The Economic Journal, **119** (*January*), 158–171. © The Author(s). Journal compilation © Royal Economic Society 2009. Published by Blackwell Publishing, 9600 Garsington Road, Oxford OX4 2DQ, UK and 350 Main Street, Malden, MA 02148, USA.

MEASURING FINANCIAL ASSET RETURN AND VOLATILITY SPILLOVERS, WITH APPLICATION TO GLOBAL EQUITY MARKETS*

Francis X. Diebold and Kamil Yilmaz

We provide a simple and intuitive measure of interdependence of asset returns and/or volatilities. In particular, we formulate and examine precise and separate measures of *return spillovers* and *volatility spillovers*. Our framework facilitates study of both non-crisis and crisis episodes, including trends and bursts in spillovers; both turn out to be empirically important. In particular, in an analysis of 19 global equity markets from the early 1990s to the present, we find striking evidence of divergent behaviour in the dynamics of return spillovers vs. volatility spillovers: return spillovers display a gently increasing trend but no bursts, whereas volatility spillovers display no trend but clear bursts.

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

For many years but especially following the late 1990s Asian crisis, much has been made of the nature of financial market interdependence, both in terms of returns and return volatilities (King *et al.*, 1994; Forbes and Rigobon, 2002). Against this background, we propose a simple quantitative measure of such interdependence, which we call a spillover index, and associated tools that we call spillover tables and spillover plots.

The intensity of spillovers may of course vary over time and the nature of any time-variation is of potentially great interest. We allow for it in an analysis of a broad set of global equity returns and volatilities from the early 1990s to the present and we show that spillovers are important, spillover intensity is indeed time-varying and the nature of the time-variation is strikingly different for returns vs. volatilities.

We proceed by proposing the spillover index in Section 1 and describing our global equity data in Section 2. We perform a full-sample spillover analysis in Section 3 and a rolling-sample analysis allowing for time-varying spillovers in Section 4. We briefly assess the robustness of our results in Section 5 and we summarise and conclude in Section 6.

1. The Spillover Index

We base our measurement of return and volatility spillovers on vector autoregressive (VAR) models in the broad tradition of Engle *et al.* (1990). Our approach, however, is very different. We focus on variance decompositions, which are already well understood and widely calculated. As we show, they allow us to aggregate spillover effects across markets, distilling a wealth of information into a single spillover measure.

The basic spillover index idea is simple and intuitive, yet rigorous and replicable, following directly from the familiar notion of a variance decomposition associated with an N-variable VAR. Roughly, for each asset i we simply add the shares of its forecast

* For helpful comments we thank the Editor and two referees, Jon Faust, Ayhan Kose, Roberto Rigobon, Harald Uhlig and the organisers and participants at the 2006 NBER International Seminar on Macroeconomics in Tallinn, Estonia, especially Michael Binder, Kathryn Dominguez, Jeff Frankel, Francesco Giavazzi, Eric Leeper, Lucrezia Reichlin and Ken West.

error variance coming from shocks to asset j, for all $j \neq i$, and then we add across all $i = 1,\ldots,N$.

To minimise notational clutter, consider first the simple example of a covariance stationary first-order two-variable VAR,

$$\mathbf{x}_t = \boldsymbol{\Phi}\mathbf{x}_{t-1} + \boldsymbol{\varepsilon}_t,$$

where $\mathbf{x}_t = (\mathbf{x}_{1t}, \mathbf{x}_{2t})$ and $\boldsymbol{\Phi}$ is a 2×2 parameter matrix. In our subsequent empirical work, $\mathbf{x}$ will be either a vector of stock returns or a vector of stock return volatilities. By covariance stationarity, the moving average representation of the VAR exists and is given by

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

where $\boldsymbol{\Theta}(L) = (\mathbf{I} - \boldsymbol{\Phi}L)^{-1}$. It will prove useful to rewrite the moving average representation as

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

where $\mathbf{A}(L) = \boldsymbol{\Theta}(L)\mathbf{Q}_t^{-1}, \mathbf{u}_t = \boldsymbol{Q}_t\boldsymbol{\varepsilon}_t, \mathrm{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbf{I}$, and $\mathbf{Q}_t^{-1}$ is the unique lower-triangular Cholesky factor of the covariance matrix of $\boldsymbol{\varepsilon}_t$.

Now consider 1-step-ahead forecasting. Immediately, the optimal forecast (more precisely, the Wiener-Kolmogorov linear least-squares forecast) is

$$\mathbf{x}_{t+1,t} = \boldsymbol{\Phi}\mathbf{x}_t,$$

with corresponding 1-step-ahead error vector

$$\mathbf{e}_{t+1,t} = \mathbf{x}_{t+1} - \mathbf{x}_{t+1,t} = \mathbf{A}_0\mathbf{u}_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},$$

which has covariance matrix

$$\mathrm{E}\left(\mathbf{e}_{t+1,t}\mathbf{e}_{t+1,t}'\right) = \mathbf{A}_0\mathbf{A}_0'.$$

Hence, in particular, the variance of the 1-step-ahead error in forecasting x_{1t} is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the 1-step-ahead error in forecasting x_{2t} is $a_{0,21}^2 + a_{0,22}^2$.

