Equity Market Spillovers in the Americas

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Abstract: Using a recently-developed measure of financial market spillovers, we provide an empirical analysis of return and volatility spillovers among five equity markets in the Americas: Argentina, Brazil, Chile, Mexico and the U.S. The results indicate that both return and volatility spillovers vary widely. Return spillovers, however, tend to evolve gradually, whereas volatility spillovers display clear bursts that often correspond closely to economic events.

Keywords: Stock market, Stock returns, volatility, Contagion, Herd behavior, Variance decomposition, Vector autoregression, Risk measurement and management

JEL Codes: G1, F3

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1. Introduction

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 for example with market-based implied volatilities.

One can extend the market-based approach by monitoring not implied volatility extracted from a single option, but rather by monitoring entire risk-neutral densities extracted from sets of options with different strike prices, as in recent powerful work by 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 measurement of *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".

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

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

We proceed as follows. In Section 2 we motivate and describe our measure of spillovers, which is based on the variance decomposition of a vector autoregression. In Section 3 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 4 we summarize and sketch directions for future research.

2. Measuring Spillovers

Here we describe a spillover index proposed recently by Diebold and Yilmaz (2009a), which we then use to measure spillovers in the Americas. The index is quite general and flexible, based directly on variance decompositions from VARs fitted to returns or volatilities. It contrasts, for example, with other approaches such as Edwards and Susmel (2001), which produce only a 0/1 "high state / low state" indicator (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 vector autoregression (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 $i = 1, ..., N$.

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

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

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 1-step-ahead forecasts) we immediately have

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

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

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

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]

3. Empirical Analysis of Stock Market Spillovers in the Americas

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

Data

We examine broad stock market returns in four South American countries: Argentina (Merval), Brazil (Bovespa), Chile (IGPA), and Mexico (IPC), from 1 January 1992 through 10 October 2008. 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 $r_{it} = 52 \bullet 100 \bullet (\Delta \ln P_{it})$. We plot the four countries' returns in Figure 1, and we provide summary statistics in Table 1.

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, open and close data, from the Monday open to the Friday close):[3]

$$\tilde{\sigma}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019\left[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})\right] - 0.383(C_{it} - O_{it})^2 ,$$

[2] Although it is beyond the scope of this paper, it will be interesting in future work to understand better the relationship of our spillover measure to others based, for example, on time varying covariances or correlations.

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

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). Now, because $\tilde{\sigma}_{it}^2$ is an estimator of the weekly variance, the corresponding estimate of the annualized weekly percent standard deviation (volatility) is $\hat{\sigma}_{it} = 100\sqrt{52 \bullet \tilde{\sigma}_{it}^2}$. 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 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 2007-8.[4]

Empirical Implementation of the Spillover Measure

We use second-order VARs (p = 2), h = 10-step-ahead forecasts, and N = 4 or 5 countries (Argentina, Brazil, Chile and Mexico, with and without the U.S.). We capture time variation in spillovers by re-estimating the VAR weekly, using a 100-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, for example, credible restrictions on the VAR's innovation covariance

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[4] The only exception is Argentina's crisis of 2001-2, during which Argentina's surge in volatility was not shared with the other countries.

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 infeasible for large N, but it is preferable when feasible as it involves no auxiliary assumptions. In our case N is quite small (4 or 5), so we can straightforwardly calculate and use variance decompositions based on all $N!$ orderings, which we do in most of this paper.

South American Spillovers

In Tables 3 and 4 we show full-sample South American spillover tables for returns and volatilities, respectively.[5] Both return and volatility spillovers are sizable; return spillovers are approximately nineteen percent, and volatility spillovers are even larger at twenty-five percent.

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. Hence in Figures 3 and 4 we show dynamic South American spillover plots for returns and volatilities, respectively, calculated using rolling 100-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.[6] The figures indicate that both return and volatility spillovers vary widely over time, and moreover that return spillovers evolve gradually whereas volatility spillovers show sharper jumps, typically corresponding to crisis events.

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

[6] The lines in Figures 3 and 4 are medians across all orderings, and the gray shaded region gives the range.

