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

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Abstract: 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, and both turn out to be empirically important. In particular, in an analysis of sixteen global equity markets from the early 1990s to the present, we find striking evidence of divergent behavior 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.

1. Introduction

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 (e.g., King, Sentana and Wadhwani, 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 2 and describing our global equity data in Section 3. We perform a full-sample spillover analysis in Section 4 and a rolling-sample analysis allowing for time-varying spillovers in Section 5. We summarize and conclude in Section 6.

2. The Spillover Index

We base our measurement of return and volatility spillovers on vector autoregressive (VAR) models in the broad tradition of Engle, Ito and Lin (1990). Our approach, however, is very different. We focus on variance decompositions, which 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 vector autoregression. Roughly, for each asset i we simply add the shares of its forecast error variance coming from shocks to asset j, for all $j \neq i$, and then we add across all $i = 1, ..., N$.

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

$$x_t = \Phi x_{t-1} + \varepsilon_t,$$

where $x_t = (x_{1,t}, x_{2,t})'$ and Φ is a 2x2 parameter matrix. In our subsequent empirical work, 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

$$x_t = \Theta(L)\varepsilon_t,$$

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

$$x_t = A(L)u_t,$$

where $A(L) = \Theta(L)Q_t^{-1}$, $u_t = Q_t\varepsilon_t$, $E(u_t u_t') = I$, and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ε_t.

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

$$x_{t+1,t} = \Phi x_t,$$

with corresponding 1-step-ahead error vector

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},$$

which has covariance matrix

$$E(e_{t+1,t} e_{t+1,t}') = A_0 A_0'.$$

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 $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = trace(A_0 A_0')$. Expressing the ratio as a percent, the *Spillover Index* is

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A_0')} \cdot 100 .$$

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

$$S = \frac{\displaystyle\sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{0,ij}^2}{trace(A_0 A_0')} \cdot 100 ,$$

and for the fully general case of a pth-order N-variable VAR, using H-step-ahead forecasts, we have

$$S = \frac{\displaystyle\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{h,ij}^2}{\displaystyle\sum_{h=0}^{H-1} trace(A_h A_h')} \cdot 100 .$$

Such generality is often useful. In the empirical work that follows, for example, we use second-order 16-variable VARs with 10-step-ahead forecasts.

3. Global Equity Market Return and Volatility Data

Our underlying data are daily nominal local-currency stock market indices, January 1992 - September 2005, taken from Datastream and Global Financial Data. We use four major indices: The Dow Jones Industrial Average for the New York Stock Exchange, the FTSE-100 index for the London Stock Exchange, the Hang Seng index for the Hong Kong Stock Exchange, and the Nikkei 225 index for the Tokyo Stock Exchange. Similarly, we use daily nominal local-currency stock market indices for 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, Wednesday-to-Wednesday. When price data for Wednesday are not available due to a holiday, we use Thursday. We then convert weekly returns from nominal to real terms using monthly consumer price indices 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 $1/4^{th}$ power of the monthly inflation rate, and we then calculate the weekly real return as $\frac{1+i_t}{1+\pi_t}-1$, 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, Brandt and Diebold (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:

$$\tilde{\sigma}^2 = 0.511(H_t - L_t)^2 - 0.019\left[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)\right] - 0.383(C_t - O_t)^2,$$

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.

4. 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 characterizing return and volatility spillovers over the entire sample, January 1992-September 2005. 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 (labeled Contributions to Others) or row sums (labeled Contributions from Others), when totaled across countries, give the numerator of the Spillover Index. Similarly, the column sums or row sums (including diagonals), when totaled 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 U.S. returns are responsible for 18.1 percent of the error variance in forecasting 10-week-ahead Mexican returns, but only 3.1 percent of the error variance in forecasting 10-week-ahead Turkish returns. That is, return spillovers from the U.S. to Mexico are larger than for the U.S. 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 large 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 1992-2005 data sample, we find that approximately thirty percent of forecast error variance comes from spillovers, both for returns (29 percent) and volatilities (31 percent). 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

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

now substantiate these assertions by moving from a static full-sample analysis to a dynamic rolling-sample analysis.

