Contagion or Interdependence in Emerging Debt Markets?

Iuliana Ismailescu[a], Hossein Kazemi[b]

[a]Pace University, USA
[b]University of Massachusetts Amherst, USA

This paper examines the evidence of contagion in emerging debt markets during two default episodes: Russia's 1998 and Argentina's 2001. We find evidence supporting the presence of contagion in the form of intra and inter-regional spillover of extreme returns. Contrary to previous studies, however, contagion seems to happen at both tails of the returns distribution. Further, the presence of contagion is not limited to the periods of credit crisis, as it also extends into more tranquil periods. To check the robustness of our results, we apply the correlation approach, which has been used to study contagion in equity and foreign currency markets. Contrary to these studies, our results show that the correlations in credit markets remain relatively stable and do not deviate significantly from their historical levels during periods of crisis. These findings lead us to conclude that there is no contagion in emerging debt markets; only interdependence. The co-movement of emerging debt markets during the crisis periods emanates from these markets' historical interdependence and is not a consequence of crises' contagious effects, as it is the case in stock and foreign exchange markets.

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1. Introduction

With increased globalization and financial market integration, a powerful shock in one market may not remain contained within that market's borders, but rather impact capital markets across the globe. Studies of financial contagion date back to the 1987 U.S. stock market crash. Not until the Asian currency collapse of 1997, however, did contagion become a major research area in international finance. Since then, the behavior of financial markets during turbulent periods has attracted attention.

While previous studies of contagion have focused on stock and foreign exchange markets, recent credit events in the US and Europe have highlighted the importance of credit markets and the potential for contagion in these markets. Historically, emerging markets have relied heavily on debt financing. For example, the net issuance of bonds and loans in emerging markets increased from 55.7 billions of U.S. dollars in 1991 to 350.7 billions in 2005. Over the same period, equity issuance rose from 5.6 billions to 78.1 billions.[1] Given the disproportionate size of emerging debt and equity markets, a negative event in debt markets could have more severe consequences, as it would affect a larger segment of capital markets. Therefore, a closer look at how financial shocks propagate in emerging debt markets should be important to investors and regulators alike. This is where we aim to contribute to the existing literature.

Previous work, focusing mostly on stock and currency markets, has examined contagion as measured by the rise in return correlations from the pre-crisis to the crisis period. Correlations, which weigh small and large returns equally, may, however, hide the cross-border impact of large returns. At times of severe turmoil, extreme negative returns are expected to be especially contagious; panicked investors are unlikely to be able to differentiate among country fundamentals and are more inclined to exit most of their emerging market positions, thereby depressing asset prices.

In order to test this hypothesis, we apply the multinomial logistic model to predict occurrences

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[1] IMF *International Capital Markets*, September 1998, p. 26, and IMF *Global Financial Stability Report*, September 2006, p. 116-119

of extreme returns in one region, given that they occur in the crisis region. After we control for regional and global factors, we find strong evidence for contagion emerging from Europe to both Asia and Latin America during the Russian crisis, and from Latin America to Europe during the Argentine default episode, but week evidence of contagion from Latin America to Asia. Applying the multinomial logistic model to the entire sample period as well as to the entire sample without the crisis episodes, we find, somewhat surprisingly, that contagion in our sample regions is as likely during periods of crisis as it is during tranquil periods. This finding leads us to conclude that increased integration of national financial markets has changed the nature of contagion. Markets react to events in other regions, even when the events are not considered to be extreme. In other words, what is commonly referred to as 'contagion' can be a mere manifestation of co-movement of emerging markets resulting from increased economic integration and exposures to a common set of factors rather than from contagious effects created by the financial crises.

As a robustness check, we employ the entire returns sample and test if there is a significant increase in correlations between the country of the crisis origin and other countries pre- to post-crisis. The results confirm our earlier findings that financial crises are not particularly contagious in emerging debt markets; available evidence points to normal reaction of one market to the arrival of new information, emanating from either domestic or foreign financial markets.

The remaining part of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes the data. Section 4 discusses the methodology and summarizes the empirical results. Section 5 concludes.

2. Literature Review

In recent years, various definitions and methodologies have been proposed to test for the presence of contagion in financial markets. King and Wadhwani (1990), Lee and Kim (1993), Baig and Goldfajn (1999), Forbes and Rigobon (2002), Chakrabarti and Roll (2002), Bekaert et al. (2005), Chiang et al. (2007), among others, define contagion as a significant post-event increase in cross-country linkages. With the exception of Forbes and Rigobon (2002), all other studies report that most national stock markets become more co-integrated after financial crises.

Forbes and Rigobon (2002) argue that increased market correlations during financial crises are caused by volatility shocks, which induce a bias in the correlation coefficients. The adjustment to the correlation coefficient they propose is similar to that advanced by Ronn et al. (2000) and Loretan and English (2000). When the correction is applied, all evidence of contagion in equity markets during the 1987 U.S. market crash, 1994 Mexican peso crisis, and 1997 East Asian crisis disappears. Corsetti et al. (2005), however, show that by imposing the adjustment, tests of contagion become biased in favor of the null of interdependence.

Hamao et al. (1990), Chakrabarti and Roll (2002), Diebold and Yilmaz (2009) measure contagion by spillovers of stock returns volatility across equity markets. Using GARCH and VAR frameworks, they find strong evidence in favor of cross-market volatility spillover and in particular from the crisis country to other economies. Additionally, Diebold and Yilmaz (2009) find evidence of divergent behavior in the dynamics of return spillovers vs. volatility spillovers from the early 1990s to the 2000s.

Eichengreen et al. (1997), Kaminsky and Reinhart (2000), Bae et al. (2003) use probit models to test the likelihood of contagion in one country given that a crisis has already occurred elsewhere. Eichengreen et al. (1997) find that, after controlling for macroeconomic and political fundamentals, a currency crisis elsewhere in the world increases the probability of a domestic speculative attack by eight percent. Kaminsky and Reinhart (2000) argue that the conditional probability of a currency crisis occurring in a given country increases with the number of countries infected elsewhere. Bae et al. (2003) find that contagion in equity markets is predictable and highly influenced by the regional interest rates, exchange rates, and conditional volatilities.