Let us examine the spillover plots more closely. First consider return spillovers. Return spillovers increase as we roll the estimation window through the end of 1994, and they surge to thirty percent immediately after the outbreak of the Mexican Tequila crisis in December 1994. Return spillovers drop to twenty percent in late 1996 (as we drop the Mexican crisis from the estimation window), but the Asian and Russian crises keep them from dropping farther. Return spillovers peak at nearly fifty 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 sub-sample 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 thirteen percent in 2004, after which they drift upward, with a jump in the first week of October 2008.

Now consider volatility spillovers, which surge to fifty percent at the outset of the Mexican crisis, and which fluctuate between forty-five and sixty 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 so 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 U.S., and the Argentine crisis of January 2002, but only slightly. The largest movements in recent years come from the U.S. subprime crisis and subsequent global financial meltdown.

Including the U.S.

We now assess whether inclusion of the U.S. affects the spillover results, by including 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 we provide summary statistics in

Table 5. With U.S. 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.

Comparisons to Asian Spillovers

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

South American return spillovers increase substantially during the Mexican, East Asian and Russian crises, after which they decline continuously until 2004, with 2004 levels close to early 1990s levels. 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 impacts 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.

As an aside, it is interesting to note that 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 show clearly divergent movements. For example, during the Mexican crisis South American volatility spillovers jumped from twenty percent to fifty percent, whereas East Asian volatility spillovers were not impacted. 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 2007-8 global liquidity/solvency crisis.

4. Summary and Directions for Future Research

We use the Diebold-Yilmaz (2009a) spillover index to assess equity return and volatility spillovers in the Americas. We study both non-crisis and crisis episodes, 1992-2008, including spillover cycles and bursts, and 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. First consider the substantive. Here we 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 (2009b).

Now consider methodological research directions. One could enrich (or specialize) the VAR on which the spillover index is based to allow for time-varying coefficients and/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 above-sketched extensions, which could be useful, for example, for imposing covariance stationarity.

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Figure 1: South American Stock Market Returns

