Asset Markets Contagion During the Global Financial Crisis

Dimitris Kenourgios*
Faculty of Economics, University of Athens, Greece

Apostolos Christopoulos
Faculty of Economics, University of Athens, Greece

Dimitrios Dimitriou
Faculty of Economics, University of Athens, Greece

This study investigates the contagion effects of the 2007–2009 global financial crisis across multiple asset markets and different regions. It uses daily return data of six asset classes: stocks, bonds, commodities, shipping, foreign exchange and real estate. A robust analysis of financial contagion is provided by estimating and comparing asymmetric conditional correlations among asset markets during stable and turmoil periods. Results provide evidence on the existence of a correlated-information channel as a contagion mechanism among the U.S. stocks, real estate, commodities and emerging Brazilian bond index. The findings also support the decoupling of BRIC equity markets from the crisis, the diversification benefits of shipping and foreign exchange value of the U.S. dollar indices, and the existence of a flight to quality mechanism from risky U.S. assets to German bonds. This evidence has important implications for portfolio diversification strategies and the future work of policymakers. (JEL: C32, F30, G15)

Keywords: global financial crisis, asset markets, contagion, asymmetric dynamic conditional correlations.

---

* Dimitris Kenourgios, University of Athens, 5, Stadiou Str., 10562, Athens, Greece. Tel.: +30 210 3689449, Fax: +30 210 3225542, E-mail: dkenourg@econ.uoa.gr.
The authors are grateful to Professor Panayiotis Theodossiou and two anonymous referees for their helpful comments that have significantly improved this manuscript. The authors also wish to acknowledge financial support from the Faculty of Economics, University of Athens through Special Account Research Grant 11105.

(*Multinational Finance Journal*, 2013, vol. 17, no. 1/2, pp. 49–76)

DOI: 10.17578/17-1/2-2

I. Introduction

The recent financial crisis, triggered by the collapse of the U.S. mortgage market in July 2007, spread rapidly into Europe and other regions and has become a global crisis. It has affected both financial systems across the globe and economic activities in virtually all developed and emerging market economies (EMEs). Its magnitude and transmission characterized it as the worst financial crisis since the Great Depression of the 1930s.

There is, apparently, a consensus over the fact that contagion is present during the 2007–09 global financial crisis (GFC, hereafter). However, the extent and intensity of contagion across asset markets around the world, as well as the changes of the dependence structures between U.S. and other financial markets are empirical issues still under investigation. Moreover, some argue that the contagion effect on EMEs has been muted and uneven (supporting the decoupling hypothesis), in part because the use of structured products was much less prevalent. On the other hand, others claim that distant events in the United States can have sharp impacts on EMEs due to the increasing global financial integration.

Generally, financial contagion is defined as an episode in which there is a significant increase in cross-market linkages after a shock occurs in one market (Forbes and Rigobon, 2002; and Kaminsky, Reinhart and Vegh, 2003, among others). There is an extensive literature on financial contagion during several crises occurred within the last three decades (see for example, Meric and Meric, 1997; and Kenourgios, Samitas and Paltalidis, 2011, among others). This literature has focused mainly on contagion effects across markets in different countries. Contagion, however, is possible in virtually any set of asset markets.[1]

This study investigates in a broader framework the existence of the correlated-information channel as a contagion mechanism for the GFC,

1. The contagion literature identifies at least three possible mechanisms by which shocks in one market may spillover into other markets. First, a correlated-information channel, where contagion can be viewed as the transmission of information from more-liquid markets or markets with more rapid price discovery to other markets (Kaminsky, Reinhart and Vegh, 2003, among others). Second, a liquidity channel, through which contagion occurs through a liquidity shock across all markets (Brunnermeier and Pedersen, 2009, and others). Third, a risk-premium channel, through which contagion occurs as negative returns in the distressed market affect subsequent returns in other markets via a time-varying risk premium (Acharya and Pedersen, 2005, and others).

