Volatility Contagion

Francis X. Diebold
University of Pennsylvania and NBER

Kamil Yilmaz*
Koc University

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Abstract

Although much has been made of the possibility of contagion in global asset markets following the late-1990s Asian crisis, the evidence remains mixed and controversial. We progress by formulating and examining precise and separate measures of *return spillovers* (multivariate linkages via the conditional means of returns) and *volatility spillovers* (multivariate linkages via the conditional variances of returns). Return contagion and volatility contagion then emerge as periods of return spillover bursts and volatility spillover bursts, respectively. Moreover, our framework facilitates study of both crisis *and* non-crisis episodes, including secular trends in spillovers. This turns out to be empirically important: in an extensive analysis of sixteen global equity markets, we find striking evidence of divergent behavior in return spillovers vs. volatility spillovers. Moving through the 1990s to the present, return spillovers display an upward trend but no contagion, whereas volatility spillovers display no trend but strong contagion.

JEL classification: F30, G15, F36.

Key words: asset market, financial crisis, emerging market, herd behavior

* Corresponding author: Professor Kamil Yilmaz, Department of Economics, Koç University, Rumelifeneri Yolu, Sariyer, Istanbul 34450, Turkey. email: kyilmaz@ku.edu.tr.

I. Introduction

Research on financial contagion dates back to October 1987 stock market crash, when the sudden collapse of the US markets on October 17th was followed by a short-lived turmoil in stock markets worldwide.[1] Despite this early interest in financial contagion, it was not until after the East Asian crisis that financial contagion became a major research area in the international finance literature. Since then, a large body of theoretical and empirical literature has studied contagion in stock, foreign exchange and fixed-income securities markets.[2]

The particular focus of the research in this area has been to quantify the degree of contagion across markets during and after the emerging market crises. In one of the earlier contributions, King and Wahdwani (1990) define contagion as a significant change in the correlation of stock returns across markets. Using this definition, they find support for contagion between the United States, the United Kingdom and Japan after the October 1987 U.S. market crash. The majority of the papers following King and Wahdwani (1990) found support for financial contagion in returns and/or volatility after the major market crises.

Recently, Forbes and Rigobon (2002) and Rigobon (2003) argue that the evidence in favor of contagion is basically erroneous and follows from several characteristics of the data used. Forbes and Rigobon (2002) show that, once these characteristics are taken into account, the support for contagion disappears and what is left is nothing but evidence in favor of interdependence of stock markets. Aside from the literature that focused on the presence of spillovers of shocks to market returns, there is a growing literature that considers the possibility of contagion taking place through spillovers of volatility across stock markets (See Engle, Ito, and Lin (1990), Edwards (2000), Edwards and Susmel (2001) and Baur (2002)).

In this paper, using separate vector autoregression (VAR) models of stock returns and range-based stock return volatility estimates for 16 stock markets, we analyze the differences in the dynamics that drive return and volatility spillovers over time. Variance decomposition analysis of the VAR model allows us to identify spillovers of shocks across markets from local shocks. In order to measure volatility, we use an efficient range-based volatility estimate that was first proposed by Garman and Klass (1980). We apply VAR model and the variance decomposition analysis to 200-week-long rolling windows of

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[1] The following quote reported by Hamao, Masulis and Ng (1987) exemplifies the extent of the effect of US stock market crash on other markets: "A sharp downward movement in the New York stock market last week triggered fear here in Japan and the Tokyo market experienced the largest drop this year. [*Nihon Keizai Shimbun (Japan Economic Journal)*]"

[2] For a review of the empirical literature on contagion see Dungey, Fry, Gonzalez-Hermosillo and Martin, 2004, and the following World Bank webpage : http://www1.worldbank.org/contagion/

stock returns and volatility measures separately. For each window, we calculate the level of the contribution of spillovers across markets to the variance of forecast errors. Plotting the total contribution of spillovers in all markets across time, we obtain a measure of spillovers across markets.

The analysis of return spillovers reveals that the integration of emerging markets into the international financial system in the early- to mid-1990s led to a continuous increase in the return spillovers across markets. However, we are not able to find evidence supporting the contagion in mean returns during and following the major financial crises.

The analysis of volatility spillovers across markets, on the other hand, shows that there was a substantial increase in the volatility spillovers across markets during and after the two major emerging market crises (East Asian and Russian). Plots of volatility spillovers leave no doubt that it was the volatility contagion that took place during and immediately after the major crises, and not the contagion in mean returns. The results for mean returns in our view support the conclusions of Forbes and Rigobon (2002) that mean returns displayed increased interdependence in 1990s. As a result of the increased market integration in 1990s, stock markets around the world became more interdependent as captured by the steady increase in return shock spillovers in the mid-1990s. Despite the ensuing emerging market crises, return shock spillovers did not decline to the levels at the beginning of 1990s.

Section II summarizes the literature on financial contagion. We discuss our empirical analysis and the results in section III. Finally, section IV concludes the paper.

II. Interdependence and Contagion

A. Literature

The interest in financial contagion started after the October 1987 stock market crash in the U.S. and the ensuing tremors in major markets around the world. The particular focus of the research in this area was to quantify the degree of contagion across markets during and after a market crash in emerging or developed markets.

In their seminal paper, King and Wadhwani (1990) construct a model of financial contagion. In a rational expectations price equilibrium framework, they model contagion between markets as an outcome of attempts by rational agents to infer price changes in one market using imperfect information about events in other markets. When the equilibrium is not a fully- revealing type, mistakes or idiosyncratic price changes in one market may be transmitted to other markets creating contagion effects. Based on this model, King and Wadhwani (1990) define contagion as a significant change in the correlation of stock returns across markets in their empirical analysis. Using daily data, they find support for contagion between the United States, the United Kingdom and Japan after the October 1987 U.S. market crash. Extending the analysis of cross-market correlation coefficients to 12 major markets, Lee and Kim (1993) also find evidence of contagion: Average cross-market correlation coefficient increased to 0.39 in the aftermath of the October 1987 U.S. stock market crash compared to 0.23 before the crash.

Baig and Goldfajn (1999) and Forbes and Rigobon (2002) refine the definition of financial contagion as a significant increase in cross-market linkages after a shock to one country or group of countries. Their definition emphasizes the possible emergence of contagion after a major financial crisis; hence they focus only on "the crisis period". In their important contribution to the literature, Forbes and Rigobon (2002) further pointed out that tests of contagion have to take into account the presence of heteroscedasticity in stock returns.[3] When returns are heteroscedastic, tests of parameter stability based on correlation coefficients are biased. Once this is taken into account and hence tests are adjusted for the presence of heteroscedasticity, the presence of mean contagion is rejected. Correcting for heteroscedasticity in stock returns, Forbes and Rigobon (2002) could not find a significant increase in stock return correlation across stock markets; they concluded there was no contagion but increased interdependence across markets.