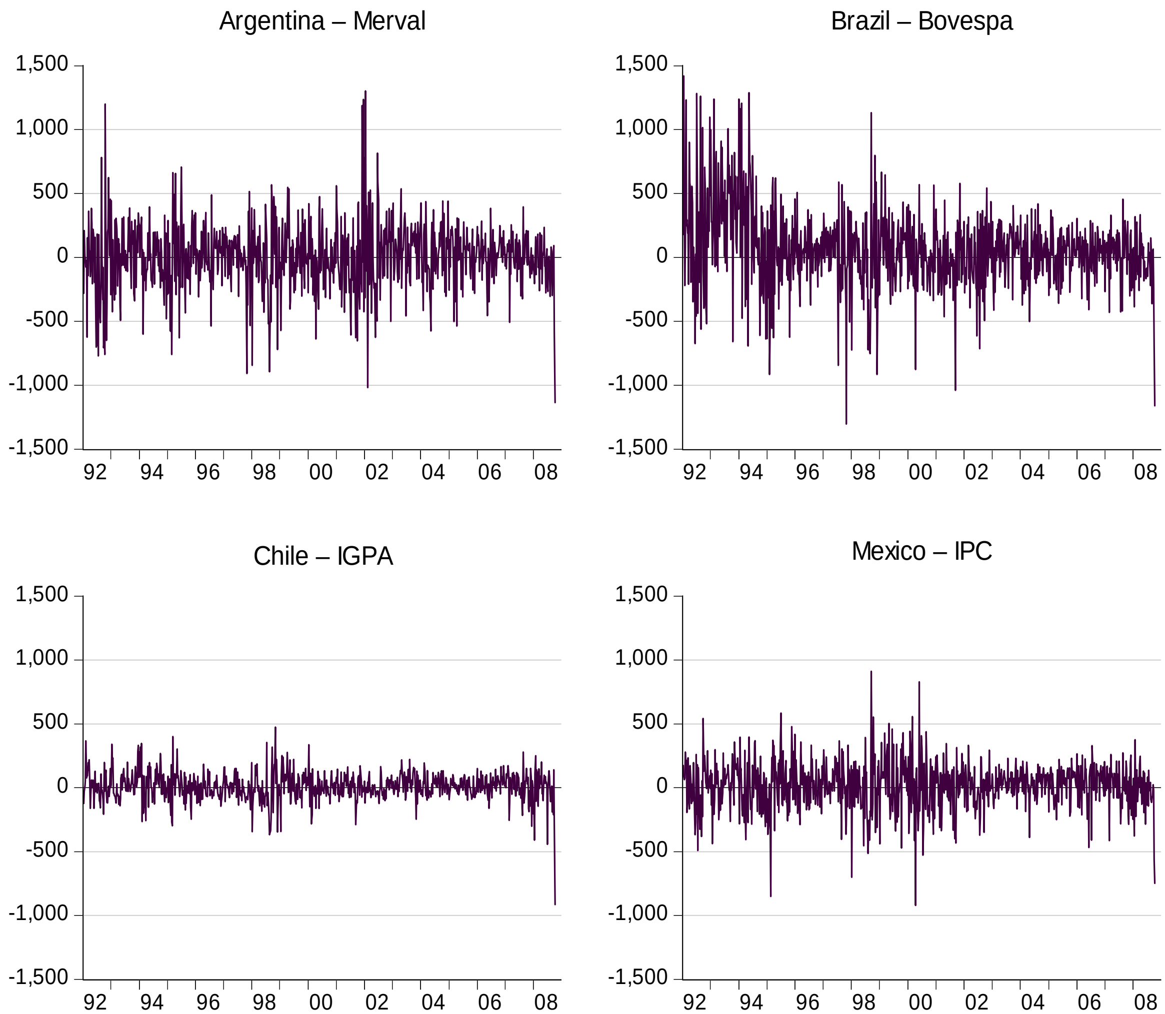

Table 1: Summary Statistics, South American Stock Market Returns

	Argentina	Brazil	Chile	Mexico
Mean	2.485	64.334	8.493	15.751
Median	19.748	55.044	8.739	28.828
Maximum	1301.99	1417.96	473.78	910.16
Minimum	-1135.39	-1303.04	-915.84	-921.24
Std. Dev.	264.78	317.84	111.77	188.51
Skewness	-0.0157	0.3913	-0.7015	-0.3191
Kurtosis	5.788	5.696	9.602	5.360
Jarque-Bera	283.398	287.633	1661.046	217.778
Probability	0.0	0.0	0.0	0.0
Observations	875	875	875	875