5. Rolling-Sample Analysis: Spillover Plots

Clearly, many changes took place during the years in our sample, 1992-2005. 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 globalization, 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" behavior, likely 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*.

In Figure 1, we present the Spillover Plot for returns. 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 Spillover Plot never declines to its early lower range. This is consistent with a maintained increase in financial market integration.

The Spillover Plot for volatilities, which we present in Figure 2, is radically different. It ranges widely and responds to economic events. Some of those events are major, such as the East Asian currency crises in late 1997 (the devaluation of Thai Baht in July 1997, the 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). Another example is 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). Both of these crises produced a large spike in volatility spillovers.

Interestingly, volatility spillovers also respond to less major (but nevertheless important and well-known) crises. For example, comparatively minor emerging market crises are reflected in small spikes in the volatility spillover measures. Indeed, during our sample period there were nine widely-acknowledged crisis events: (1) The Mexican crisis of December 1994 - January 1995, (2) the East Asian crisis of October - December 1997, (3) the Russian crisis of August - September 1998, (4) the Brazilian crisis of January 1999, (5) the Turkish Crisis of December 2000 - February 2001, (6) the U.S. terrorist attack of September 11, 2001, (7) the Argentinean Crisis of November 2001, (8) the downgrading to junk status of GM and Ford debt, followed by a short-lived reversal of international capital flows from emerging market economies, of March 2005, (9) the intense reversal of capital flows from emerging markets of May-June 2006. *All* of these events generated increases in volatility spillovers, as shown in Figure 2, whereas *none* generated movements in return spillovers.

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 vector autoregressive variance decompositions. 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 sixteen global equity markets from the early 1990s to the present, we find striking evidence of divergent behavior in the dynamics of return spillovers vs. volatility spillovers. 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.

Although we have not reported them here in order to conserve space, we have performed several variations on the basic theme reported here, and our results appear robust. Such

variations include but are not limited to the VAR lag order, the width of the rolling VAR estimation window, and the forecast horizon for variance decompositions.

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Table 1

Descriptive Statistics, Global Stock Market RETURNS, 1/1992 – 9/2005

	United States	United Kingdom	Hong Kong	Japan	Indonesia	South Korea	Malaysia	Philippines
	US	**UK**	**HKG**	**JPN**	**IDN**	**KOR**	**MYS**	**PHL**
Mean	0.00112	0.00057	0.00130	-0.00079	-0.00033	0.00011	0.00014	-0.00056
Median	0.00186	0.00156	0.00219	0.00041	0.00142	-0.0007	0.00040	-0.00091
Maximum	0.0976	0.1349	0.1370	0.1205	0.1684	0.1657	0.2791	0.1349
Minimum	-0.0932	-0.1035	-0.1423	-0.1024	-0.1304	-0.1797	-0.2101	-0.1550
Std. Dev.	0.0211	0.0228	0.0349	0.0302	0.0353	0.0427	0.0361	0.0364
Skewness	-0.1607	0.2515	-0.4493	0.0388	-0.0965	-0.0495	0.4289	0.1019
Kurtosis	5.18	6.90	4.48	4.21	5.62	4.76	11.80	4.51
	Singapore	**Taiwan**	**Thailand**	**Argentina**	**Brazil**	**Chile**	**Mexico**	**Turkey**
	SGP	**TAI**	**THA**	**ARG**	**BRA**	**CHL**	**MEX**	**TUR**
Mean	0.00067	0.00006	-0.00070	0.00008	0.00187	0.00080	0.00087	0.00050
Median	-0.00018	0.00167	0.00036	0.00429	0.00734	0.00102	0.00154	0.00191
Maximum	0.1467	0.1485	0.1930	0.2571	0.3054	0.0946	0.1739	0.2589
Minimum	-0.1165	-0.1160	-0.1397	-0.2216	-0.2786	-0.1136	-0.1319	-0.3313
Std. Dev.	0.0300	0.0371	0.0412	0.0546	0.0593	0.0210	0.0382	0.0680
Skewness	0.0674	0.0498	0.2416	-0.3485	-0.5742	-0.0109	-0.0140	-0.2868
Kurtosis	5.43	3.98	4.41	4.84	7.40	6.02	4.55	5.55

Notes: Returns are in real terms and measured weekly, Wednesday-to-Wednesday. The sample size is 717. See text for details.