where a shock to one financial market (source of contagion) signals economic news that is directly or indirectly relevant for security prices in other markets. It uses six different asset classes: stocks from several regions (aggregate stock indices for Developed Europe, Developed Pacific, Emerging Europe, Emerging Latin America, Emerging Asia and BRIC), bonds (German ten-year Bund and Brazilian twenty-year bond indices), commodities (S&P Goldman Sachs Commodity Index), shipping (Baltic Dry Index), foreign exchange (Trade Weighted Exchange index-TWEI) and real estate (MSCI Real Estate Investment Trust- REIT index). The U.S. equity market (S&P500) and the U.S. real estate (MSCI REIT) are considered as sources of contagion. The analysis provides a global perspective as it uses aggregate stock and bond market indices from both developed and emerging regions, and representative global indices of commodities, shipping and foreign exchange. Understanding the nature of the time variation in the correlations between different assets has crucial implications for asset allocation and risk management.

Early research on financial contagion used a range of different methodologies, such as cointegration and vector error correction models, models of interdependence, ARCH and GARCH specifications, models of asymmetries and nonlinearities, principle components and spillover models and the correlation breakdown analysis (Dungey et al., 2005). However, since the thought-provoking paper of Forbes and Rigobon (2002), scholars have been using more advanced techniques to avoid the restrictions of the above approaches (a heteroskedasticity problem when measuring correlations, a problem with omitted variables, contagion must involve a dynamic increment in correlation, e.t.c.). These are dynamic conditional correlation-DCC models (Chiang, Jeon and Li, 2007; Kenourgios, Samitas and Paltalidis, 2011), regime switching models (Boyer, Kumagai and Yuan, 2006) and copulas with and without regime-switching (Okimoto, 2008).

To provide a robust analysis of financial contagion, the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello, Engle and Sheppard (2006), who generalized the DCC-GARCH model of Engle (2002), is employed. This process has several advantages over other members of GARCH family models.[2]

---

2. A large body of literature applies several variants of GARCH models to accommodate the possibilities of non-normalities and asymmetries in the variance of returns (see for example, Bekaert, Harvey and Lumsdaine, 2002). However, most of the GARCH family models assume that correlation coefficients are constant over the sample period, while

More specifically, it interprets asymmetries broader than just within the class of GARCH models (does not assume constant correlation coefficients over the sample period), allows for series-specific news impact and smoothing parameters, permits conditional asymmetries in correlation dynamics and accounts for heteroskedasticity directly by estimating correlation coefficients using standardized residuals. Moreover, this specification overcomes the problem with omitted variables (e.g., economic fundamentals, risk perception and preferences, especially in EMEs), while it is well suited to investigate the presence of asymmetric responses in conditional variances and correlations during periods of negative shocks.

This approach is motivated by the standard definition in the literature of contagion as a change in the linkages between markets following a distress event above and beyond what can be explained by fundamentals. To test for the existence of a correlated-information channel as a contagion mechanism, this study examines whether average conditional correlations among markets, and especially between the "crisis" indices returns (U.S. S&P 500 and REIT) and the returns of other market indices, increase during the crisis period. Moreover, we examine the dynamic patterns of correlation changes during the turmoil period by regressing the estimated time-varying conditional correlations with a constant and a "crisis dummy" variable. To identify the crisis period, key financial and economic news events from official data sources are used (Federal Reserve Bank of Saint Louis, 2009; and Bank for International Settlements, 2009). This allows examining directly whether cross-market linkages during the 2007–2009 GFC (crisis period) differed from those during the pre-crisis period (2000–2007). The results indicate the existence of a contagion mechanism among the U.S. stocks, real estate, commodities and emerging Brazilian bond index. The findings also support the decoupling of BRIC equity markets from the developed U.S. and Pacific equity market indices, the diversification benefits of shipping and foreign exchange value of the U.S. dollar indices, and a flight to quality from the U.S. assets (stocks and real estate) to the German Bund.

