Equity Market Spillovers in the Americas

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Many aspects of financial markets merit monitoring in risk management and portfolio allocation contexts, including (and perhaps especially) in contexts of interest to central banks. Much recent attention, for example, has been devoted to measuring and forecasting return volatilities and correlations, as in the case of market-based implied volatilities. One can extend the market-based approach by monitoring not implied volatility extracted from a single option, but rather entire risk-neutral densities extracted from sets of options with different strike prices (Gray and Malone, 2008). This is consistent with the density forecasting perspective on risk measurement advocated by Diebold, Gunther, and Tay (1998) and several of the references therein.

In many contexts, however, derivatives markets are not available for the objects of interest. Such is the case in this paper, in which we focus on measuring spillovers in equity returns and equity return volatilities. In particular, we consider cross-country stock market spillovers in the Americas, asking how much of the forecast error variance of a country's broad stock market return (or volatility) is due to shocks in other countries' markets. There are simply no derivatives markets from which one might obtain "implied spillovers."

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We therefore use a non-market-based spillover estimator, which turns out to be quite effective. It is widely applicable, simple, and intuitive, yet also rigorous and replicable. It facilitates the study of both crisis and noncrisis episodes, including trends and cycles (and bursts) in spillovers. Finally, although it conveys useful information, it nevertheless sidesteps the contentious issues associated with the definition and existence of episodes of contagion or herd behavior.[1]

We proceed as follows. In section 1 we motivate and describe our measure of spillovers, which is based on the variance decomposition of a vector autoregression. In section 2 we use our spillover measure to assess stock market spillovers in the Americas in recent decades, focusing on both return and volatility spillovers. In section 3 we summarize our work and sketch directions for future research.

1. Measuring Spillovers

This section describes a spillover index proposed in an earlier work (Diebold and Yilmaz, 2009), which we then use to measure spillovers in the Americas. The index is quite general and flexible, based directly on variance decompositions from vector autoregressions (VARs) fitted to returns or volatilities. It contrasts with approaches such as Edwards and Susmel (2001), which produce only a binary indicator of a high or low state (our index varies continuously) and which are econometrically tractable only for small numbers of countries (our index is simple to calculate even for large numbers of countries).

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

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

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

where $\mathbf{x}_t = (x_{1,t}, x_{2,t})'$ and $\mathbf{\Phi}$ is a 2 x 2 parameter matrix. In our subsequent empirical work, $\mathbf{x}_t$ is either a vector of stock returns or

1. On contagion (or lack thereof), see, for example, Edwards and Rigobon (2002) and Forbes and Rigobon (2002).

a vector of stock return volatilities. By covariance stationarity, the moving average representation of the VAR exists and is given by

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

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

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

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

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

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

with corresponding one-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

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

Hence, in particular, the variance of the one-step-ahead error in forecasting $\mathbf{x}_{1,t}$ is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the one-step-ahead error in forecasting $\mathbf{x}_{2,t}$ 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 following questions. What fraction of the one-step-ahead error variance in forecasting x_1 is due to shocks to x_1 and what fraction is due to shocks to x_2? And similarly, what fraction of the one-step-ahead error variance in forecasting x_2 is due to shocks to x_1 versus shocks to x_2?

Let us define own-variance shares to be the fractions of the one-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 one-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: $x_{1,t}$ shocks that affect the forecast error variance of $x_{2,t}$, with relative contribution $\tilde{a}_{0,21}^2 = [a_{0,21}^2 / (a_{0,21}^2 + a_{0,22}^2)]$, and $x_{2,t}$ shocks that affect the forecast error variance of x_{1t}, with relative contribution $\tilde{a}_{0,12}^2 = [a_{0,12}^2 / (a_{0,11}^2 + a_{0,12}^2)]$. Hence the total spillover is given by $\tilde{a}_{0,12}^2 + \tilde{a}_{0,21}^2 = [a_{0,12}^2 / (a_{0,11}^2 + a_{0,12}^2)] + [a_{0,21}^2 / (a_{0,21}^2 + a_{0,22}^2)]$. We can convert the total spillover to an easily interpreted index by expressing it as a ratio of the sum of relative contributions to the forecast error variance, which is $(\tilde{a}_{0,11}^2 + \tilde{a}_{0,12}^2) + (\tilde{a}_{0,21}^2 + \tilde{a}_{0,22}^2) = 2$. With the ratio expressed as a percent, the spillover index is

$$S = \frac{\tilde{a}_{0,12}^2 + \tilde{a}_{0,21}^2}{2} \cdot 100.$$

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 p^{th}-order N-variable VAR (but still using one-step-ahead forecasts), we immediately have

$$S = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{a}_{0,ij}^2}{N} \cdot 100.$$