Table 2

Descriptive Statistics, Global Stock Market VOLATILITY, 1/1992 – 9/2005

	US	**UK**	**HKG**	**JPN**	**IDN**	**KOR**	**MYS**	**PHL**
Mean	0.00043	0.00051	0.00106	0.00076	0.00091	0.00138	0.00093	0.00066
Median	0.00025	0.00025	0.00057	0.00053	0.00036	0.00069	0.00027	0.00033
Maximum	0.00595	0.00926	0.03794	0.00798	0.02074	0.01869	0.04592	0.01798
Minimum	1.98E-05	1.14E-05	1.55E-05	1.88E-05	3.97E-07	8.22E-10	4.41E-06	4.74E-06
Std. Dev.	0.00058	0.00083	0.00216	0.00082	0.00178	0.00204	0.00306	0.00145
Skewness	4.330	5.248	9.839	3.473	4.918	3.63574	9.9146	8.06104
Kurtosis	29.221	41.012	141.313	21.203	36.495	20.574	121.400	85.161
	SGP	**TAI**	**THA**	**ARG**	**BRA**	**CHL**	**MEX**	**TUR**
Mean	0.00045	0.00085	0.00118	0.00204	0.00225	0.00018	0.00104	0.00344
Median	0.00018	0.00053	0.00063	0.00096	0.00115	8.21E-05	0.00053	0.00165
Maximum	0.0105	0.01376	0.01699	0.03371	0.06133	0.00816	0.02871	0.07689
Minimum	6.21E-07	9.38E-06	5.22E-05	6.41E-06	1.22E-08	1.77E-07	7.18E-07	6.67E-07
Std. Dev.	0.00082	0.00104	0.0017	0.00344	0.00445	0.00043	0.00189	0.00572
Skewness	5.201	4.648	4.393	4.761	7.331	11.232	7.694	6.442
Kurtosis	44.325	43.029	30.862	32.769	74.263	178.011	89.782	66.010

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 6/2004 – 9/2005. The sample size is 717. See text for details.

