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Contagion between emerging markets: Evidence from 2007 crisis?

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ABSTRACT

This study examines whether contagion exists between 8 emerging countries and Turkey. The credit default spreads (CDS) of 9 emerging countries are used to test contagion effect around 2007 crisis. The dynamic conditional correlation model results suggest time varying correlation patterns that seem to change significantly following the crisis. When we consider the volatility spillover dynamics, we see that both the extent and direction of volatility transmission changes after the crisis. Both DCC and volatility spillover analyses suggest that there is some form of transmission between the CDS returns of emerging markets, but the extent of the effect differs from one pair of countries to the other. Hence, investors must consider every market on its own right to assess the potential gain from diversification or to optimize hedging activities. Overall the results suggest that emerging economies are immune to global financial conditions and contagion significantly exits between these economies.

Keywords: contagion, CDS, dcc models, volatility spillover

JEL codes: F21, G01, G15

1) Introduction

In the last decades, the frequency of crises in emerging countries and their contagion has drawn worldwide attention. The 'tequila' crisis of 1994, the Asian crisis of 1997, the Russian crisis of 1998, the Turkish and Argentina crisis of 2000-2001, and recently the 2007 financial crisis are examples of episodes of high correlation between emerging financial markets. In each of these crises, emerging countries faced severe market dislocations and their financial architecture has changed noticeably. In addition to domestic challenges, dramatic movements are also seen in the cross-country correlations between emerging markets during these crises. The understanding of comovements between emerging markets is important for both investors and policy makers, especially if the nature of the comovements change around crisis. The potential gains to be achieved by international diversification are mainly determined by the degree of integration of domestic and foreign markets. International portfolio diversification relies mainly on low correlation which enables the investor to reduce total portfolio risk without reducing return. However, recent liberalisation of capital flows and financial globalization has increased the integration of emerging countries and limits the diversification potential for investors. Policy makers also closely watch the comovements in markets and how volatility is transmitted across them in order to formulate appropriate policies to avoid the likely contagion. As we have experienced in the recent crisis such policies may be crucial in limiting the impact of global crisis on local financial markets.

In the literature, a number of studies have empirically examined the pattern of correlations between emerging country stock returns. Relatively recent studies implied that the correlations between emerging market returns may not be constant through time and they tend to rise during periods of crises. The focus of most of the studies in this line of literature was on stock markets. The studies also concentrated on the transmission of shocks between developed countries, from developed to emerging market countries, and to a lesser extent between emerging markets.

This study contributes to the literature in at least three points. First, contrary to general use of stock market or bond market returns, we choose Credit Default Spreads (CDS) to study the cross-country interdependence. The CDS reflects the risk perception of the investors on the country. Therefore, the results of this study are of interest to all global investors that have a portfolio (or plan to form a portfolio) of all kinds of financial instruments issued in that country, and not just to investors in CDS markets. Second, this paper shows how investors' attitude has changed by comparing the cross-country correlations of emerging markets before and after 2007 financial crisis. In that respect, the Dynamic Conditional Correlation (DCC) model is used in order to avoid potential biases arising from high volatility in the sample period. The DCC models carry the flexibility of univariate GARCH models, but they are not as complex as the multivariate GARCH models (Engle, 2002) in that they do not run into the dimensionality problem. Hence, DCC models enable the estimation of large covariance matrices in a less complicated and time efficient manner. Our results show that correlations converge after the 2007 crisis. We find that contagion exists between emerging markets. Third, after concluding that correlation between market returns increases after the crisis, we utilize the Cheung-Ng procedure to test for Granger causality in variance before and after the 2007 crisis. Our results imply that volatility spillover is a process with possible feedback effects and that the degree and the direction of spillover are subject to change around the crisis.

The paper is organized as follows: Section 2 presents the literature review on the correlations between markets during financial crisis periods. Section three describes the data sets and section four presents the methodologies used in the study. Section five discusses the empirical results and section six concludes.

2. Cross-market Correlations

Several studies have empirically examined the cross-market correlations using different data sets and markets and find evidence of contagion. Some of the important previous literature in this area are Longin and Solnik (1995), Baig and Goldfajn (1999), Forbes and Rigobon (2002) and Bekaert, Harvey and Ng (2005).

