VOLATILITY CO-MOVEMENTS IN EMERGING BOND MARKETS: IS THERE SEGMENTATION BETWEEN GEOGRAPHICAL AREAS?

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Abstract

This paper analyses the dynamic interrelationship between sovereign bond spreads in ten emerging markets. It investigates the nature of the volatility transmission in secondary bond markets through conditional covariance estimates obtained by orthogonal methods. This approach, which combines PCA with GARCH volatility modelling, filters away idiosyncratic news and focuses on spreads dynamics driven by common factors. We find convincing evidence of co-movements between spread changes; more within than across geographical areas. Conditional covariations increase in periods of turbulence and subsequently subside. The time varying minimum variance artificial portfolios, which are used here for model validation, show that, in spite of systemic risk, international portfolio diversification is still a powerful strategy for risk reduction.

Keywords: bond yields, O-GARCH, O-EWMA, contagion.
JEL Classification Codes: F30, G12, G14, G15.

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A surge in capital inflows in the early 1990s was followed, in many emerging countries, by episodes of financial distress. The Mexican crisis of 1994, the Asian turmoil of 1997, the Russian and the Brazilian episodes of 1998-1999 and, more recently, the crises in Turkey and Argentina of 2000-2001 brought about sudden capital outflows, rising costs of borrowing and higher interest rate volatility. Restrictions to capital market access caused a generalised increase in developing-country interest rates, including those of debt instruments issued by countries that had little in common with the epicentre of the crisis.

Sovereign bond yields, however, and spreads over US Treasuries in particular, convey the market assessment of a country's creditworthiness and the associated default risk. A relevant preliminary question in addressing the issue of spread co-movements is, thus, whether the pricing of capital flows to emerging markets is influenced by fundamental variables. Because of the high frequency nature of the data, we can not introduce them directly in our analysis. This shortcoming does not seem to be too severe. The studies by Cline and Barnes (1997), Min (1998) and, more recently, of Arora and Cerisola (2000) do not come up with clear cut results on the role of fundamentals. Conversely, studies by Zhang (1999) and Kamin (2002), investigating the impact of moral hazard on spreads, provide some support for the hypothesis that domestic macroeconomic variables do influence spread dynamics. The role of credit ratings as possible indicators of spread behaviour is also controversial. Preliminary analyses by Cantor and Packer (1996) and Kamin and von Kleist (1999) find that fundamentals explain ratings but are inconclusive about the relation between spreads and ratings. Using a sample encompassing the latest crises, Sy (2001) finds a significant negative relation between spread levels and ratings. The growing dispersion of spreads for similarly rated countries during periods of crisis suggests, however, that credit ratings are unable to make the due discrimination in cases of financial turmoil.

Assessment of the reaction of emerging country bond spreads to shifts in creditor country interest rates is of great relevance for our research. Here again, previous empirical findings prove somewhat disappointing. Arora and Cerisola only find a significant positive impact of the

U.S. federal funds target interest rates.[i] Cline and Barnes (1997) with secondary Eurobond market spreads and Min (1998) and Kamin and von Kleist (1999) with primary ones find evidence of a positive but statistically insignificant impact of U.S. interest rates. Eichengreen and Mody (1998.a), again using primary market data, find a puzzling significant negative relationship between spreads and U.S. interest rate increases. They attribute this both to a decline in the supply of emerging market bonds, which raises their prices and reduces the corresponding spreads, and to a “selectivity bias” i.e. to a smaller low quality high spread issuance in periods of U.S. credit tightening. Kaminsky and Schmukler (2001) explain these contrasting results as due to a “vulnerability” effect. They find that fragile economies (classified so according to international credit ratings) are more severely affected by changes in US interest rates precisely because economic vulnerability triggers a substantial reaction of the domestic financial market to external events.

National yield spread interlinkages can be given a standard economic and/or financial rationale. Economies are related through trade and financial flows, and shifts in the economic fundamentals of one country may affect its neighbours. Changes in market sentiment do sometimes, in periods of growing uncertainty, go beyond fundamentals and generate “contagion” phenomena.[ii]

Several interpretations of the latter can be found in a burgeoning literature. Calvo and Mendoza (1995, 2000) point out that since information acquisition in emerging markets is expensive, investors tend to follow the market rather than to analyse market fundamentals. Kodres and Pritsker (2002) and Schinasi and Smith (2000) attribute contagion-like behaviour to cross-market hedging by rational investors. Kaminky and Reinhart (1999, 2000) emphasise the magnifying role of international bank lending and exposure to a common creditor. Valdés (1997) and Calvo (1998), in turn, focus on the role of liquidity constraints in generating contagion-like results as liquidity needs in one particular asset may lead to fund withdrawals from another asset (or country), impairing its financial credibility.

The question as to whether spreads are related to global events and tend to co-move, possibly because of contagion-like phenomena, or, rather, are influenced by local idiosyncratic shocks, is analysed by Edwards and Susmel (2000), Scherer and Avellaneda (2000) and Mauro et al. (2002). This paper, which focuses on high frequency dynamics and disregards fundamentals, follows their line of research. It analyses the behaviour of daily spreads on sovereign bonds from 10 emerging countries located in Asia and Latin America from October 1999 to April 2002. Each spread is measured as the interest rate difference between the annualized yield on an emerging country sovereign bond denominated in U.S. dollars and the benchmark yield, i.e. the annualized yield of a U.S. bond of the same maturity.

The research is innovative from both the empirical and the methodological point of view.

(i) International comparisons are facilitated by the use of homogeneous secondary yield spreads on bonds denominated in U.S. dollars. We thus avoid the biases associated with the use of Brady bonds and primary market yields, discussed in the literature. [iii]

(ii) The research combines robust variance-covariance matrix estimation with the multivariate conditional variance parameterization based on Principal Components Analysis set forth by Alexander and Leigh (1997). This approach is used to filter away idiosyncratic news and to focus only on spread dynamics driven by common factors. It provides a computationally simple alternative to the (Kalman filter) signal extraction procedure of King and Wadhwani (1990) and Lin et al. (1994). Conditional covariation among spreads within and across geographical areas is directly investigated using two techniques for modelling conditional heteroskedasticity. Accurate assessment of the importance of contagion-like phenomena, of great relevance to the financial analyst, then becomes straightforward.

(iii) An innovative model validation technique, based on the estimation of time-varying minimum variance artificial portfolios is set out in the last section. A significant drawback in the calibration of large multivariate conditional variance models is here accounted for.

We find convincing evidence of co-movement between spread changes; more within than across geographical areas. Their conditional covariation seems to increase in periods of turbulence and subsequently to subside, in line with some recent work by Edwards and Susmel (2000, 2001).

A word of caution is called for here. Volatility spillovers or co-movements may also be caused by shifts in the risk aversion of agents reacting to shocks in the bond market. The co-movements will tend to return to their previous dynamics as new information on the fundamentals becomes available to investors. In this context it will not be possible to draw a clear distinction between contagion and gradual dissemination of information.

The research is organised in the following way. Section 1 describes the multivariate conditional variance estimation techniques implemented in the empirical analysis; section 2 provides preliminary statistical analysis of the sovereign bond spread time series; section 3 investigates the spread difference covariation within and across the two geographical areas under investigation and goes on to discuss the economic and financial aspects; section 4 outlines and applies the model validation techniques; section 5 concludes the paper.

1. Principal components and volatility modelling

Correlation analysis per se does not produce an exhaustive representation of the complexity of the connections between spreads. Accurate analysis of the latter is, however, of great relevance for the portfolio investment decisions of financial analysts. Principal Components Analysis (PCA) provides useful insights into asset co-movements, and the following section considers it in some detail. Its relevance has recently been enhanced with extension to volatility modelling by Ding (1994), Alexander and Leigh (1997), Alexander (2001) and Tsay (2002). In these papers the principal components structure is used, in various ways, in order to infer the conditional volatility and cross volatility behaviour of a set of variables from the volatility of a small number of principal components.

1.1 Principal components analysis

By exploiting the potential information redundancy in multivariate data sets, PCA is applied with the aim of identifying the pattern of the co-movements reducing the dimensionality of the data with minimal loss of information. This is achieved projecting the data onto fewer dimensions, so that the maximum amount of information, measured in terms of variability, is retained in the smaller number of dimensions. In this way PCA transforms a set of N correlated variables into a smaller subset of M ≤ N uncorrelated variables (principal components) that are orthogonal linear combinations of the original ones. The first component will have the maximum possible variance, the second the maximum possible variance among those uncorrelated with the first and so on.

Let y_i, $i = 1,\ldots,N$ be a Tx1 vector of spread first differences and $x_i = (y_i - \bar{y}_i)/s_i$ be the corresponding standardized spread vector where $\bar{y}_i$ and s_i are the unconditional sample mean and standard deviation. x_i is a column of the TxN matrix, X ,of standardized spread differences. Principal components analysis is based on the eigenvalue eigenvector decomposition of the (correlation) matrix $\Sigma = X' X / T$.

The principal components transformation of *X* reads as

$$Z = X\Gamma \tag{1}$$

where *Z* is a TxN matrix of principal components, each column of which, z_i *(i=1,…,N),* is a Tx1 principal component vector.

Each column of Γ, g_i, is the ith eigenvector of the NxN (correlation) matrix Σ and is ordered according to the size of the corresponding eigenvalue l_i. It is also called the ith vector of principal components loadings. $\Sigma\Gamma = \Gamma\Lambda$ where Λ is the diagonal eigenvalue matrix with ordered entries $l_1 \geq l_2 \geq ... \geq l_N$.