Variance decompositions allow us to split the forecast error variances of each variable into parts attributable to the various system shocks. More precisely, for the example at hand, they answer the questions: What fraction of the 1-step-ahead error variance in forecasting x_1 is due to shocks to x_1? Shocks to x_2? And similarly, what fraction of the 1-step-ahead error variance in forecasting x_2 is due to shocks to x_1? Shocks to x_2?

Let us define *own variance shares* to be the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_i, for $i = 1,2$, and *cross variance shares, or spillovers,* to be the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_j, for $i,j = 1,2,\ i \neq j$. There are two possible spillovers in our simple two-variable example: x_{1t} shocks that affect the forecast error variance of x_{2t} (with contribution $a_{0,21}^2$) and x_{2t} shocks that affect the forecast error variance of x_{1t} (with contribution $a_{0,12}^2$). Hence the total spillover is $a_{0,12}^2 + a_{0,21}^2$. We can convert total spillover to an easily-interpreted index by expressing it relative to total forecast error variation, which is $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = \mathrm{trace}(\mathbf{A}_0\mathbf{A}_0)$. Expressing the ratio as a percentage, the *Spillover Index* is

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{\operatorname{trace}\left(\mathbf{A}_0\mathbf{A}_0'\right)} \times 100.$$

Having illustrated the Spillover Index in a simple first-order two-variable case, it is a simple matter to generalise it to richer dynamic environments. In particular, for a p^{th}-order N-variable VAR (but still using 1-step-ahead forecasts) we immediately have

$$S = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{0,ij}^2}{\operatorname{trace}\left(\mathbf{A}_0\mathbf{A}_0'\right)} \times 100,$$

and for the fully general case of a p^{th}-order N-variable VAR, using H-step-ahead forecasts, we have

$$S = \frac{\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{h,ij}^2}{\sum_{h=0}^{H-1} \operatorname{trace}\left(\mathbf{A}_h\mathbf{A}_h'\right)} \times 100.$$

Such generality is often useful. In much of the empirical work that follows, for example, we use second-order 19-variable VARs with 10-step-ahead forecasts.

2. Global Equity Market Return and Volatility Data

Our underlying data are daily nominal local-currency stock market indexes, January 1992–November 2007, taken from Datastream and Global Financial Data. We examine seven developed stock markets (in the US, UK, France, Germany, Hong Kong, Japan and Australia) and twelve emerging markets (Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico and Turkey).

We calculate returns as the change in log price, Friday-to-Friday. When price data for Friday are not available due to a holiday, we use Thursday. We then convert weekly returns from nominal to real terms using monthly consumer price indexes from the IMF's *International Financial Statistics*. To do so we assume that the weekly inflation rate π_t is constant within the month, in which case we can calculate it simply as the $1/4^{\text{th}}$ power of the monthly inflation rate, and we then calculate the weekly real return as $(1 + i_t)/(1 + \pi_t) - 1$, where i_t is the weekly nominal return. We provide a variety of descriptive statistics for returns in Table 1.

We assume that volatility is fixed within periods (in this case, weeks) but variable across periods. Then, following Garman and Klass (1980) and Alizadeh *et al.* (2002), we can use weekly high, low, opening and closing prices obtained from underlying daily high/low/open/close data to estimate weekly stock return volatility:

$$\begin{aligned}\tilde{\sigma}^2 = {} & 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] \\ & - 0.383(C_t - O_t)^2,\end{aligned}$$