Longin and Solnik (1995) using a GARCH (1,1) model show that the international market correlations are unstable over the period of 1960-1990. They also find that correlation rises in the periods of high volatility. In a later study, Longin and Solnik (2001) point out that conditional correlation distribution must be correctly assessed in order to test the impact of changing volatility. They argue that conditional correlations are primarily influenced by market trends. Similar results with Longin and Solnik (1995) are reported by Baig and Goldfajn (1999) who test for the significance of the increase in cross-market correlations during East Asian crisis. They find that correlations in currency and sovereign spreads increase significantly during East Asian crisis and they also present evidence of contagion in currency and equity markets. Evidence on regional interdependence of volatility patterns is found in Edwards and Susmel (2001). Using weekly stock return data, they find that the correlations among Latin American markets increase for a short period of time during high volatility periods caused by international crisis. Their results suggest high volatility interdependence between Latin American markets; however, this does not constitute contagion. Forbes and Rigobon (2002) also argue that volatility has an impact on high cross-market correlations. They discussed contagion based on stock market correlations during the 1997 Asian crisis, the 1994 Mexican devaluation, and the 1987 U.S. market crash. They show that there is no increase in unconditional correlation coefficients during these turbulence periods. They discuss that cross-correlations can be overestimated during highly volatile periods and present a method to correct this bias. In their study, they define contagion as a significant increase in cross-market correlations after a shock. According to their definition, although there exists a high correlation between two markets, if the correlation does not increase significantly after the shock, the linkage between two markets will be treated as interdependence and not as contagion.

Bartram and Wang (2005) criticize the method of Forbes and Rigobon and suggest that a correction of unconditional correlation coefficient estimated during high volatility periods may not always be needed in the real world. In addition, they imply that perception of high volatility as a statistical bias will limit the benefits of international diversification. Nevertheless, we use the same definition of contagion and interdependence in our study with Forbes and Rigobon (2002), because this narrow definition enables us to compare before and after crisis periods in a straightforward way.

Bekaert, Harvey and Ng (2005) investigate whether correlations across countries increase in crisis periods. They analyze 22 countries national equity markets selected from developed and emerging markets for the period of 1980-1998 and find significant increases in residual correlation between equity markets in Asian crisis period however they can not find evidence of additional contagion caused during Mexican crisis. These different results in the study imply that the changes in correlation patterns can vary for different crisis scenarios.

In a recent study, Chen, Wang and Tu (2009) investigate the correlated default of Argentina, Brazil, Mexico and Venezuela using daily closing quotes of sovereign credit default swaps. Their main result is that correlations among sample countries increase during Argentina 2001 debt crisis though the evidence of contagion is less significant for Mexico suggesting that credit quality of a country can be a determinant of credit dependence.

3. Data and Methodology

The emerging markets Argentina (ARG), Brazil (BRA), Bulgaria (BUL), Croatia (CRO), Hungary (HUN), Mexico (MEX), Russia (RUS), South Africa (SOA), and Turkey (TUR) are selected to study the cross-country correlations. Contrary to the general use of stock market or bond market returns, Credit Default Spreads (CDS) are used. Credit default swap is the most standard instrument traded in credit derivatives markets. In a credit default swap, the protection buyer pays a periodic fee, expressed as an annualised percentage of the notional value of the transaction, over the life of the transaction; and protection seller agrees to compensate the losses following a credit event of a reference entity. Because of its simplicity and flexibility, this instrument appeals to all types of customers and according to British Bankers' Association's survey, it dominates the credit derivatives market. Therefore, the dynamics of the spreads is a good representative of how global investors view these markets. The study covers a period of nearly 4 years, from January 3, 2006 to September 5, 2009. Credit default swap data of 9 emerging countries are obtained from the Bloomberg history server.

We first investigate the stationarity of the data via the Dickey-Fuller GLS detrended (DF-GLS) and the point optimal (PO) tests by Elliot et al. (1996) and the Z-alpha test by Ng and Perron (2001) (NP). The traditional augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are avoided due to their low power (see Maddala and Kim, 1998). All variables are then transformed into centered logarithmic returns.

Financial data usually contain time dependent variance. Univariate GARCH models solve the problem of stochastic volatility in time series. This presence implies that asset returns are not independently distributed over time. Especially, broad downward movements remind agents about this varying nature of market volatility. In today's globally integrated financial markets, such movements not only provoke changes in volatility but also affect levels of correlations between different countries' assets. In *normal times,* it is expected that countries with similar economic characteristics, have higher correlation and country specific factors determine the risk perception of investors. However in *stressed times*, country specific factors loose their importance and correlation patterns change. This change actually takes the form of correlation peaking. Therefore, in multivariate asset case, in addition to stochastic volatility, correlations between assets are also time-varying.

Due to their highly parameterized characteristics, multivariate GARCH models like VEC, BEKK or diagonal VEC suffer from the curse of dimensionality. Since in these models all of the variance and covariance parameters are estimated simultaneously, researchers are restricted to portfolios with limited number of assets. However, large time-varying covariance matrices play a dominant role in portfolio management. In their paper Engle and Sheppard (2001) introduce a new approach to multivariate GARCH modeling; Dynamic Conditional Correlation (DCC) models. By their own words; "*this class of multivariate GARCH models differs from other specifications in that univariate GARCH models are estimated for each asset series, and then, using the standardized residuals resulting from the first step, a time-varying correlation matrix is estimated using a simple specification*". Therefore with DCC, estimating high dimensional covariance matrices becomes less time consuming and simpler.