The ith principal component

$$z_i = Xg_i \qquad (2)$$

has zero mean and variance l_i. With the latter appropriately normalized it is possible to measure the fraction of the variance of the original data explained by the corresponding principal component. Similarly, the sum of the first M normalized eigenvalues indicates how much variation is explained by the first M principal components.[iv]

The first principal component z_1 is a linear combination of the original variables, using as loadings the entries of vector g_1, which has maximum variance among all the linear combinations of the spread differences subject to the constraint that $g_1' g_1 = 1$; the second principal component z_2 is a linear combination of the original variables that are uncorrelated with the first principal component and such that $g_2' g_2 = 1$, with the largest variance and so on.

System (1) can be inverted and the original variables may be stated as a function of principal components. Thus

$$X = Z\Gamma' \qquad (3)$$

where Γ being orthonormal, $\Gamma^{-1} = \Gamma'$. System (3) is the principal components representation of the variables in *X*.

1.2 A two-step volatility modelling procedure[v]

Any vector $x_i = (y_i - \bar{y}_i) / s_i$ can be written in extended form as a function of M $\leq$ N principal components as follows:

$$y_i = \bar{y}_i + z_1 g_{i1} s_i + z_2 g_{i2} s_i + ... + z_M g_{iM} s_i + e_i \qquad (4)$$

which simplifies to

$$y_i = \bar{y}_i + z_1 g^*_{i1} + z_2 g^*_{i2} + ... + z_M g^*_{iM} + e_i \qquad (5)$$

(i=1, …N).

where $g^*_{ij} = g_{ij} s_i \; (i = 1,...,N; \quad j = 1,...,M)$ are "denormalized" factor loadings. They provide a measure of the relative change in the value of the ith spread difference in reaction to a shock in the jth principal component.

Equation(5) quantifies the effect of global (the z_i principal components) and idiosyncratic (e_t) factors on the spreads. Global factors are associated with shocks to international fundamentals, country specific shocks which affect the fundamentals of other countries or internationally contagious psychology shifts. Local or idiosyncratic factors may be changes in domestic fundamentals and market mood.

In matrix notation, the principal components decomposition of the spread differences becomes

$$Y = \bar{Y} + Z\Gamma^{*\prime} + U \qquad (6)$$

where $\bar{Y}$ and U are TxN matrices of mean and residual terms, respectively, and Γ^* is the NxM matrix of denormalized factor weights g^*_{ij}.

Principal components are orthogonal to the error terms in U and, taking variances, the NxN covariance matrix of Y, V, can be formulated as

$$V = \Gamma^* A \Gamma^{*\prime} + V_U \qquad (7)$$

V_U is the NxN covariance matrix of the error terms and A is the MxM covariance matrix of the M principal components.[vi] Ignoring the error covariance matrix V_U, we obtain the following approximation of the variance covariance matrix of the spread differences

$$V = \Gamma^* A \Gamma^{*\prime} \tag{8}$$

Principal components are orthogonal by definition and their unconditional variance covariance matrix is given by the diagonal matrix of their variances as unconditional covariances are nil. Heteroskedasticity in daily financial data suggests that conditional rather than unconditional second moments be used in the analysis. In this case the diagonal specification does not strictly apply and, as pointed out by Engle (2000), has to be imposed as a preliminary restriction.
Two approaches are used to quantify the conditional variances of the principal components, the GARCH and the EWMA (Exponentially Weighted Moving Average) procedures.
The standard univariate GARCH(1,1) model is

$$z_{jt} = c + u_{jt} \tag{9}$$

$$s_{jt}^2 = w + a u_{jt-1}^2 + b\, s_{jt-1}^2 \tag{9'}$$

where z_{jt} is the jth principal component obtained in a first stage principal components analysis of the spread differences, u_{jt} is the conditional mean residual and s_{jt}^2 is the corresponding conditional variance.
In the case of asymmetric response to news, the Threshold GARCH(1,1) specification of Glosten et al. (1993) is used to model the conditional variance.

$$s_{jt}^2 = w + a u_{jt-1}^2 + b\, s_{jt-1}^2 + g S_{t-1} u_{jt-1}^2 \tag{9''}$$

where $S_{t-1} = \begin{cases} 1 & if \quad u_{jt-1} < 0 \\ 0 & if \quad u_{jt-1} \geq 0 \end{cases}$

As usual, it is assumed that the leverage coefficient γ is positive as “bad” news has a greater impact on volatility than “good”.

The EWMA conditional variance is parameterized as

$$s_{jt}^{2} = l u_{jt-1}^{2} + (1 - l) s_{jt-1}^{2} \tag{10}$$

where λ is a smoothing constant that lies between 0 and 1. The smaller λ (and the larger (1-λ)), the stronger the persistence of the volatility and the lesser its reaction to u_{jt-1}^{2}, i.e. to news from the previous time period.[vii]

The PCA structure is then used to recover the volatilities and cross volatilities of the spread time series from a diagonal matrix of conditional variances of the M principal components, according to equation (8). We thus obtain large NxN conditional covariance (correlation) matrix estimates using but a small number of principal components volatility estimates.

2. The data

The sample period extends from 26 October 1999 to 15 April 2002. The data set includes spreads on foreign currency denominated sovereign debt instruments issued by 10 countries located in Latin America and Asia, namely Argentina, Brazil, Chile, Mexico, Venezuela, China, South Korea, Malaysia, Singapore and the Philippines (see figure 1). The bonds are denominated in U.S. dollars and have maturities in the range of 8 to 10 years. They are provided by Bloomberg; details on the maturity of the assets are set out in table1.[viii] Emerging market bond spreads started to decline at the end of 1999 as the negative impact of the Russian crisis of the previous year tended to fade away. The recovery of emerging market issuance lasted until March 2000. This was brought about by the beneficial effect of a range of events, such as the upgrading of the Mexican debt and the re-negotiation of the Russian one and a steady increase in oil prices. The peak in emerging asset prices coincided with the March peak of the Nasdaq stock index.[ix]

Table1. Data description

	Currency	Maturity Mm/yy	Coupon	Issuer	Issuer Rating S&P's Oct.-1999	Issuer Rating S&P's April-2002	Benchmarks Type	Yield	Maturity
Latin America									
Argentina	USD	04/09	11.75	Rep. of Argentina	BB	SD	T bond	5.5	05/09
Brazil	USD	10/09	14.5	Rep. of Brazil	B+	BB-	T bond	6	08/09
Chile	USD	04/09	6.875	Rep. of. Chile	A-	A-	T bond	5.5	05/09
Mexico	USD	03/08	8.625	U.S. of Mexico	BB	BBB-	T bond	5.625	05/08
Venezuela	USD	06/07	9.125	Rep.of Venezuela	B	B	T bond	6.625	05/07
Asia									
China	USD	12/08	7.3	Rep.of China	BBB	BBB	T bond	4.75	11/08
South Korea	USD	04/08	8.875	Rep. of Korea	BBB	BBB+	T bond	5.625	05/08
Malaysia	USD	06/09	8.75	Govt. of Malaysia	BBB	BBB	T bond	5.5	05/09
Philippines	USD	04/08	8.875	Rep. of Philippines	BB+	BB+	T bond	5.625	05/08
Singapore	USD	08/09	7.875	Dev. Bank of Sing.	A-	A-	T bond	6	08/09

Source Bloomberg

As U.S. stock prices started to decline, the emerging market bond prices followed suit and the spreads rose. A summer respite was only short-lived. From September 2000 onwards, a fall in Nasdaq, political turmoil in Argentina and fears of a banking crisis in Turkey brought about a substantial increase in bond spreads. In January 2001 the announcement of multilateral aid packages for these two countries and new US interest rate cuts eased the tensions on the global bond market.

In February and in March, however, the Turkish crisis and the growing uncertainty about the solvency of Argentina debt brought about a reduction in issuance and a new widening of spreads. In the second quarter of the year any potential benefit arising from a new cut in U.S. interest rates was more than offset by renewed concern about Argentina and Brazil. In April the Argentine $30 bn “non distressed” bond exchange was well accepted and triggered a temporary reduction in most of the spreads analysed here. The gains from this swap-exchange were lost shortly afterwards. Investor risk aversion rose in the aftermath of September 11 as mounting uncertainty combined with bleak short term economic prospects.

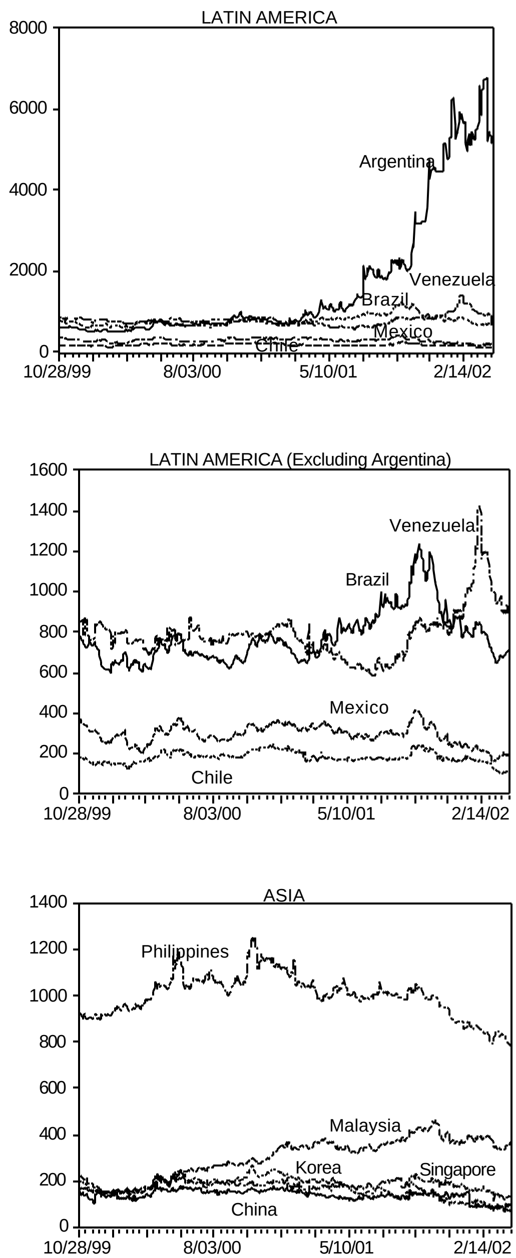
Flight to quality tended to dry up higher risk credit markets and exert an upward pressure on high yield bond spreads, although to a lesser degree than expected thanks to resilient investors’ discriminating behaviour. By the end of the year, recovery forecasts and growing appetites for risk (to pre-September 11 levels) brought about a marked compression of spreads on emerging market bonds, with the notable exception of Argentina’s. A common pattern that contributes to persistence in conditional covariations is set out in the analysis below.