Regardless of the methodology used, tests for contagion in international markets may yield biased results if the data suffer from heteroskedasticity, omitted variables, and simultaneous equation problems. Rigobon (2001) proposes new procedures that provide consistent estimates even in the presence of these problems.

3. Data

We base our study on U.S. dollar-denominated fixed income securities issued by emerging market governments and traded in international markets. Historically, the U.S. dollar has been the primary currency choice of sovereign obligors. U.S. dollar denominated debt issues consistently exceeded 60% of the annual total issues in the second half of the 1990s and early 2000s.[2] Since some of the issues lack enough liquidity to be used directly as the basis of this study, we utilize the JP Morgan's EMBI Global country indexes collected from Datastream. EMBI Global are value-weighted indexes comprised mainly of U.S. dollar-denominated Brady bonds, Eurobonds, and traded loans[3] with a maturity requirement of at least 2 ½ years for initial entry and at least a year to maintain inclusion, a minimum issue size of $500 million, and daily price availability.[4]

In order to maximize the number of indices, the sample starts on May 30, 1997, when Thailand EMBI Global index was created, and ends on April 29, 2004, when the South Korean EMBI Global index was discontinued. This period includes the 1998 Russian crisis and the 2001 Argentine government default. The three regions on which we focus our analysis are East Asia, Eastern Europe, and Latin America. Seventeen emerging markets within these three regions have active bond indices in Datastream during the relevant period: China, Malaysia, the Philippines, South Korea, and Thailand in East Asia; Bulgaria, Croatia, Poland, Russia, and Turkey in Eastern Europe; and Argentina, Brazil, Colombia, Mexico, Panama, Peru, and Venezuela in Latin America.

Table 1
Descriptive statistics for emerging market daily index returns

	Min (%)	Max (%)	Mean (%)	StDev (%)	Skewness	Kurtosis
Asia						
China	-1.912	2.292	0.034	0.327	-0.248	4.796
Malaysia	-7.358	5.150	0.038	0.595	-1.494	35.523
Philippines	-5.223	5.719	0.039	0.622	-0.435	13.962
South Korea	-7.112	4.403	0.034	0.478	-3.348	59.269
Thailand	-16.467	6.138	0.039	0.874	-4.941	97.099
Europe						
Bulgaria	-13.363	9.258	0.057	1.154	-1.738	30.177
Croatia	-8.984	10.374	0.028	0.811	-0.320	56.557
Poland	-5.041	4.117	0.036	0.457	-0.735	17.236
Russia	-26.502	25.165	0.076	2.279	-0.283	31.989
Turkey	-12.304	12.604	0.057	1.062	-0.911	32.894
Latin America						
Argentina	-13.800	9.635	-0.023	1.572	-1.374	16.907
Brazil	-10.784	12.075	0.055	1.402	-0.716	12.233
Colombia	-7.648	5.823	0.044	0.869	-1.468	18.199
Mexico	-6.969	4.113	0.048	0.632	-1.455	21.455
Panama	-9.665	4.516	0.039	0.750	-2.490	33.922
Peru	-10.716	7.469	0.052	1.207	-1.025	11.172
Venezuela	-16.904	7.129	0.054	1.238	-2.330	32.870

[2] IMF *International Capital Markets*, August 2001, and IMF *Global Financial Stability Report*, September 2005

[3] EMBI Global country indexes also include fixed and floating instruments, bonds and loans with embedded options and warrants, callable bonds, but no convertible bonds are eligible for inclusion.

[4] The "daily price availability" requirement may create some sort of survivorship bias by excluding bonds that are in or near default, as these bonds tend to be more illiquid. Given that JP Morgan continued reporting Russia and Argentina's US dollar-denominated bond indexes after both government defaults, however, alleviates some of these concerns.

Table 2
Correlations of daily index returns within regions and across regions

	CHN	MAL	PHL	SKO	THA	BUL	CRO	PLD	RUS	TUR	ARG	BRA	COL	MEX	PAN	PER	VEN
China	1.0000										0.0731	0.0955	0.0076	0.0868	0.0819	0.0778	0.1372
Malaysia	0.4836	1.0000									0.0763	0.1552	0.1087	0.1062	0.1126	0.1389	0.1473
Philippines	0.1021	0.2152	1.0000								0.1240	0.2084	0.1443	0.1909	0.1741	0.2190	0.2518
South Korea	0.3903	0.4149	0.3587	1.0000							0.0994	0.1630	0.0760	0.1573	0.1782	0.1402	0.2293
Thailand	0.2515	0.3259	0.2417	0.6086	1.0000						0.0782	0.1159	0.0494	0.1110	0.1278	0.0996	0.1594
Bulgaria	0.0632	0.1598	0.4679	0.4506	0.3542	1.0000											
Croatia	0.0317	0.0691	0.2298	0.2809	0.1204	0.4177	1.0000										
Poland	0.3326	0.2767	0.3721	0.4770	0.3199	0.5590	0.3481	1.0000									
Russia	0.0360	0.1457	0.3441	0.3067	0.2357	0.5611	0.3315	0.3552	1.0000								
Turkey	0.0856	0.0551	0.3013	0.2338	0.1765	0.2862	0.1757	0.2275	0.1703	1.0000							
Argentina	0.0536	0.1048	0.3347	0.2163	0.1572	0.4088	0.2103	0.2788	0.2929	0.1915	1.0000						
Brazil	0.0088	0.1403	0.4427	0.3292	0.2160	0.5956	0.3288	0.3874	0.4728	0.2683	0.4947	1.0000					
Colombia	0.1009	0.2236	0.3153	0.2988	0.1630	0.4030	0.3691	0.3659	0.2920	0.2082	0.2682	0.4592	1.0000				
Mexico	0.1985	0.3066	0.5005	0.4760	0.3522	0.6730	0.3582	0.5682	0.5080	0.2909	0.4579	0.7200	0.4603	1.0000			
Panama	0.0881	0.1539	0.4237	0.3452	0.3001	0.6183	0.3526	0.4519	0.4817	0.2456	0.3887	0.6071	0.3893	0.6760	1.0000		
Peru	0.0602	0.1617	0.3903	0.3241	0.2341	0.5560	0.2876	0.4099	0.4237	0.2137	0.3652	0.6046	0.4060	0.5931	0.5692	1.0000	
Venezuela	0.0622	0.1363	0.3287	0.2990	0.2060	0.5310	0.2719	0.3417	0.4593	0.1761	0.3684	0.6042	0.3300	0.6063	0.5278	0.5130	1.0000

Notes: The correlations in the upper right corner are between returns of Latin American indices on day *t* and those of Asian indices on day *t*+1.