In the first step of DCC modeling, univariate GARCH models for centered logarithmic returns of credit default swaps of Brazil, Argentina, Turkey, Croatia, Hungary, South Africa, Mexico, Russia and Bulgaria, under the GJR-GARCH(1,1) specification are estimated. This specification allows for the asymmetric impact of positive and negative shocks to returns on the volatility. GJR-GARCH(1,1) model of Glosten, Jagannathan and Runkle (1993) is represented as follows:

$$r^i_t=\sigma^i_t.z_t \quad (1)$$

$$\sigma^i_t = \alpha^i_0 + \alpha^i_1 (r^i_{t-1})^2 + \delta^i I[r^i_{t-1}<0] (r^i_{t-1})^2 + \beta^i \sigma_{t-1} \quad (2)$$

under the constraints;

$$\alpha^i_1 + \beta^i + ½ \delta^i < 1 \text{ and } \alpha^i_0 >0, \ \alpha^i_1 >0, \ \beta^i \geq 0, \alpha^i_1 + \delta^i \geq 0.$$

where, r^i_t is the logarithmic return of CDS of the country i at time t, where $r^i_t \sim N(0,\sigma^i_t)$ and $\{ z_t \}$ is i.i.d. normally distributed with zero mean and unit variance, I is the identity function, and δ is the leverage parameter, for figuring out the asymmetric effect of the price moves to the volatility.

In the second step, the time varying correlation matrix is calculated. The proposed dynamic correlation structure by Engle and Sheppard (2001) is given below:

$$Q_t = (1- \alpha_1- \beta)S + \alpha_1(\varepsilon_{t-1} \varepsilon'_{t-1}) + \beta Q_{t-1} \quad (3)$$

$$H_t = D^*_t R_t D^*_t \quad (4)$$

where R is the correlation matrix, ε is the standardized residuals from the first stage, S is the unconditional covariance of standardized residuals, and D^* is the diagonal standard deviations matrix from the first stage.

Next we employ the Cheung and Ng (1996) procedure to test for any volatility spillovers among the emerging markets under study. The Cheung-Ng procedure allows the use of univariate GARCH models to estimate the conditional time varying variances and enables to identify the lag at which the causality is observed. The Granger causality in variance test works with the squared standardized residuals ($v_{it} = \varepsilon_{it}^2$) from the GARCH specifications in (1) and (2), where i=1, 2. The cross correlation functions between v_{it} are derived ($\hat{\rho}_{v_1 v_2}(k)$). The test statistic $\sqrt{T}\hat{\rho}_{v_1 v_2}(k)$ (where T is the number of observations) derived from the cross correlations is asymptotically normal.

4. Empirical Results and Discussions

The series that are modeled via GARCH models must be stationary. Therefore, we check the stationarity of the centered logged returns using three different unit root tests. The unit root test results are summarized in Table 1. Note that we divided the time period into two as before and after 2007 crisis and checked the stationarity of the series for both periods and for the full sample.