Investors’ underweight positions in risky liabilities (which initially at least included Brazilian assets) explain why the Argentine debt swap, in early December, and the ensuing default, at the end of the month, exerted short lived effects on the rest of the asset class bonds.

In early 2002 emerging market bonds once again grew more attractive, including those issued by the Brazilian authorities, and the spreads accordingly shrank.

This result was linked to expectations of impending U.S. economic recovery and to recognition that the Argentinean crisis had somehow been shored up. The market absorbed $22bn new emerging country bonds issued by investment-grade borrowers. By the end of March renewed concern about the continuity of economic policy in Brazil after the elections fed through to a weaker *real* and a shortening of maturities for domestic debt. The ensuing difficulties in absorbing Brazilian bond issues resulted in a spread increase, which by mid-April was affecting other Latin American bonds as well. Emerging country bond issues also reflected the mood of the market, declining by 2 percent, from $82 bn in 1999 to $80.5 bn in 2000.

Figure 1. Emerging Market Bond Spreads



This trend continued during the first three quarters of 2001. Primary markets echoed the sentiments in the secondary markets, a sharp reduction in Latin American issuance being partially offset by a pickup in European – and some resilience in Asian – issuance. In November, as capital markets reopened to emerging country issuers after September 11, bond sales rose and allowed substantial amounts of pre-financing.

As a whole, in 2001 total bond issues ($89.4 bn) exceeded those of the two previous years but remained below the pre-Asian crisis levels.

Table 2 provides some preliminary information on the behaviour of daily spreads and spread changes. ADF statistics fail to reject the null of a unit root – a rather surprising result, but corroborated by the large standardised spectral density estimates at zero frequency, which suggest persistent deviations from trend.

At the same time, the zero frequency spectral density estimates of the spreads' first differences are significantly different from zero – a finding, which excludes over-differencing. The spreads have differing means and volatilities. Those on Latin American bonds tend to be higher, on average, than those on the Asian ones (534 basis points and 234 basis points respectively). This result holds even if we drop from the Latin American sample the large Argentinean bond spread. Standard deviations are higher in countries with low rating bond issues. Indeed, in Latin America spread volatility in Argentina is larger than in Chile. In Asia spread volatility is large in the Philippines and small in China and Singapore, countries showing a better credit rating.

The impact of ratings on the spread levels is not so clear-cut. The stylised rule would require that low ratings be associated with large spreads (and vice versa) and that similar ratings correspond to similar spreads. Bonds issued in Singapore and Korea have analogous ratings and, indeed, their spreads lie in a similar range.

This finding does not seem to apply across geographical areas. Countries with similar ratings but located in different geographical areas, such as the Philippines and Mexico, have markedly different spreads.

Table 2. Sovereign Spreads: Descriptive Statistics

Spreads are expressed in basis points – levels and first differences

a) *Latin America*

	Argentina	Brazil	Chile	Mexico	Venezuela	Lat. Am.
Levels						
Mean	1167	771	179	292	790	740
Std. Dev.	1663	129	28	49	124	914
ADF (lags)	-1.36(2)✣*	-1.84(1)*	-1.96(2)*	-2.27(1)*	-2.17(1)✣*	
Spectrum at 0 frequency	44.02	41.36	32.60	32.33	37.86	
(std.error)	(14.17)	(13.32)	(10.49)	(10.41)	(12.19)	
First Differences						
Mean	7.12	-0.10	-0.09	-0.25	0.13	1.36
Std. Dev.	136.	17.5	7.87	8.75	27.8	63.0
Skewness	-0.07	0.38	0.03	-0.12	0.45	0.13
Kurtosis	52.3	8.51	12.3	5.25	38.2	230
ADF (lags)	-22.7(1)	-23.7(0)	-17.3(2)	-23.2(0)	-30.1(0)	
Spectrum at 0 frequency	0.57	1.05	0.40	0.92	0.44	
(std.error)	(0.18)	(0.34)	(0.12)	(0.29)	(0.14)	

b) *Asia*

	China	South Korea	Malaysia	Philippines	Singapore	Asia
Levels						
Mean	139	170	303	1001	179	358
Std. Dev.	22	43	83	91	21	331
ADF (lags)	-2.89(3)✣*	-0.79(2)*	-2.29(1)✣*	-1.72(1)✣*	-2.54(3)*	
Spectrum at 0 frequency	34.54	41.25	46.63	40.23	30.85	
(std.error)	(11.12)	(13.28)	(13.01)	(12.95)	(9.53)	
First differences						
Mean	-0.07	-0.20	0.22	-0.24	-0.06	-0.07
Std. Dev.	8.05	6.53	6.57	12.6	8.64	8.76
Skewness	-0.13	0.31	-0.11	-0.45	-0.47	-0.38
Kurtosis	9.23	8.00	5.81	13.1	7.93	14.8
ADF (lags)	-17.1(2)	-21.2(1)	-25.6(0)	-23.8(0)	-19.7(2)	
Spectrum at 0 frequency	0.14	0.53	0.79	0.71	0.17	
(std.error)	(0.04)	(0.17)	(0.25)	(0.23)	(0.06)	

Notes. *: no rejection of the unit root hypothesis at 5 percent significance level; ✣ : the ADF test includes both time and constant trend.

Investors' assessment seems to go beyond credit ratings and charge a risk premium geared on the expected future evolution of a country's creditworthiness. A country characterized by higher interest rate volatility, i.e by greater market risk, will have to pay a higher interest premium.[x]

First differences can be given similar interpretation. They are affected by a high degree of kurtosis, which does not seem to be compatible with a Gaussian distribution. Positive, on average, in Latin America, because of worsening expectations vis-à-vis Argentinean insolvency, they are negative in Asia, where the overall economic outlook is improving.

Correlation indexes of daily spreads provide an interesting preliminary measure of interdependence. The analysis focuses on the first difference of the spreads since the computation of consistent unconditional covariance and correlation matrices requires that the time series be (weakly) stationary. First difference estimation, however, is affected by the presence of several outliers due to marked spread shifts in periods of turbulence which, in turn, bias the classical Pearson correlation estimator. The variance covariance MCD[xi] (minimum covariance determinant) procedure of Rousseuw and Van Driessen (1999) is used here in order to obtain consistent estimates, set out in table 3.[xii] In Latin America the robust correlation between Argentinean, Brazilian and Mexican spread changes is positive and exceeds 40 percent. The correlations with the Venezuelan spreads are somewhat looser, but still above 25 percent. Chile alone seems to be relatively isolated from the major markets of the area. In Asia the correlation between Chinese, South Korean, Singaporean and Malaysian spreads is well above 50 percent. The Philippine spread changes seem to be somewhat isolated from regional developments and weakly, but positively, correlated with the Argentinean, Brazilian and Mexican spreads. Correlation between Latin American and Asiatic spread changes is surprisingly strong, often beyond the 40 percent mark. It reaches 62 percent between Mexico and Malaysia and 56 percent between Mexico and South Korea, suggesting that intermediate rating spreads move together across geographical areas.[xiii]

Table 3. Sovereign Spreads: First differences Correlations (Robust MCD estimates)

	Argentina	Brazil	Mexico	Chile	Venezuela	China	South Korea	Malaysia	Singapore	Philippines
Argentina	1.00									
Brazil	**0.56**	1.00								
Mexico	**0.42**	**0.60**	1.00							
Chile	**0.19**	**0.25**	**0.39**	1.00						
Venezuela	**0.25**	**0.39**	**0.46**	**0.35**	1.00					
China	**0.16**	**0.32**	**0.53**	**0.47**	**0.46**	1.00				
South Korea	**0.22**	**0.40**	**0.56**	**0.35**	**0.33**	**0.59**	1.00			
Malaysia	**0.19**	**0.40**	**0.62**	**0.50**	**0.54**	**0.70**	**0.61**	1.00		
Singapore	**0.18**	**0.30**	**0.54**	**0.47**	**0.49**	**0.65**	**0.56**	**0.78**	1.00	
Philippines	**0.08**	**0.03**	**0.01**	**-0.21**	**-0.22**	**-0.10**	**-0.03**	**-0.24**	**-0.22**	1.00

3. Spread co-movements

This section investigates if and how emerging market spread changes co-move according to Principal Components Analysis (PCA) and investigates their volatility using the O-GARCH and O-EWMA procedures set out above. The large conditional covariance estimates provide an accurate description of within and across area interlinkages. This has relevant implications for portfolio analysis. A high degree of co-movement among emerging market bond spreads reduces the benefits of holding a portfolio of bonds issued by a variety of emerging countries rather than a single one. Conversely, a low degree of co-movement suggests that portfolio diversification be a good strategy.