The data include daily close index levels that are used to compute daily close-to-close returns for the 17 U.S. dollar-denominated bond indices. Table 1 provides descriptive statistics of the dollar-denominated country index returns. Except for Argentina, daily returns were on average positive over the sample period. Volatilities were much higher in Europe and Latin America than in Asia. Non-zero skewness and high kurtosis are indicative of the departure of the emerging market (EM) index returns from the Gaussian distribution.

Table 2 contains correlations between the 17 index returns. Generally, correlations within each region are higher than correlations across regions. The most highly correlated region is Latin America, where the correlation coefficients between Brazil, Panama, Peru, Mexico, and Venezuela are all above 0.50. Across regions, except for the Philippines, Asia displays little correlation with either Europe or Latin America, whereas Bulgaria, Poland and Russia have high correlations with most Latin American countries in the sample. Because of time zone differences, events taking place in Latin America will be reflected in Asian markets with a day lag. Thus, we consider same-day correlations between Latin American countries and Asian countries, as well as correlations between returns in Latin America in day t and Asia in day t+1. Lead-lag correlations are reported in the upper right corner of Table 2. Contemporaneous correlations between Latin American and Asian countries, and those separated by one day are comparable.

4. Methodology and empirical results

4.1. Contagion in extreme returns

In this section, we examine contagion in extreme returns based on a methodology developed by Bae et al. (2003), which measure financial contagion with joint occurrences of large returns. We adopt this technique and use multinomial logistic regressions to predict occurrences of large returns in our sample regions. Using this model, we can predict the probability of having a high number of co-exceedances (simultaneous large returns) in one region given a high number of co-exceedances in another region. We define an exceedance as an extreme return that lies either above the 95th percentile or below the 5th percentile of the index daily returns. In this part of our study we use daily returns of regional bond indices for Asia, Europe, and Latin America, in addition to the 17 country bond indices described in Section 2.

Throughout this section we separately examine the returns in the top and bottom tails of the returns distribution. The number of co-exceedances equals i if i countries in the same region experience high positive (negative) returns on the same day. If no simultaneous extreme returns occur in a day, i = 0. If all seven Latin American countries experience simultaneous high positive (negative) returns in a day, i = 7. Since our sample contains five European and five Asian countries and few days have five simultaneous extreme returns in any region of our sample, we combine the days with four or more co-exceedances, and report five categories for i, from i = 0 for days with no extreme returns, to $i \geq 4$ for days with four or more co-exceedances. The number of days with positive and negative co-exceedances within each region are provided in Table 3.

During the sample period, Asia and Europe experienced approximately the same number of days with four or more positive co-exceedances (9 in Europe and 8 in Asia) or with four or more negative co-exceedances (15 in Asia and 20 in Europe). Given the higher number of Latin American countries in our sample, the number of days with four or more simultaneous extreme returns (both positive and negative) is significantly higher in Latin America than in Europe or Asia. That the number of days in the highest category of negative co-exeedances exceeds that of positive co-exceedances is no surprise given that the period includes two financial crises.

In order to test for contagion resulting from the Russian and Argentine government defaults, we explore the effect of the number of co-exeedances in the crisis region on the number of co-exceedances in the other regions. We define the Russian and Argentine crisis periods as two-year periods centered on August 17, 1998 and November 06, 2001, respectively.[5] Since the two financial crises originated in Europe and Latin America, we look at contagion from Europe to Asia and Latin America during the Russian crisis, and from Latin America to Asia and Europe during the Argentine crisis. Because Asian markets are closed when Latin markets open, we use next day returns for Asian countries to test for contagion from Latin America.

Table 3
Summary statistics of co-exceedances

	Number of days with *i* co-exceedances in the top tails, *i* = 0 to ≥4					Number of days with *i* co-exceedances in the bottom tails, *i* = 0 to ≥4				
	≥4	3	2	1	0	≥4	3	2	1	0
Asia										
China	7	18	20	42	1,453	11	16	23	37	1,462
Malaysia	8	21	29	29	1,453	14	21	26	26	1,462
Philippines	5	10	19	53	1,453	9	11	14	53	1,462
South Korea	8	23	32	24	1,453	15	22	22	28	1,462
Thailand	8	15	26	38	1,453	13	14	25	35	1,462
Total	8	29	63	186	1,453	15	28	55	179	1,462
Europe										
Bulgaria	9	22	31	25	1,432	19	21	28	19	1,463
Croatia	9	12	22	44	1,432	19	12	19	37	1,463
Poland	8	17	16	46	1,432	18	10	13	46	1,463
Russia	8	16	21	42	1,432	19	21	19	28	1,463
Turkey	4	5	12	66	1,432	11	8	11	57	1,463
Total	9	24	51	223	1,432	20	24	45	187	1,463
Latin America										
Argentina	16	9	17	45	1,381	22	5	8	52	1,405
Brazil	24	12	27	24	1,381	37	18	12	20	1,405
Colombia	16	9	28	34	1,381	21	12	16	38	1,405
Mexico	29	12	18	28	1,381	43	14	9	21	1,405
Panama	22	15	20	30	1,381	37	12	13	25	1,405
Peru	22	10	19	36	1,381	33	14	13	27	1,405
Venezuela	27	8	25	27	1,381	31	9	9	38	1,405
Total	32	25	77	224	1,381	45	28	40	221	1,405

Note that contagion may arise internally within the region and not as a spillover from another region. To control for such contagion we include the conditional volatility of the non-crisis region in our analysis, estimated as a GARCH(1,1) process. We expect volatility to be positively correlated with the probability of having a large number of co-exceedances in the region.