Table 1. Stationarity check for centered logged returns

	FULL SAMPLE			BEFORE 2007 CRISIS			AFTER 2007 CRISIS		
	DF-GLS	PO	NP	DF-GLS	PO	NP	DF-GLS	PO	NP
	Intercept			Intercept			Intercept		
ARG	-4.422434a (9)	0.140076a (2)	-22.6478a (9)	-4.565562a (3)	0.247144a (0)	-41.4564a (3)	-4.931798a (3)	0.512349a (2)	-37.8116a (3)
BRA	-25.83026a (0)	0.067929a (0)	-472.211a (0)	-16.22767a (0)	0.256580a (0)	-195.354a (0)	-1.496320 (9)	0.432977a (0)	-2.10182 (9)
BUL	-2.871769a (9)	0.203695a (2)	-11.4636b (9)	-0.254774 (6)	1.443988b (0)	3.51323 (3)	-0.969610 (9)	1.546231a (2)	-0.75747 (9)
CRO	-13.99513a (2)	0.060216a (0)	-270.037a (2)	-4.446329a (3)	0.681874a (1)	-25.8060a (3)	-1.355581 (9)	0.472647a (0)	-2.42028 (9)
HUN	-17.18865a (1)	0.067648a (1)	-355.056a (1)	-10.76648a (1)	0.425616a (1)	-139.913a (1)	-2.231322b (6)	0.355378a (0)	-8.22624b (6)
MEX	-25.63975a (0)	0.076904a (0)	-470.988a (0)	-4.728550a (3)	0.419108a (3)	-46.1635a (3)	-19.50301a (0)	0.122581a (0)	-274.363a (0)
RUS	-25.64699a (0)	0.070482a (0)	-470.984a (0)	-16.91910a (0)	0.165067a (0)	-198.017a (0)	-4.717797a (0)	0.214410a (0)	-32.2191a (4)
SOA	-10.91283a (3)	0.059958a (0)	-171.005a (3)	-6.664059a (2)	0.493446a (0)	-82.2600a (2)	-1.442081 (8)	0.573113a (0)	-2.49044 (8)
TUR	-1.683037c (14)	0.134961a (0)	-3.97474 (14)	-1.481462 (6)	0.693155a (0)	-4.69931 (6)	-1.948768b (8)	0.432584a (0)	-4.57205 (8)
	Intercept and trend			Intercept and trend			Intercept and trend		
ARG	-11.91929a (2)	0.446929a (0)	-205.536a (2)	-17.54429a (0)	0.500789a (0)	-146.790a (1)	-8.551269a (2)	0.787160a (2)	-102.375a (2)
BRA	-25.87272a (0)	0.228215a (0)	-472.499a (0)	-16.07530a (0)	0.605189a (0)	-194.180a (0)	-3.163401b (9)	0.541924a (0)	-8.78813 (9)
BUL	-8.703835a (3)	0.525593a (2)	-107.731a (3)	-3.029791b (3)	1.474162a (0)	-16.0653c (3)	-2.498696 (9)	0.795585a (0)	-6.07301 (9)
CRO	-14.56357a (2)	0.196222a (0)	-294.978a (2)	-4.389223a (3)	1.728574a (1)	-25.4697a (3)	-3.952433a (6)	0.560561a (0)	-20.8616b (6)
HUN	-17.91180a (1)	0.244620a (1)	-375.817a (1)	-9.987161a (1)	0.928196a (1)	-122.834a (1)	-6.641254a (3)	0.501110a (0)	-64.6779a (3)
MEX	-25.58761a (0)	0.220325a (0)	-470.449a (0)	-4.969448a (3)	1.500595a (3)	-54.3231a (3)	-19.73243a (0)	0.360067a (0)	-275.468a (0)
RUS	-25.02634a (0)	0.223701a (0)	-466.151a (0)	-16.61727a (0)	0.527797a (0)	-196.656a (0)	-7.836410a (3)	0.396567a (0)	-88.0294a (3)
SOA	-25.31249a (0)	0.210570a (0)	-468.310a (0)	-6.775628a (2)	0.883769a (0)	-76.7739a (2)	-4.796162a (3)	0.651364a (0)	-35.0065a (3)
TUR	-3.207737b (14)	0.312215a (0)	-7.85966 (14)	-7.202089a (1)	0.826861a (0)	-83.6318a (1)	-5.802532a (3)	0.549485a (0)	-49.1063a (3)

Notes: Superscripts a, b, and c represent significance at 1, 5, and 10% respectively

Although there are slightly conflicting test results, overall the stationarity checks indicate that all returns are stationary in levels for all time periods. This is true for return series of all countries. Furthermore, the AR(1) equations exhibit no serial correlations but show significant ARCH effects (not reported here but available upon request). Therefore, we proceed with the GARCH modeling.

GJR-GARCH(1,1) estimation results for the variance equations are given in Table 2 below. Note that all coefficients are significant (except the leverage coefficient for Croatia) and they satisfy the given constraints. A negative δ implies that a decline in the CDS premium of the country has a negative effect on the volatility of that country. It is well known that CDS premium increases with an increase in country's default risk, therefore a decline in CDS premium is a good news and good news have downward effect on volatility. The leverage effect is significant in all countries except Croatia. There are no ARCH effects or severe autocorrelation remaining in the residuals.

Table 2. The GJR-GARCH(1,1) results

$$\sigma^i_t = \alpha^i_0 + \alpha^i_1 (r^i_{t-1})^2 + \delta^i I[r^i_{t-1}<0] (r^i_{t-1})^2 + \beta^i \sigma_{t-1}$$

	ARG	**BRA**	**BUL**	**CRO**	**HUN**	**MEX**	**RUS**	**SOA**	**TUR**
α_0	1,95E-05	1,97E-05	5,69E-06	5,74E-06	1,78E-05	7,65E-06	1,51E-05	2,29E-05	1,40E-05
α_1	0,24053	0,18447	0,12416	0,19608	0,26362	0,20281	0,28407	0,24066	0,13717
δ	-0,13304	-0,15922	-0,05786	-0,01996	-0,04406	-0,17428	-0,15086	-0,11813	-0,09475
β	0,75083	0,84881	0,88925	0,8137	0,74134	0,87491	0,76753	0,7535	0,85445

Notes: All coefficients are significant (at 1% significance level), except the leverage coefficient for Croatia.

Next we compute the dynamic conditional correlations. The dynamic conditional correlations of all countries with Turkey are shown in Figure 1.