Figure 2: South American Stock Market Volatilities

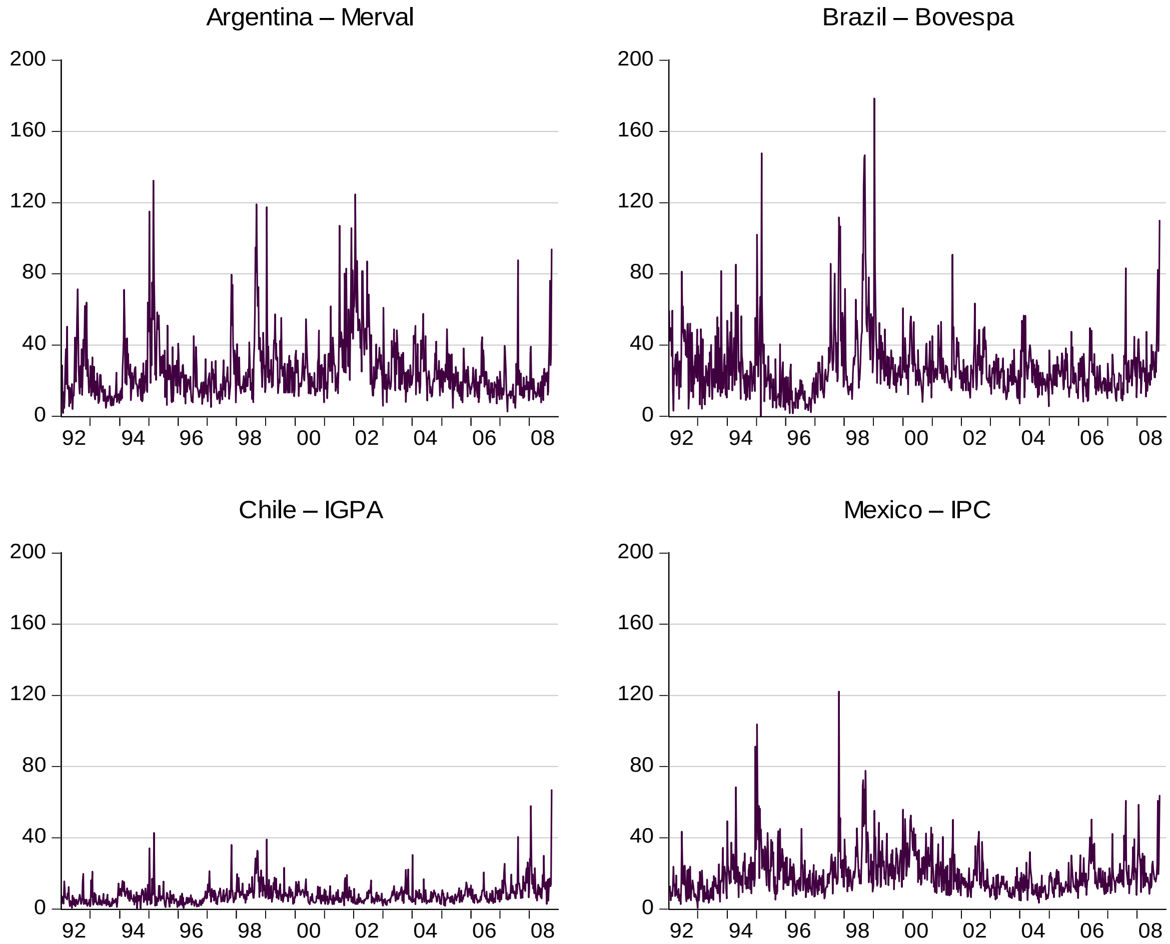

Table 2: Summary Statistics, South American Stock Market Volatilities

	Argentina	**Brazil**	**Chile**	**Mexico**
Mean	25.628	27.758	7.974	19.639
Median	20.939	23.882	6.646	16.705
Maximum	132.40	178.58	66.859	122.174
Minimum	1.826	0.0797	0.3032	0.6110
Std. Dev.	17.425	18.233	5.852	12.232
Skewness	2.249	2.846	3.500	2.426
Kurtosis	10.122	16.886	25.136	13.974
Jarque-Bera	2587.2	8211.4	19651.3	5248.5
Probability	0.0	0.0	0.0	0.0
Observations	875	875	875	875

Table 3: Return Spillovers, Full Sample

	ARG	BRA	CHL	MEX	Contribution From Others
ARG	97.63	0.09	0.24	2.04	2.4
BRA	15.84	83.51	0.01	0.63	16.5
CHL	13.61	8.33	75.57	2.50	24.4
MEX	22.38	5.77	3.06	68.79	31.2
Contribution to Others	51.8	14.2	3.3	5.2	74.5
Contribution Including Own	149.5	97.7	78.9	74.0	Index = 18.6%

Table 4: Volatility Spillovers, Full Sample

	ARG	BRA	CHL	MEX	Contribution From Others
ARG	96.00	0.69	1.81	1.51	4.0
BRA	28.27	67.59	0.60	3.54	32.4
CHL	14.12	14.86	70.98	0.04	29.0
MEX	18.67	11.36	4.00	65.97	34.0
Contribution to Others	61.1	26.9	6.4	5.1	99.5
Contribution Including Own	157.1	94.5	77.4	71.1	Index = 24.9%