3.1 Principal component analysis

The analysis is implemented on a geographical area basis, i.e. on the Latin American spreads (on bonds issued by Argentina, Brazil, Mexico, Chile and Venezuela) and on the Asian spreads (on bonds issued by South Korea, China, Singapore, Malaysia and the Philippines). The spreads of the two areas are then examined together. In table 4 can be found the loadings of the first 2 (or 3) principal components obtained with the robust correlations provided by the MCD estimator procedure. In the regional analyses of panel a, the explanatory power of the first 2 principal components is above the 70 percent mark.

The high level of integration among bond markets of the same region is indicated by the emergence of a first component which accounts for 66 and 51 percent, respectively, of the data variance in Asia and Latin America, and dwarfs the explanatory power of the remaining components. This result is to be interpreted in relation to the volatility of the spreads and may be biased by the presence of extreme events, such as the Argentine crisis.

Table 4. Sovereign Spreads Differences: Principal Components Analysis

First components calculated using robust correlation matrices

	a) Regional		b)Inter-regional		
	Latin America				
	PC1	PC2	PC1	PC2	PC3
PC loadings					
Argentina	0.430	-0.544	-0.197	-0.554	-0.375
Brazil	0.520	-0.330	-0.288	-0.465	-0.251
Mexico	0.512	0.005	-0.370	-0.230	0.042
Chile	0.341	0.630	-0.289	0.192	-0.144
Venezuela	0.409	0.446	-0.312	0.078	-0.304
Proportion of variance explained by PC	0.51	0.20			
Cumulative proportion of variance	0.51	0.71			
Eigenvalues	2.6	0.96			
	Asia				
	PC1	PC2			
PC loadings					
South Korea	-0.429	-0.314	-0.340	-0.053	0.406
China	-0.493	-0.141	-0.366	0.162	0.258
Singapore	-0.508	0.001	-0.376	0.229	0.123
Malaysia	-0.517	0.004	-0.403	0.195	0.089
Philippines	0.219	-0.939	0.084	-0.513	0.660
Proportion of variance explained by PC	0.66	0.19	0.46	0.15	0.09
Cumulative proportion of variance	0.66	0.85	0.46	0.61	0.70
Eigenvalues	3.33	0.93	4.64	1.45	0.98

Table 5. Proportion of Total Variation Accounted for by the First Principal Component

	Robust Correlation Estimates	
	Full set	Maximum dropping one country
Latin America	51%	63% dropping Chile
Asia	66%	82% dropping the Philippines
Inter-regional	46%	51% dropping the Philippines or Argentina

The analysis was thus repeated on a sub-sample ending in May 2001, a time interval characterised by a relatively modest overall variance. The first principal components, in this case, accounted for an even larger fraction of the total variance, suggesting that strong co-movements within a geographical area are not a prerogative of market turbulence. [xiv]

The signs of the loading may be of help in identifying a pattern of co-movement among country spreads and providing a tentative economic and/or financial interpretation of the principal components.

In Latin America, the loadings of the first principal component (see the first column of table 4, panel a) are all of the same sign and may represent the effect of a widespread regional shock on the spread changes. In Asia the loadings of the first principal component have the same sign but for the Philippines; the Philippine spread – as evidenced in the correlation analysis above – shows a degree of independence from the remaining spreads of the area.

In each emerging area the second principal component identifies a de-coupling effect of regional (area-specific) impulses. In Latin America, the loadings of Argentinean and Brazilian spreads have the opposite sign to those of the Chilean, Mexican and Venezuelan spreads. Similarly, in Asia the Chinese, South Korean and Philippine spreads shift in the opposite direction to the (very small) Singaporean and Malaysian ones.

The results from the two-area analysis are set out in table 4, panel *b*. The first principal component (see column 3) accounts for 46 percent of the total variation of the data and identifies a significant cross-regional commonality between Latin America and Asia. The second principal component may represent the onset of the Argentine crisis as it links the Argentinean, Brazilian, Mexican and Philippine spreads. The behaviour of the Philippines appears somewhat idiosyncratic in comparison with the other Asiatic countries in the sample. The third principal component does not provide additional information of interest and may be interpreted as an area specific factor.

In table 5 can be found the percentages of total data variation explained by the first principal component when one country at a time is excluded from the sample. Significant improvements in explanatory power are obtained dropping the Chilean, Philippine or Argentinean spread changes. We refrained from doing so, however, because their large factor loadings, especially those associated with the second factor, suggest that they play a relevant autonomous role in their respective geographical areas.

The estimates of this section corroborate the hypothesis of marked international co-movements of spread changes within and, to a lesser extent, across geographical areas. Local idiosyncratic factors explain but a minor proportion of spread change variability (usually less than 30 percent). A more detailed analysis of the results is unfortunately hampered by the very nature of the statistical procedure, interpretation of the principal components and of the corresponding factor loadings being only indirect.

In the next section the conditional volatility of the components identified in table 4 is used to build surprisingly large conditional covariance matrices of the spread changes for the geographical areas in the sample. They provide information on risk variation and covariation that is of great relevance to the financial analyst.

3.2 Analysis of the conditional covariation of the spreads

Following the tenets of the two-step procedure set out above, analysis proceeds with the parameterisation of the conditional variances of the principal components. Table 6 gives preliminary information on their statistical properties. Some evidence is found of serial correlation. Their main characteristic, however, seems to be a generalised departure from normality, evidenced by a high degree of kurtosis and possibly due to heteroskedasticity. Indeed, with only one exception the Ljung Box Q-statistics detect a significant serial correlation of the square of the time series – a symptom, in this context, of volatility clustering. The apparent homoskedasticity of the second principal component from the analysis of the combined areas (see the statistics in row 6) may be due to a regime shift at the onset of the Argentine crisis reducing the power of the test. The homogeneity hypothesis is rejected if we filter away this event with an OLS regression on a dummy variable which takes value 0 up to the date of default of the Argentine debt in January 2002, and subsequently 1.

Table 6. Descriptive Statistics of the Principal Components

		Levels		Squared			
		LB-Q(1) [prob]	*LB-Q(5) [prob]*	*LB-Q(1) [prob]*	*LB-Q(5) [prob]*	*Skew*	*Kurt*
Latin America	PC1	3.08[0.06]	3.84[0.5]	6.50[0.01]	14.0[0.02]	0.09	5.44
	PC2	9.67[0.0]	17.55[0.0]	0.98[0.32]	9.55[0.08]	0.12	10.41
Asia	PC1	28.47 [0.0]	39.02[0.0]	9.62[0.00]	12.6[0.02]	-0.20	5.32
	PC2	3.29[0.07]	13.09[0.0]	13.16[0.0]	30.8[0.00]	-0.32	10.78
Inter-regional	PC1	5.91[0.0]	9.87[0.07]	5.91[0.0]	12.67[0.0]	-0.13	5.04
	PC2	1.35[0.0]	5.44[0.36]	0.35[0.54]	0.37[0.6]	0.11	7.25
	PC3	0.12[0.7]	4.97[0.41]	7.24[0.0]	34.4[0.0]	-0.27	6.22

Impact of the Argentina Crisis on the second PCA in the inter-regional system

Endogenous variable	*Coef. DUMMY*	*Standard Error*	*D.W.*	*(OLS Resid)^2* LB-Q(1)*	*LB-Q(5)*
PC2	2.06	0.70	2.15	7.12[0.0]	19.01[0.0]

Notes. *pre-crisis period; LB-Q(j): Ljung Box Q statistics for jth order serial correlation

Univariate GARCH(1,1) models are used to parameterise the conditional volatilities of the principal components. The quality of fit of the estimates set out in table 7, panel a, is satisfactory; the coefficients are significant and the standardized residuals are serially uncorrelated, showing no evidence of residual arch.[xv] Symmetric models analogous to the system (9)-(9') above seem to capture the conditional variance behaviour of the two Latin American components (see rows 1 and 2).

The conditional mean estimates of equation (9) are not given in the table for lack of space. Large β coefficient estimates (and hence large $\alpha+\beta$ sums) indicate that shocks to the conditional variances take a long time to die out.

Following Lamoureux and Lastrapes (1990), we attribute this result to a shift in volatility brought about, here, by the joint effect of September 11 and the Argentine crisis.

Volatility persistence is less evident in the GARCH estimates of the conditional variances of the Asian spreads set out in rows 3 and 4. The volatility of the first principal component reacts asymmetrically to news and is here parameterised with the TGARCH(1,1) model (equations (9) and (9”) above).

Table 7. Univariate GARCH and EWMA analysis

$$s_{jt}^2 = w + au_{jt-1}^2 + b s_{jt-1}^2 \qquad (9')$$

$$s_{jt}^2 = w + au_{jt-1}^2 + b s_{jt-1}^2 + gS_{t-1}u_{jt-1}^2 \qquad (9'')$$

$$s_{jt}^2 = l u_{jt-1}^2 + (1 - l) s_{jt-1}^2 \qquad (10)$$

Panel a		*GARCH Variance equation*					***J-B***	***LB-Q(1) [prob]***	
		w	*a*	*b*	*g*	Dummy		***St. Res***	***St.Res²***
Latin America	PC1	0.02 (0.02)	0.04 (0.02)	0.95 (0.03)			124.2	2.65[0.1]	3.09[0.07]
	PC2	0.01 (0.01)	0.09 (0.03)	0.91 (0.04)			297.2	0.15[0.7]	0.03[0.9]
Asia	PC1	0.29 (0.09)	0.09 (0.04)	0.74 (0.05)	0.09 (0.06)		59.9	0.06[0.7]	0.1[0.7]
	PC2	0.13 (0.06)	0.22 (0.09)	0.65 (0.10)			436.9	0.37[0.5]	0.00[0.9]
Inter-regional	PC1	0.25 (0.15)	0.07 (0.04)	0.84 (0.07)	0.03 (0.06)		108.8	0.00[0.9]	0.92[0.3]
	PC2	0.24 (0.08)	0.13 (0.03)	0.59 (0.11)		0.51 (0.18)	135.9	2.32[0.1]	0.40[0.5]
	PC3	0.06 (0.02)	0.18 (0.03)	0.77 (0.04)			87.8	0.13[0.7]	0.81[0.04]

Panel b		*EWMA variance equation*	***J-B***	***LB-Q(1) [prob]***	
		l		***St.Res***	***St.Res²***
Latin America	PC1	0.021 (0.004)	133.5	2.84[0.1]	6.48[0.0]
	PC2	0.060 (0.005)	336.1	10.51[0.0]	0.39[0.5]
Asia	PC1	0.179 (0.004)	14675	18.08[0.0]	0.01[0.9]
	PC2	0.252 (0.003)	78586	15.58[0.0]	0.12[0.7]
Inter-regional	PC1	0.039 (0.006)	243.7	5.21[0.0]	7.91[0.0]
	PC2	0.013 (0.003)	291.5	1.43[0.2]	1.00[0.3]
	PC3	0.095 (0.008)	104.5	1.13[0.3]	0.33[0.6]

Notes: J-B Jacque-Bera test statistics; LB- Q(j): Ljung Box Q statistics for jth order serial correlation

In the two-area estimation (Latin America plus Asia) set out in rows 5 to 7 the conditional variance of the first principal component is quantified by a TGARCH(1,1) and the conditional variances of the remaining two principal components by symmetric GARCH(1,1) models. In the variance estimates of the second principal component a dummy for the Argentine crisis has appreciable explanatory power.