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

Table 1

Descriptive Statistics, Global Stock Market Returns, 10/1/1992–23/11/2007

	United States US	United Kingdom UK	France FRA	Germany GER	Hong Kong HKG	Japan JPN	Australia AUS
Mean	0.00108	0.00038	0.00096	0.00148	0.00144	−0.00048	0.00100
Median	0.00249	0.00134	0.00116	0.00375	0.00266	0.00080	0.00212
Maximum	0.08015	0.09915	0.10981	0.12942	0.13616	0.11076	0.07044
Minimum	−0.15445	−0.08823	−0.12169	−0.14036	−0.20150	−0.11425	−0.05281
Std. Dev.	0.02086	0.02071	0.02709	0.02950	0.03479	0.02878	0.01610
Skewness	−0.72791	−0.10964	−0.13368	−0.27980	−0.44671	−0.02000	−0.19040
Kurtosis	7.606	4.780	4.143	5.182	5.912	3.968	3.875
	Indonesia IDN	S. Korea KOR	Malaysia MYS	Philippines PHL	Singapore SGP	Taiwan TAI	Thailand THA
Mean	0.00057	0.00048	0.00052	0.00001	0.00090	0.00032	−0.00055
Median	0.00163	0.00163	0.00084	0.00036	0.00147	0.00236	0.00080
Maximum	0.18192	0.17486	0.24264	0.15988	0.18363	0.18671	0.21783
Minimum	−0.20091	−0.21828	−0.19102	−0.22084	−0.24265	−0.14154	−0.17293
Std. Dev.	0.03827	0.04210	0.03220	0.03536	0.03069	0.03566	0.03905
Skewness	−0.29091	−0.33285	0.13408	−0.31194	−0.61057	0.01157	0.14976
Kurtosis	7.594	6.209	11.137	7.128	12.996	5.211	5.429
	Argentina ARG	Brazil BRA	Chile CHL	Mexico MEX	Turkey TUR		
Mean	−0.00002	0.00225	0.00112	0.00134	−0.00183		
Median	0.00338	0.00448	0.00102	0.00365	−0.00035		
Maximum	0.24283	0.21935	0.09088	0.17031	0.31552		
Minimum	−0.20193	−0.25158	−0.07129	−0.17829	−0.38140		
Std. Dev.	0.05120	0.05548	0.02093	0.03599	0.06477		
Skewness	0.02265	−0.29569	0.07717	−0.30595	−0.27740		
Kurtosis	5.467	5.077	4.507	5.352	7.147		

Notes: Returns are in real terms and measured weekly, Friday-to-Friday. The sample size is 829. See text for details.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

Table 2

Descriptive Statistics, Global Stock Market Volatility, 10/1/1992–23/11/2007

	US	UK	FRA	GER	HKG	JPN	AUS
Mean	0.00042	0.00049	0.00075	0.00083	0.00099	0.00072	0.00023
Median	0.00025	0.00024	0.00043	0.00035	0.00050	0.00050	0.00015
Maximum	0.00595	0.00926	0.01013	0.01630	0.03794	0.00798	0.01045
Minimum	0.00002	0.00001	0.00003	0.00001	0.00002	0.00002	0.00001
Std. Dev.	0.00056	0.00079	0.00104	0.00148	0.00204	0.00079	0.00044
Skewness	4.4198	5.4561	4.2555	4.8072	10.2854	3.5656	16.3669
Kurtosis	30.742	44.801	27.337	34.111	156.420	22.417	361.967
	IDN	KOR	MYS	PHL	SGP	TAI	THA
Mean	0.00088	0.00128	0.00085	0.00065	0.00045	0.00079	0.00111
Median	0.00036	0.00064	0.00024	0.00033	0.00020	0.00049	0.00056
Maximum	0.02074	0.01869	0.04592	0.01798	0.01050	0.01376	0.02356
Minimum	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00003
Std. Dev.	0.00169	0.00192	0.00287	0.00137	0.00081	0.00099	0.00179
Skewness	5.0567	3.8836	10.5119	8.3102	5.3390	4.7681	5.7314
Kurtosis	39.067	23.236	137.335	92.211	45.602	45.597	52.310
	ARG	BRA	CHL	MEX	TUR		
Mean	0.00187	0.00210	0.00021	0.00102	0.00317		
Median	0.00085	0.00108	0.00010	0.00053	0.00152		
Maximum	0.03371	0.06133	0.00816	0.02871	0.07689		
Minimum	0.00001	0.00000	0.00000	0.00000	0.00000		
Std. Dev.	0.00327	0.00419	0.00048	0.00180	0.00539		
Skewness	4.9933	7.7243	8.8249	7.8728	6.7978		
Kurtosis	35.897	82.961	113.737	96.061	73.763		

Notes: Volatilities are for Monday-to-Friday returns. The mnemonics are as in Table 1. We calculate Chile's volatility using the Santiago Stock Exchange IGPA Index for 1/1992–5/2004 and the Santiago Stock Exchange IPSA index for June 2004 onward. The sample size is 829. See text for details.

where H is the Monday-Friday high, L is the Monday-Friday low, O is the Monday open and C is the Friday close (all in natural logarithms). We provide descriptive statistics for volatilities in Table 2.

3. Full-sample Analysis: Spillover Tables

Here we provide a full-sample analysis of global stock market return and volatility spillovers. As part of that analysis, we propose decomposing the Spillover Index into all of the forecast error variance components for variable i coming from shocks to variable j, for all i and j.