Figure 3. Spillover Plot, Returns

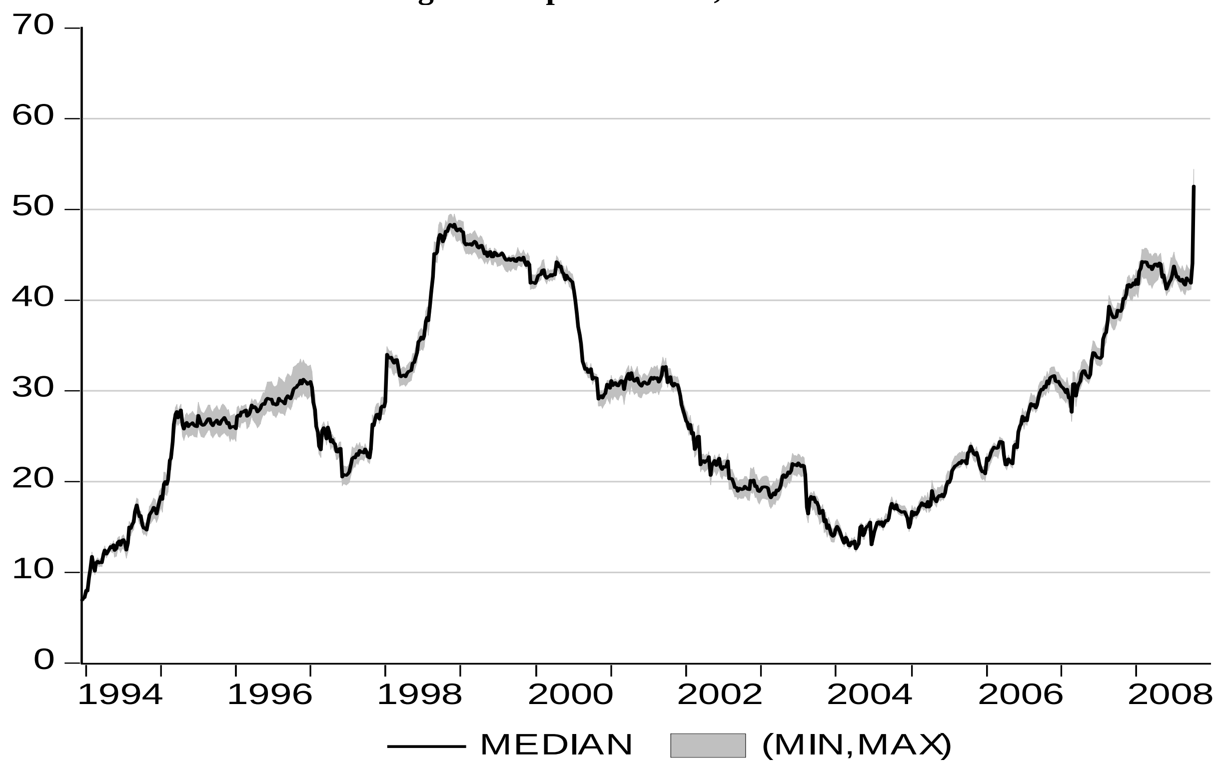

Figure 4: Spillover Plot, Volatilities

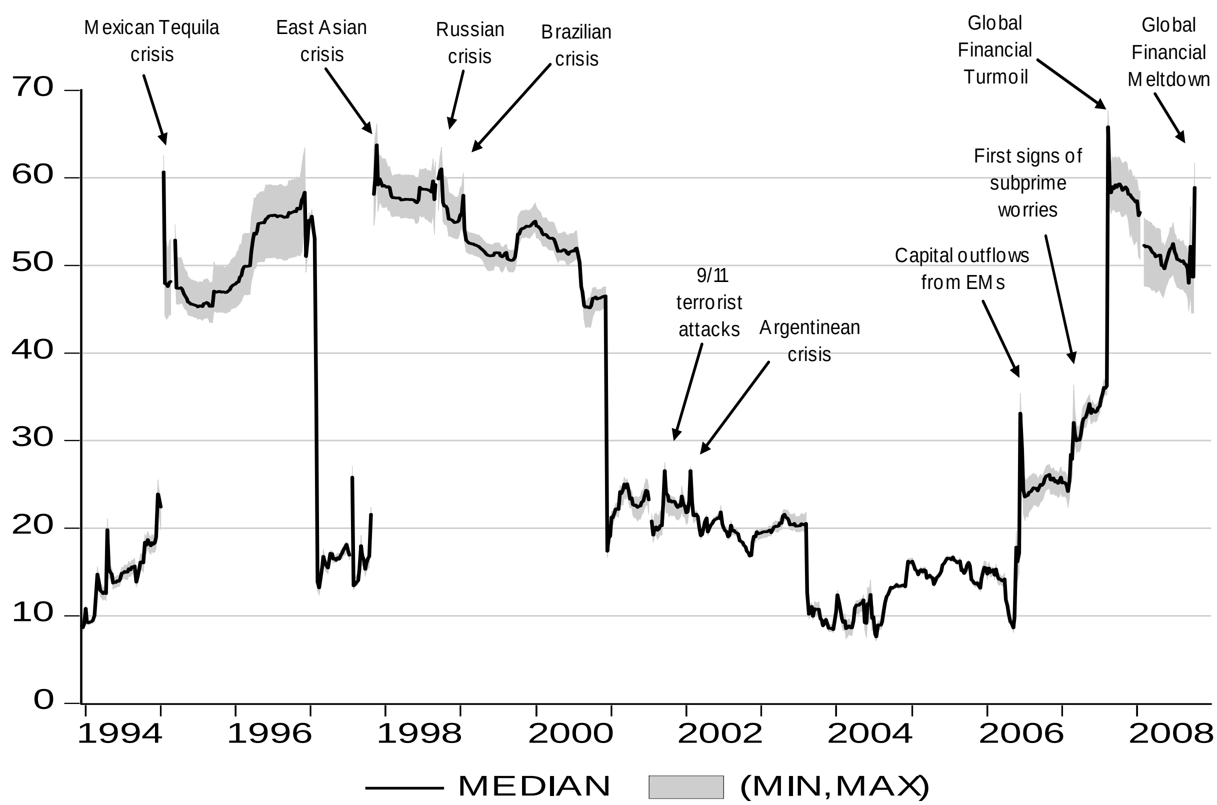

Figure 5: U.S. Stock Market Returns and Volatilities

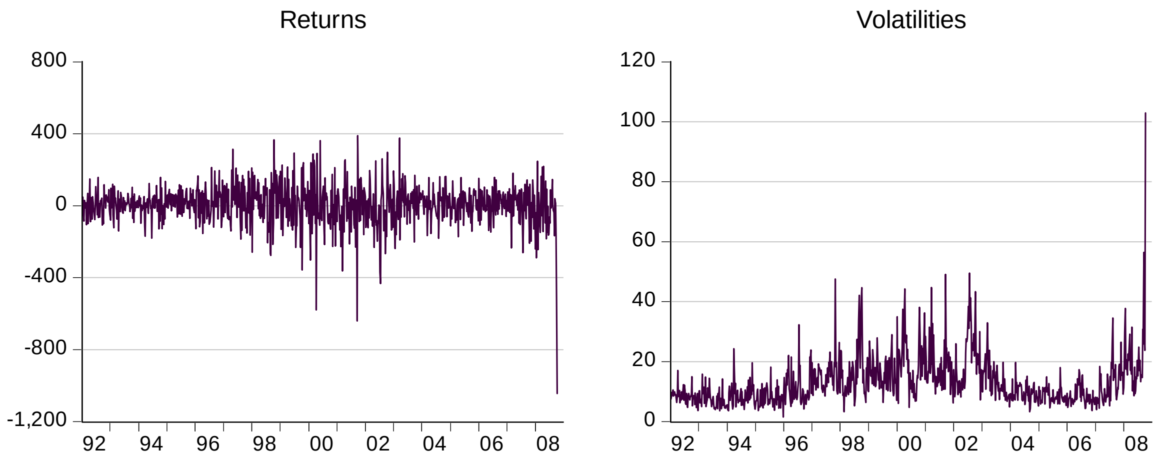

Table 5: Summary Statistics, U.S. Stock Market Returns and Volatilities

	Returns	**Volatility**
Mean	4.533	13.146
Median	11.966	10.645
Maximum	389.60	102.959
Minimum	-1044.36	1.539
Std. Dev.	115.60	8.220
Skewness	-1.322	2.870
Kurtosis	12.924	21.627
Jarque-Bera	3845.7	13850.8
Probability	0.0	0.0
Observations	875	875

Figure 6: Return Spillovers, With and Without U.S.