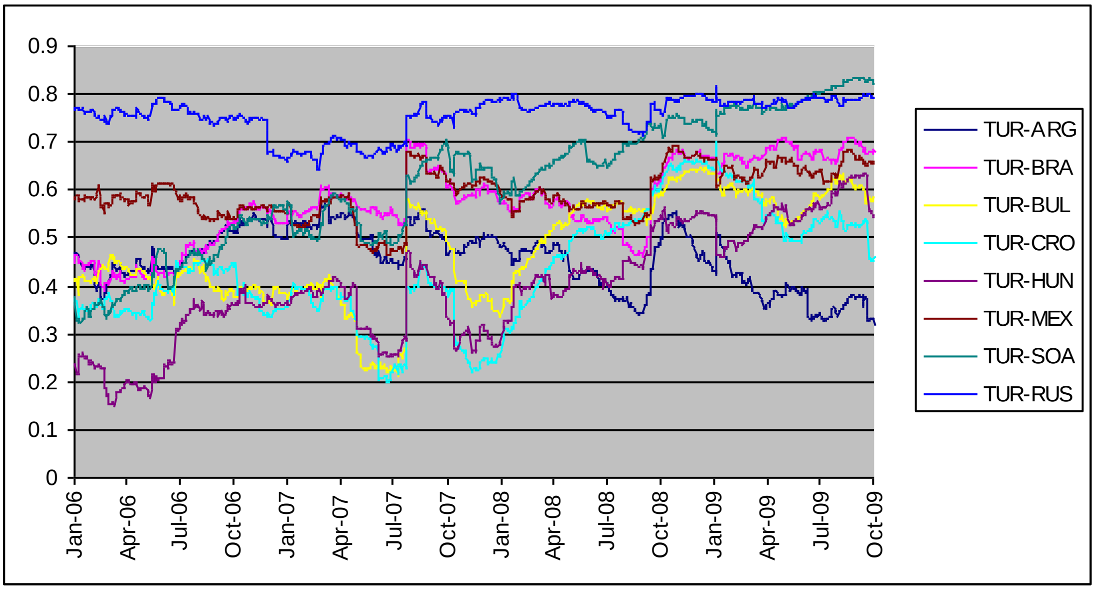

Figure 1. Dynamic conditional correlations between 8 emerging markets with Turkey

The cross correlations between all emerging countries changed significantly in the analysis period. However, as it is seen from the graph, the correlation with Argentina appears to be the least effected from the contagion effects of the 2007 financial crises. For all the data set with the exception of Argentina, an increase in the credit default swap correlations is evident in the 2006-2009 period. Dramatic movements are especially seen in the cross-correlations between emerging markets after Lehman Bothers default in July 2007. Our study shows that cross-correlations between emerging markets increase to very high levels during the crisis periods as compared to the levels before the crises. The depth of the crisis is beyond expectations and the cross-country correlations overshoot in the third quarter of 2007. Until then, the low level of correlations between Turkey and Hungary, Croatia, South Africa, Bulgaria, Brazil, and Mexico prove that investors have differentiated between their investments and local factors are dominating the portfolio selection decision. A sharp increase has been seen in the third quarter of 2007 and the cross-country correlation between emerging markets has risen up. Before September 2007, Turkey's correlation with other 7 emerging countries has an average of 50 percent within the range of 30-70 percent. After September 2007, average correlation between Turkey and other emerging countries has increased to 60. It can be seen from the Figure 1 that the minimum correlation level has reached to 40 percent after September 2007 and the range has narrowed considerably. As a result of this correlation overshooting right after the financial crisis, the international diversification opportunity has decreased significantly. Between January 2006 and October 2009, average cross-country correlations have always been positive. The minimum correlation is 16 percent and is observed between Hungary and Turkey before the crisis. The maximum level is 83 percent and is observed between Turkey and South Africa after the crisis. South Africa is a good example of showing the drastic change in the cross-country correlations. In the first quarter of 2006, the correlation between South Africa and Turkey has an average of 35 percent.

The DCC results also suggest that the transmission of shocks between the markets differ after the crisis. To examine whether the dynamics of the volatility spillover changed around the crisis we conduct Granger causality in variance analyses for the two sub-periods as well as the full sample. The summary results for the full sample, before the crisis period, and after the crisis period are reported in Tables 3 through 5, respectively. Note that there is significant bidirectional contemporaneous spillover between all pairs of countries, but we only report the Granger causality effects here. The contemporaneous link is broken only for the Argentina-Hungary pair.