This study contributes to the literature in the following aspects. First, it sheds new light on the contagion literature by examining the existence of an asymmetric propagation mechanism across global asset markets during the GFC. The AG-DCC GARCH model is well suited to examine

---

their multivariate variants suffer from the curse of dimensionality.

asymmetric conditional correlation dynamics (stronger contagion during negative shocks) and elucidates how vulnerable different asset classes are to global shocks. This approach has not been used before to examine contagion effects among asset markets during the GFC, to the best of our knowledge. Second, this study differs from the existing literature, since it uses an extensive data set of six asset markets. In this broader framework, this study identifies which of the asset markets are more prone to financial contagion. Third, the analysis of contagion of the GFC is also of great importance, given the existing debate on whether the contagion effect on EMEs has been muted and uneven (decoupling hypothesis) or not.

The structure of the paper is organized as follows. Section II presents the literature review and section III provides the methodological issues applied in this study. The data used for the empirical analysis and the crisis period identification are presented in section IV. Section V reports the empirical results. Finally, concluding remarks are stated in section VI.

II. Literature Review

In the literature, it is widely recognized that correlations and linkages among different asset classes evolve over time as macroeconomic conditions change and new information is released (see for example, Brenner, Pasquariello and Subrahmanyam, 2009, among others). The literature on the international impact of the GFC on global asset markets is still developing.

Dungey et al. (2008) propose a model capable of fitting a series of crisis episodes occurred in the 1998–2007 period, uncovering evidence of contagion in all cases, with signs of serious contagion during the Russian and the U.S. subprime crises. Fry, Martin and Tang (2008) confirm the existence of contagion in the context of the U.S. subprime crisis, utilizing Markov switching models. Dooley and Hutchison (2009) provide evidence on the decoupling of emerging markets from early 2007 to summer 2008, while thereafter responded very strongly to the deteriorating situation in the U.S. financial system and real economy. Bekaert et al. (2011) analyze the equity market transmission of the 2007-09 GFC to sector portfolios in 55 countries and support that the crisis did not seem to have spread indiscriminately across countries and economic sectors. Kenourgios and Padhi (2012) focus on both equity and bond markets of emerging economies around the world and provide evidence on the contagion effects of the subprime crisis, the global impact of the Russian default, the regional aspect of the Asian crisis and the isolated nature of the Argentine turmoil. Baur (2012) studies the transmission of shocks from the financial sector to ten non-financial sectors in 25 major developed and emerging stock markets and finds that no country and sector was immune to the adverse effects of the GFC.

Longstaff (2010) provides strong evidence of contagion in financial markets (CDOs, stock market, treasury bonds, corporate bonds), and supports that financial contagion was propagated primarily through liquidity and risk-premium channels, rather than through a correlated-information channel. Aloui, Ben Aossa and Nguyen (2011) find strong evidence of time-varying dependence between each of the BRIC equity markets and the U.S. markets, but the dependency is stronger for commodity-price dependent markets than for finished-product export-oriented markets. Guo, Chen and Huang (2011) provide evidence on contagion among the stock market, real estate market, credit default market, and energy market during the financial crisis period, within a Markov regime-switching VAR framework. Finally, Chan et al. (2011) examine the relationships between returns over different asset classes (U.S. stocks and bonds, oil, gold and real estate) and find a "tranquil" regime characterized by a flight from quality (from gold to stocks), and a "crisis" regime with evidence of contagion between stocks, oil and real estate.

III. Methodology: The AG-DCC Model

Firstly, we specify the returns equation as follows:

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t,\ \ \varepsilon_t \left| \Omega_{t-1} \sim N\left(0, H_t\right)\right. \tag{1}$$

where $r_t = \left[r_{1t}, r_{2t}\right]'$ is a 2 × 1 vector including each returns series and $\varepsilon_t = \left[\varepsilon_{1t}, \varepsilon_{2t}\right]'$ is a 2 × 1 vector of innovations, which has a normal distribution conditional on the information set at time $t-1\left(\Omega_{t-1}\right)$. We include an AR(1) term, following the conventional approach of the DCC framework. Next, the conditional variance-covariance matrix is specified as follows:

$$H_t = E\left[\varepsilon_t, \varepsilon_t'\right] = D_t P_t D_t \tag{2}$$

where P_t is the time-varying conditional correlation matrix and D_t is the diagonal matrix of the conditional standard deviation from univariate GARCH models with $\sqrt{h_{i,t}}$ on the ith diagonal.[3] In this study, the element in D_t is assumed to follow the univariate GARCH (1,1) model as:

$$h_{i,t} = \omega + \alpha_1 h_{i,t-1} + \beta_1 \varepsilon_{i,t-1}^2 \tag{3}$$

where $z_{i,t} = r_{i,t} / \sqrt{h_{i,t}}$ is a random variable with zero mean and unit variance and $h_{i,t}$ is the conditional variance of the returns series. In order to ensure positive and stable conditional variances, the coefficients must satisfy the constraints $a_1 > 0$ and $a_1 + \beta_1 < 1$ (persistence). Furthermore, a random variable $z_{i,t}$ is assumed to have a generalized error distribution.

By obtaining the conditional variances from equation (3), the evolution of the correlation in the standard DCC model (Engle, 2002) is given by:

$$Q_t = (1 - a - b)\bar{P} + a z_{t-1} z_{t-1}' + b Q_{t-1} \tag{4}$$

where $\bar{P} = E[z_t z_t']$ and α and b are scalars such that $\alpha + b < 1$. The model described by equation (4), however, does not allow for asset-specific news and smoothing parameters or asymmetries.

The evolution of the asymmetric generalized DCC (AG – DCC) model (Cappiello, Engle and Sheppard, 2006) is provided by:

$$\begin{aligned} Q_t &= (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) \\ &\quad + A' z_{t-1} z_{t-1}' A + G' n_{t-1} n_{t-1}' G + B' Q_{t-1} B \end{aligned} \tag{5}$$

---

3. Cappiello, Engle and Sheppard (2006) follow an extensive model selection procedure to estimate univariate volatility by fitting univariate GARCH specifications to each of the return series and selecting the best one according to the Bayesian information criterion. The reason for this procedure is to minimize the risk that the univariate models will provide inconsistent correlation estimates. However, Engle and Sheppard (2005) find that the estimation of univariate models has little consequence, and as many univariate models produce relatively similar volatility patterns, the correlations would be relatively insensitive to the model at least within a reasonable class.

where $\bar{P}$ and $\bar{N}$ are the unconditional correlation matrices of z_t and n_t and A, B and G are $k \times k$ parameter matrices. The negative standardized residuals for asymmetric impacts n_t are defined by $n_t = I\left[z_t < 0\right] \otimes z_t$ where I[.] is an indicator function that takes a value of one if the argument is true and zero otherwise, while "⊗" indicates the Hadamard product.

Within the setting provided by the AG-DCC model (equation 5), the time- varying correlation matrix is calculated by the following formula:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{6}$$

where Q_t^* is a diagonal matrix with a square root of the ith diagonal of Q_t on its ith diagonal position.

IV. Data and Crisis Identification

The data set comprises daily closing market indices from various regions and six different asset classes around the world. This study uses six Morgan Stanley Capital International (MSCI) developed and emerging aggregate equity market indices (Developed Europe, Developed Pacific, Emerging Europe, Emerging Latin America, Emerging Asia and BRIC), and the U.S. S&P 500. The other five asset classes are bonds (German ten-year Bund index and Brazilian twenty-year bond index), commodities (S&P Goldman Sachs Commodity Index), shipping (Baltic Dry Index), foreign exchange (Trade Weighted Exchange index) and real estate (MSCI U.S. Real Estate Investment Trust index).[4] Following the conventional methodology, assets returns are calculated as the first difference of the natural log of each price index.