We begin by characterising return and volatility spillovers over the entire sample, January 1992–November 2007. Subsequently we will track time variation in spillovers via rolling window estimation. We report Spillover Indexes for returns and volatility in the lower right corners of Tables 3 and 4, respectively. Before discussing them, however, let us describe the rest of the two tables, which we call *Spillover Tables*. The *ij*th entry in the Table is the estimated contribution *to* the forecast error variance of country i (returns in Table 3, volatility in Table 4) coming *from* innovations to country j (again, returns in Table 3, volatility in Table 4).[1] Hence the off-diagonal column sums (labelled

[1] The results are based on weekly vector autoregressions of order 2 (selected using the Schwarz criterion), identified using a Cholesky factorisation with the ordering as shown in the column heading, and 10-week-ahead forecasts.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

Table 3

Spillover Table, Global Stock Market Returns, 10/1/1992–23/11/2007

	From																			
To	US	UK	FRA	GER	HKG	JPN	AUS	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR	Contribution From Others
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	6
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	44
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	63
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	72
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	30
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	22
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	43
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	23
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	27
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	31
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	37
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	57
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	26
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	42
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	25
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	34
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	34
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	43
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	14
Contribution to others	292	84	31	11	81	19	11	31	14	16	10	8	6	12	21	9	3	8	7	675.0
Contribution including own	386	140	68	39	151	97	68	108	86	85	73	51	79	70	97	75	68	65	92	Spillover index = 35.5%

Notes: The underlying variance decomposition is based upon a weekly VAR of order 2, identified using a Cholesky factorisation with the ordering as shown in the column heading. The (i, j)-th value is the estimated contribution to the variance of the 10-week-ahead real stock return forecast error of country i coming from innovations to real stock returns of country j. The mnemonics are defined as in Table 1.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

Table 4

Spillover Table, Global Stock Market Volatility, 10/1/1992–23/11/2007

To	From																			
	US	UK	FRA	GER	HKG	JPN	AUS	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR	Contribution From Others
US	63.9	14.9	3.9	1.9	4.9	0.2	1.8	0.3	1.6	0.9	0.4	2.6	0.3	0.1	0.1	0.0	0.1	0.2	2.0	36
UK	22.9	54.5	5.0	1.3	7.4	0.5	2.1	0.3	1.0	0.8	0.1	2.4	0.2	0.2	0.4	0.2	0.1	0.1	0.7	46
FRA	24.0	32.8	27.3	0.2	5.4	0.2	2.8	0.4	0.3	1.2	0.4	2.4	0.2	0.3	0.6	0.3	0.1	0.1	0.9	73
GER	26.9	29.5	13.6	13.7	4.8	0.2	3.9	0.2	0.2	1.3	0.8	2.0	0.2	0.4	0.6	0.3	0.1	0.2	1.0	86
HKG	2.0	0.5	0.7	0.0	87.7	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	12
JPN	2.7	3.3	0.4	0.7	1.6	82.9	0.1	0.1	0.9	1.1	0.1	1.6	0.3	0.0	0.6	0.3	0.3	0.2	2.8	17
AUS	8.9	2.2	0.3	0.6	43.9	0.2	34.7	1.2	1.7	1.3	0.1	2.8	0.1	1.0	0.1	0.2	0.2	0.3	0.1	65
IDN	2.8	0.9	0.3	1.0	6.1	0.3	0.6	71.4	6.9	2.3	2.5	2.8	0.7	0.0	0.0	0.3	0.2	0.2	0.9	29
KOR	2.5	0.6	0.4	0.4	9.1	1.0	1.0	10.3	67.5	1.3	0.9	2.5	0.8	0.2	0.1	0.1	0.2	0.3	0.8	32
MYS	1.3	0.6	0.3	0.6	7.2	1.0	0.9	0.8	1.7	70.7	3.1	6.1	0.3	0.5	0.9	0.6	0.1	1.5	1.9	29
PHL	2.1	0.3	0.3	0.4	8.9	0.3	0.4	8.8	3.0	6.1	66.7	1.5	0.2	0.2	0.2	0.2	0.1	0.2	0.3	33
SGP	12.5	4.1	0.6	0.1	12.2	0.8	0.8	7.6	7.2	2.8	1.5	45.8	0.5	0.1	0.7	0.7	0.0	0.7	1.2	54
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	69.0	0.2	0.4	0.8	0.2	0.7	1.3	31
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	73.9	0.1	0.5	0.1	0.7	0.2	26
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	81.0	0.9	0.8	0.6	1.0	19
BRA	4.5	2.3	1.4	0.3	12.6	0.4	3.3	1.0	0.3	10.0	0.7	3.4	0.5	0.3	11.7	45.2	0.3	0.9	0.8	55
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	26
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	44.1	1.1	56
TUR	2.8	1.7	0.8	0.7	3.9	0.3	1.2	0.3	1.1	2.7	0.5	0.9	4.0	0.1	0.7	0.3	0.2	1.1	76.8	23
Contribution to others	138	98	32	10	170	7	30	38	41	40	16	45	10	5	27	14	3	8	17	749.6
Contribution including own	202	153	59	23	258	90	65	109	108	111	83	91	79	79	108	59	77	52	94	Spillover Index = 39.5%

Notes: The underlying variance decomposition is based upon a weekly VAR of order 2, identified using a Cholesky factorisation with the ordering as shown in the column heading. The (i, j)-th value is the estimated contribution to the variance of the 10-week-ahead stock return volatility forecast error of country i coming from innovations to the stock return volatility of country j. We calculate Chile's volatility using the Santiago Stock Exchange IGPA Index for January 1992–May 2004, and using the Santiago Stock Exchange IPSA index for June 2004 onward. The mnemonics are defined as in Table 1.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

Contributions to Others) or row sums (labelled Contributions from Others), when totalled across countries, give the numerator of the Spillover Index. Similarly, the column sums or row sums (including diagonals), when totalled across countries, give the denominator of the Spillover Index.