Table 3

Spillover Table, Global Stock Market RETURNS, 1/1992-9/2005

|		US	UK	HKG	JPN	IDN	KOR	MYS	PHL	SGP	TAI	THA	ARG	BRA	CHL	MEX	TUR	Contribution From Others
							F R O M											
	US	95.4	0.4	1.0	0.4	0.0	0.4	0.1	0.8	0.3	0.1	0.2	0.4	0.2	0.2	0.0	0.1	**5**
	UK	39.1	57.8	0.2	0.5	0.3	0.1	0.2	0.7	0.0	0.1	0.4	0.0	0.1	0.0	0.1	0.4	**42**
	HKG	16.0	9.0	70.9	0.3	0.2	0.4	1.0	0.1	0.1	0.6	0.4	0.1	0.5	0.4	0.0	0.1	**29**
	JPN	11.4	3.4	2.2	79.4	0.1	0.4	0.4	0.2	0.0	0.5	0.5	0.0	0.0	1.2	0.3	0.1	**21**
	IDN	6.4	1.9	5.7	1.0	79.0	1.3	0.3	0.6	0.4	0.2	0.7	0.9	0.5	0.3	0.6	0.2	**21**
	KOR	6.8	3.7	6.6	4.2	1.4	75.5	0.1	0.5	0.0	0.1	0.4	0.4	0.2	0.1	0.1	0.1	**24**
	MYS	4.1	1.5	11.0	0.5	7.6	1.0	72.8	0.1	0.1	0.1	0.1	0.2	0.5	0.1	0.1	0.0	**27**
T O	PHL	8.8	1.7	7.1	0.2	7.5	1.5	2.3	66.0	0.3	0.8	1.8	1.5	0.0	0.1	0.2	0.1	**34**
	SGP	15.8	5.6	18.8	1.5	4.0	1.6	6.9	1.7	41.4	0.5	0.7	0.6	0.6	0.2	0.0	0.0	**59**
	TAI	7.7	1.5	4.9	2.5	0.3	1.5	1.9	0.2	0.7	77.7	0.2	0.1	0.0	0.2	0.3	0.2	**22**
	THA	7.9	3.3	7.9	0.1	9.7	3.7	3.6	1.2	0.9	0.3	59.2	1.1	0.2	0.4	0.3	0.1	**41**
	ARG	7.5	2.0	1.8	0.9	0.7	0.2	0.2	0.6	0.7	1.2	0.5	82.6	0.1	0.3	0.6	0.2	**17**
	BRA	12.8	0.9	1.9	1.3	0.1	0.8	1.0	0.6	0.2	0.2	0.2	7.6	71.6	0.2	0.4	0.2	**28**
	CHL	8.2	1.0	4.9	0.9	1.8	0.1	0.5	0.2	0.9	0.6	1.6	4.0	5.7	68.3	1.0	0.2	**32**
	MEX	18.1	3.9	3.8	0.8	0.2	0.6	0.1	0.2	0.2	0.3	0.5	9.2	4.0	1.2	56.8	0.1	**43**
	TUR	3.1	1.9	0.5	1.0	0.8	0.4	0.3	0.1	0.6	0.3	0.7	0.4	0.7	0.4	0.5	88.1	**12**
Contribution To Others		174	42	78	16	35	14	19	8	6	6	9	26	13	5	5	2	**458**
Contribution Including Own		269	100	149	96	114	89	92	74	47	84	68	109	85	74	61	90	**Spillover Index = 29%**

Notes: We present variance decompositions based upon a weekly vector autoregression of order 2 identified using a Cholesky factorization 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.