Alternatively, contagion may be caused by global factors, rather than by regional crises. In past decades, the T-bill rate has been a sensitive indicator of the global economy. In general, elevated levels of the T-bill rate have been associated with global economic contractions, while significant declines have been linked to periods of global expansion. During the most recent crisis periods, however, we have noticed a decline in T-bill rates caused by the "flight to quality," which may affect the general relationship between the T-bill rate and the global economic expansion. In order to

[5] We consider the Russian crisis to have begun on August 17, 1998 when the Russian government and the Central Bank of Russia announced the gradual devaluation of the ruble, the 90-day repayment suspension on certain foreign loans, and the imminent restructuring of approximately $40 billion of outstanding short term treasury securities. We also select November 06, 2001 as the beginning of the Argentine crisis, when Argentina conducted a second debt swap, exchanging $60 billion of bonds with an average interest rate of 11-12% for extended maturity notes carrying only 7% interest rate. International bond rating agencies considered it an effective default. One month later, Argentina announced it could no longer guarantee payment on foreign debt (Hornbeck, 2002).

control for contagion in emerging debt markets caused by global economic cycles, we add the 90-day T-bill rate (from Datastream) to our analysis. We expect a positive relationship between the T-bill rate and the probability of negative co-exceedances and a negative relationship with the probability of positive co-exceedances.

Existing literature on contagion shows that investors' sentiment has played an increasing role in the cascading effects of financial crises. Consistent with McGuire and Schrijvers (2003) and Remolona et al. (2007), we use VIX as a proxy for the investor's attitude towards global risk.[6] An increase (decline) in the volatility index is assumed to signal a rise in investors' aversion toward (tolerance of) global risk. We expect a positive relationship between VIX and the probability of negative co-exceedances and a negative relationship with the probability of positive co-exceedances.

The logit model is estimated separately for top tails and bottom tails of return distributions. The probability of j co-exceedances on any given day is denoted by P_j, and expressed as:

$$P_j = \exp(\boldsymbol{x}'\boldsymbol{\beta}_j) / [1 + \sum_{k=1}^{K} \exp(\boldsymbol{x}'\boldsymbol{\beta}_k)], \quad j \geq 1 \tag{1}$$

where K is the number of categories, $\boldsymbol{x}'$ is the transpose matrix of covariates, and $\boldsymbol{\beta}_k$ is the matrix of regression parameters associated with the k-th category. The base case, of no simultaneous extreme returns, has the probability:

$$P_0 = 1 / [1 + \sum_{k=1}^{K} \exp(\boldsymbol{x}'\boldsymbol{\beta}_k)] \tag{2}$$

We estimate the multinomial logit model using the maximum likelihood method, which is carried out with Fisher's scoring algorithm. To measure the goodness-of-fit of multinomial logit models we use the pseudo-R^2 of Cragg-Uhler

$$pseudoR^2 = 1 - \left(\frac{L_\omega}{L_\Omega} \right)^{2/n} \tag{3}$$

where L_Ω is the maximum likelihood function for the unrestricted (full) model, L_ω is the maximum likelihood function for the restricted model (when all β's are set to zero), and n is the sample size. The results for contagion from Europe during the Russian crisis are reported in Table 4, whereas those from Latin America during the Argentine crisis in Table 5. In both tables, β_{ij} is the coefficient of the i-th covariate that corresponds to a number of j co-exceedances in the region. β_{0j} are the intercept coefficients, β_{1j} are the parameters of the conditional volatility in the non-crisis region, β_{2j} the coefficients of the number of co-exceedances in the crisis region, β_{3j} the coefficients of the T-bill rate, and β_{4j} the coefficients of VIX, where j = 1, 2, 3, and 4. As mentioned before, the case j = 4 encompasses all days with 4 or more co-exceedances in a region.

As the coefficients in a multinomial logit model are difficult to interpret, we also compute marginal effects of the covariates on the probabilities P_j and their standard deviations at the covariates' unconditional mean values. The marginal effects measure the marginal changes in the response probabilities for any given unit change in the independent covariate.[7] Under each model in Tables 4 and 5, the left column lists the regression estimates and the right column reports the marginal effects.

Consistent with previous work on contagion in extreme returns (see Bae et al., 2003), we find conditional volatility to be a significant cause of intra-regional contagion; as expected, a rise in the regional volatility increases the probability of simultaneous extreme returns, both negative and positive, but the effect diminishes as the number of co-exceedances rises. For example, when we explore contagion from Europe to Asia (Table 4), a one percent rise in the conditional volatility in

[6] VIX is the Chicago Board Options Exchange Volatility Index. It is based on the volatility implied by options contracts on the S&P 500 index and is an estimate of future volatility.

[7] See Greene (2003), pp. 667-675, for a detailed discussion on how to compute the marginal effects and their asymptotic variances.

Asia boosts the probability of one positive extreme return by 0.456 percent, while it increases the probability of three joint positive extreme returns by only 0.008 percent.[8] On the other hand, the effects of the T-bill rate and investor's risk aversion on the probabilities of co-exceedances are inconsistent with our expectations and, in general, are mixed in all regions.