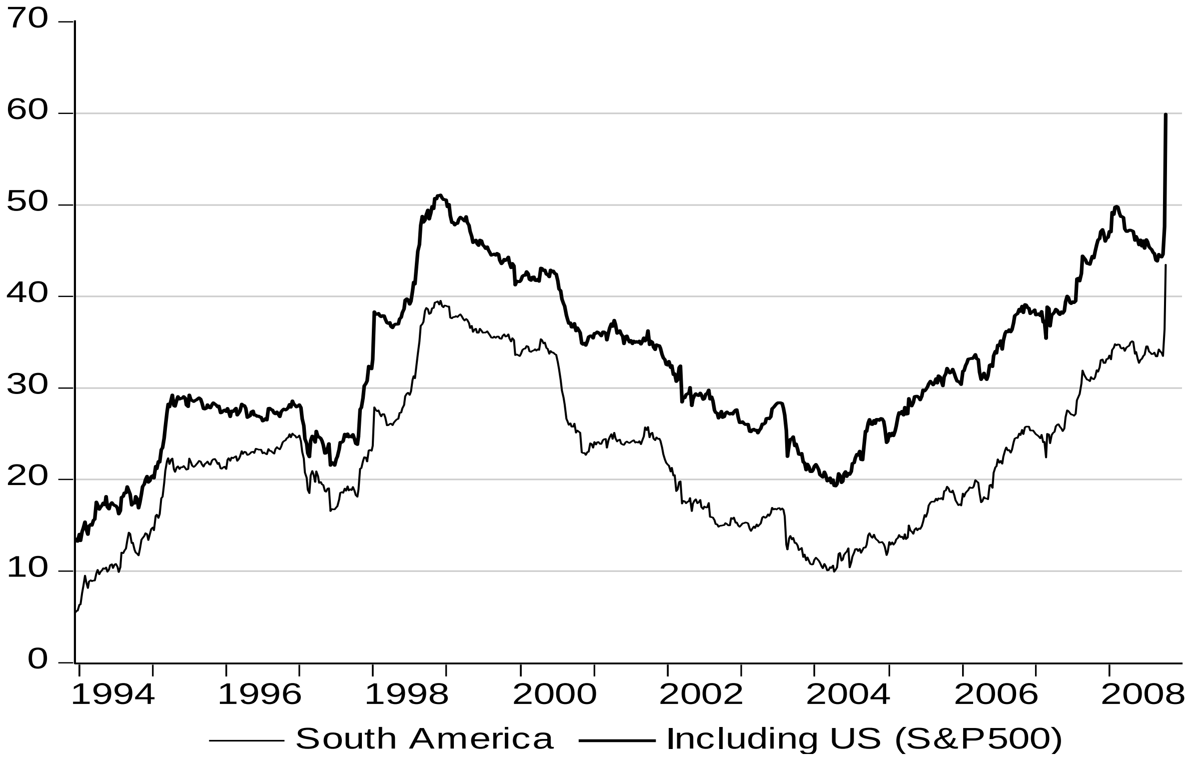

Figure 7: Volatility Spillovers, With and Without U.S.