Forbes and Rigobon (2002) and Rigobon (2003) point out the econometric problems with the correlation coefficient-based analysis. As their main objective is to conduct an analysis that corrects for these problems, they overlook the obvious question about the variation in volatility over time: If it is the time-varying volatility that played a quite significant role in driving the correlation coefficients up, one has to study the source of change in volatility and account for the possibility of volatility spillovers across markets.

Corsetti, Pericoli and Sbracia (2005) criticize Forbes and Rigobon's (2002) methodology on the grounds that it implicitly takes the variance of stock returns in the country where the crisis originates as a proxy for the volatility of the common factor affecting all markets. They show that failing to distinguish between common and country-specific components of market returns induces a bias towards the null hypothesis of 'no contagion'.

While the more influential contributions in the literature focused on correlation of returns across stock markets, there have been a limited number of studies that analyzed spillovers of volatility across

[3] *"If two markets show a high degree of co-movement during periods of stability, even if the markets continue to be highly correlated after a shock to one market, this may not constitute contagion. According to this definition, it is only contagion if cross-market co-movement increases significantly after the shock. If the co-movement does not increase significantly, then any continued high level of market correlation suggests strong linkages between the two economies that exist in all states of the world". Forbes and Rigobon (2002).*

markets as a form of financial contagion. Both GARCH and VAR frameworks have been used to estimate the variance-covariance transmission mechanisms between countries. Engle, Ito, and Lin (1990) applied both GARCH and VAR models to test for spillovers in daily exchange rate volatility across Japanese and American foreign exchange markets. They found support for the "meteor shower" hypothesis rather than the "heat waves" hypothesis that implies the presence of intra-daily volatility spillovers from one foreign exchange market to the other. Using the GARCH framework, Hamao, Masulis and Ng (1990) analyze short-run price volatility spillovers across London, New York and Tokyo stock markets around the 1987 U.S. market crash. They find evidence of price volatility spillovers from New York to London, from New York to Tokyo and from London to Tokyo but not in other directions. Edwards (1999), on the other hand, estimated a GARCH model of interest rate volatility and found evidence in support of contagion effects from Mexico to Argentina but not to Chile. He interprets this result as an evidence of the curtailing effect of capital controls on volatility contagion in fixed income securities. Applying univariate and bivariate switching volatility models to weekly stock returns for a group of Latin American countries, Edwards and Susmel (2001) find strong evidence of volatility co-movements across countries, especially among the Mercosur countries. In addition, they show that high-volatility episodes are, in general, short-lived, lasting from 2 to 12 weeks.

B. Why volatility contagion across markets?

An increase in volatility in a single isolated stock market is important itself because of its implications about the risk associated with holding stocks and the weight of stocks in the portfolio allocation. In a single isolated market, investors would be interested in volatility, because volatility moves exactly in the opposite direction with returns during a crisis. While returns are declining, volatility shuts up. Hence, there is a place for volatility based derivatives in the "optimal" portfolio.

In integrated stock markets, volatility in one market and its correlation with volatility in other markets is important for two reasons. First, an increase in the correlation of volatilities means an increase in the fourth moment matrix of returns. If the kurtosis of returns in one market increases and hence the returns distribution becomes more fat-tailed, the other markets will follow suit. In other words, volatility contagion is important, because it means the risks faced by stock investors will be higher in other markets if there is volatility contagion.

Another reason for studying volatility is the recent interest of investment houses in developing derivatives and futures products that follow volatility in stock returns. A recent example is the VIX index. While these efforts are currently limited to Chicago Board Option Exchange (CBOE), in the future similar products can be developed in other markets. In that case, an important issue in determining the value of these derivative products will be the comovement of volatility and/or volatility contagion across markets.

Forbes and Rigobon (2002) are not able to find empirical evidence in favor of contagion in means, once the return correlations across markets are corrected for changing return volatility. However, focusing on contagion in means, they ignore the question about the source of variation in volatility over time: If the change in volatility played a significant role, what is the source of change in volatility?

However, as we will see below, using their definition, there is substantial volatility contagion following the East Asian and Russian crises. We reach this conclusion, because in our analysis once the data for the East Asian crisis (to be more specific October 1997 when Hong Kong market was affected by the developments in other markets of the region) is included in the analysis, our measure of volatility spillover (especially the volatility spillover from Hong Kong to other markets) jumps up.

The general definition of contagion should be broad enough to account for the following: Some country has 'to get sick' first before spreading the virus to others. For that reason, this definition fits better. However, one has to define sickness first. Let's take one country suffering from a major financial crisis. This problem may spread to another country because of the presence of underlying conditions that make the other country vulnerable to the virus. The spread of the Asian flu from Thailand to other countries in the region after August 1997 is an example in mind. However, once major economies in the region are affected by the Thai crisis, a country - such as Hong Kong - which was otherwise healthy and not susceptible to the virus, was bound to get the virus. It caught up the virus even though its economy was in a better shape compared to others. Until then, Asian flu was viewed as a regional phenomenon. Once Hong Kong got the virus in mid-October, the so-called East Asian crisis started to affect markets all around the world. The analogy of virus being carried through air travel between different countries of the region is also relevant. Once the virus arrives at the regional hub, then it is likely to spread outside the region and affect world markets.

There are limitations to the analysis of contagion based on correlation coefficients. Correlation coefficient based analysis does not allow lead-lag relationship between returns and volatilities across markets. It only considers a symmetric contemporaneous relationship, whereas contagion is inherently a non-symmetric phenomenon that requires one to capture the lead-lag relationship between returns or volatilities across markets.

Using GARCH model of returns to analyze the contagion is also problematic. While GARCH model allows one to incorporate volatility spillovers in the model, it does not allow one to incorporate volatility measures for all markets at once. Furthermore, GARCH model does not allow for the endogeneity of all return or volatility measures.

III. Empirical Analysis

A. Returns and Volatility

The stock market indices in local currency are obtained from the Datastream and Global Financial Data. We cover four financial centers. These markets and the corresponding indices are the Dow Jones Industrial Average for the NYSE, FTSE-100 index for the London Stock Exchange, Hang Seng index for the Hong Kong Stock Exchange and Nikkei 225 index for the Tokyo Stock Exchange. In addition, we use data for 12 emerging markets: Indonesia, S. Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico and Turkey.