One difficulty in testing for contagion is that there is no a single event to act as a definite catalyst behind the turmoil periods. Compared to other financial crises (e.g., Asian crisis in 1997-98 and internet

4. The TWEI is a weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group of major U.S. trading partners. The MSCI U.S. REIT Index broadly and fairly represents the equity REIT opportunity set with proper investability screens to ensure that the index is investable and replicable. The index represents approximately 85% of the U.S. REIT universe.

bubble crisis in 2001), many researchers determine the crisis length ad-hoc based on major economic and financial events (Forbes and Rigobon, 2002). Other studies use Markov regime switching models to identify the crisis period endogenously (Boyer, Kumagai and Yuan, 2006; and Dungey et al., 2011). On the other hand, other researchers extend models to allow for structural breaks in mean and/or dynamics and choose to include a break on a specific date according to their expectations and inspection of the data (Cappiello, Engle and Sheppard, 2006). It is worth to mention that, in order to define correctly the crisis period, studies on financial contagion are in some degree arbitrary. According to Baur (2012), even studies that avoid discretion in the definition of the crisis period use discretion in the choice of the econometric model to estimate the location of the crisis period in time.

The sample period is from February, 29, 2000 till May, 5, 2009 and is divided as follows: (i) Pre-crisis period: 29/2/2000-31/7/2007; (ii) Post-crisis period: 1/8/2007-5/5/2009. For the specification of the crisis period length, this study is based on key financial and economic news events obtained from official data sources. Specifically, it uses timelines provided by the Federal Reserve Board of St. Louis (2009) and the Bank for International Settlements (BIS, 2009).[5] According to these timelines, the end of July 2007 is considered as the starting date of the crisis. The crisis start is justified by the deterioration of liquidity in the money market during August 2007 following negative announcements by investment banks and leading to central bank intervention. The period that marks the end of this crisis (early 2009) can be characterized by the absence of negative news and a financial market rally (a phase described as “stabilization and tentative signs of recovery”, according to the official timelines).[6]

Table 1 reports the summary statistics for the equity returns. All emerging markets have positive equity mean returns with almost positive skewness and low excess kurtosis over the sampling period, with the exception of BRICs. On the contrary, developed equity market indices display negative mean returns with negative skewness and

---

5. Recently, Baur (2012) uses both key financial/economic events and estimates of excess volatility to identify the GFC period. He finds that estimates of a crisis regime are all located within the crisis period based on economic and financial news events.

6. This length of the crisis period has been used by several studies so far (Dooley and Hutchison, 2009; Bekaert et al., 2011).

TABLE 1. Descriptive Statistics for Stock Markets (2000 – 2009)

	BRIC	DEUR	DPAC	S&P500	EMASIA	EMEUR	EMLAMER
Mean	0.047	–0.019	–0.023	–0.046	0.007	0.037	0.054
Median	0.209	0.047	0.043	0.018	0.109	0.213	0.202
Max.	1.426	1.249	1.763	1.288	2.517	2.333	1.875
Min.	–4.049	–1.018	–1.036	–1.975	–1.718	–2.078	–1.789
St. deviation	2.213	1.676	1.698	1.878	1.982	2.595	2.416
Skewness	–4.443	–0.247	–0.041	–1.248	0.313	0.055	–0.467
Kurtosis	7.927	1.299	1.591	2.223	2.925	1.973	1.617
Jarque-Bera	39386.9	6681.14	11134.9	25116.4	46042.9	18686.4	11648.7
prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table presents descriptive statistics for each of the seven stock market indices' returns. The Jarque–Bera statistic rejects normality at the 1% level for all indices.

TABLE 2. Descriptive Statistics for Asset Markets (2000 – 2009)

	BRAZ	BUND	COMM	REIT	SHIP	TWEI
Mean	0.016	0.010	0.036	0.039	0.013	–0.005
Median	0.038	0.017	0.038	0.077	0.145	–0.005
Max.	2.738	3.285	1.356	1.721	1.802	2.894
Min.	–3.469	–3.850	–1.399	–2.199	–2.786	–3.213
St. deviation	1.688	0.393	1.952	2.663	2.291	0.381
Skewness	–5.585	–0.075	–0.138	–0.099	–1.736	–0.061
Kurtosis	1.990	1.593	9.622	1.529	2.950	1.364
Jarque-Bera	25739.3	11165.8	2933.8	10095.6	47722.4	7567.2
prob.	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table presents descriptive statistics for each of the six asset market indices' returns. The Jarque-Bera statistic rejects normality at the 1% level for all indices.

positive kurtosis, while the U.S. market is the worst equity return performer.