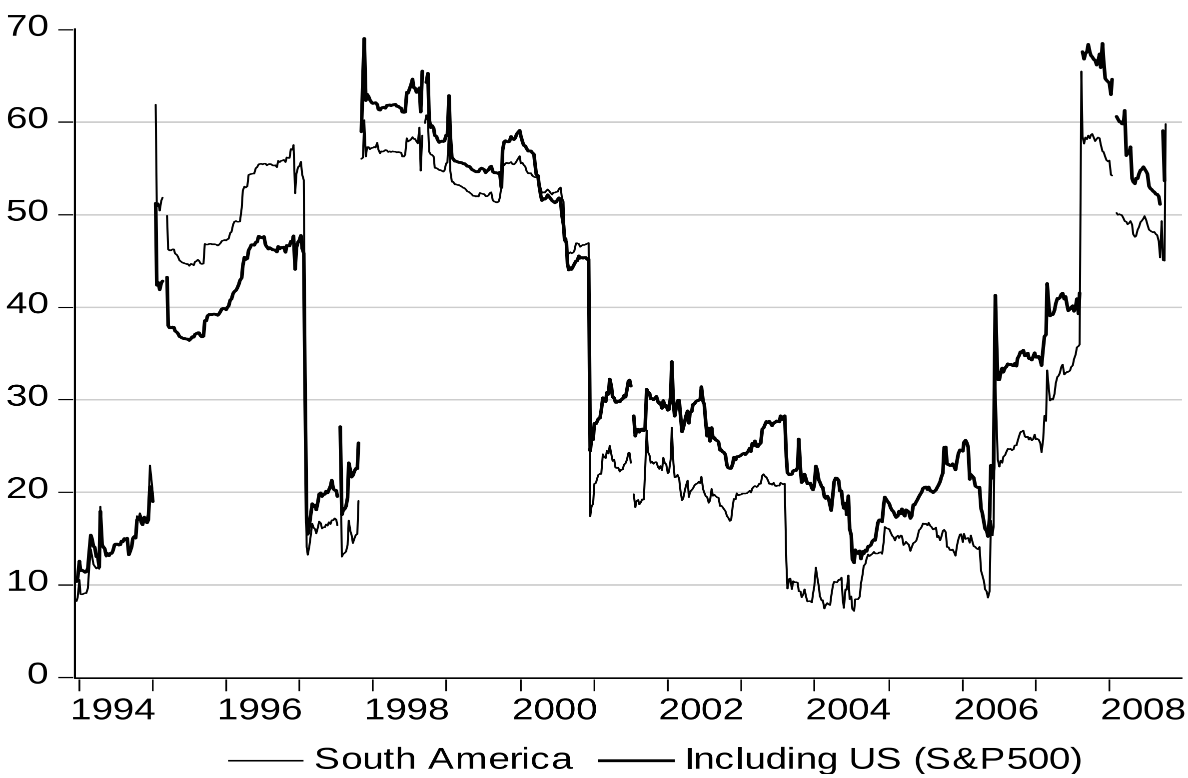

Figure 8: Comparative South American and East Asian Return Spillovers

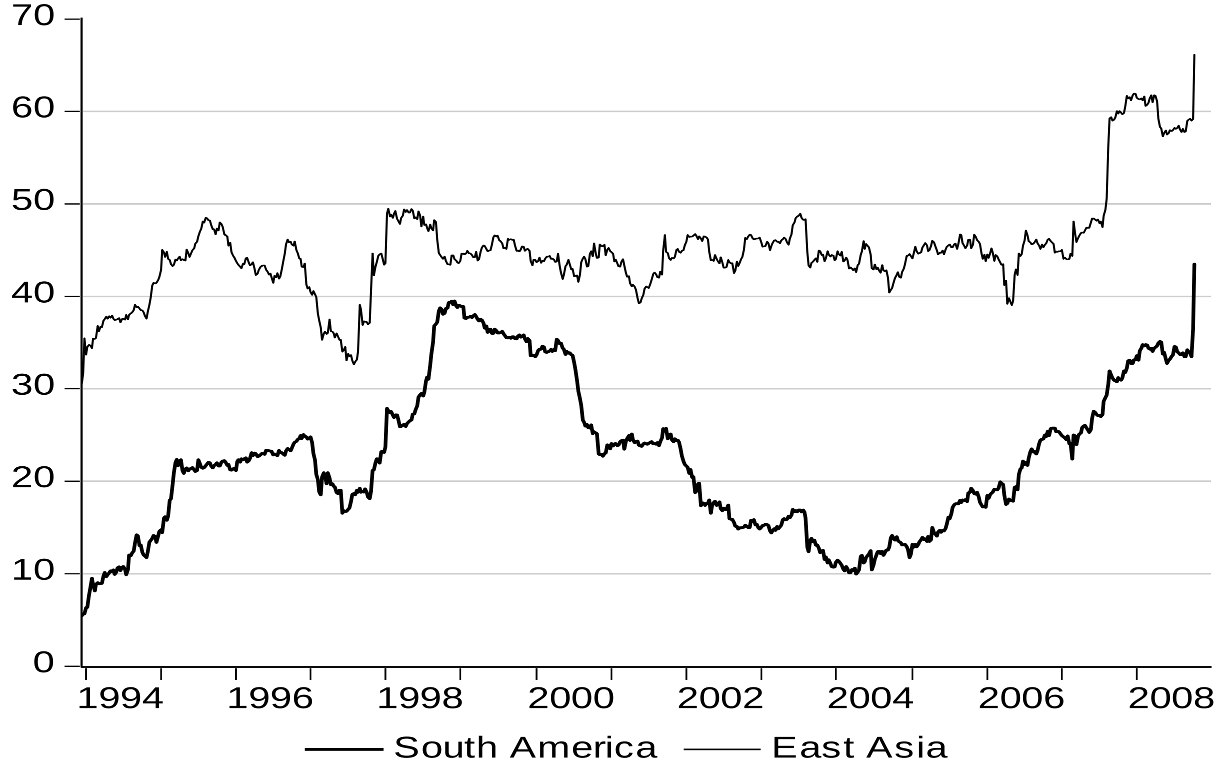

Figure 9: Comparative South American and East Asian Volatility Spillovers