Following Garman and Klass (1980) and Parkinson (1980), we use daily high, low, opening and closing prices to obtain an efficient estimate of the weekly unconditional variance of stock returns. We use the unconditional volatility estimate ($\tilde{\sigma}^2$) proposed by Garman and Klass (1980):

$$\begin{aligned}\tilde{\sigma}^2 = {} & 0.511(H_t - L_t)^2 - 0.019\left[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)\right] \\ & - 0.383(C_t - O_t)^2\end{aligned} \tag{1}$$

$\tilde{\sigma}^2$ corresponds to σ_4^2 in Garman and Klass (1980) and is calculated using the natural logarithms of the **O**pening, **C**losing, **H**ighest and **L**owest prices of the session. Garman and Klass (1980) show that $\tilde{\sigma}^2$ is the minimum variance unbiased volatility estimator. Indeed, it is 7.4 times more efficient than the standard variance estimate calculated from close-to-close prices. Garman and Klass (1980) suggest to use other unconditional volatility estimates that are easier to calculate compared to $\tilde{\sigma}^2$. Since they all are less efficient, we do not use those measures in our study.

Both stock returns and volatility measures are calculated for the January 1992-September 2005 period. Weekly nominal returns are Wednesday-to-Wednesday returns. When data for Wednesday is not available due to official holiday, we use Thursday or Tuesday price indices to calculate the returns. Monthly consumer price indices from International Financial Statistics of the IMF are used to deflate the weekly nominal returns to obtain real returns.[4]

Daily Open, High, Low, Close values for each stock index is converted to weekly frequency in order to eliminate some of the random idiosyncratic shocks to each market. Monday morning opening values and the Friday afternoon closing values are taken as the weekly open and close values, respectively, for each stock index. The highest and the lowest value from Monday to Friday are taken as the weekly

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[4] Weekly inflation rate is assumed to be constant over a month and defined as 1/4th power of the monthly inflation rate. *Ex-post* weekly real return is calculated as one plus the nominal weekly return divided by one plus the weekly inflation rate minus one.

high and weekly low, respectively. In Table A1 and A2, we present summary measures of stock market returns and volatility for the whole sample period.

B. VAR Model of Returns and Volatility

We use VAR model as the basis of our empirical analysis; and the variance decomposition in particular to obtain estimates of spillovers of return and volatility shocks across markets. VAR framework provides us with a simple yet powerful tool of analysis of spillovers across markets. As we have already discussed above, Engle *et. al.* (1990) was the first study that analyzed volatility spillovers across markets using the VAR framework. In order to study the possible effects of a shock in one market on volatility in other markets, they use the impulse response functions. Instead of impulse response functions, we use the decomposition of the variance of forecast errors in order to identify spillovers of shocks from idiosyncratic shocks. Unlike impulse response functions, the variance decomposition analysis allows us to sum spillover effects on all markets and obtain a single measure of spillover relative to idiosyncratic shocks.

Instead of focusing only on crisis episodes, we use all the data on returns and volatility available for our empirical analysis. Furthermore, departing from the literature, we assume that the dynamics of returns and volatility are not necessarily governed by a single process throughout a period of substantial change in the world financial system and especially in emerging markets. Estimating the VAR model for rolling windows of 200 weekly observations, we allow VAR parameters and hence spillovers across markets to change over time.

In order to explain our empirical methodology in detail, we first conduct the analysis of VAR for return and volatility over the full sample (January 1992-September 2005). Decomposition of the variance of forecast errors for returns and volatility are reported in Tables 1 and 2, respectively. Each cell entry in Table 1 measures the contribution of a standard deviation shock to returns in one market (column) on the variance of the mean squared forecast error of volatility in the same market or in another market (row) at the end of a 10-week horizon.[5] For example, we learn from Table 2 that a standard deviation shock to volatility in Hang Seng (Hong Kong) contributed 5.6% and 7.8% of the variance of the forecast error of the volatility in the US and UK stock markets, respectively. Summing the entries row-wise excluding the diagonal entry (reported in the last column), we obtain the total contribution of a volatility shock in one market to forecast error variance in all other markets. A column-wise sum, on the other hand, (again excluding the diagonal element) provides a measure of the total contribution of volatility shocks in other markets to the variance of the forecast error in a particular market. Looking at the HKG column and row

[5] We use a 10-week forecast horizon to measure the impact and calculate how much of the volatility forecast error in one market is explained by volatility shocks in other markets.

in Table 2, we observe that shocks to Hang Seng return volatility contributed 8.5% (127 points out of a total of 1500 points) of the variance of the forecast error in other markets. Shocks in other markets, on the other hand, altogether contributed only 11% of the variance of forecast errors in Hong Kong. When we sum all entries of the *contribution by others* column (or the *contribution to others* row), we obtain a measure of volatility spillovers among the 16 markets included in the VAR analysis. For the full sample, the volatility spillovers contributed close to one-third (498 points out of a total of 1600 points) of the variance of forecast error in all markets. A comparison of Table 1 and Table 2 reveals that the total measure of spillovers of the mean return shocks across markets (458 points out of 1600 points) is close to total spillovers of volatility shocks (498 points) over the full sample.[6]

Both impulse response and variance decomposition analyses are based on Cholesky factorization. As a result, they are subject to a bias introduced by the ordering of variables in the VAR model. Any change in the ordering can change the impulse responses and/or the variance decomposition. In our rolling window estimation framework, however, this should not be a problem as it would have been in the analysis of a fixed sample. As long as the objective of the analysis is to follow the behavior of the total spillovers (return or volatility) over time rather than to identify the direction of spillovers, one can use the variance decompositions to analyze how the contribution of return and volatility shock spillovers to the sum of the forecast error variance over all markets behaves over time. As the ordering of the variables is the same over all rolling windows considered, the change in the measure of spillovers over time is not effected by the ordering of variables.

Over the period of our analysis, there have been 7 episodes of crises or worldwide shocks:

1. December 1994 - Mexican crisis (12/14/94-2/1/95)
2. October 1997 – East Asian crisis (10/15/97-12/24/97)
3. August 1998 – Russian crisis (7/29/98-9/16/98)
4. January 1999 - Brazilian crisis
5. December 2000- February 2001 - Turkish Crisis
6. November 2001 - Argentinean Crisis
7. March 2005 – GM/Ford bonds given the junk status, followed by a short-lived reversal of international capital flows from emerging market economies.

[6] Variance decomposition results are not sensitive to the use of a 10-week horizon. When we evaluate the variance decomposition over a 5-week horizon, mean return and volatility spillover measures are equal to 458 and 470 points, respectively.