Table 4
Spillover Table, Global Stock Market VOLATILITY, 1/1992-9/2005

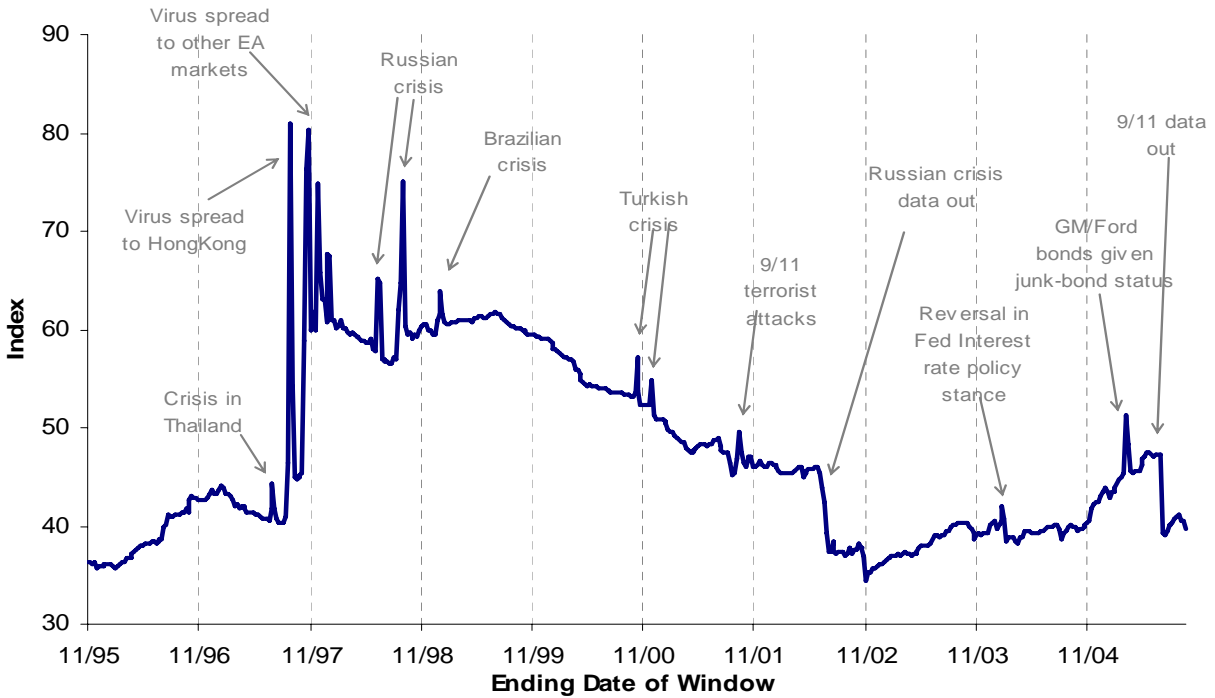|								**FROM**										
		US	**UK**	**HKG**	**JPN**	**IDN**	**KOR**	**MYS**	**PHL**	**SGP**	**TAI**	**THA**	**ARG**	**BRA**	**CHL**	**MEX**	**TUR**	**Contribution From Others**
T O	**US**	69.1	17.2	5.6	0.2	0.3	1.4	0.8	0.6	1.7	0.2	0.1	0.2	0.1	0.1	0.1	2.3	**31**
	UK	28.9	57.1	7.8	0.5	0.4	1.0	0.5	0.1	1.2	0.2	0.2	0.5	0.3	0.2	0.4	0.7	**43**
	HKG	1.7	0.5	89.0	0.1	0.5	1.2	0.5	1.6	3.0	0.6	0.7	0.0	0.1	0.0	0.1	0.3	**11**
	JPN	3.4	3.2	1.8	84.8	0.0	0.7	1.0	0.2	1.0	0.2	0.0	0.5	0.3	0.1	0.0	2.7	**15**
	IDN	2.3	0.7	6.6	0.5	73.4	7.1	2.2	2.8	2.2	0.7	0.1	0.0	0.1	0.3	0.1	0.9	**27**
	KOR	4.1	0.7	9.0	1.1	10.6	68.5	1.2	1.1	1.6	0.7	0.3	0.1	0.2	0.0	0.1	0.7	**31**
	MYS	1.1	0.6	7.6	1.2	0.9	1.5	72.1	3.3	4.8	0.4	0.5	1.1	0.7	0.2	1.8	2.3	**28**
	PHL	1.3	0.3	9.2	0.4	8.9	3.3	6.4	67.1	1.2	0.1	0.3	0.3	0.3	0.2	0.3	0.5	**33**
	SGP	10.1	3.9	13.5	1.0	8.0	7.6	2.6	1.6	47.1	0.7	0.2	1.1	0.6	0.0	0.5	1.5	**53**
	TAI	9.3	0.3	2.6	0.6	0.6	8.8	0.8	2.0	0.5	71.4	0.5	0.3	0.9	0.1	0.5	0.9	**29**
	THA	0.6	0.8	11.4	0.3	4.5	3.5	0.4	1.3	7.5	0.5	67.5	0.1	0.5	0.1	0.8	0.2	**32**
	ARG	2.8	1.3	3.0	0.5	0.3	0.1	2.2	0.2	0.4	0.3	0.7	85.0	1.0	0.3	0.7	1.1	**15**
	BRA	2.7	2.3	13.7	0.3	1.0	0.3	10.4	0.8	2.5	0.5	0.2	14.0	48.2	0.1	1.9	1.0	**52**
	CHL	0.5	0.6	4.3	0.1	1.0	0.2	3.2	0.1	0.7	0.3	0.2	5.4	7.4	75.8	0.2	0.1	**24**
	MEX	5.8	1.2	27.1	0.3	0.5	0.5	2.7	0.4	1.5	0.2	0.7	7.4	3.0	0.6	47.2	1.0	**53**
	TUR	3.2	1.5	4.1	0.4	0.4	1.0	2.7	0.5	0.7	3.8	0.1	0.8	0.2	0.4	1.3	79.0	**21**
Contribution To Others		**78**	**35**	**127**	**7**	**38**	**38**	**38**	**17**	**30**	**9**	**5**	**32**	**16**	**3**	**9**	**16**	**498**
Contribution Including Own		**147**	**92**	**216**	**92**	**111**	**107**	**110**	**84**	**77**	**81**	**72**	**117**	**64**	**79**	**56**	**95**	**Spillover Index = 31%**