The Spillover Table, then, provides an 'input–output' decomposition of the Spillover Index. For example, we learn from Spillover Table 3 (for returns) that innovations to US returns are responsible for 22.2% of the error variance in forecasting 10-week-ahead Mexican returns but only 3.0% of the error variance in forecasting 10-week-ahead Turkish returns. That is, return spillovers from the US to Mexico are larger than for the US to Turkey. As another example, we see from Table 4 (volatility) that total volatility spillovers from Hong Kong to others (that is, Hong Kong Contributions to Others) are much larger than total volatility spillovers from others to Hong Kong (Hong Kong Contributions from Others).

The key substantive summary result to emerge from Tables 3 and 4 is that, distilling all of the various cross-country spillovers into a single Spillover Index for our full 1992–2007 data sample, we find that almost 40% of forecast error variance comes from spillovers, both for returns (36%) and volatilities (40%). Hence spillovers are important in both returns and volatilities and, on average – that is, unconditionally – return and volatility spillovers are of the same magnitude.

However, at any given point in time – that is, conditionally – return and volatility spillovers may be very different and, more generally, their dynamics may be very different. We now substantiate these assertions by moving from a static full-sample analysis to a dynamic rolling-sample analysis.

4. Rolling-sample Analysis: Spillover Plots

Clearly, many changes took place during the years in our sample, 1992–2007. Some are well-described as more-or-less continuous evolution, such as increased linkages among global financial markets and increased mobility of capital, due to globalisation, the move to electronic trading and the rise of hedge funds. Others are better described as bursts that subsequently subside, such as the various Asian currency crises around 1997.

Given this background of financial market evolution and turbulence, it seems unlikely that any single fixed-parameter model would apply over the entire sample. Hence the full-sample Spillover Tables and Spillover Indexes obtained earlier, although providing a useful summary of 'average' behaviour, are likely to miss the potentially important secular and cyclical movements in spillovers. To address this issue, we now estimate the models using 200-week rolling samples, and we assess the extent and nature of spillover variation over time via the corresponding time series of Spillover Indexes, which we examine graphically in *Spillover Plots*.

We present the Spillover Plot for returns in Figure 1. It is largely uneventful, displaying a gently increasing trend but little else. Notice that even as the estimation window moves beyond the mid-1990s, the return Spillover Plots never decline to their earlier lower range. This is consistent with a maintained increase in financial market integration. In recent years, however, the upward trend in the return Spillover Plot has become steeper.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

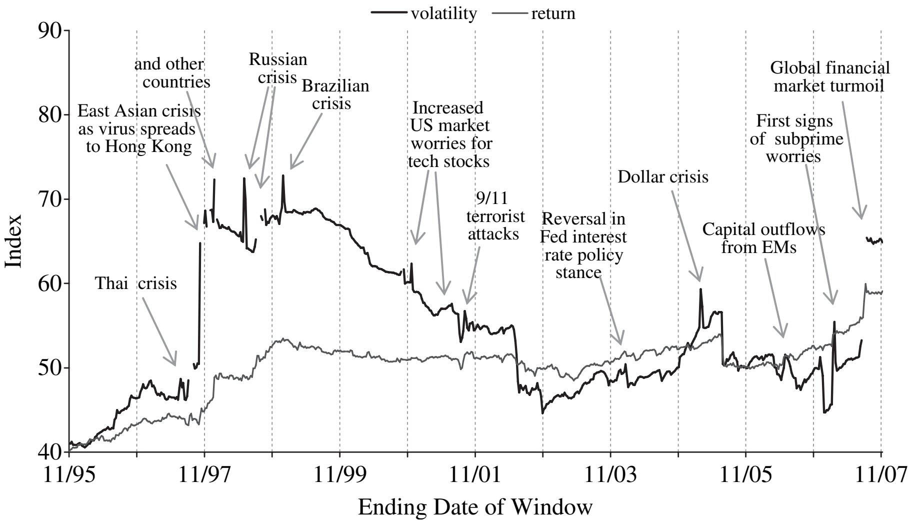

Fig. 1. *Spillover Plot, Global Stock Market Returns and Volatility,* 11/1995–11/2007
Notes: We plot moving return and volatility Spillover Indexes, defined as the sum of all variance decomposition 'contributions to others' from Tables 3 and 4, respectively, estimated using 200-week rolling windows. See text for details.