Our rolling window estimation of VAR models does not create a hierarchy of crisis episodes. Instead, in our framework, plotting the measures of return and volatility spillovers, it is possible to find out the importance of each crisis episode in terms of the tremors felt in other markets. In other words, the data speaks for itself.

In Figures 1 and 2, we present the contribution of return and volatility shock spillovers, respectively, to the sum of the variances of forecast errors in all markets. The difference between the return and volatility spillover plots is clear. In Figure 2, there are spikes in the volatility spillovers as the volatility estimates for major and minor crises periods are included in the rolling window. The different stages of East Asian (devaluation of Thai Baht in July 1997, spread of the virus to Hong Kong in October 1997 and its further spread to other major economies of the region such as S. Korea, Malaysia and Indonesia until January 1998) and Russian (the first wave of the crisis can be brought under control by the announcement of an IMF support package in June 1998 and the final outbreak of the crisis in August 1998) crises are revealed by large spikes in the volatility spillover measure.

Minor emerging market crises (Brazilian and Turkish) are reflected in small spikes in the volatility spillover measures, once the data pertaining to these crises episodes are included in the rolling sample window. What differentiated Brazilian and Turkish crises from the East Asian and the Russian crises is the anticipation of the crisis. While both countries had fundamental problems in their economies that made investors expect some sort of a crisis in these countries, the East Asian crisis was completely unanticipated. Especially the spread of the virus to Hong Kong was completely unanticipated. Once Hong Kong caught the virus, other economies of the region that had already become vulnerable were expected to be affected. A similar case is true for Russian crisis. Even though, Russian government started to have difficulties in June 1998, once the IMF rescue package was announced nobody expected the government to declare moratorium as early as August. Once the moratorium was declared, many European and American investors were caught off-guard. The unanticipated nature of the August 1998 Russian crisis, therefore, generated substantial degree of volatility spillovers across European and American markets as well as many emerging markets. [7]

The volatility spillovers measure also captures the increased volatility in world financial markets following the Federal Reserve's interest rate policy reversal in February 2004 and the short-lived capital flows reversal away from emerging markets in March 2005. Furthermore, the effects of major crises and the worldwide shocks of the 9/11 terrorist attacks on stock markets are further revealed by close to 10 percentage point drops in the volatility spillover measure, once data pertaining to those episodes are left out of the rolling window. Contrary to the case of volatility, return spillovers measure does not reveal

[7] We need to remind the reader that Russian stock market is not included in our sample.

any sensitivity to the major shocks or crises (Figure 1). Instead, return spillovers measure is characterized by a smooth upward move as the window is rolled to include mid-1990s observations in the model.

We check the stability of the VAR model for every 200-week long window. As can be seen in Figure A1, the maximum eigenvalue of VAR parameter estimates for returns is less than one for all 200-week long return windows. In the case of the VAR model of volatility (Figure A2), maximum eigenvalue of the VAR parameter estimates exceed 1.0 in only 9 windows. These nine windows mostly correspond to the spikes during the East Asian and Russian crises that we observe in Figure 2. As there are eigenvalues that lie outside the unit circle, VAR model is not stable for those 9 windows. Based on this information, in Figure 3, we plot the volatility spillover measures after dropping the calculated volatility spillover measures for those 9 windows. As a result of dropping the volatility spillover measures based on unstable VAR model, the contribution of volatility spillovers does not reach to 90 % any more. Instead, the maximum volatility spillover achieved is approximately 65% of the overall variance of the forecast errors. Despite this large difference, however, dropping the volatility spillover measures based on unstable VAR model does not generate any qualitative change in the results reported in Figure 2.

In Figure 3, we report the return spillovers along with the volatility spillovers for VAR models with stable parameters. The difference between the return and volatility spillovers becomes even more visible in Figure 3. Both return and volatility spillovers follow an upward trend in the pre-East Asian crisis. However, as soon as the window is rolled to cover the data for the East Asian crisis period, the volatility spillovers jump up by 25 percentage points, whereas there is no change in the return spillovers. The difference between the volatility and return spillovers continues as long as the rolling windows cover the East Asian and Russian crisis episodes.

The case for the East Asian crisis is observed in Figure 3. As soon as the data pertaining to the major crisis episodes are included in the rolling window, the volatility spillover measure jumps up significantly. While spillovers of volatility shocks accounted for approximately 45% of the overall forecast error variance before the inclusion of data for the East Asian crisis (from October to the end of 1997), once these observations are included, the contagion measure jumps up close to 70% of the overall variance. As the window is rolled further to include data for the next couple of months, the volatility spillover measure drops off, but to a level that is significantly above the pre-crisis period. In the case of the East Asian crisis, the volatility spillover measure drops from 80% to 60%.

Looking at Figures 2 and 3, it is not possible to conclude that what holds for the East Asian crisis also holds for the Russian crisis. The increase in the spillover measures as the post-crisis data are included is only less than 3%. We think that this is solely a result of the simultaneous effects of the observations for the two crises. Dropping observations pertaining to the East Asian crisis, we plot the volatility spillovers for rolling windows in Figure 4. What we have observed for the East Asian crisis is clearly repeated for the Russian crisis: Once the volatility spillovers come down after the crisis, they end up at a higher level than before the crisis. Once the volatility data for the initial impact of the crisis are included, the VAR model captures the substantial degree of volatility contagion in the first couple of weeks of the crisis. However, as the window is rolled further, the contagion effect continues to exist. Removing the data pertaining to the crisis period does not only clear away the spikes, but also most of the level differences before and after the crisis. (See Figure 4)

Figure 5 reveals that return spillover effects of the East Asian and Russian crises on the world stock markets are not negligible, yet they are not as important as the effects of the two crisis on the volatility spillover measure that we observed in Figure 4. What is important about return spillovers is their apparent increase in a matter of 2 years. The return shock spillovers that account for 35% of the total forecast error variance for windows that cover 1993 through 1995 slowly but steadily increased as the window is rolled. By the time the window covered the data for the East Asian crisis, the return spillovers accounted for more than 40% of the overall variance of forecast errors. As the data pertaining to East Asian and Russian crises are included in the windows, the contribution of return shock spillovers continues to increase and surpass 45% of the total variance of the forecast errors.

The increase in return spillovers across markets was a secular upward trend over a period of two years. As the window is rolled further into the future, the return spillovers across markets do not decline. We interpret this result as an evidence of increased market integration over the period, and hence increased interdependence across markets during a period of substantial portfolio flows to emerging markets. Reversing the approach followed by Forbes and Rigobon (2002), we remove the data pertaining to these episodes from the sample and plot the return and volatility spillovers through VD. The behavior of overall return and volatility spillovers across markets are quite different. The return spillovers measure continues to have an upward trend even after the removal of the crisis episodes from the sample.