Notes: We present variance decompositions based upon a weekly vector autoregression of order 2 identified using a Cholesky factorization 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 the Santiago Stock Exchange IPSA index for June 2004-September 2005. The mnemonics are defined as in Table 1.

Figure 1
Spillover Plot, Global Stock Market RETURNS, 11/1995-9/2005
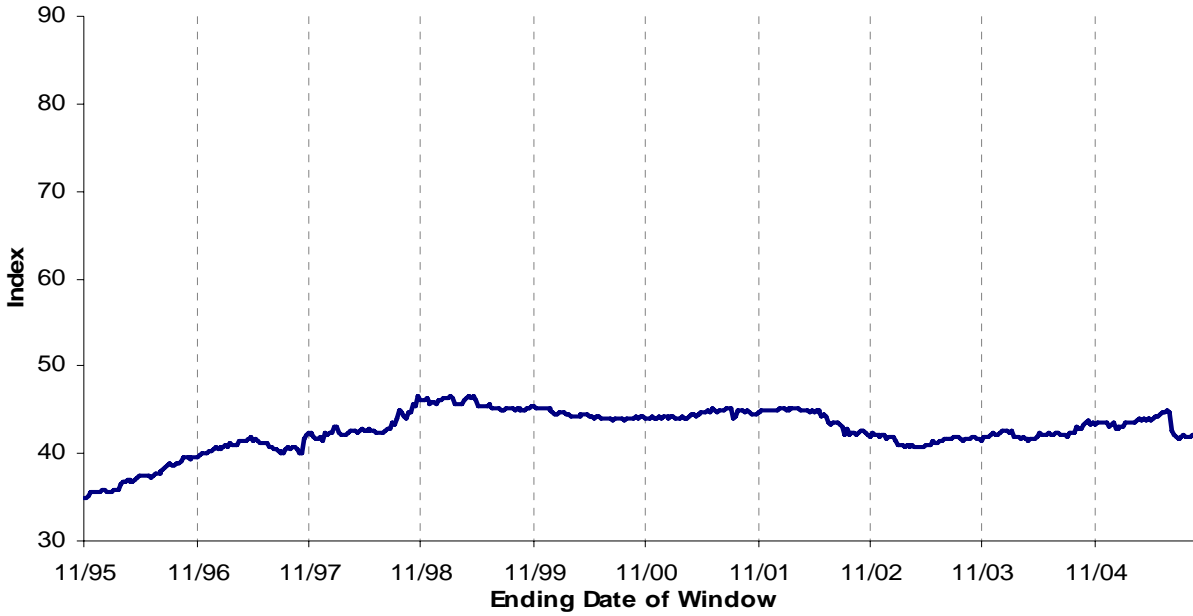
Notes: The return Spillover Index is the sum of all variance decomposition "contributions to others" from Table 3, estimated using a 200-week rolling window. See text for details.

Figure 2
Spillover Plot, Global Stock Market VOLATILITY, 11/1995-9/2005

Notes: The volatility Spillover Index is the sum of all variance decomposition "contributions to others" from Table 4, estimated using a 200-week rolling window. See text for details.