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

$$S = \frac{\sum_{k=0}^{h-1} \sum_{i,j=1, i \neq j}^{N} \tilde{a}_{k,ij}^2}{N} \cdot 100.$$

The generality of our spillover measure is often useful, and we exploit it in our subsequent empirical analysis of return and volatility spillovers in the Americas.[2]

2. Although it is beyond the scope of this paper, future work could profitably explore the relationship of our spillover measure to others based, for example, on time-varying covariances or correlations.

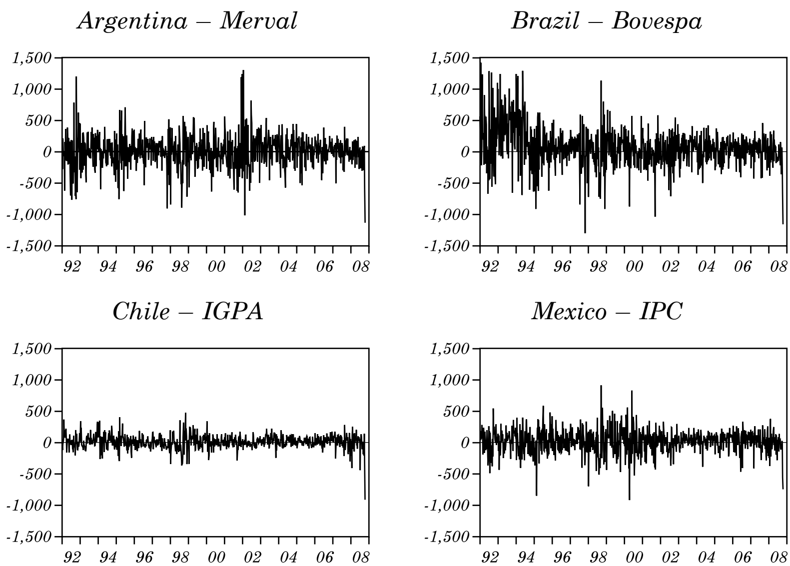
2. Empirical Analysis of Stock Market Spillovers in the Americas

Here we examine stock market spillovers in the Americas, focusing on both return and volatility spillovers.

2.1 Data

We examine broad stock market returns from 1 January 1992 through 10 October 2008 in four South American countries: Argentina (Merval), Brazil (Bovespa), Chile (IGPA), and Mexico (IPC). We measure returns weekly, using underlying stock index levels at the Friday close, and we express them as annualized percentages. The annualized weekly percent return for market i is $r_{it} = 52 \cdot 100 \cdot (\Delta \ln P_{it})$. We plot the four countries' returns in figure 1, and we provide summary statistics in table 1.

Figure 1. South American Stock Market Returns



Source: Authors' computations.

Table 1. Summary Statistics: South American Stock Market Returns

Statistic	*Argentina*	*Brazil*	*Chile*	*Mexico*
Mean	2.49	64.33	8.50	15.75
Median	19.75	55.04	8.74	28.82
Maximum	1,301.99	1,417.96	473.78	910.16
Minimum	−1,135.39	−1,303.04	−915.84	−921.24
Standard deviation	264.78	317.84	111.77	188.51
Skewness	−0.02	0.39	−0.70	−0.32
Kurtosis	5.79	5.70	9.60	5.36
Jarque-Bera	283.40	287.63	1,661.05	217.78
Probability	0.00	0.00	0.00	0.00
No. observations	875	875	875	875

Source: Authors' computations.