Another difference between the return and volatility spillover measures can be observed towards the end of the 1990s. After the upward trend in the mid-nineties, the return spillover measure stays high around 45% and slightly declines down to 42% as the data pertaining to the crises episodes are dropped out of the sample. The volatility spillovers measure, on the other hand, declines substantially. As the window is rolled further and observations pertaining to the crises episodes are dropped out of the sample window, the volatility spillover measure declines and returns to levels lower than the pre-crises levels (see Figure 3). The fact that it is the volatility spillover but not the return spillover measure that turns to its levels in the pre-crises period (mid-1990s) can be interpreted as an evidence of contagion in volatility and interdependence in means. As the crisis periods pass, the volatility spillovers diminish, but the markets continue to be integrated and hence there is not much change in the measure of return spillovers, which we claim captures the interdependence.

Above we have already emphasized that our analysis was not subject to the criticism that the results were driven by the ordering of variables in the VAR model. As the ordering of the variables is the same throughout all windows considered, we claim that results are not due to a particular ordering of the markets. While this claim is true, it helps to show evidence that the results are robust to the ordering of variables. However, it is an impossible task to consider all possible alternative orderings of variables, total number of which is equal to the factorial of 16. Instead, we follow a more practical, yet satisfactory approach to the robustness check with respect to the ordering of variables in the analysis of volatility spillovers. We take the original ordering of the markets as in Table 1. In each round we change the ordering by moving the market that is at the head of the list to the end of the list and calculate the volatility spillover index for all rolling windows. This way, we consider 15 possible alternatives and allow each market to be listed first and the last.

Then we obtain the minimum and maximum values of the spillover indices for all 15 alternatives in each rolling window. The differences between the minimum and maximum index values, on the one hand, and the original spillover index, on the other, are displayed in Figure 6. If our results were driven by the fact that the four major markets are included first in the ordering, we would expect the spillover index calculate with all four major markets at the end of the list should substantially deviate from the original volatility spillover index in Figure 2. As can be seen in Figure 6, we obtain at most 2.5 percentage point discrepancy in absolute value between the minimum and the original index, and at most 1.5 percentage point discrepancy in absolute value between the maximum and the original index. Furthermore, for the windows covering the East Asian and Russian crises the discrepancies do not exceed 1.5 percentage points. A maximum discrepancy of 1.5 percentage points is too small compared to a 40-some percentage-points jump in the volatility spillover index with the inclusion of the East Asian crisis data. This partial robustness check therefore shows that our results are not driven by a particular ordering of variables.

IV. Conclusions

Using separate VAR models of return and range-based volatility estimates for 16 stock markets, we analyzed the possible differences in the dynamics that drive return and volatility spillovers over time. Variance decomposition analysis of the VAR model allowed us to identify spillovers of return and volatility shocks from the idiosyncratic shocks.

As a result of the increased market integration in the nineties, stock markets around the world became more interdependent and this was captured by the steady increase in return spillovers in the mid-1990s. Despite the ensuing emerging market crises, the return spillovers did not decline to the levels at the beginning of 1990s. We are also unable to find a significant increase in return spillovers across markets during or after emerging market crises.

On the other hand, the variance decomposition analysis of the VAR model for volatility shows that there was a substantial increase in the volatility spillovers across markets during and after the major emerging market (East Asian and Russian) crises. Plots of volatility spillovers leave no doubt that it was the volatility contagion, not the contagion in mean returns that took place during and immediately after the major crises.

These findings lead us to conclude that while the increased integration of emerging stock markets into international financial system led to an increased interdependence in returns during the 1990s, severe volatility contagion took place as the emerging market economies were hit by major financial crises in the second half of 1990s.

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Table 1
Vector Autoregressive Variance Decomposition
Weekly Real Stock Market Returns
10-Week-Ahead Forecasts, 1/1992-9/2005

								FROM									
		US	**UK**	**HKG**	**JPN**	**IDN**	**KOR**	**MYS**	**PHL**	**SGP**	**TAI**	**THA**	**ARG**	**BRA**	**CHL**	**MEX**	**TUR**	**Contribution From Others**
	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**
	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**
TO	**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**	

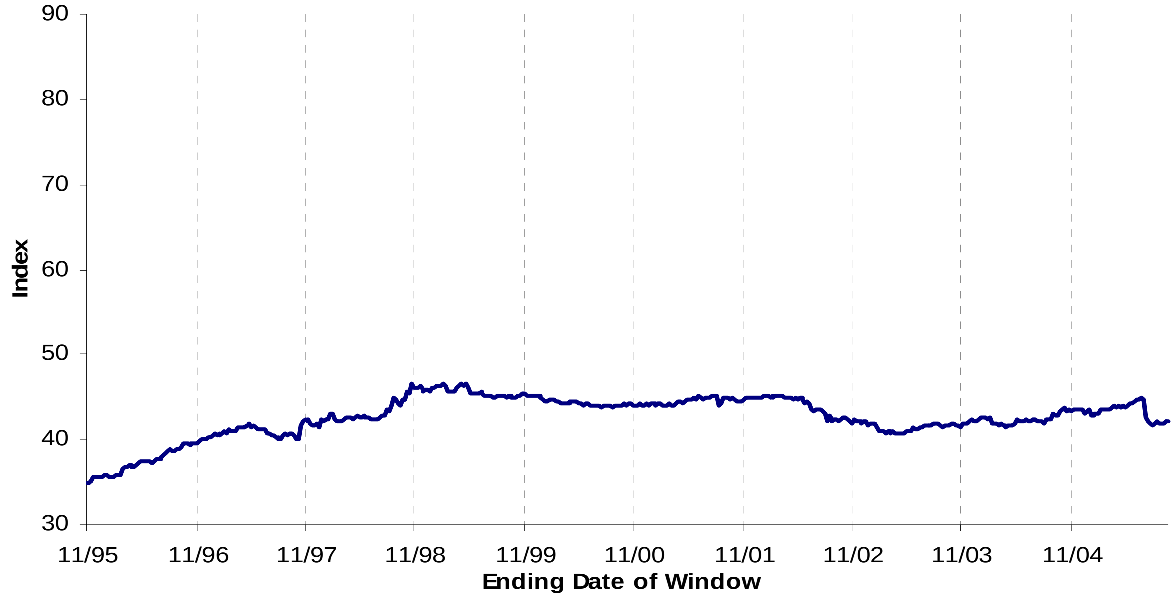
Notes: We present variance decompositions based upon a vector autoregression of order 2 identified using a Cholesky factorization with the ordering as shown in the column heading. The (i, j)-th value is the estimated contribution TO the variance of the 10-week-ahead real stock return forecast error of country i coming FROM innovations to real stock returns of country j. The mnemonics are defined as in the appendix Table A1.