We also present the Spillover Plot for volatility in Figure 1. It is radically different, ranging widely and responding to economic events. Some of those events are major, including

(1) the East Asian currency crisis in late 1997 (the devaluation of Thai Baht in July 1997, then spread to Hong Kong in October 1997 and further spread to other major economies in the region such as South Korea, Malaysia and Indonesia through January 1998),
(2) the June–August 1998 Russian crisis (the first wave was controlled by the IMF's announcement of a support package in June 1998 and the final outbreak occurred in August 1998),
(3) the intense reversal of capital flows from emerging markets following strong signals from the US Federal Reserve of likely additional hikes in the Fed Funds rate during May–June 2006 and finally,
(4) the financial market turmoil associated with the subprime mortgage market that started in July–August 2007, as well as the first signs of the problem in March 2007.

Additional important events generating volatility spillovers include

(1) the Brazilian crisis of January 1999,
(2) the US terrorist attack of September 11, 2001, and
(3) the 'dollar crisis' of March 2005, associated with remarks from policy makers in several emerging and industrialised countries (South Korea, Russia, China, India and Japan) indicating that they were considering central bank reserve diversification away from the US dollar.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

In any event, the key insight is that many well-known events produced large volatility spillovers, whereas, with the possible exception of the recent subprime episode (which generates the highest value of the volatility Spillover Index since the East Asian crisis of 1997–8), *none* produced return spillovers.[2]

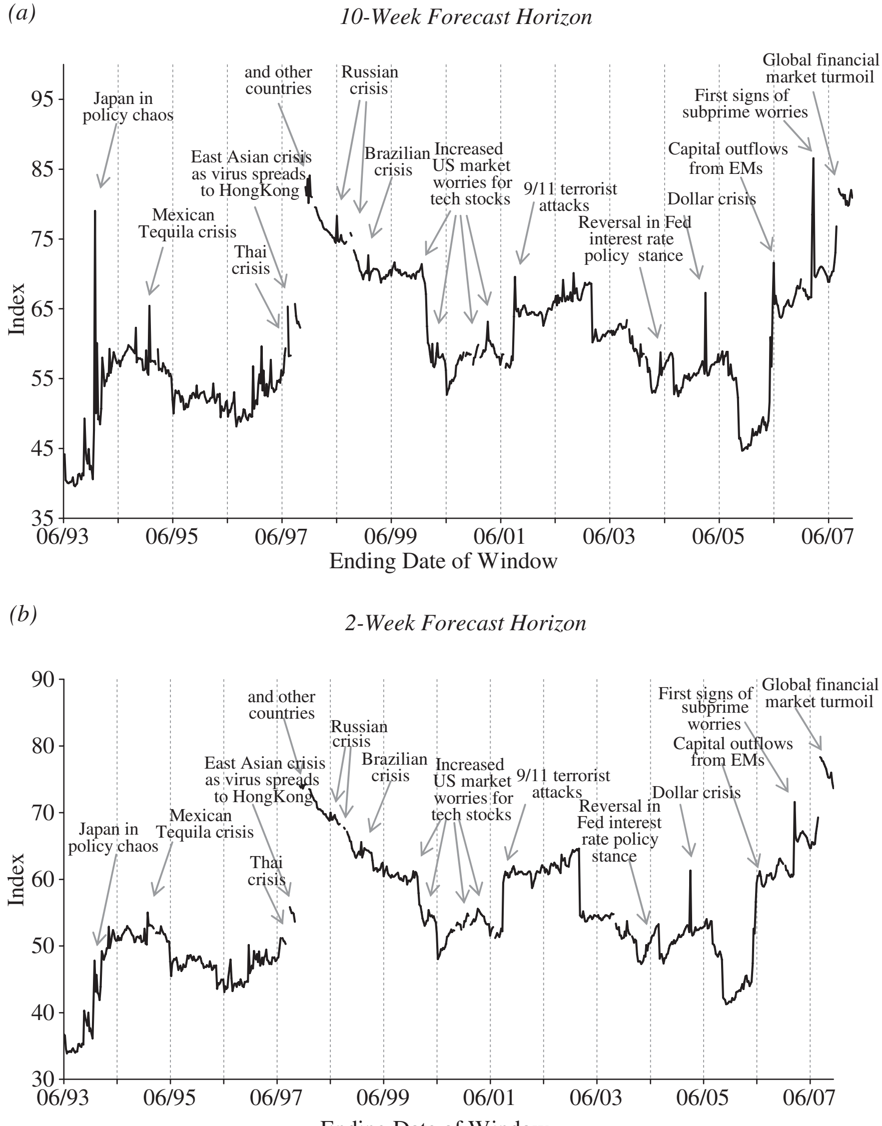

Fig. 2. *Spillover Plot, Global Stock Market Volatility,* 6/1993–11/2007
Notes: We plot a moving volatility Spillover Index, defined as the sum of all variance decomposition 'contributions to others' from Table 4, estimated using 75-week rolling windows. See text for details.