Table 4
Contagion from Europe during the Russian crisis

	Top Tails				Bottom Tails			
	(1)		(2)		(3)		(4)	
	Coeff.	Marginal effects1)	Coeff.	Marginal effects	Coeff.	Marginal effects	Coeff.	Marginal effects
	To Asia		To Latin America		To Asia		To Latin America	
β_{01}(int)	-1.659	-18.019	4.199	0.254	-11.893***	-1.066***	3.558	0.245
β_{02}	-0.204	-0.019	0.355	0.003	-21.668***	-0.330***	-0.142	-0.008
β_{03}	10.558	1.310	-0.352	-0.007	-21.453*	-0.074*	4.671	0.081
β_{04}	19.102	0.009	-5.925	-0.010	-20.045**	-0.106*	-13.989*	-0.102*
β_{11}(shat)	4.339***	45.557***	1.057**	0.059**	0.760	0.068	0.542	0.032
β_{12}	4.205***	8.256**	1.610***	0.053***	1.630	0.025	1.685***	0.031**
β_{13}	6.977***	0.772	1.629**	0.017*	1.078	0.004	1.680***	0.029**
β_{14}	6.178*	0.003	2.372***	0.004	1.914	0.010	1.080	0.007
β_{21}(count)	0.395	3.975*	0.752**	0.043**	0.556**	0.051***	1.639***	0.106***
β_{22}	0.954***	2.042**	0.679**	0.022**	0.392	0.005	1.840***	0.032***
β_{23}	1.126**	0.128	1.265***	0.014**	1.089**	0.004	1.792***	0.029**
β_{24}	2.740**	0.001	2.218***	0.003	1.429***	0.008**	2.846***	0.019**
β_{31}(T-bill)	-0.417	-4.169	-1.616**	-0.093***	1.488**	0.133***	-1.596**	-0.106***
β_{32}	-0.970	-2.065	-1.486**	-0.048**	2.765**	0.042**	-0.800	-0.013
β_{33}	-3.799**	-0.453	-1.249	-0.013	2.476	0.009	-1.891*	-0.032*
β_{34}	-6.996**	-0.003	-0.790	-0.001	2.542	0.013*	1.294	0.010
β_{41}(VIX)	-0.014	-0.135	-0.007	-0.001	0.081	0.007*	0.033	0.002
β_{42}	-0.033	-0.070	0.077	0.003	0.134	0.002*	-0.075	-0.001
β_{43}	-0.081	-0.010	0.008	0.000	0.126	0.000	-0.057	-0.001
β_{44}	-0.019	-0.000	0.023	0.000	0.056	0.000	0.043	0.000
Pseudo-R^2	0.586		0.567		0.617		0.555	

Notes: This table reports the results of the multinomial logit regression model during the Russian crisis. The logit model is estimated separately for the top and bottom tails. The covariates are the conditional volatility of the non-crisis regional index (shat), the number of co-exceedances in Europe (count), the T-bill rate (T-bill), and VIX. The conditional volatilities are estimated as GARCH(1,1) processes. β_{0j} are the intercept coefficients, β_{1j} are the parameters corresponding to shat, β_{2j} the coefficients of count, β_{3j} the coefficients of T-bill, and β_{4j} the coefficients of VIX. Significance at 1, 5, and 10% levels is denoted by ***, **, and *, respectively.

[8] The interpretation we provide for the marginal effects in Table 4 must be read with caution, as we calculate them at the covariates' unconditional means only. Calculating the marginal effects for isolated covariates' values provides an incomplete picture unless the probabilities are linear functions of the covariates. A visual representation of the response probabilities of extreme positive returns to conditional volatility in each region of our sample (not reported) suggests that the relationship between response probabilities and conditional volatility is approximately linear for most volatility values, only to become exponential-like when volatility is in the upper end (about 1.7 percent per day and higher).

Table 5
Contagion from Latin America during the Argentine crisis

	Top Tails				Bottom Tails			
	(1)		(2)		(3)		(4)	
	Coeff.	Marginal effects	Coeff.	Marginal effects	Coeff.	Marginal effects	Coeff.	Marginal effects
	To Asia		To Europe		To Asia		To Europe	
β_{01}(int)	-4.083***	-0.384***	-2.836***	-0.307***	-7.912***	-0.518***	-3.681***	-0.464***
β_{02}	-2.660	-0.018	-8.252***	-0.234***	-8.321***	-0.102**	-8.293***	-0.176***
β_{03}	-9.800***	-0.108***	-8.581**	-0.068**	-7.176**	-0.021	-9.160**	-0.018
β_{04}	-23.072***	-0.039			0.185	0.000	-51.494	-0.000
β_{11}(shat)	5.200*	0.511**	1.212**	0.141**	6.203*	0.401**	0.827	0.110*
β_{12}	-2.891	-0.031	2.569***	0.072***	6.544	0.079	0.656	0.012
β_{13}	2.476	0.022	-0.316	-0.005	26.299***	0.082*	-0.154	-0.001
β_{14}	15.858*	0.026			6.458	0.002	5.257	0.000
β_{21}(count)	0.272	0.025*	0.516***	0.060***	0.517***	0.034***	0.570***	0.073***
β_{22}	1.015***	0.009**	1.046***	0.029***	0.509	0.006*	0.919***	0.019***
β_{23}	0.495	0.005	0.220	0.001	-0.231	-0.001	1.970***	0.004
β_{24}	0.453	0.001			0.072	0.000	10.194	0.000
β_{31}(T-bill)	0.137	0.013*	0.147	0.015	0.503***	0.033***	0.318***	0.040***
β_{32}	0.230	0.002	0.494***	0.014***	0.363	0.004*	0.711***	0.015***
β_{33}	0.349	0.004*	0.674*	0.006**	-0.321	-0.001	1.026**	0.002
β_{34}	0.793*	0.001			-3.271	-0.001	1.036	0.000
β_{41}(VIX)	0.002	-0.000	-0.014	-0.002	0.070**	0.005**	0.008	0.001
β_{42}	-0.088	-0.001	0.049	0.002	0.035	0.000	0.061	0.001
β_{43}	0.135	0.002**	0.077	0.001	-0.177	-0.001	-0.034	-0.000
β_{44}	0.375***	0.001			0.024	0.000	0.120	0.000
Pseudo-R^2	0.653		0.718		0.621		0.690	

Notes: This table reports the results of the multinomial logit regression model during the Argentine crisis. The logit model is estimated separately for the top and bottom tails. The covariates are the conditional volatility of the non-crisis regional index (shat), the number of co-exceedances in Latin America (count), the T-bill rate (T-bill), and VIX. The conditional volatilities are estimated as GARCH(1,1) processes. β_{0j} are the intercept coefficients, β_{1j} are the parameters corresponding to shat, β_{2j} the coefficients of count, β_{3j} the coefficients of T-bill, and β_{4j} the coefficients of VIX. Significance at 1, 5, and 10% levels is denoted by ***, **, and *, respectively.