We also measure return volatilities (standard deviations) weekly. In the tradition of Garman and Klass (1980), we estimate weekly return volatilities using weekly high, low, opening, and closing prices obtained from underlying daily high, low, opening, and closing data, from the Monday open to the Friday close:[3]

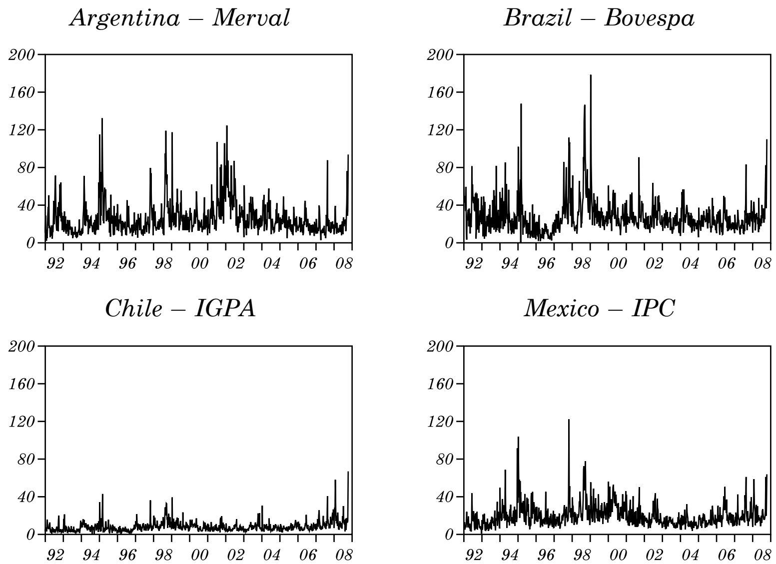
$$\tilde{\sigma}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019\begin{bmatrix}(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ -2(H_{it} - O_{it})(L_{it} - O_{it})\end{bmatrix} - 0.383(C_{it} - O_{it})^2,$$

where H is the Monday–Friday high, L is the Monday–Friday low, O is the Monday opening price, and C is the Friday closing price (all in natural logarithms). Because $\tilde{\sigma}_{it}^2$ is an estimator of the weekly variance, the corresponding estimate of the annualized weekly percent standard deviation (volatility) is $\hat{\sigma}_{it} = 100\sqrt{52 \cdot \tilde{\sigma}_{it}^2}$. We plot the four countries' volatilities in figure 2, and we provide summary statistics in table 2.

Figures and tables 1 and 2 highlight several noteworthy aspects of return and volatility behavior. First, Chilean returns tend to be both

3. See also Parkinson (1980); Alizadeh, Brandt, and Diebold (2002).

Figure 2. South American Stock Market Volatilities



Source: Authors' computations.

Table 2. Summary Statistics: South American Stock Market Volatilities

Statistic	*Argentina*	*Brazil*	*Chile*	*Mexico*
Mean	25.63	27.76	7.97	19.64
Median	20.94	23.88	6.65	16.71
Maximum	132.40	178.58	66.86	122.17
Minimum	1.83	0.08	0.30	0.61
Standard deviation	17.43	18.23	5.85	12.23
Skewness	2.25	2.85	3.50	2.43
Kurtosis	10.12	16.89	25.14	13.97
Jarque-Bera	2,587.20	8,211.40	19,651.30	5,248.50
Probability	0.00	0.00	0.00	0.00
No. observations	875	875	875	875

Source: Authors' computations.

smaller and less variable, on average, than those of the other South American countries. Second, periods of very high volatility typically correspond to financial and economic crises and are typically common across markets. For example, volatility in all stock markets surges during the Mexican tequila crisis of 1995, the East Asian crisis of 1997, the Russian and Brazilian crises of 1998 and 1999, and the global financial crisis of 2007–08.[4]

2.2 Empirical Implementation of the Spillover Measure

We use second-order VARs ($p = 2$), h = ten-step-ahead forecasts, and N = four or five countries (Argentina, Brazil, Chile, and Mexico, with and without the United States). We capture time variation in spillovers by reestimating the VAR weekly, using a hundred-week rolling estimation window. We compute the spillover index only when the parameters of the estimated VAR imply covariance stationarity.

A key issue is identification of the VAR. Traditional orthogonalization using the Cholesky factor of the VAR innovation covariance matrix produces variance decompositions that may depend on ordering. Several partial fixes are available. First, one could attempt a structural identification if credible restrictions on the VAR's innovation covariance matrix could be imposed, but such is usually not the case. Second, building on Faust (1998), one could attempt to bound the range of spillovers corresponding to all $N!$ variance decompositions associated with the set of all possible VAR orderings. Third, building on Pesaran and Shin (1998), one could attempt to make the variance decomposition invariant to ordering.