[2] We provide weekly updated spillover plots, for both returns and volatilities, at http://data.economicresearchforum.org/erf/SpillOverIndex.aspx?lang = en.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

5. Robustness

We now perform some simple variations on our basic analysis, with an eye toward checking robustness with respect to the rolling window width, the forecast horizon, and the ordering of the VAR.

In Figure 2 we show Spillover Plots produced using a shorter 75-week rolling window width, and two variance decomposition forecast horizons. (We use the original 10-week forecast horizon in panel 2(*a*) and a shorter 2-week horizon in panel 2(*b*)). Our earlier

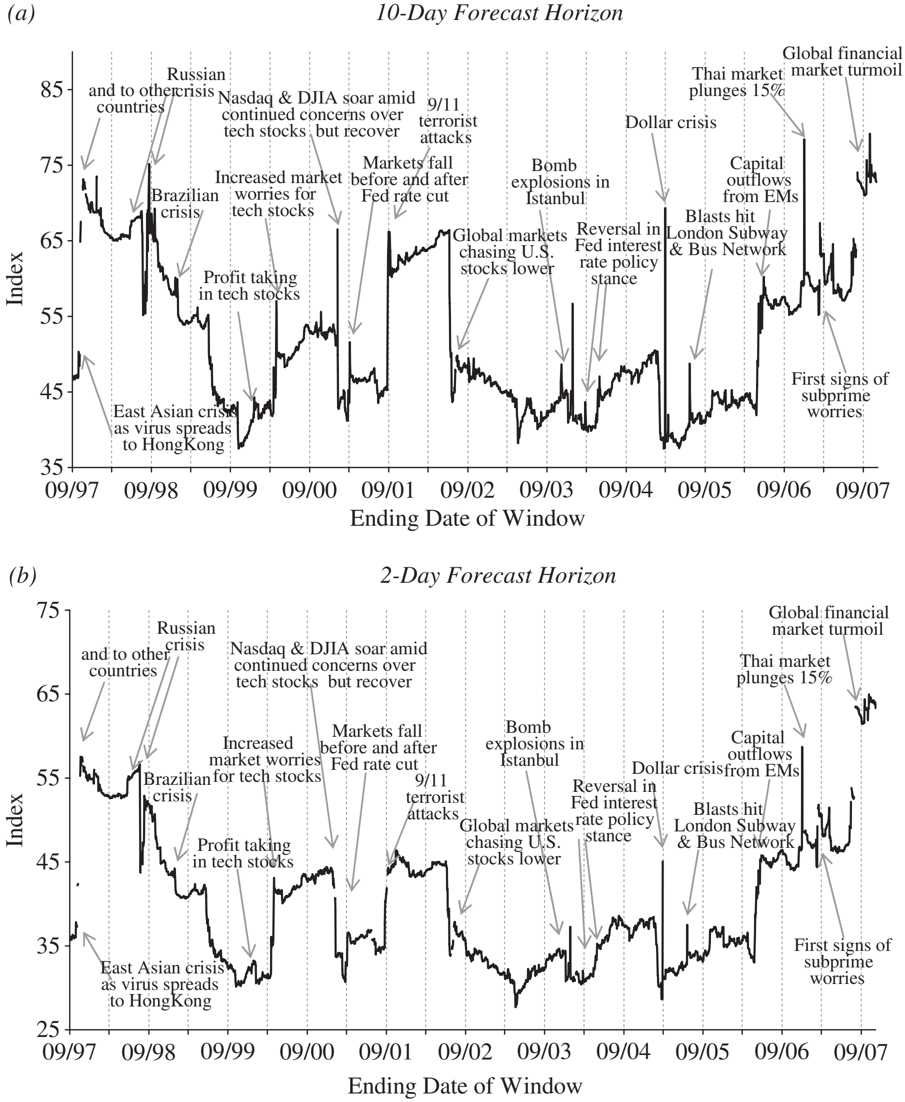

Fig. 3. *Spillover Plots, Global Stock Market Volatility,* 12/1996–11/2007
Notes: We plot a moving volatility Spillover Index, defined as the sum of all variance decomposition 'contributions to others' from Table 4, estimated using 200-day rolling windows. See text for details.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

results appear largely robust to all variations. The reduced smoothing due to the shorter window width, moreover, lets us track movements in volatility spillovers with greater resolution.