The conditional variance analysis of the principal components is completed using the EWMA approach. The model estimates (equations (9) and (10)) are set out in panel b of table 7. The size of the smoothing constant λ suggests that, here too, volatility persistence is more severe in Latin America. The quality of fit is, on the whole, less satisfactory than with the corresponding GARCH estimates; standardised residuals are serially correlated in four cases out of seven and heteroskedastic in another two cases. The decline in the quality of the estimates is probably due to the implicit I-GARCH restrictions that are imposed with the EWMA parameterisation – restrictions that fail to capture the mean reverting nature of the principal components.[xvi]

The conditional variance-covariance matrix of spread differences is computed with the orthogonal procedures discussed in section 1. For each area, the loadings obtained with the first stage principal components analysis set out in table 4 are denormalised and combined with the diagonal matrix of the conditional variances of the corresponding principal components according to equation (8). It should be noted that we are estimating here the conditional covariation of spread differences in response to international information (such as the Argentine crisis) that affects the conditional variation of the first 2 (or 3) principal components. In this sense the effect of the idiosyncratic local news is filtered away with the principal components which are discarded from the analysis.[xvii]

Figures 2, 3, and 4 show 10 by 10 conditional variance-covariance estimates of the two-area system obtained using both the O-GARCH and the O-EWMA procedures. The 55 graphs depict the evolution over time of 10 conditional variance and 45 conditional covariance time series. The O-EWMA approach plays here a subordinate role and is used to assess the relative accuracy of the corresponding O-GARCH estimates. It relies on conditional variance estimates that are less sensitive to outliers but tend to simplify the dynamics of volatility.

The conditional variances and covariances of the Latin American spread differences are set out in figure 2. Besides the powerful, generalized impact of the events of September 2001, it is the Argentine crisis which plays the dominant role, exerting a major impact on the volatility of the Brazilian and Mexican spreads and a smaller one on the Chilean and Venezuelan spreads. The marked and lasting increase of Argentinean, Brazilian and Mexican spread conditional covariation in the first months of 2002 can be seen as a symptom of (pure) contagion in the Calvo and Reinhart sense (1996). The divergence in the macroeconomic conditions of these countries contradicts the hypothesis of a spread covariation based on economic fundamentals.

Chilean and Venezuelan covariances behave differently. They do peak at the onset of the Argentine crisis of December 2001, but then decline rapidly and return to their pre-crisis levels by the end of the following month.

In figure 4 the Asiatic conditional variances, with the notable exception of the Philippines, are smaller in absolute value. They shift in reaction to extra area events, such as the Argentine default crisis, and are strongly affected by the shock of September 11. (The cross area interlinkages are investigated below.) As for the Philippines, we find evidence of idiosyncratic behaviour as compared with the other countries of the area. The covariances between the Philippine and Malaysian and Singaporean spreads are negative and further decrease over the last months of the sample, while those with the Chinese and Korean spreads, if mostly positive, are very small in absolute value. This relative isolation probably reflects the joint effect of a huge foreign debt outstanding and hefty claims by U.S. banks – financial features that the Philippines share more with the Latin American than with the Asian countries in the sample (the "common creditor" effect).

The cross area covariances of figure 3 provide information on the timing of contagion phenomena that could not be found in the correlation and principal components analysis above.

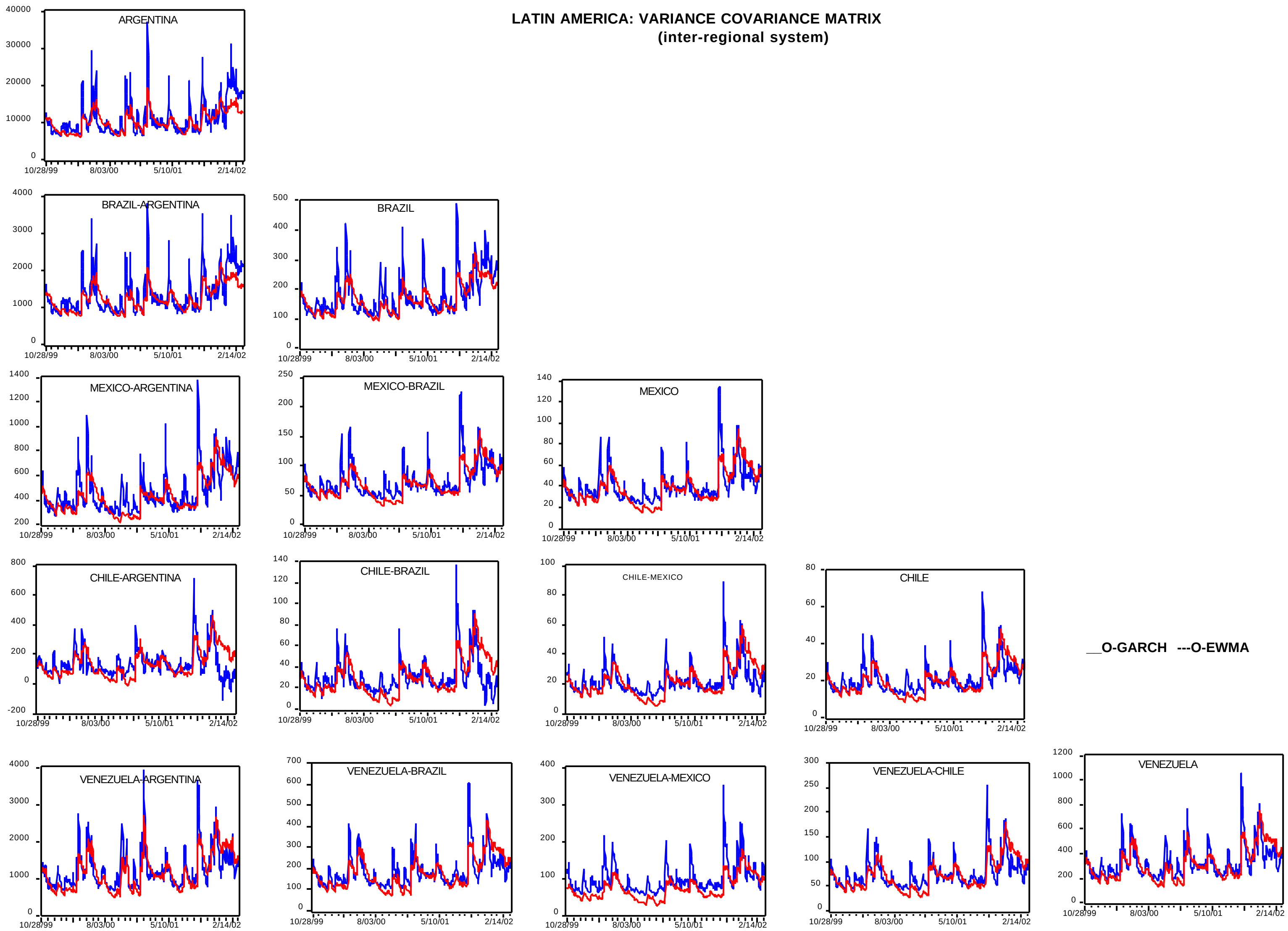

LATIN AMERICA: VARIANCE COVARIANCE MATRIX
(inter-regional system)
ARGENTINA
BRAZIL-ARGENTINA
BRAZIL
MEXICO-ARGENTINA
MEXICO-BRAZIL
MEXICO
CHILE-ARGENTINA
CHILE-BRAZIL
CHILE-MEXICO
CHILE
__O-GARCH ---O-EWMA
VENEZUELA-ARGENTINA
VENEZUELA-BRAZIL
VENEZUELA-MEXICO
VENEZUELA-CHILE
VENEZUELA
10/28/99
8/03/00
5/10/01
2/14/02

Figure 2.