Table 3. Full sample Granger causality in variance test results

	ARG	BRA	BUL	CRO	HUN	MEX	RUS	SOA	TUR
ARG	-	1.7361[c] (4)	2.3868[b] (1) 2.1972[b] (2) 1.8878[c] (4)	1.9114[b] (2)	No	2.1963[b] (2)	4.1820[a] (1) 2.9436[a] (4)	3.6055[a] (4)	2.4099[b] (2) 3.2802[a] (4)
BRA	2.3133[b] (4)	-	2.2862[b] (1)	1.7031[c] (1) 1.9118[c] (2)	No	No	2.1837[b] (4)	2.2203[b] (4)	2.6403[a] (4)
BUL	No	4.6462[a] (6)	-	1.6899[c] (1)	1.8118[c] (2)	5.3099[a] (6)	3.4696[a] (6)	No	2.1551[b] (6)
CRO	2.0325[b] (6)	2.6062[a] (6)	4.2362[a] (1)	-	2.5432[b] (6)	1.8476[c] (2) 4.7099[a] (6)	1.9402[c] (6)	1.8725[c] (4) 2.4277[b] (6)	1.9486[c] (6)
HUN	No	No	1.6868[c] (4)	No	-	No	-1.7770[c] (2)	3.2742[a] (4)	No
MEX	1.8042[c] (4)	2.7221[a] (4)	1.9294[c] (1) 2.2957[b] (4)	2.0370[b] (1)	No	-	2.3580[b] (4)	1.8541[b] (2) 2.3705[b] (4)	3.7011[a] (4)
RUS	2.0436[b] (4)	2.6350[a] (4)	1.9524[c] (4)	No	No	1.8194[c] (4)	-	2.6384[a] (4)	3.1054[a] (4)
SOA	No	2.1226[b] (4)	1.8259[c] (1) 2.1451[b] (4)	3.1289[a] (1)	1.7892[c] (1)	1.8601[b] (4) 3.0888[a] (7)	No	-	2.6311[a] (4)
TUR	No	No	No	No	2.4244[b] (1) 2.4482[b] (2)	No	No	1.9795[b] (4)	-

Notes: The entries are Cheung and Ng (1996) test statistics for the null hypothesis that the row variable does not Granger cause the column variable in variance. The lags by which Granger causality in variance occurs are in parentheses. Superscripts a, b, and c represent significance at 1, 5, and 10% respectively.

Table 4. Before crisis Granger causality in variance test results

	ARG	BRA	BUL	CRO	HUN	MEX	RUS	SOA	TUR
ARG	-	No	No	No	2.1429^{b} (1)	1.6937^{b} (1)	3.1887^{a} (1) 2.0099^{b} (4)	2.3462^{b} (4)	2.6249^{a} (4)
BRA	3.5131^{a} (4)	-	1.7168^{c} (1) 2.1161^{b} (4)	1.8967^{c} (4)	2.1368^{b} (1) 1.7072^{c} (4)	2.1200^{b} (4)	2.3221^{b} (4)	2.6763^{a} (4)	3.2110^{a} (4)
BUL	3.6761^{a} (5)	6.9570^{a} (6)	-	1.6645^{c} (6)	1.9805^{b} (1) 3.0708^{a} (6)	7.5279^{a} (6)	5.93112^{a} (6)	2.3707^{b} (6)	4.4833^{a} (6) -1.7003^{c} (7)
CRO	2.0200^{b} (6)	4.0113^{a} (6)	4.4177^{a} (1)	-	3.0226^{a} (1) 2.7065^{a} (6)	3.6795^{a} (6)	1.7309^{b} (4) - 1.7134^{b} (5) 3.2916^{a} (6)	3.4716^{a} (6)	3.3267^{a} (6)
HUN	No	2.0522^{b} (6)	2.5652^{b} (1)	No	-	1.8283^{c} (6)	2.4751^{b} (6)	No	No
MEX	3.1129^{a} (4)	-2.0714^{b} (1) 3.2239^{a} (4)	2.9367^{a} (1) 2.1971^{b} (4)	2.1138^{b} (1) 1.9367^{c} (4)	1.8466^{c} (1) 2.5222^{b} (4)	-	3.1757^{a} (4) 2.2625^{b} (6)	3.5961^{a} (4) -1.6539^{c} (7)	3.8876^{a} (4)
RUS	2.0268^{b} (4)	1.8119^{c} (2) 2.4068^{b} (4)	No	-1.7442^{b} (7)	No	No	-	1.6759^{c} (1) 2.1348^{b} (4)	2.2473^{b} (4)
SOA	No	No	No	1.6744^{c} (1)	2.0369^{b} (1)	No	No	-	1.7516^{c} (6)
TUR	1.8732^{c} (4)	2.3283^{b} (4) 2.0864^{b} (5)	No	No	1.8535^{c} (1) 1.8703^{c} (2)	1.7887^{c} (5)	2.0492^{b} (4)	1.6643^{c} (1) 3.6109^{a} (4)	-

Notes: The entries are Cheung and Ng (1996) test statistics for the null hypothesis that the row variable does not Granger cause the column variable in variance. The lags by which Granger causality in variance occurs are in parentheses. Superscripts a, b, and c represent significance at 1, 5, and 10% respectively.