In Figure 3 we show Spillover Plots produced using a still-shorter 75-day rolling window width, and very short 10-day and 2-day variance decomposition forecast horizons. Our results again appear robust to window width and forecast horizon. Indeed

Fig. 4. *Maximum and Minimum Spillovers, Global Stock Market Volatility,* 11/1995–11/2007
Notes: We plot maximum and minimum volatility spillovers across a variety of alternative VAR orderings, estimated using 200-week rolling windows. In panel (*a*) we present results for 18 'rotated' orderings corresponding to moving US to last, and then moving UK to last, and so on. In panel (*b*) we present results for fifty randomly-chosen orderings. See text for details.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

they are also robust to choice of volatility estimator: We conduct the analyses underlying Figure 3 using daily, as opposed to weekly, range-based volatilities.[3]

In Figure 4 we explore robustness to VAR ordering, plotting maximum and minimum volatility spillovers across a variety of alternative VAR orderings, estimated using 200-week rolling windows. Computational considerations generally prohibit exploration of robustness of volatility Spillover Plots to all $N!$ possible variable orderings of an N-variable VAR. (In our case, for example, $N = 19$, resulting in roughly 10^{17} possible orderings.) Hence in panel 4(a) we present results for eighteen 'rotated' orderings corresponding to moving the US to last, and then moving the UK to last, and so on, and in panel 4(b) we present results for fifty randomly-chosen orderings. Throughout, the spillover range is small and the same patterns are clearly revealed.

6. Summary and Concluding Remarks

We have proposed a simple framework for measuring linkages in asset returns and return volatilities. In particular, we have formulated and examined precise measures of *return spillovers* and *volatility spillovers* based directly on the familiar notion of variance decompositions in vector autoregressions. Our spillover measures have the appealing virtue of conveying important and useful information while nevertheless sidestepping the contentious issue of definition and existence of episodes of 'contagion' so vigorously debated in recent literature such as Forbes and Rigobon (2002).

Our framework facilitates study of both crisis and non-crisis episodes, including trends as well as bursts in spillovers. In an analysis of nineteen global equity markets from the early 1990s to the present, we find striking evidence of divergent behaviour in the dynamics of return spillovers vs. volatility spillovers. To a good approximation, return spillovers display no bursts but a gently increasing trend, presumably associated with the gradually increasing financial market integration of the last fifteen years. Volatility spillovers, in contrast, display no trend but clear bursts associated with readily-identified 'crisis' events. Why this should be so is a tremendously interesting question, albeit one about which existing theory evidently has little to say. We hope that our measurement will stimulate new theory that speaks to the distinction between return and volatility spillovers.

As for future work, there are several interesting directions for extension. On the theoretical side, it would be interesting to attempt to bound the range of spillovers corresponding to all $N!$ variance decompositions associated with the set of all possible VAR orderings – e.g., building on Faust (1998) – or to produce spillover plots based on variance decompositions invariant to ordering; e.g., building on Pesaran and Shin (1998). On the substantive empirical side, it will be interesting to analyse volatility spillovers not only in stock markets, but also within and across other financial markets, as well as in cross-country real activity and inflation.

[3] Because of different holidays, one or more markets may be closed on any day. To circumvent this problem, we set missing days' volatilities equal to previous-day observations. We also assume that all stock markets are closed on Christmas day, New Year's Eve, and Easter, because an overwhelming majority of markets are closed then.

© The Author(s). Journal compilation © Royal Economic Society 2009

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

University of Pennsylvania and NBER
Koc University

Submitted: 8 January 2007
Accepted: 3 April 2008

References

Alizadeh, S., Brandt, M.W. and Diebold, F.X. (2002). 'Range-based estimation of stochastic volatility models', *Journal of Finance*, vol. 57(3) (June), pp. 1047–92.

Engle, R.F., Ito, T. and Lin, W-L. (1990). 'Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market', *Econometrica*, vol. 58(3) (May), pp. 525–42.

Faust, J. (1998). 'The robustness of identified VAR conclusions about money', *Carnegie-Rochester Conference Series on Public Policy*, vol. 49 (December), pp. 207–44.

Forbes, K.J. and Rigobon, R. (2002). 'No contagion, only interdependence: Measuring stock market comovements', *Journal of Finance*, vol. 57(5) (October), pp. 2223–61.

Garman, M.B. and Klass, M.J. (1980). 'On the estimation of security price volatilities from historical data', *Journal of Business*, vol. 53(1) (January), pp. 67–78.

King, M., Sentana, E. and Wadhwani, S. (1994). 'Volatility and links between national stock markets', *Econometrica*, vol. 62(4) (July), pp. 901–33.

Pesaran, M.H. and Shin, Y. (1998). 'Generalized impulse response analysis in linear multivariate models', *Economics Letters*, vol. 58(1) (January), pp. 17–29.

Downloaded from https://academic.oup.com/ej/article/119/534/158/5089555 by chonbuk national univ. user on 06 March 2023

© The Author(s). Journal compilation © Royal Economic Society 2009