CROSS-AREA COVARIANCES
(inter-regional system, _O-GARCH -- O-EWMA)

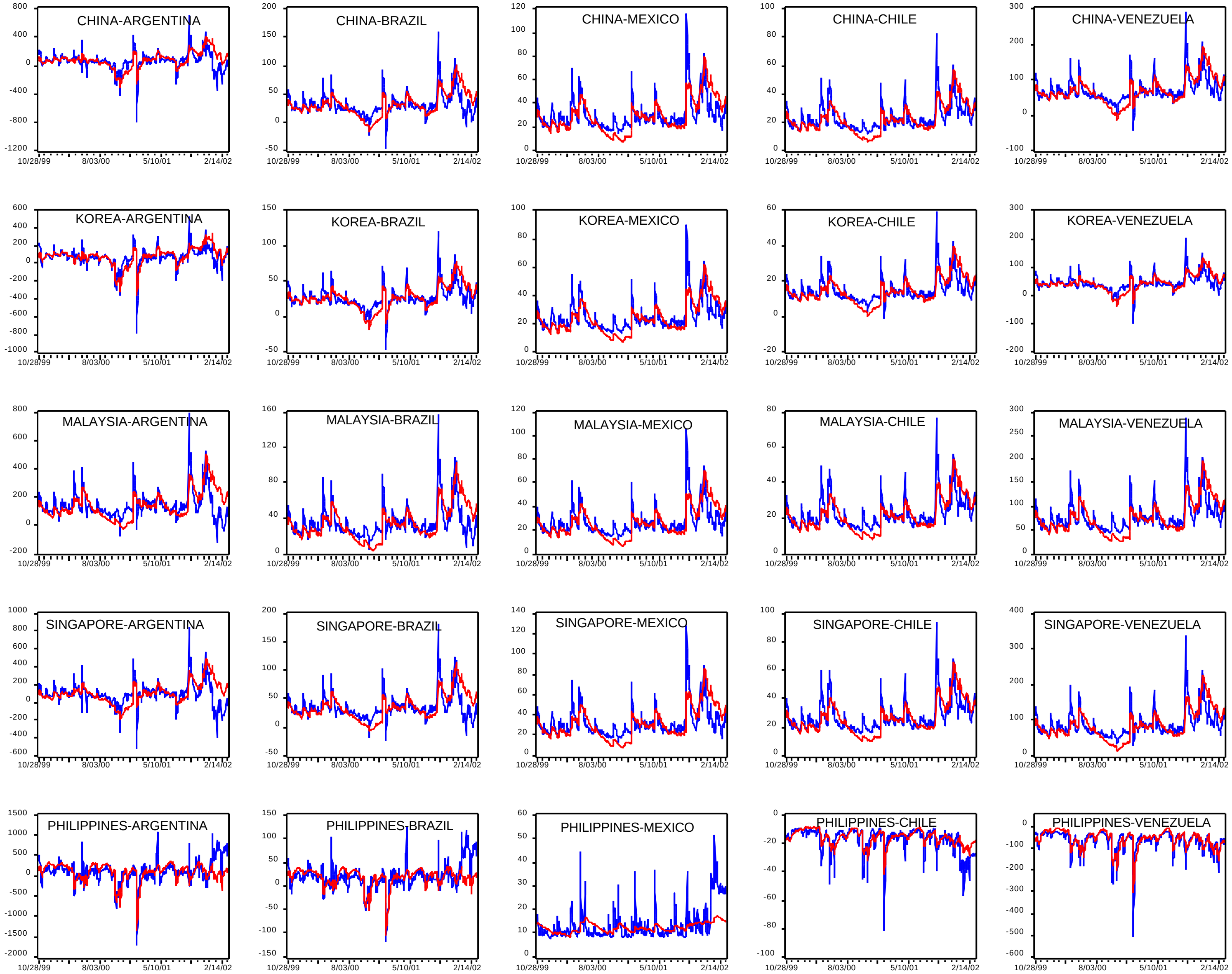
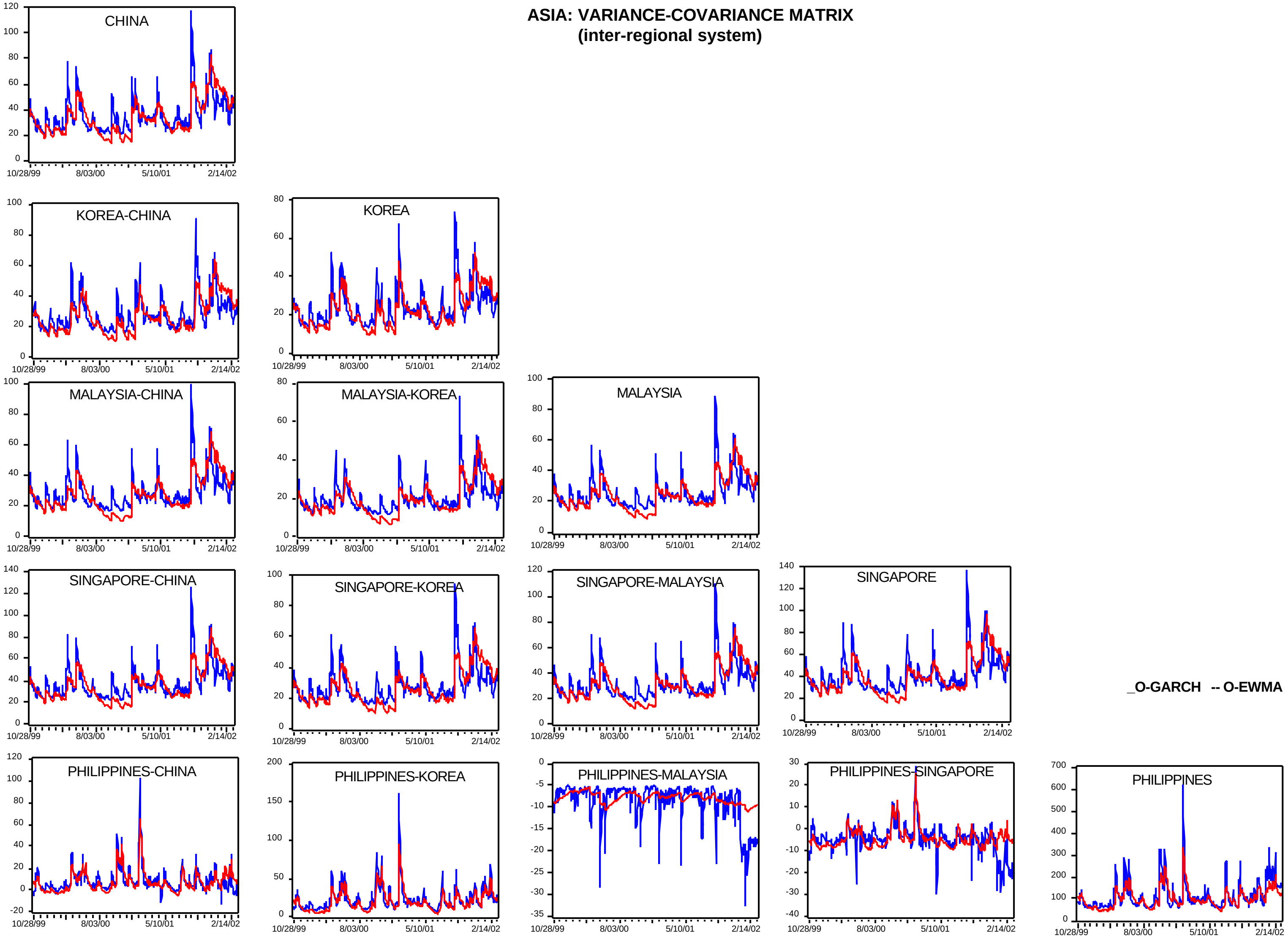


Figure 3.



ASIA: VARIANCE-COVARIANCE MATRIX
(inter-regional system)
CHINA
KOREA-CHINA
KOREA
MALAYSIA-CHINA
MALAYSIA-KOREA
MALAYSIA
SINGAPORE-CHINA
SINGAPORE-KOREA
SINGAPORE-MALAYSIA
SINGAPORE
PHILIPPINES-CHINA
PHILIPPINES-KOREA
PHILIPPINES-MALAYSIA
PHILIPPINES-SINGAPORE
PHILIPPINES
_O-GARCH -- O-EWMA
10/28/99
8/03/00
5/10/01
2/14/02

Figure 4.

September 11 2001 operates like a watershed; prior to that date the recurrent runs on Argentinean bonds and the subsequent surges in spread volatility affect mostly Latin American spreads as if some kind of (geographical) area segmentation were to hold. Conditional covariances among Latin American and Asian spreads, very small in absolute value, are, in some cases, even negative (e.g. during the February-March 2001 joint crises of Turkey and Argentina). The four months that follow September 11 are characterised by temporary but sharp increases in the variances and covariances of the sample.[xviii] The surge in volatility due to the Argentine default crisis brings about increases in the conditional variances of the Asian spreads along with positive shifts in their conditional covariances with the Latin American spreads, a stylized characteristic of financial contagion. Conditional covariances between spreads on bonds issued in China, South Korea, Singapore and Malaysia, on the one hand, and in the Latin American countries, on the other hand, grow substantially and share common patterns. The conditional covariances among Latin American spreads are larger than those between Latin American and Asian spreads which, in turn, dominate those among the Asian ones. This finding corroborates the hypothesis that some kind of turbulence originating in Latin American financial markets tended to spread to the Asiatic ones.[xix]

At the end of January 2002, the easing of financial conditions results in a generalised decrease in conditional variances and covariances. As pointed out above in section 2, the effects of the Argentine default on emerging bond markets are less persistent than expected. By February 2002 the conditional covariances between the Argentine and Asiatic spread differences become negative, indicating that the respective volatilities, again, follow different paths.