Finally, one could simply calculate the entire set of spillovers corresponding to all $N!$ variance decompositions associated with the set of all possible VAR orderings. This brute-force approach is unfeasible for large N, but it is preferable when feasible as it involves no auxiliary assumptions. In our case, N is quite small (four or five), so we can straightforwardly calculate and use variance decompositions based on all $N!$ orderings, which we do in most of this paper.

4. The only exception is Argentina's crisis of 2001–02, during which Argentina's surge in volatility was not shared with the other countries.

2.3 South American Spillovers

Tables 3 and 4 present full-sample South American spillover tables for returns and volatilities, respectively.[5] Both return and volatility spillovers are sizable: return spillovers are approximately 19 percent, and volatility spillovers are even larger at 25 percent.

Table 3. Return Spillovers: Full Sample

Country	*Argentina*	*Brazil*	*Chile*	*Mexico*	*Contribution from others*
Argentina	97.63	0.09	0.24	2.04	2.4
Brazil	15.84	83.51	0.01	0.63	16.5
Chile	13.61	8.33	75.57	2.50	24.4
Mexico	22.38	5.77	3.06	68.79	31.2
Contribution to others	51.8	14.2	3.3	5.2	74.5
Contribution incl. own	149.5	97.7	78.9	74.0	Index = 18.6%

Source: Authors' computations.

Table 4. Volatility Spillovers: Full Sample

Country	*Argentina*	*Brazil*	*Chile*	*Mexico*	*Contribution from others*
Argentina	96.00	0.69	1.81	1.51	4.0
Brazil	28.27	67.59	0.60	3.54	32.4
Chile	14.12	14.86	70.98	0.04	29.0
Mexico	18.67	11.36	4.00	65.97	34.0
Contribution to others	61.1	26.9	6.4	5.1	99.5
Contribution incl. own	157.1	94.5	77.4	71.1	Index = 24.9%

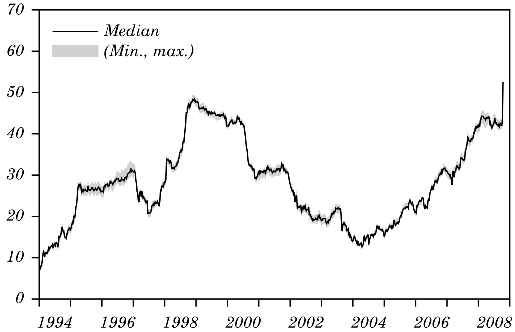
Source: Authors' computations.

One can view tables 3 and 4 as providing measures of spillovers averaged over the full sample. Of greater interest are movements in spillovers over time. Figures 3 and 4 depict dynamic South American

5. The VAR ordering is Argentina, Brazil, Chile, Mexico. Subsequently, we consider all possible orderings.

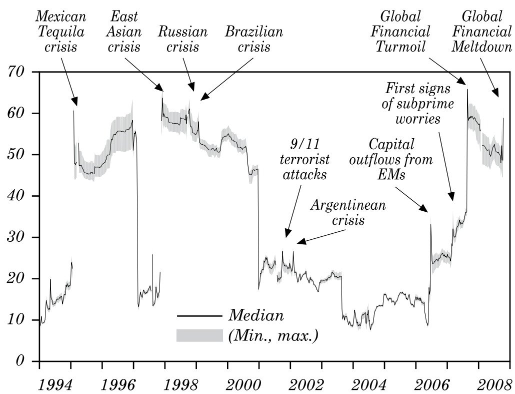
spillover plots for returns and volatilities, respectively, calculated using rolling hundred-week VAR estimation windows. Rather than relying on any particular VAR ordering for Cholesky-factor identification, we calculate the spillover index for every possible VAR ordering. The figures indicate that both return and volatility spillovers vary widely over time and that return spillovers evolve gradually, whereas volatility spillovers show sharper jumps, typically corresponding to crisis events.

Figure 3. Spillover Plot: Returns[a]



Source: Authors' computations.
a. The lines in the figure are medians across all orderings; the gray shaded region gives the range.

Figure 4. Spillover Plot: Volatilities[a]



Source: Authors' computations.
a. The lines in the figure are medians across all orderings; the gray shaded region gives the range.