Table 5. After crisis Granger causality in variance test results

	ARG	BRA	BUL	CRO	HUN	MEX	RUS	SOA	TUR
ARG	-	No	No	No	2.1429b (1)	1.6937b (1)	3.1887a (1) 2.0099b (4)	2.3462b (4)	2.6249a (4)
BRA	3.5131a (4)	-	1.7168c (1) 2.1161b (4)	1.8967c (4)	2.1368b (1) 1.7072c (4)	2.1200b (4)	2.3221b (4)	2.6763a (4)	3.2110a (4)
BUL	3.6761a (5)	6.9570a (6)	-	1.6645c (6)	1.9805b (1) 3.0708a (6)	7.5279a (6)	5.93112a (6)	2.3707b (6)	4.4833a (6) -1.7003c (7)
CRO	2.0200b (6)	4.0113a (6)	4.4177a (1)	-	3.0226a (1) 2.7065a (6)	3.6795a (6)	1.7309b (4) - 1.7134b (5) 3.2916a (6)	3.4716a (6)	3.3267a (6)
HUN	No	2.0522b (6)	2.5652b (1)	No	-	1.8283c (6)	2.4751b (6)	No	No
MEX	3.1129a (4)	-2.0714b (1) 3.2239a (4)	2.9367a (1) 2.1971b (4)	2.1138b (1) 1.9367c (4)	1.8466c (1) 2.5222b (4)	-	3.1757a (4) 2.2625b (6)	3.5961a (4) - 1.6539c (7)	3.8876a (4)
RUS	2.0268b (4)	1.8119c (2) 2.4068b (4)	No	-1.7442b (7)	No	No	-	1.6759c (1) 2.1348b (4)	2.2473b (4)
SOA	No	No	No	1.6744c (1)	2.0369b (1)	No	No	-	1.7516c (6)
TUR	1.8732c (4)	2.3283b (4) 2.0864b (5)	No	No	1.8535c (1) 1.8703c (2)	1.7887c (5)	2.0492b (4)	1.6643c (1) 3.6109a (4)	-

Notes: The entries are Cheung and Ng (1996) test statistics for the null hypothesis that the row variable does not Granger cause the column variable in variance. The lags by which Granger causality in variance occurs are in parentheses. Superscripts a, b, and c represent significance at 1, 5, and 10% respectively.

Table 3 provides some interesting overall results. First of all, all CDS returns considered in this article either receive or transmit volatility. At first glance it is seen that there is no volatility spillover from Turkey to the three Latin American countries, Bulgaria, and Croatia. However, the Turkish CDS returns are influenced by volatility spillovers from all other countries, except for Hungary. The time dependent variance of Argentina on the other hand seems to Granger cause the variance in all other countries except for Hungary. Mexico also transmits volatility to all other markets except for Hungary. Likewise, there is volatility spillover from all countries (except for Bulgaria) to South Africa, and to Bulgaria (except for Turkey). Secondly, all spillovers are positive with the exception of unidirectional causality from Hungary to Russia; however, the test statistic is barely significant at 10% significance level. Therefore, we can argue that whenever the two markets are linked, the transmission process works in the same direction. That is, an increase in the volatility of CDS spread of one country leads to an increase in the volatility of the CDS spread of the other.

The Cheung-Ng procedure also enables us to examine when the causality occurs. We can examine the timing of the causality and distinguish between the main effects and the feedback effects when there is bidirectional causality. For example, a close look at the results in Table 3 reveals the fact that out of a total number of 63 significant spillovers 28 of them (44.4%) happen on lag 4, 12 (19%) on lag 1, 11 (17.5%) on lag 6, 11 on lag 1 (17.5%), 10 on lag 2 (15.9%). This distribution suggests that investors must take into consideration the timing of a response of one market to a shock in the volatility of another market. As an example for the timing of feedback effects, one can observe that the bidirectional causality between Mexico and Argentina occurs at different lags.

Although there is bidirectional causality in variance between Argentina and Brazil at lag 4. Causality from Argentina to Mexico occurs within 2 days, whereas there seems to be a feedback from Mexico to Argentina on the fourth day. Actually, all significant volatility spillovers to Argentina (except the one from Brazil) may be viewed as feedback effects or as market adjustment mechanism, since Argentina influences them at earlier lags. Furthermore, in 11 cases the volatility spillover from one market to the other one spreads over time. For example, from Argentina to Bulgaria significant spillover is detected for the 1st, 2nd, and the 4th lags.

The comparison of significant volatility spillovers before and after the 2007 crisis from Tables 4 and 5 also reveal interesting results. Upon first sight, it looks like there are more non-Granger causalities ("No" entries) in Table 4 than Table 5. Turkey for example, has an effect on only one country (Hungary) and is affected by 6 countries. After the crisis, there is significant volatility transfer form Turkey to 6 other emerging markets and Turkey is influenced by 7 other markets.

Before the crisis Argentina seems to be a source of volatility transmission without any feedbacks, however after the crisis the volatility in other markets (Brazil, Bulgaria, Croatia, Mexico, Russia, and Turkey) start leading the volatility in Argentina. Overall, Tables 4 and 5 seem to be telling us similar stories for all emerging markets. Therefore, we conclude that there is more volatility transmission after the crisis. This finding is inline with the literature claiming that there is more integration across emerging markets after a crisis.