After controlling for regional and global factors, our findings indicate that the probability of having a large number of co-exceedances in one region is highly influenced by the number of co-exceedances in the crisis region, although the relationship displays a regional pattern. For example, for Asian countries, contagion emanating from Europe during the Russian crisis (Table 4) is stronger than contagion originating in Latin America during the Argentine default episode (Table 5); the probability of having simultaneous extreme returns in Asia increases with the number of co-exceedances in Europe, but is less affected by the number of co-exceedances in Latin America. Alternatively, Europe and Latin America contaminate each other with almost equal intensity.

These findings imply that the effects of the Russian crisis spilled over to both Asia and Latin America, whereas the impact of Argentina’s default was more visible in Europe. Note that some coefficients in Tables 4 and 5 are highly significant, while their associated marginal effects are not. This finding clearly reflects the non-linear relationship between the response probability function and the independent covariates.

The pseudo-R^2s of the models reported in Tables 4 and 5 reveal little difference in how effective our covariates are at explaining contagion for positive returns compared to contagion for negative returns. Also, the p-values of the Wald χ^2 test statistic used to test for symmetry of contagion in extreme returns in both tables (not reported), indicate that contagion is as likely for positive returns as it is for negative returns for all regions considered.[9]

The symmetry of contagion in extreme returns of emerging debt reported in Tables 4 and 5 comes as a surprise. During periods of increased volatility, it is expected that extreme negative returns will be especially contagious, but not positive returns. In light of our finding, we are wondering whether contagion arises only during periods of high volatility, or emerging markets also experience the same degree of contagious effects in more tranquil periods, in which case interdependence would be a better term than contagion.

To answer this question, we rerun the tests in Tables 4 and 5 for the entire sample period from which we eliminate the two crises. The results summarized in Table 6 show that contagion from Europe to Asia and Latin America and from Latin America to Asia and Argentina has the same pattern during the crisis periods as during the tranquil period. This finding suggests that the simultaneous movements of extreme bond returns across regions are not caused by financial crises, but are a permanent feature of emerging debt markets. In short, there is no contagion in emerging debt markets, only interdependence.

Table 6
Contagion during the tranquil period

	From Europe				From Latin America			
	To Asia		To Latin America		To Asia		To Europe	
	Top Tails	Bottom Tails	Top Tails	Bottom Tails	Top Tails	Bottom Tails	Top Tails	Bottom Tails
β_{01}(int)	-3.339***	-4.919***	-2.733***	-3.063***	-3.598***	-5.045***	-2.952***	-4.217***
β_{02}	-2.945	-10.940***	-4.638***	-6.114***	-2.855	-12.984***	-5.844***	-8.810***
β_{03}	-9.278***	3.956	-7.173***	-5.740*	-9.675***	1.322	-10.246*	-25.165***
β_{04}	-0.646	-7.248***	-5.454*	-2.244	-1.072	-7.973***	-4.371	-31.374
β_{11}(shat)	3.462	4.276	2.231***	2.704***	3.573	4.409	3.066***	3.967***
β_{12}	6.660*	14.213***	2.261*	3.676***	7.002*	17.090***	0.235	3.689**
β_{13}	9.320**	-23.877*	3.952**	2.948	9.162**	-18.250	13.910***	11.629***
β_{14}	8.803**	8.387**	2.388	0.856	10.717**	9.022**	0.795	-4.546
β_{21}(count)	0.204	0.984***	0.059	0.593**	0.390**	0.703***	0.612***	0.571***
β_{22}	1.085***	1.256***	0.824***	1.015***	1.000***	1.161***	0.429	1.320***
β_{23}	1.248***	1.485***	1.148***	2.572***	0.608**	0.822***	2.284***	2.541***
β_{24}	1.062**	1.370***	1.301***	2.861***	-0.292	1.083***	1.359*	9.671
β_{31}(T-bill)	0.035	0.030	-0.057	0.012	0.005	0.034	-0.119	-0.269***
β_{32}	0.293	0.124	0.096	-0.092	0.412**	0.071	0.280*	-0.005
β_{33}	-0.043	-0.070	-0.343*	-0.252	0.052	0.009	-0.787	-0.621
β_{34}	0.097	-1.222	0.154	-0.030	0.256	-0.474*	0.584	1.671
β_{41}(VIX)	0.005	0.036	0.010	0.001	0.014	0.043	-0.014	0.031
β_{42}	-0.199	0.080	0.008	0.051	-0.245	0.121	0.074	0.111*
β_{43}	0.080	-0.087	0.078	0.061	0.109	-0.034	-0.281	0.395**
β_{44}	-0.343*	0.101	-0.056	-0.179	-0.349*	0.085	-0.260	-0.413
Pseudo-R^2	0.692	0.644	0.807	0.778	0.691	0.659	0.726	0.691

Notes: This table reports the results of the multinomial logit regression model during the tranquil period. The logit model is estimated separately for the top and bottom tails. The covariates are the conditional volatility of the non-crisis region (shat), the number of co-exceedances in the crisis region (count), the T-bill rate (T-bill) and VIX. The conditional volatilities are estimated as GARCH(1,1) processes. β_{0j} are the intercept coefficients, β_{1j} are the parameters corresponding to the conditional volatilities, β_{2j} the coefficients of the variable count, β_{3j} the coefficients of the T-bill rate, and β_{4j} the coefficients of VIX. Significance at 1, 5, and 10% levels is denoted by ***, **, and *, respectively.

[9] To test the robustness of the results reported in Tables 4 and 5, we also define exceedances as returns that lie two standard deviations away from the (unconditional) sample mean. With this new definition, the response probabilities are much smaller, but results are largely similar to those reported in Tables 4 and 5.

4.2. Robustness check

We perform a robustness check based on the entire returns distribution using the correlation framework. Under the correlation framework, a crisis is contagious if there is a significant increase in correlations between the country of the crisis origin and other countries pre- to post-crisis. Forbes and Rigobon (2002) argue that increased market correlations during financial crises are caused by volatility shocks - which induce a bias in the correlation coefficients, and propose an adjustment to the correlation coefficient. Corsetti et al. (2005), however, show that by imposing the adjustment, existing tests of contagion are biased in favor of the null of interdependence.