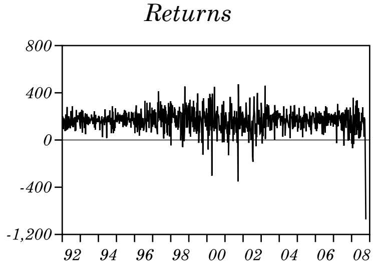
A closer examination of the spillover plots reveals that return spillovers increase as we roll the estimation window through the end of 1994, and they surge to 30 percent immediately after the outbreak of the Mexican tequila crisis in December 1994. Return spillovers drop to 20 percent in late 1996 (as we drop the Mexican crisis from the estimation window), but the Asian and Russian crises keep them from dropping further. Return spillovers peak at nearly 50 percent after the outbreak of the full-fledged Russian crisis in September 1998, and they decline substantially when we drop the Russian crisis from the subsample window. Surprisingly, return spillovers fail to increase during the Brazilian crisis of January 1999. Instead, they continue their secular downward movement, dropping as low as 13 percent in 2004, after which they drift upward, with a jump in the first week of October 2008.

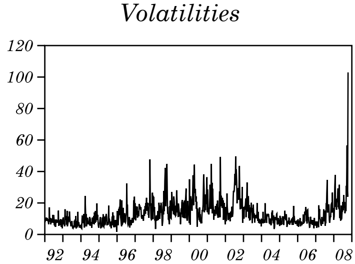
Volatility spillovers, in turn, surge to 50 percent at the outset of the Mexican crisis and fluctuate between 45 and 60 percent before plunging when we drop the crisis from the estimation window. Volatility spillovers again surge during the East Asian crisis of 1997, and they remain high as long as we include the East Asian crisis in the estimation window. Volatility spillovers are also affected by the Russian crisis of September 1998, the Brazilian crisis of January 1999, the 9/11 terrorist attacks in the United States, and the Argentine crisis of January 2002, but only slightly. The largest movements in recent years come from the U.S. subprime crisis and the subsequent global financial meltdown.

2.4 Including the United States

To assess whether the inclusion of the United States affects the spillover results, we include S&P 500 returns and volatilities in the analysis, in addition to the original four South American countries. We plot U.S. returns and volatilities in figure 5 and provide summary statistics in table 5. When the United States is included, return spillovers are always higher and the wedge is roughly the same over time, as shown in figure 6. Volatility spillovers, in contrast, are lower before the Asian crisis and higher afterward, as shown in figure 7.

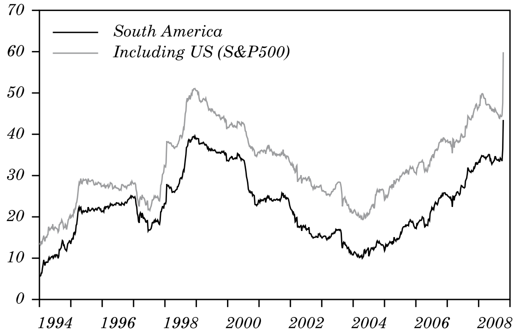
Figure 5. U.S. Stock Market Returns and Volatilities





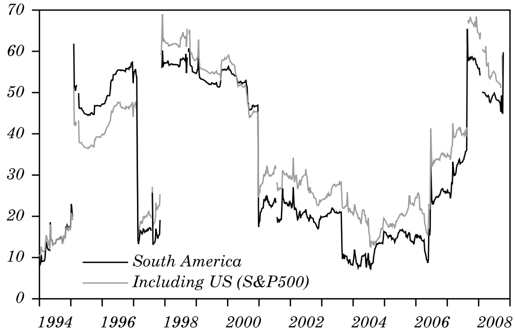
Source: Authors' computations.

Figure 6. Return Spillovers, with and without the United States



Source: Authors' computations.

Figure 7. Volatility Spillovers, with and without the United States



Source: Authors' computations.

Table 5. Summary Statistics: U.S. Stock Market Returns and Volatilities

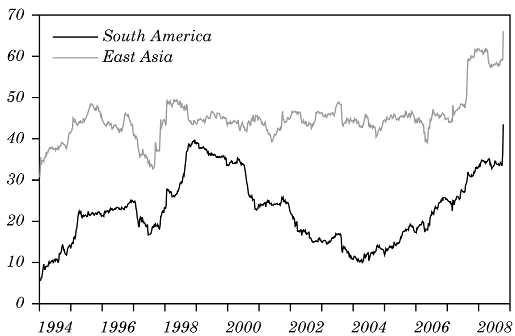
Statistic	*Returns*	*Volatility*
Mean	4.53	13.15
Median	11.97	10.65
Maximum	389.60	102.96
Minimum	−1,044.36	1.54
Standard deviation	115.60	8.22
Skewness	−1.32	2.87
Kurtosis	12.92	21.63
Jarque-Bera	3,845.70	13,850.80
Probability	0.00	0.00
No. observations	875	875

Source: Authors' computations.