Regarding the timing of the spillovers, relatively larger economies such as Argentina, Brazil, Mexico, and Russia tend to have an impact on others within 4 lags;

whereas, the impacts of the smaller economies like Bulgaria and Hungary on others exhibit themselves after 4 periods. Within a bi-directional causality framework this suggests that there are feedback effects of volatility spillover. Note that there are two negative test statistics in Table 5 (Mexico to Brazil and Mexico to SOA); however, their impact is offset by larger positive statistics in other periods.

Table 6 categorizes the significant volatility spillover cases as uni- and bi-directional causality for all time periods.

Table 6. Direction of Significant Volatility Transfers

	Before 2007 Crisis		After 2007 Crisis		Full Sample	
	Bidirectional	Unidirectional	Bidirectional	Unidirectional	Bidirectional	Unidirectional
1	Arg-Cro	Arg to Bra	Arg-Mex	Arg to Hun	Arg-Bra	Arg to Bul
2	Bul-Mex	Arg to Bul	Arg-Rus	Arg to SOA	Arg-Cro	Arg to SOA
3	Bul-SOA	Arg to Hun	Arg-Tur	Bra to Arg	Arg-Mex	Arg to Tur
4	Cro-Hun	Arg to Mex	Bra-Bul	Bra to SOA	Arg-Rus	Bra to Tur
5	Cro-Mex	Arg to Rus	Bra-Cro	Bul to Arg	Bra-Bul	Bul to Tur
6	Hun-Tur	Arg to SOA	Bra-Hun	Bul to Rus	Bra-Cro	Cro to Hun
7		Arg to Tur	Bra-Mex	Bul to SOA	Bra-Rus	Cro to Rus
8		Bra to Bul	Bra-Rus	Bul to Tur	Bra-SOA	Cro to Tur
9		Bra to Rus	Bra-Tur	Cro to Arg	Bul-Cro	Hun to Rus
10		Cro to SOA	Bul-Cro	Cro to Hun	Bul-Hun	Mex to Tur
11		Cro to Tur	Bul-Hun	Cro to Tur	Bul-Mex	Rus to SOA
12		Hun to Bul	Bul-Mex	Hun to Rus	Bul-Rus	Rus to Tur
13		Hun to Mex	Cro-Mex	Mex to Rus	Cro-Mex	Tur to Hun
14		Hun to SOA	Cro-Rus	Mex to SOA	Cro-SOA	
15		Mex to Tur	Cro-SOA	Rus to SOA	Hun-SOA	
16		Rus to Bul	Hun-Mex	SOA to Hun	Mex-Rus	
17		Rus to Hun	Mex-Tur	Tur to Hun	Mex-SOA	
18		Rus to SOA	Rus-Tur		SOA-Tur	
19		Rus to Tur	SOA-Tur			
20		SOA to Mex				
21		SOA to Tur				

One interesting observation is that, before the crisis 38 pair wise matching did not produce any significant Granger causality in variance test statistics; whereas, the number of insignificant test statistics declines to 17 in the after crisis period. Furthermore, the number of bi-directional causality has increased from a before crisis number of 6 to an after crisis number of 19. The number of significant variance spillovers increases from a total of 33 (counting bi-directional effects twice) before crisis to a total of 55 after the crisis. These observations suggest that the emerging market credit default spreads contribute more to each others' forecasts after the crisis.

According to table 6, volatility spillover becomes a bi-directional phenomenon for most CDS spreads after the crisis. This, in addition to the different timings of causality, suggests that possible feedback effects must be taken into account in investigating volatility transmissions.

The comparison of the unidirectional volatility spillovers before and after crisis periods shows that the direction of volatility is subject to change for some countries. The before crisis causalities from Argentina to Bulgaria, Hungary to South Africa, Russia to Bulgaria, Russia to Hungary, South Africa to Mexico are all reversed after the crisis. This implies that the financial crisis has altered the risk perceptions of the investors for these economies significantly.

Both DCC and volatility spillover analyses suggest that there is some form of transmission between the CDS returns of emerging markets, but the extent of the effect differs from one pair of countries to the other. Hence, investors must consider every market on its own right to assess the potential gain from diversification or to optimize hedging activities.

5. Conclusions

The question asked in this study is whether the cross-correlations between emerging economies are constant. To answer this question, we use credit default swaps of 9 emerging countries during January 2006 and September 2009. Our point while selecting this time period is to cover 2007 crisis so we can compare the low and high volatility periods. Our results show that emerging economies are immune to global financial conditions and contagion significantly exits between these economies. This fact is especially correct during the turbulence periods as an adverse shock to an emerging country can lead to a reduction in positions in other emerging countries.

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