In this section we extend the methodology of Chakrabarti and Roll (2002) and calculate the arithmetic average of correlation coefficients of EM bond index returns of each region, and across-regions, before and after crises. We also compute the arithmetic average of the standard deviations of the region's bond index returns. Using these averages we investigate whether correlations and standard deviations of returns vary across periods. First, we consider each region individually and test whether the statistics mentioned above increase from the pre-crisis period to the crisis period. Second, we repeat the test across regions.

Since emerging market bond index returns do not follow a normal distribution (see Table 1), the simplest approach to test for differences in correlations and standard deviations of returns is bootstrapping. The point estimates are the actual differences in correlations and standard deviations either across periods or across regions. To test their statistical significance, we extend the technique used by Chakrabarti and Roll (2002) and bootstrap for the point estimates' confidence intervals.

As the returns of all 17 bond indexes in our sample are autocorrelated of order one, we first model their returns as AR(1) processes, separately for the pre-crisis and crisis periods. Thus, we obtain two sets of residuals, one for the pre-crisis, the other for the crisis period. Resampling for the point estimate involves resampling from the pools of residuals.

For example, suppose that we want to test whether the average correlation of European bond indexes increases from the Russian pre-crisis to the Russian crisis period. In our sample, the Russian pre-crisis period spans 305 days, whereas the Russian crisis period covers 252 days. Thus, we first randomly sample (with replacement) 305 residuals from the pool corresponding to European indexes in the pre-crisis period. We then add them to the bootstrapped values associated with the European bond index returns in the Russian pre-crisis period, calculate the correlation coefficients for each pair of European countries, and compute the average correlation for the resulting ten correlation coefficients. In order to preserve the dynamic specifications of bond indexes during each sub-period, the bootstrapped values are also modeled as AR(1) processes.

We repeat this procedure for the Russian crisis period. In the end, we compute the correlation difference. The random sampling is repeated 10,000 times, generating a sampling distribution for the difference in correlations. This information is used to create 90%, 95% and 99% confidence intervals for the correlation difference. The statistical significance of the actual correlation difference is judged by its position relative to the confidence intervals. Table 7 provides all tests' point estimates and their 95% confidence intervals resulting from bootstrapping. The results for the Russian crisis are reported in the left columns. Those for the Argentine crisis are tabulated in the right columns.

Although not statistically significant, volatilities increase in all sample regions during the Russian crisis period, and decline in half of the regions and pairs of regions during the Argentine default episode. Furthermore, correlations within- and across-regions do not change significantly during either crisis, and do not rise or decline from the pre-crisis to the crisis period. This result differs from earlier works of Baig and Goldfajn (1999), and Chakrabarti and Roll (2002), where Asian currency and stock markets and European stock markets become more correlated during the Asian crisis period than before.

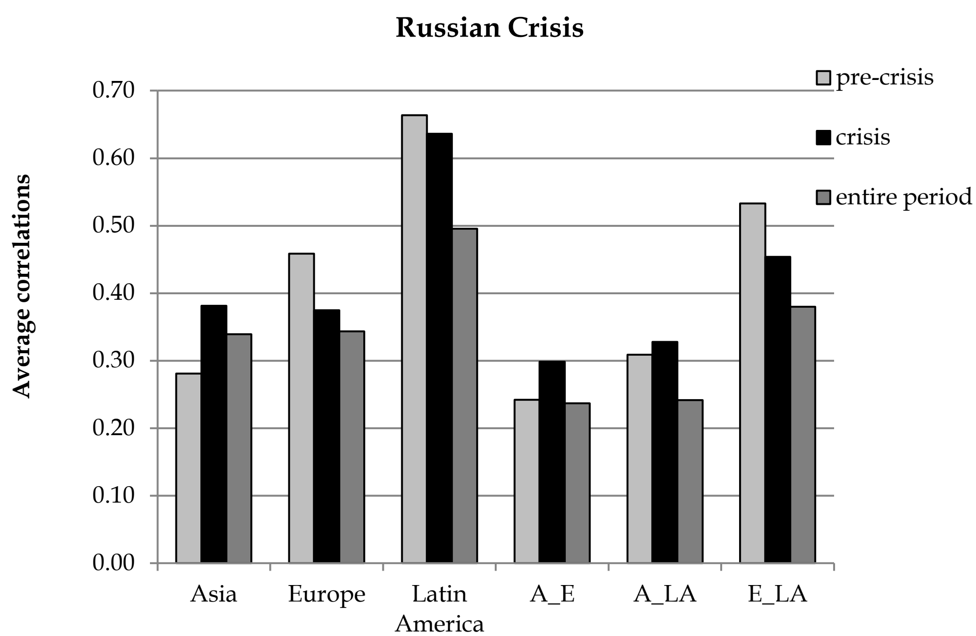
In summary, the above results confirm our earlier findings that financial crises are not contagious in emerging debt markets, which simply react to each other based on their traditional

Table 7
Comparisons of correlations and standard deviations of daily returns across periods

	Russian crisis		Argentine crisis	
	Crisis-Pre-crisis		*Crisis-Pre-crisis*	
	Correlation	Standard Deviation	Correlation	Standard Deviation
Asia	0.100 (-0.094, 0.297)	0.111 (-0.142, 0.360)	0.142 (0.030, 0.254)	-0.039 (-0.104, 0.029)
Europe	-0.084 (-0.253, 0.111)	1.209 (0.836, 1.585)	-0.120 (-0.205, -0.049)	-0.276 (-0.361, -0.192)
Latin America	-0.027 (-0.055, 0.172)	0.984 (0.644, 1.317)	-0.181 (-0.252, -0.110)	0.429 (0.255, 0.592)
Europe&Asia	0.056 (-0.135, 0.235)	0.660 (0.391, 0.934)	0.002 (-0.080, 0.079)	-0.158 (-0.214, -0.099)
Asia&LatAmerica	0.019 (-0.172, 0.174)	0.548 (0.301, 0.801)	-0.029 (-0.143, -0.001)	0.195 (0.103, 0.283)
Europe&LatAmerica	-0.079 (-0.196, 0.084)	1.097 (0.765, 1.417)	-0.146 (-0.251, -0.099)	0.076 (-0.032, 0.176)

Notes: Changes in correlations and standard deviations of daily returns across periods and regions are compared against bootstrapped values. In each cell, the top and bottom numbers are the point estimate and the corresponding 95% confidence interval, respectively. The Russian pre-crisis and crisis periods span from May 30, 1997 through August 16, 1998 and from August 17, 1998 through August 16, 1999, respectively. The Argentine pre-crisis and crisis periods span from August 14, 2000 through November 05, 2001 and from November 06, 2001 through November 05, 2002, respectively. Asian markets are closed when Latin markets open. To assess the influence of Argentine crisis on Asian markets, we considered next day returns for Asian countries.