Table 2
Vector Autoregressive Variance Decomposition
Weekly Stock Market Return Volatility
10-Week-Ahead Forecasts, 1/1992-9/2005

		FROM																
		US	**UK**	**HKG**	**JPN**	**IDN**	**KOR**	**MYS**	**PHL**	**SGP**	**TAI**	**THA**	**ARG**	**BRA**	**CHL**	**MEX**	**TUR**	**Contribution From Others**
	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**
T O	**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**	

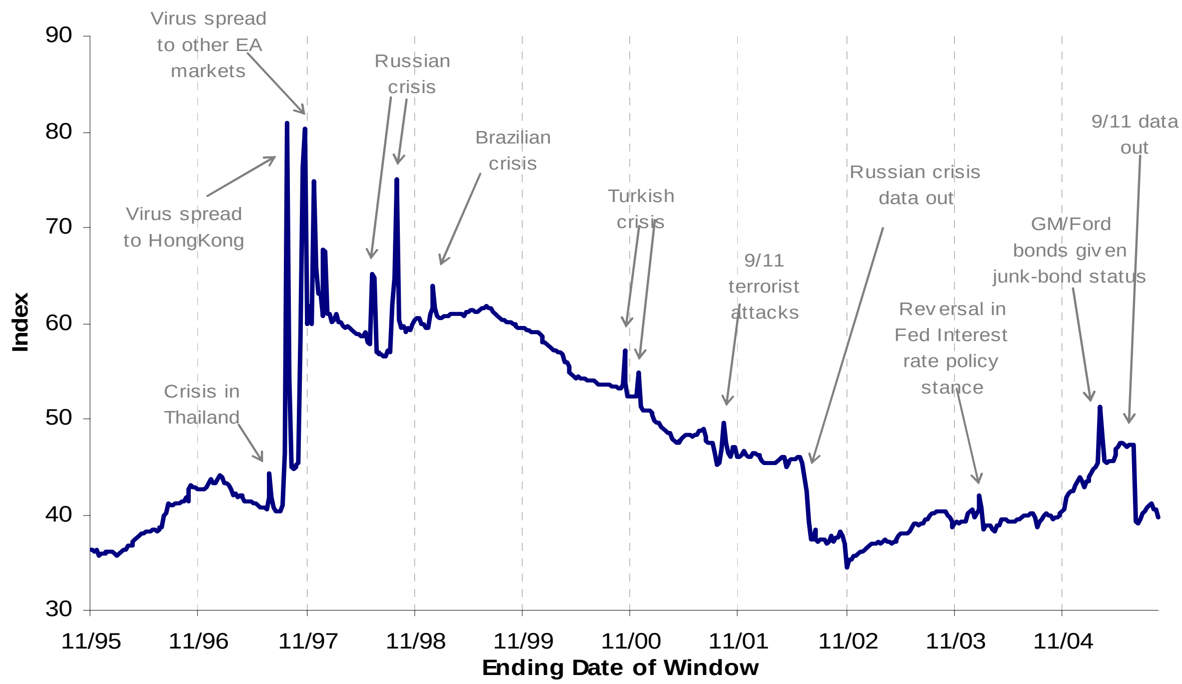
Notes: See Notes to Table 1. Chile's volatility measure is calculated from Santiago Stock Exchange IGPA Index for January 1992-May 2004 period, from Santiago Stock Exchange IPSA index for June 2004-September 2005 period.

Figure 1
Return Spillover Index (1/1992-9/2005)



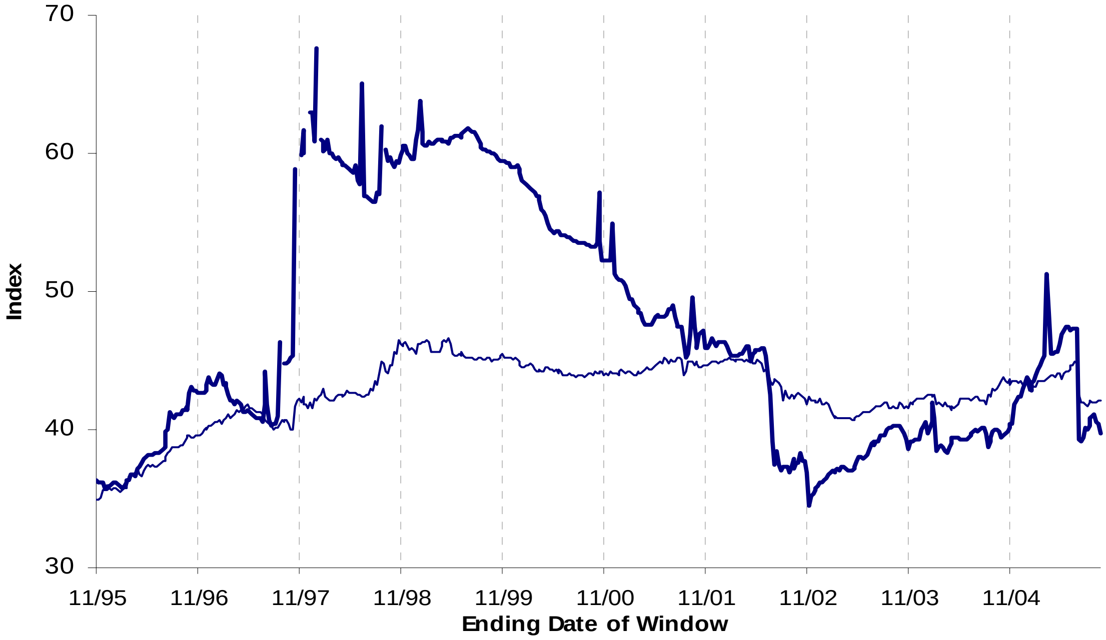
Notes: The spillover index was constructed per the description in the text, based upon a vector autoregression of order 2, estimated using a 200-week rolling window.