4. Model validation

Conditional variance parameterization is notoriously difficult and prone to specification errors. The problem is compounded, here, by the sheer dimension of the multivariate analysis as major simplifications are introduced in order to ensure computational tractability. Principal components are only unconditionally orthogonal (Engle, 2000) and the assumption of zero unconditional correlations is imposed a priori. At the same time, the number of principal components is small if compared to the number of time series included in each multivariate analysis. These sources of inaccuracy call for a thorough calibration of the models. The approach suggested by Alexander involves a comparison of the O-GARCH estimates with those obtained using alternative FIML multivariate procedures. It cannot be implemented here since, given the large number of time series involved, multivariate GARCH models estimation fails to converge.[xx]

We introduce two alternative procedures. In the first the original spread difference time series, filtered whenever necessary in order to eliminate serial correlation, are divided by the corresponding conditional standard errors provided by the O-GARCH 10 country models and squared. LB Q-tests for serial correlation are then performed using both the standardized and non standardized time series. The test statistics which correspond to the former - set out in columns 3 to 6 of table 8 - are consistently smaller and, in 5 countries out of 10, fail to detect heteroskedasticity. Our conditional variance estimates seem to capture reasonably well the dynamics of the second moments of the spread differences. The tests, repeated using standard errors from each geographical area in isolation, provide similar results and are not reported for lack of space.

A second and more stringent approach is introduced in order to assess the accuracy of the conditional covariation among spread differences. It is based on estimation of a minimum variance (bond) portfolio à la Markowitz using conditional and unconditional estimates of the variance covariance matrix set out in equation (7).

In the heteroskedastic time period under investigation the O-GARCH estimates, if consistent, will provide time varying portfolio weights that will outperform - using the portfolio variance minimization criterion - the weights derived from the unconditional variance estimates.[xxi]

Table 8. L B Q-tests for heteroskedasticity

Country	$(D\mathbf{spread})^2$			O-GARCH $(D\mathbf{spread}/\ \hat{s}\ )^2$		
	LB-Q(1) [prob]	***LB-Q(5) [prob]***	***LB-Q(10) [prob]***	***LB-Q(1) [prob]***	***LB-Q(5) [prob]***	***LB-Q(10) [prob]***
Argentina	0.02 [0.87]	25.31 [0.00]	31.36 [0.00]	0.18 [0.67]	12.67 [0.03]	14.52 [0.15]
Brazil	8.39 [0.00]	30.42 [0.00]	53.84 [0.00]	2.97 [0.08]	8.75 [0.11]	33.23 [0.00]
Mexico	2.83 [0.09]	10.64 [0.06]	12.71 [0.24]	5.62 [0.02]	10.16 [0.07]	12.62 [0.24]
Chile	4.90 [0.03]	20.03 [0.00]	23.31 [0.01]	2.20 [0.14]	21.57 [0.00]	22.31 [0.01]
Venezuela	22.97 [0.00]	83.69 [0.00]	88.61 [0.00]	16.92 [0.00]	54.64 [0.00]	57.24 [0.00]
China	7.22 [0.01]	12.00 [0.03]	21.73 [0.02]	0.01 [0.91]	0.55 [0.99]	14.92 [0.13]
South Korea	6.05 [0.01]	9.14 [0.10]	13.01 [0.22]	0.21 [0.64]	0.92 [0.96]	1.35 [0.99]
Malaysia	29.30 [0.00]	41.47 [0.00]	50.26 [0.00]	7.75 [0.00]	10.76 [0.06]	18.70 [0.04]
Singapore	19.22 [0.00]	22.76 [0.00]	25.73 [0.00]	16.28 [0.00]	18.72 [0.00]	21.09 [0.02]
Philippines	4.83 [0.03]	33.48 [0.00]	34.81 [0.00]	1.26 [0.25]	22.76 [0.00]	23.44 [0.01]

Notes. LB- Q(x): Ljung Box Q-test for xth order serial correlation.

Minimum variance portfolios are computed with Latin American, Asiatic and combined areas spread differences. Conditional estimates correspond to a policy of daily portfolio rebalancing: new weights are computed each trading day using the expected conditional moments provided by the O-GARCH procedures, together with the corresponding minimum portfolio variance. The entries in column 3 of table 9 are the mean values of the latter, computed over the whole sample. Columns 1 and 2 contain the variances of the optimum portfolios with no rebalancing obtained, respectively, with the unconditional variance covariance estimates of the spreads and with the unconditional estimates of the PCA variance covariance matrix (7).

The 9 portfolios seem to be successful in reducing volatility risk as their variances are much smaller than those of the single spread differences.

Similarly, the variances of the inter area (10 asset) portfolios are consistently smaller than those of the Latin American and Asiatic 5 asset ones. In spite of cross area contagion a policy of diversification with assets from a different geographical area reduces portfolio risk. The PCA procedure produces portfolio with smaller variances. The figures in square brackets of columns 2 and 3 indicate a substantial risk reduction as compared with the corresponding estimates of column 1. The improvement is more appreciable with the O-GARCH procedure. The latter seems to be more efficient in the selection of optimum portfolio weights in all cases.

Table 9. Portfolio Variance Analysis

Country	*Unconditional Variances*	*Unconditional Variances PCA*	*O-GARCH Approach*
Cross Area Portfolio	46.04	19.48[57%]	19.24[58%]
Latin America Portfolio	41.47	28.23[31%]	28.14[32%]
Asian Portfolio	37.41*	33.70[10%]	28.55[24%]
Argentina	2217.50		
Brazil	312.48		
Mexico	77.27		
Chile	63.20		
Venezuela	549.92		
China	64.41		
South Korea	43.27		
Malaysia	43.51		
Singapore	75.32		
Philippines	162.13		

*excluding the Philippines

On the whole the results of this section fail to identify significant distortions in the conditional covariance matrix estimates set out above, in spite of their complexity.

5. Conclusion

The purpose of this paper is to investigate volatility co-movements of daily spreads on sovereign emerging bonds. Research is carried out both within and across geographical areas, integrating robust variance covariance matrix estimation with the multivariate conditional variance parameterization based on Principal Components Analysis. The dynamics of spread co-movements are analysed using conditional estimates of the variance covariance matrix, obtained from orthogonal methods (O-GARCH and O-EWMA).

With this approach we are able to filter away idiosyncratic factors and focus on common factors alone. Thus empirical analysis addresses the issue of contagion identified by an increase in the market volatility of common drivers.

The intra-regional analysis detects signs of contagion in Latin America, where - in most cases - the increase in volatility has long-lasting effects. In Asia, shifts in spread covariation, brought about by Argentine and other extra area shocks, tend to be less persistent as a result of some sort of geographical segmentation.

At the inter-regional level, conditional covariances seem to increase in the turbulent period which followed September 11 2001, pointing to some kind of temporary contagion originating in Latin American financial markets and affecting the Asian ones. Indeed, covariances between the common factors of Asiatic and Argentinean spread differences move from positive to negative territory in the Argentine post crisis period – evidence of a de-coupling in the spread volatility dynamics.

Estimation of minimum variance portfolios, used here as a model validation technique, shows that our empirical analysis has important implications for international portfolio management. In spite of systemic risk, international portfolio diversification is still a powerful strategy for risk reduction.

Bibliography

Alexander, C., Leigh, C.T., 1997. On the Covariance Matrices used in Value-at-Risk Models, Journal of Derivatives 4, 50-62.

Alexander, C., 2001. Market Models, A Guide to Financial Data Analysis, John Wiley & Sons, Sussex.

Arora, V., Cerisola, M., 2000. How Does U.S. Monetary Policy Influence Economic Conditions in Emerging Markets?. IMF Working Paper 00/148.

Bollerslev, T., Wooldridge, J.M., 1992. Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances, Econometric Reviews 11, 143-172.

Calvo, G.A., 1998. Varieties of Capital Market Crises, in: Calvo, G., King, M. (Eds.), The Debt Burden and Its Consequences for Monetary Policy, International Economic Association Proceedings, Macmillan, London.

Calvo, G.A., Mendoza, E.G., 1995. Reflections on Mexico's Balance-of-Payments Crisis: A Chronicle of a Death Foretold. mimeo, University of Maryland.

Calvo, G.A., Reinhart, C.M., 1996. Capital Flows to Latin America: Is There Evidence of Contagion Effects, in: Calvo, G., Goldstein, M., Hochreiter, E. (Eds.), Private Capital Flows to Emerging Markets, Institute of International Economics, Washington, available also at http://www.puaf.umd.edu/papers/reinhart.

Calvo, G.A., Mendoza, E.G., 2000. Rational Contagion and the Globalisation of Securities Markets. Journal of International Economics 51, 79-113.

Cantor, R., Packer, F., 1996. Determinants and Impact of Sovereign Credit Ratings. FRBNY, Economic Policy Review, 37-53.

Cline, W.R., Barnes, K.J.S., 1997. Spreads and Risk in Emerging Market Lending. IIF Research Papers n. 97-1.

Corsetti, G., Pericoli, M., Sbracia, M., 2001. Correlation Analysis of Financial Contagion: What One Should Know before Running a Test. Temi di Discussione n. 408, Bank of Italy.

Ding, Z., 1994. Time Series Analysis of Speculative Returns. Ph.D. Dissertation. Dept. of Economics, University of California, San Diego.

Edwards, S., Susmel, R., 2000. Interest Rate Volatility and Contagion in Emerging Markets. Evidence from the 1990s. NBER Working Paper Series n. 7813.

Edwards, S., Susmel, R., 2001. Volatility Dependence and Contagion in Emerging Equity Markets. NBER Working Paper Series n. 8506.

Eichengreen, B., Mody, A., 1998.a. What Explains Changing Spreads on Emerging Market Debt: Fundamentals or Market Sentiment?. NBER Working Paper Series n. 6408.

Engle, R.F., 2000. Dynamic Conditional Correlation – A Simple Class of Multivariate GARCH Models. PDF version available from http://weber.ucsd.edu/~mbacci/engle/cv.html.

Frankel, J., Schmukler, S., Serven, L., 2000. Global Transmission of Interest Rates: Monetary Independence and the Currency Regime. World Bank Working Paper Series n. 2424.