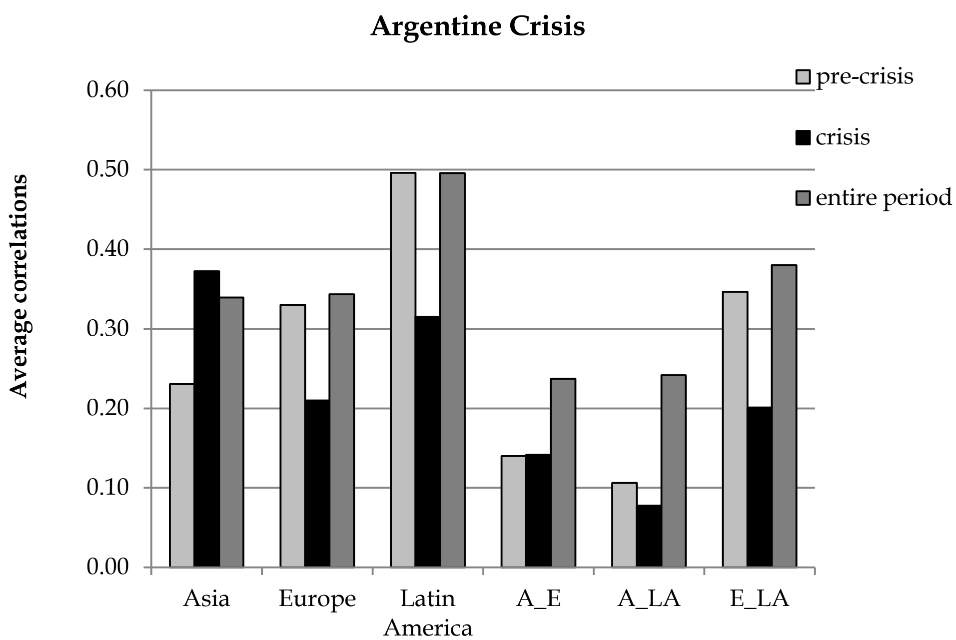
Figure I
Average correlations before and after the Russian crisis vs. the entire period



Notes: A_E, A_LA, and E_LA are the correlations between Asia and Europe, Asia and Latin America, and Europe and Latin America, respectively.

relationships. Figures I and II display the average correlations of the three sample regions and pairs or regions during both crises, as well as during the entire sample period. In most cases these correlations either remain close to their historical levels during both crises or decline slightly with the crisis onset. The simultaneous movement of markets both in tranquil and crisis periods could be explained by common external factors such as global risk premia, changes in U.S. stock and high-yield bond markets (Longstaff et al., 2009; Westphalen, 2001), trade and/or financial linkages (Eichengreen et al., 1997; Glick and Rose, 1999; Kaminsky and Reinhart, 2000) or investor sentiment (McGuire and Schrijvers, 2003).

Figure II
Average correlations before and after the Argentine crisis vs. the entire period



Notes: A_E, A_LA, and E_LA are the correlations between Asia and Europe, Asia and Latin America, and Europe and Latin America, respectively.

The above findings are both good and bad news for the sovereign debt holder. The good news is that correlations do not increase significantly during post-crisis compared to the pre-crisis period; this indicates that investors can count on continued benefits of diversification during crisis periods. This is particularly true for international investors who are exposed to sovereign Asian, European, and Latin American bond markets. The bad news is that these regions, especially Latin American and European debt markets, are highly correlated intra- and inter-region and, consequently, the diversification benefits are limited.

5. Conclusions

While most contagion studies have improved our understanding of the transmission of shocks across foreign exchange and stock markets, few have explored contagion in bond markets. This paper examines the behavior of debt markets during a period that covers two financial crises: the Russian crisis of 1998 and the Argentine crisis of 2000, and searches for evidence of contagion in credit markets of emerging economies during these two crises.

Using a multinomial logistic model, we find evidence supporting the presence of contagion in the form of intra and inter-regional spillover of extreme returns. Contrary to popular beliefs, however, we find evidence supporting the presence of contagion in terms of both extreme positive and negative returns. Additionally, the presence of contagion is not limited to the periods of credit crisis; strong interdependence during the entire sample period covering both crisis and tranquil periods is observed. We find that contagion in emerging European and Latin American debt markets is as likely during periods of crisis as it is during more tranquil periods, leading us to conclude that what we have called contagion in these markets is in fact interdependence.

To examine the robustness of our results, we apply the correlation approach, which has been used to study contagion in equity and foreign currency markets. Contrary to the existing studies, which show a significant increase in correlations among equities and foreign currencies during financial crises, our results show that the correlations in credit markets do not deviate much from their historical levels either in times of crisis or in more tranquil periods. This leads us to conclude that financial crises do not have contagious effects in emerging debt markets, which respond to one another based on their traditional relationships rather than regime shifts.

An important implication of our results to the international investor is that the benefits from international diversification are far smaller for the bond investor than for the stockholder. Previous literature has shown that a negative shock to an emerging country can tighten the linkage between stock returns across countries, confounding investors' ability to diversify their investments. At such times, investors may want to trim their international holdings to limit their risk. In this paper we argue that constant high linkages in debt markets expose the bond investor to even greater risks during both tranquil and crisis periods. Thus, since countries and securities react differently to sovereign shocks, combining stocks and bonds from different emerging markets as well as stocks and bonds from emerging and developed markets could provide significant advantages over equity-only or debt-only portfolios.

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