Figure 2
Volatility Spillover Index (1/1992-9/2005)



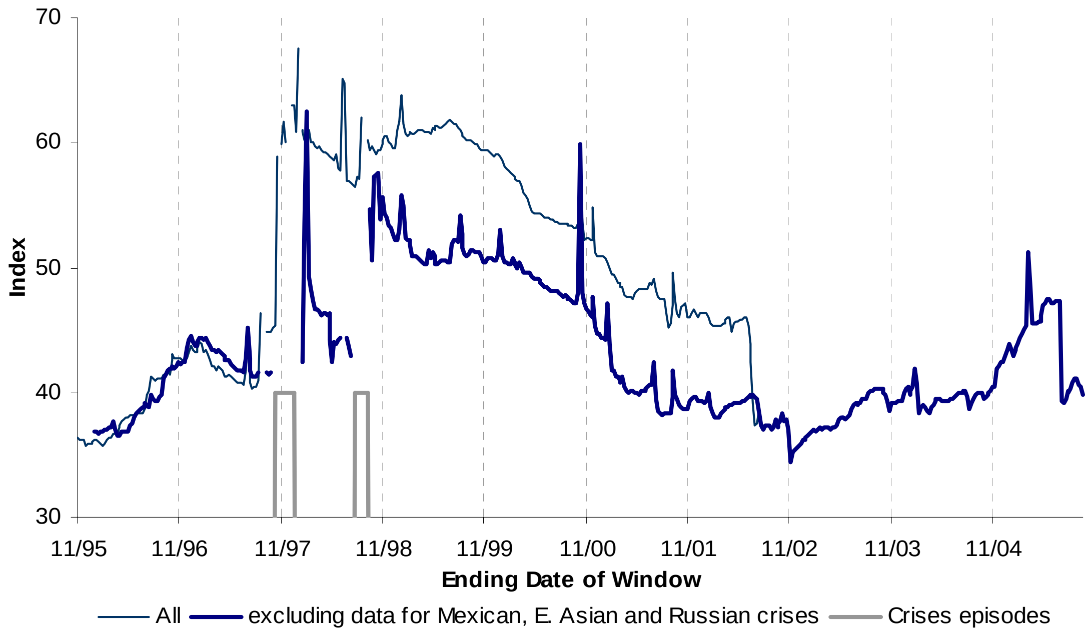
Notes: The spillover index was constructed per the description in the text, based upon a vector autoregression of order 2, estimated using a 200-week rolling window.

Figure 3
Return and Volatility Spillover Index (1/1992-9/2005)
Excluding Windows for Which VAR Model Stability is Rejected



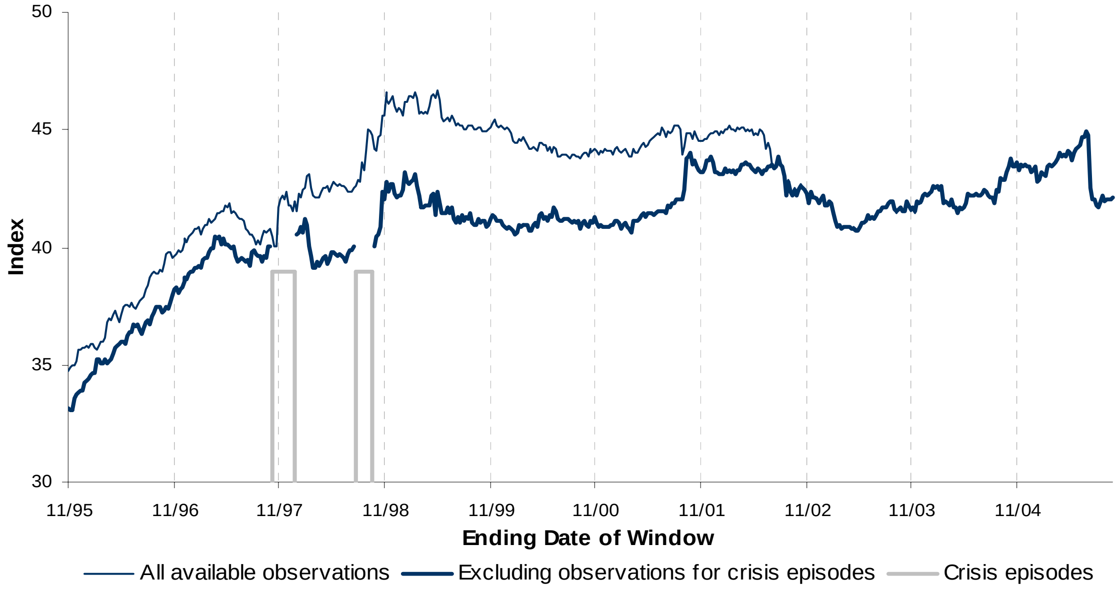
Notes: The spillover index was constructed per the description in the text, based upon a vector autoregression of order 2, estimated using a 200-week rolling window.

Figure 4
Volatility Spillover Index (1/1992-9/2005)
Excluding Windows for Which VAR Model Stability is Rejected and Major Crisis Episodes



Notes: The spillover index was constructed per the description in the text, based upon a vector autoregression of order 2, estimated using a 200-week rolling window.

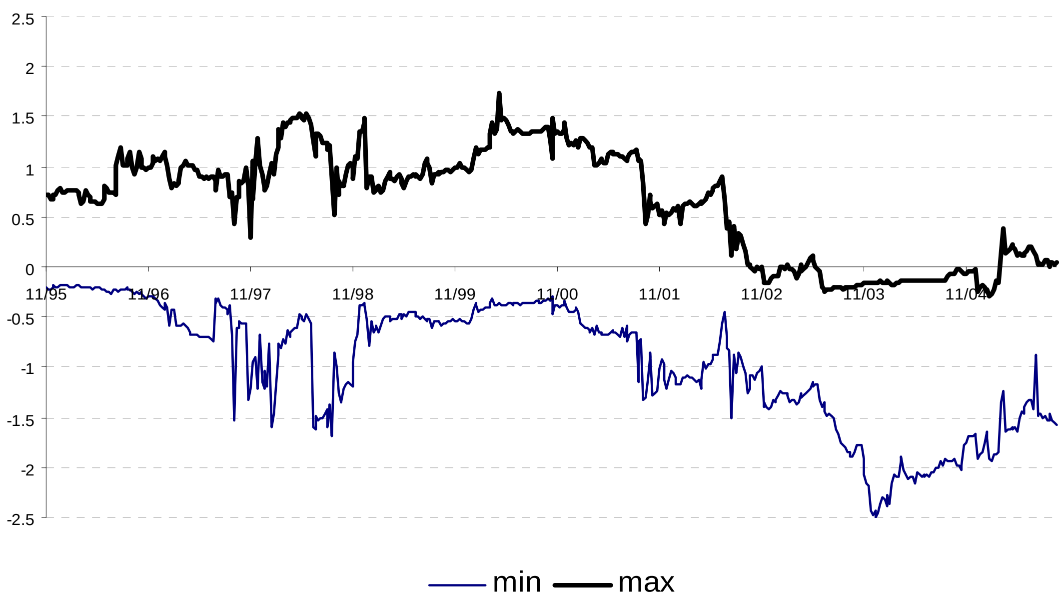
Figure 5
Return Spillover Index (1/1992-9/2005)
Excluding Crisis Episodes



Notes: The spillover index was constructed per the description in the text, based upon a vector autoregression of order 2, estimated using a 200-week rolling window.