Forbes, K., Rigobon, R., 2002. No Contagion Only Interdependence: Measuring Stock Market Co-movements. Journal of Finance 57, forthcoming.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, Journal of Finance, 48, 1779-1801.

Kamin, S.B., von Kleist, K., 1999. The Evolution and Determination of Emerging Market Credit Spreads in the 1990s. Board of Governors of the Federal Reserve System, International Finance Discussion Papers n. 653.

Kamin, S.B., 2002. Identifying the Role of Moral Hazard in International Financial Markets. International Finance Discussion Papers n.736. Board of Governors of the Federal Reserve System.

Kaminsky, G.L., Reinhart, C.M., 1999. The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. American Economic-Review 89, 473-500.

Kaminsky, G.L., Reinhart, C.M., 2000. On Crises, Contagion and Confusion. Journal of International Economics 51, 145-168.

Kaminsky, G.L., Schmukler, S., 2001. Emerging Market Instability: Do Sovereign Ratings Affect Country Risk and Stock Returns? World Bank Working Paper n. 2678.

King, M.A., Wadhwani, S., 1990. Transmission of Volatility between Stock Markets. Review of Financial Studies 3, 5-33.

Kodres, L.E., Pritsker, M., 2002. A Rational Expectations Model of Financial Contagion. Journal of Finance 57, 768-799.

Lamoureux, C.G., Lastrapes, W.D., 1990. Persistence in Variance, Structural Change, and the GARCH Model. Journal of Business and Economic Statistics 8, 225-234.

Lin, W.L., Engle, R.F., Ito, T., 1994. Do Bulls and Bears Move across Borders? International Transmission of Stock Returns and Volatility. Review of Financial Studies 7, 507-538.

Maronna, R.A., Yohai, V.J., 1995. The Behavior of the Stahel-Donoho Robust Multivariate Estimator. Journal of the American Statistical Association 90, 330-341.

Masson, P., 1998. Contagion: Monsoonal Effects, Spillovers and Jumps between Multiple Equilibria. IMF Working Paper 98/142.

Mauro, P., Sussman, N., Yafeh, Y., 2002. Emerging Market Spreads: Then versus Now. Quarterly Journal of Economics 117, 695-733, forthcoming.

Min, H.G., 1998. Determinants of Emerging Market Bond Spread. Do Economic Fundamentals Matter?. World Bank Working Paper in International Economics n. 1899.

Rocke, D.M., 1996. Robustness Properties of S-Estimators of Multivariate Location and Shape in High Dimension. Annals of Statistics 24, 1327-1345.

Rousseuw, P.J. and Van Driessen, K., 1999. A Fast Algorithm for the Minimum Covariance Determinant Estimator. Technometrics 41, 212-223.

Scherer, K.P., Avellaneda, M., 2000. All for One...One for All?: A Principal Component Analysis of the Latin American Brady Bond Debt from 1994 to 2000. NYU Courant Institute of Mathematical Sciences Working Paper, available on the SSRN network.

Schinasi, G.J., Smith, R.T., 2000. Portfolio Diversification, Leverage, and Financial Contagion. IMF Staff Papers 47, 159-176.

Sy, A.N.R., 2001. Emerging Market Bond Spreads and Sovereign Credit Ratings. Reconciling Market Views with Economic Fundamentals. IMF Working Paper 01/165.

Tsay, R.S., 2002, Analysis of Financial Time Series, John Wiley & Sons, New York.

Valdés, R., 1997. Emerging Markets Contagion: Evidence and Theory. Documento de Trabajo del Banco Central de Chile, March.

Zhang, X.A, 1999, Testing for Moral Hazard in Emerging Market Lending. Institute of International Finance Working Paper n. 99-1.

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[i] Empirical evidence of high sensitivity of local short term developing countries' interest rates to the US 3 month T bill rate, regardless of the exchange rate regime, is also found by Frankel et al. (2000).

[ii] Calvo and Reinhart (1996) and Masson (1998) draw a distinction between fundamentals based contagion, which arises when the infected country is connected to others via trade and/or financial links, and pure contagion (or herding). The latter is due to a shift in market sentiment without links with economic fundamentals. It is associated with self-fulfilling expectations and multiple equilibria.

[iii] Factors which increase the perceived risk of emerging market bonds and raise secondary market spreads may have the opposite effect on primary market spreads if riskier borrowers leave the market and low-risk low-spread borrowers only launch new issues.

[iv] The proportion of variation explained by the ith principal component is λ_i / (trace of Λ) and the proportion explained by the first M principal components is $\sum_{i=1}^{M} \lambda_i$ / (trace of Λ). The trace of the eigenvalue matrix is equal to *N*, the number of variables in the system (it coincides with the trace of the correlation matrix Σ) and the previous ratios become, respectively, λ_i / N and $\sum_{i=1}^{M} \lambda_i / N$.

[v] This section draws upon Alexander (2001).

[vi] *V* will always be positive semi-definite and may not be strictly positive definite if M<N. Strict positive definiteness holds, however, if the principal components representation of the original variables is accurate and the principal components included in the analysis account for a significant proportion of the total variance of the data set.

[vii] Equation (10) is the recursive formulation of the EWMA volatility specification. The exponentially weighted moving average of the squared innovations is formulated as $\sigma_{jt}^2 = \lambda \sum_{i=1}^{\infty} (1-\lambda)^{i-1} u_{t-i}^2$. σ_{jt}^2 will shift immediately after a shock. The effects of the latter will gradually disappear over time at a rate that depends upon the dimension of λ. The initial value of the recursion will be quantified in the estimates below by the unconditional variance of the time series under investigation.

[viii] Brady bonds have been excluded from the data set since the corresponding spreads may fail to reflect the real creditworthiness of the borrower. In a detailed study Kamin and von Kleist (1999) have shown that the presence of a collateral introduces potentially distortive complexity in the pricing mechanism along with higher transaction costs.

[ix] See IMF's "Emerging Market Financing from Capital Markets", May 2001, and "Quarterly Report on the Emerging Market Financing", May 2001.

[x] Eichengreen and Mody (1998.a) attribute the high level of spreads on sovereign bonds issued by Latin American countries to the high level of their external indebtedness.

[xi] Mahalanobis distances corroborate the choice of the robust estimation procedure: the distances based on the classical estimates identify few outliers whereas those based on the MCD covariance estimates reveal a fair number.

[xii] Alternative techniques have been recently set out in order to deal with this problem such as the Donoho-Stahel robust covariance estimator or the M-estimator (discussed respectively in Maronna and Yohai, 1995, and Rocke, 1996). We repeated the estimation with these techniques obtaining analogous results. They were discarded because the first 2 (or 3) principal components obtained with them explained a smaller fraction of the overall data variability than the principal components computed using the correlation matrices obtained with the MCD estimator.

[xiii] The stability of the correlation matrix in the presence of a volatility shift is of relevance for our analysis. We have performed the t-tests of Forbes and Rigobon (2002) and have found that the increase in volatility that follows September 11 does not affect the spread difference correlation matrix.

[xiv] The estimates are not included in the paper for lack of space.

[xv] Standard errors are based on the robust QMLE procedure provided by Bollerslev and Wooldridge (1992) since Jarque-Bera normality test statistics suggest that the standardized residuals be non normal.

[xvi] If, in equation (9') we posit that $a+b=1$, we have an I-GARCH(1,1) model. In this case the unconditional variance is not defined and the term structure of the GARCH forecasts does not converge; an I-GARCH (1,1) is strictly stationary but not (generally) covariance stationary. The EWMA model is an I-GARCH(1,1) model in which it is further assumed that $w=0$ and $a=l$. Since $w=0$, the stationary distribution for s_t^2 in (10) is a degenerate distribution with point mass at zero, u_{jt} and s_t^2 have moments but they are all trivially zero.

[xvii] We focus on variances and covariances since, as pointed out by Corsetti et al. (2001) they are more informative, in periods of turbulence, than correlation coefficients.

[xviii] Whether this phenomenon is due to an overall increase in the risk aversion of portfolio managers after September 11 or, alternatively, to the different nature of the last Argentine shock, far more severe than the previous ones, is beyond the scope of this paper.

[xix] Here too the post September 11 behaviour of Philippine spread covariation is rather anomalous. Positive and persistent with the Argentinean, Brazilian and Mexican spreads, it becomes negative with the Chilean and Venezuelan ones. This result may be due to the relatively weak reaction of the last two spreads to the Argentine crisis, evidenced in the Latin American analysis of figure 2.

[xx] It should be noted, moreover, that both O-GARCH and O-EWMA approaches filter away idiosyncratic news, while standard multivariate GARCH parameterizations do not, which reduces their relevance as validation benchmark.

[xxi] Let the spread difference be a proxy for the emerging market bond excess return in a Markowitz world with no short selling restrictions, no borrowing and no lending. Assume that portfolio composition is determined only on the basis of risk criteria. If $w=(w_1,\dots,w_N)'$ is the Nx1 vector of portfolio weights and the variance covariance matrix of "returns" is given by equation (7), the portfolio variance is then $w'Vw$. The investor is assumed to solve the constrained minimization problem $min_{/w}\ w'Vw\ s.t.\ \sum_{i=1}^{N} w_i = 1.$

The portfolio weights of the minimum variance point on the efficient frontier take the value $w_i^o = p_i \Big/ \sum_{i=1}^{N} p_i$, where p_i is the sum of the elements of the ith column of V^{-1} and $\sum_{i=1}^{N} p_i$ the sum of all the entries of V^{-1}. The variance of the (global) minimum variance portfolio is then $1/\sum_{i=1}^{N} p_i$ .Matrix V is matrix (7) in the text that is the sum of the (conditional) covariance matrix of the spread differences and of the corresponding (conditional) diagonal matrix of the idiosyncratic error terms.