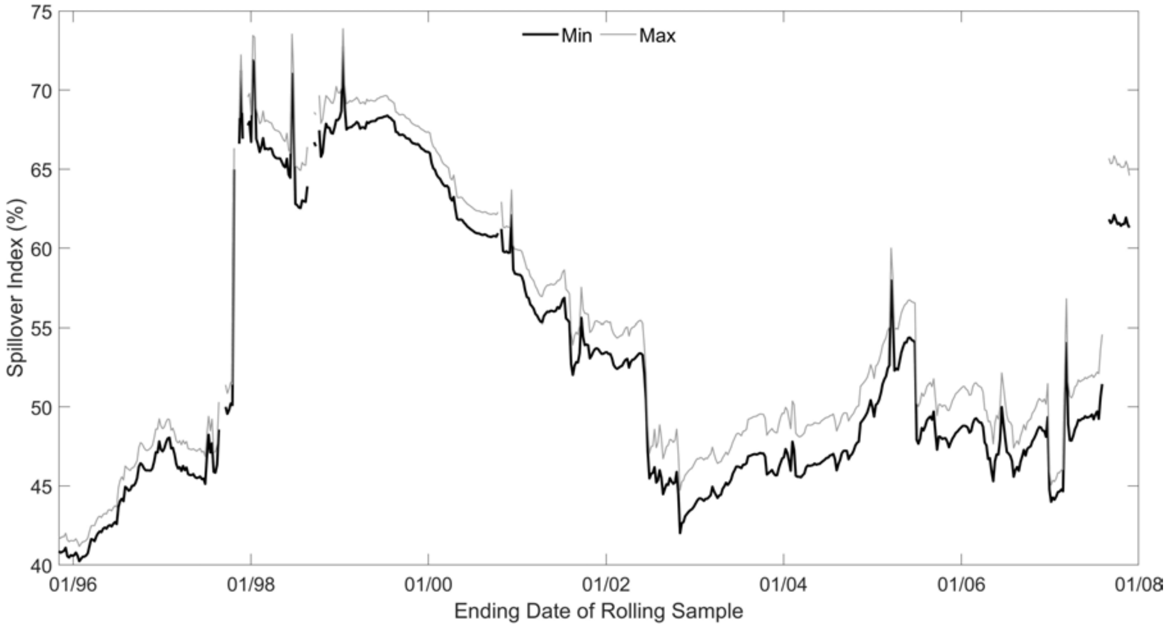


(a) Weekly volatility spillover index, 2-weeks-ahead

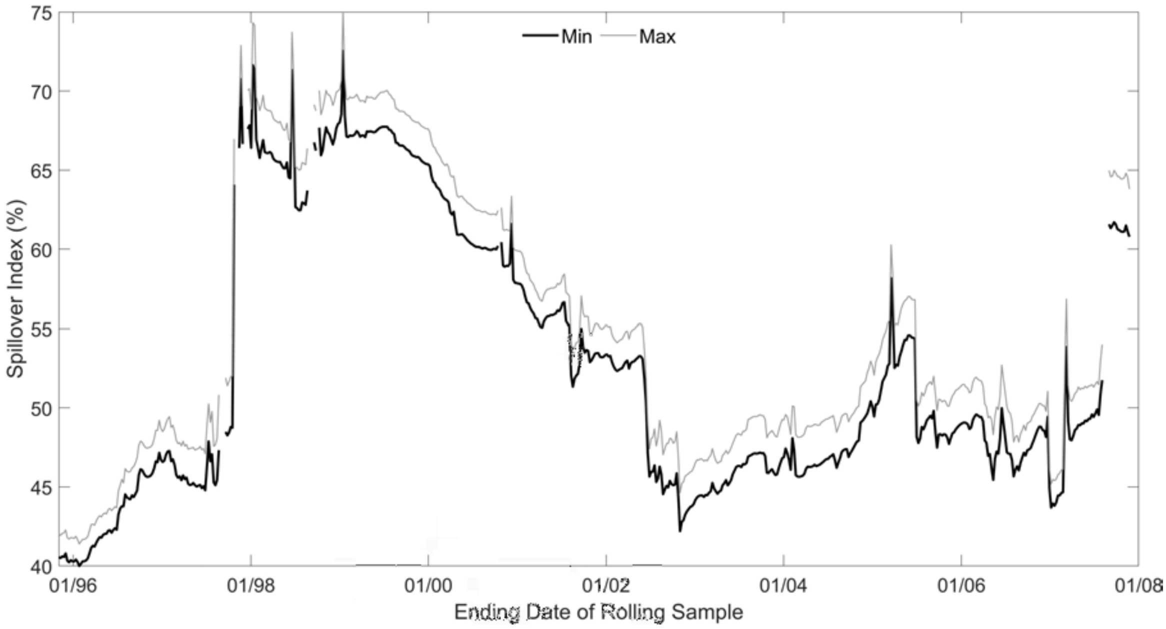


(b) Weekly volatility spillover index, 10-weeks-ahead

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)