Figure 6

Robustness of Results to Alternative Ordering of the Variables
Minimum and Maximum values of volatility spillover index for 15 alternative orderings - Difference from the Original Spillover index



APPENDIX

Figure A1
Moduli of Dominant Eigenvalues, VAR(2)
Returns Models Estimated Using 200-Day Rolling Windows, 1/1992-9/2005

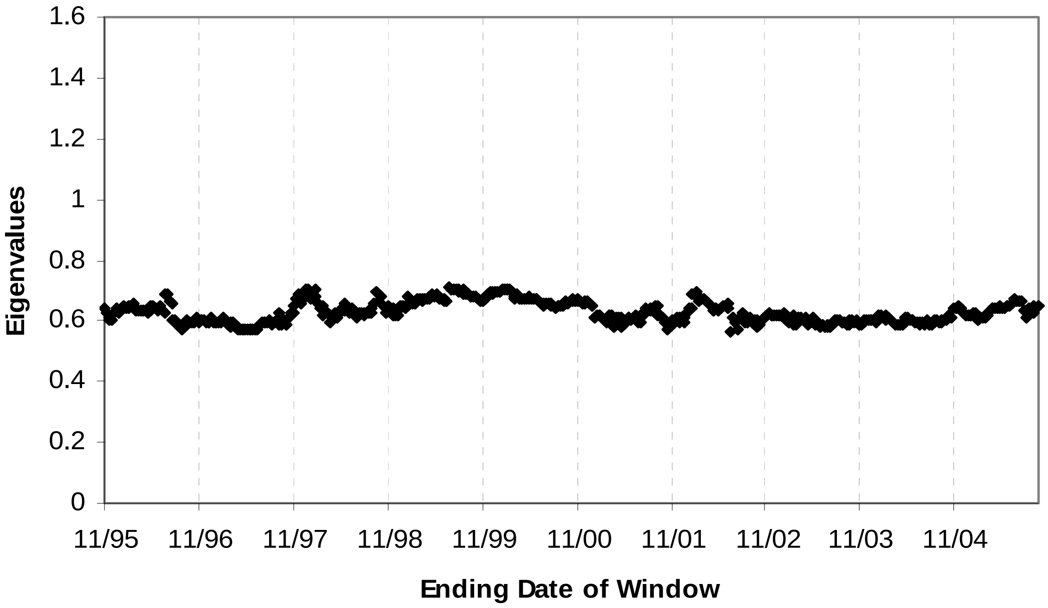


Figure A2
Moduli of Dominant Eigenvalues, VAR(2)
Volatility Models Estimated Using 200-Day Rolling Windows, 1/1992-9/2005

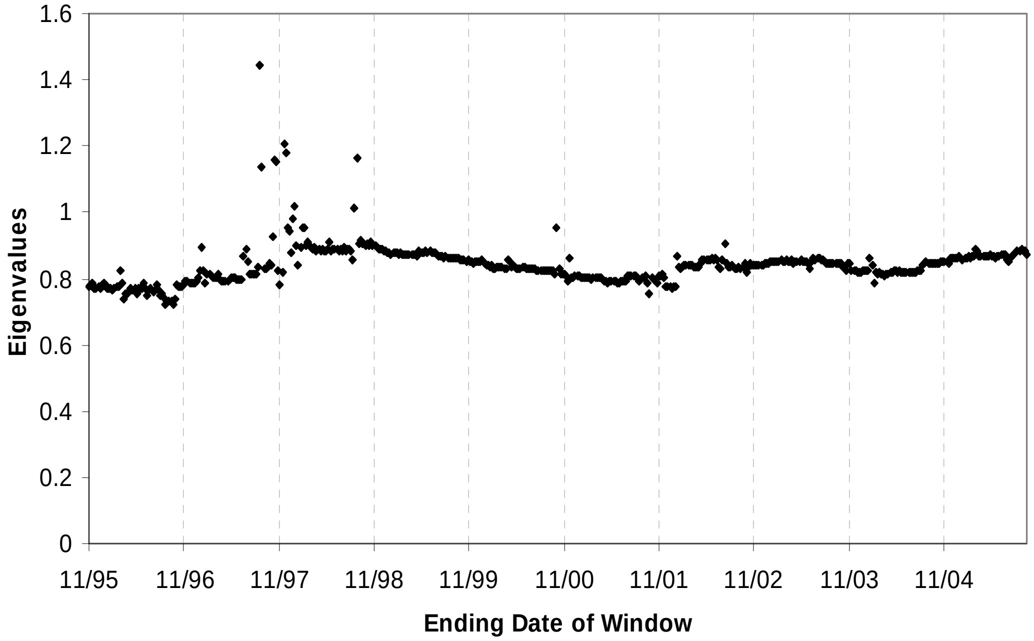


Table A1

Weekly Wednesday Real Stock Returns - Descriptive Statistics
January 1992 – September 2005

	United States US	United Kingdom UK	Hong Kong HKG	Japan JPN	Indonesia IDN	South Korea KOR	Malaysia MYS	Philipinnes 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 SGP	Taiwan TAI	Thailand THA	Argentina ARG	Brazil BRA	Chile CHL	Mexico MEX	Turkey 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: We present summary statistics of weekly stock returns for sixteen broad country market indexes. In each case the Jarque-Bera normality test (not shown) rejects normality at the 0.01 level or better. The sample size is 717.

Table A2

Weekly Garman-Klass Volatility Estimates - Descriptive Statistics
(January 1992 – September 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: We present summary statistics of weekly Garman-Klass volatility estimates for sixteen broad country market indexes. In each case the Jarque-Bera normality test (not shown) rejects normality at the 0.01 level or better. The sample size is 717. The mnemonics are defined as in Table A1 above. Chile's volatility measure is calculated from Santiago Stock Exchange IGPA Index for January 1992-May 2004 period, from Santiago Stock Exchange IPSA index for June 2004-September 2005 period.