2.5 Comparisons to Asian Spillovers

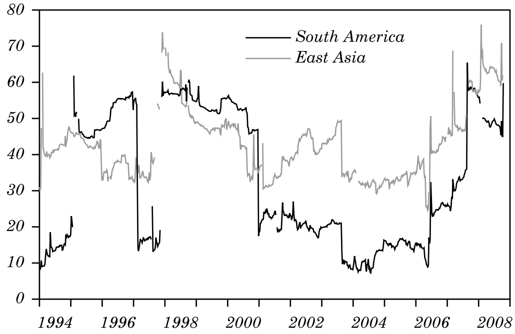
Figures 8 and 9 compare South American return and volatility spillovers to those of ten East Asian countries (namely, Australia, Hong Kong, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan, and Thailand). The figures demonstrate that South American spillover patterns do not simply track global patterns, although they are not unrelated.

Figure 8. Comparative South American and East Asian Return Spillovers



Source: Authors' computations.

Figure 9. Comparative South American and East Asian Volatility Spillovers



Source: Authors' computations.

South American return spillovers increase substantially during the Mexican, East Asian, and Russian crises, after which they decline continuously until 2004, when they approach the levels of the early 1990s. They increase in 2005 and 2006 during the brief capital outflows from emerging markets in 2006, and they also jump in the first week of October 2008.

East Asian return spillovers, in contrast, are nearly flat from the East Asian crisis until recently. Following the first round of the global financial crisis in July–August of 2007, East Asian return spillovers increase sharply, and they again increase sharply during the financial meltdown in the first week of October 2008.

Return spillovers increase in both South America and East Asia in the early 1990s, but the increase was bigger for South America, especially around the Mexican crisis. Moreover, the Mexican crisis affects South American return spillovers for much longer than East Asian spillovers. Return spillovers increase in both regions during the East Asian crisis, whereas the Russian crisis affects only South America.

Return spillover patterns generally indicate that South American stock markets are not as well integrated as East Asia's. Perhaps the presence of the major Japanese stock market, together with Hong Kong's function as a regional hub, facilitates financial integration and spillovers. Many believe that hub markets play a critical role in spreading shocks, and South America lacks a hub like Hong Kong.

Volatility spillover patterns in South America and East Asia are also quite different. Sometimes they are clearly divergent. For example, during the Mexican crisis South American volatility spillovers jumped from 20 percent to 50 percent, whereas East Asian volatility spillovers were not affected. Other times volatility spillovers move similarly in the two regions. For example, volatility spillovers in both regions respond significantly during both the East Asian crisis and the 2007–08 global liquidity/solvency crisis.

3. Summary and Directions for Future Research

We use the Diebold-Yilmaz (2009) spillover index to assess equity return and volatility spillovers in the Americas. We study both noncrisis and crisis episodes in the 1992–2008 period, including spillover cycles and bursts. Both turn out to be empirically important. In particular, we find striking evidence of divergent behavior in the dynamics of return spillovers and volatility spillovers: return spillovers display gradually evolving cycles but no bursts, whereas volatility spillovers display clear bursts that correspond closely to economic events.

There are several important directions for future research, both substantive and methodological. Substantively, this paper has focused only on cross-country equity market spillovers, but one could also examine within-country (single equity) spillovers, as well as other asset classes and multiple asset classes. In the current environment, for example, spillovers from credit markets to stock markets are of obvious interest. In all cases, moreover, one could also attempt to assess the direction of spillovers, as in Diebold and Yilmaz (2011).

Possible directions for methodological research include enriching (or specializing) the VAR on which the spillover index is based to allow for time-varying coefficients or factor structure, possibly with regime switching as in Diebold and Rudebusch (1996). One could also perform a Bayesian analysis in the framework adopted here or in the extensions sketched above, which could be useful for imposing covariance stationarity.

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