Table 2 provides summary statistics for the other asset markets. Positive mean returns are observed for the two bond indices (Brazil and Germany), as well as for the commodity, real estate and shipping indices, with negative skewness and positive kurtosis. This is not the case for the TWEI, which exhibits negative mean return, confirming the depreciation of the USD against the other foreign currencies due to the financial crisis. Finally, the relevant Jarque-Bera statistics indicate rejection of the normality hypothesis for both equity and other asset markets' returns.

Figure 1 illustrates the evolution of the seven aggregate stock market indices during the period 2000-2009. The figure shows strong co-movements among all emerging equity markets and significant declines in the levels during 2008, while the developed markets exhibit a weaker downturn movement during the crisis period. Figure 2 illustrates the performance of the other asset market indices for the same period. The graph shows a strong downturn co-movement among U.S. REIT, Baltic Dry and S&P GSC indices during 2008, while TWEI and the two bond indices seem to be the least affected or even unaffected by the GFC.

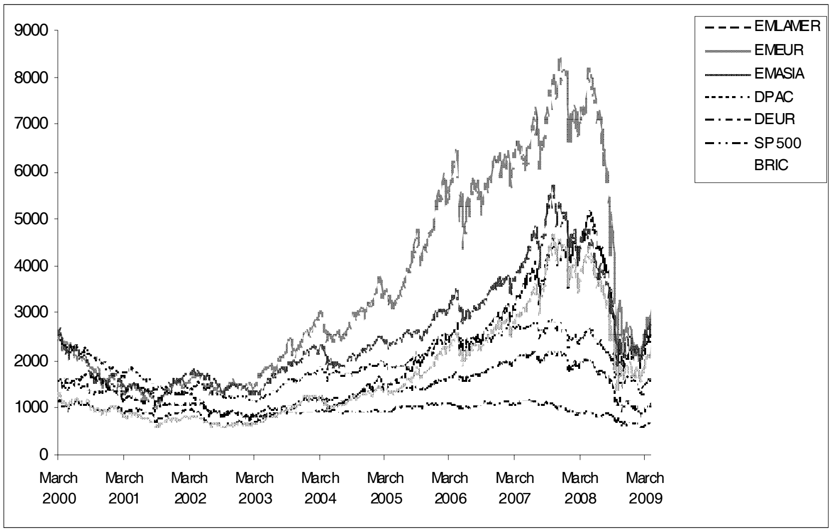

FIGURE 1.— Stock Market Indices 2000-2009

Note: The graph shows the evolution of seven aggregate stock indices during the entire sample period (29/02/2000 - 5/05/2009). The correspondence between regions and stock indices is: EMLAMER: Emerging Latin America; EMEUR: Emerging Europe; EMASIA: Emerging Asia; DPAC: Developed Pacific; DEUR: Developed Europe; SP 500: U.S. S&P 500; BRIC: Brazil, Russia, India and China. The closing prices of EMEUR, EMASIA and BRIC equity indices have been multiplied by 10 in order to have all stock indices expressed in thousand points.

V. Empirical Results

A. Unconditional Average Correlations

Tables 3 and 4 summarize information about the distribution of the unconditional average correlations among the seven stock indices and among all asset markets, respectively, during stable (pre-crisis) and crisis periods. T-test statistics are employed in order to examine whether unconditional correlations are significantly different across the two periods. Specifically, the null hypothesis (H_0) is tested against the one-sided alternative (H_1) that the turmoil unconditional correlations are greater at the 10%, 5% and 1% significance levels.[7]

7. The t-test statistic assumes a Gaussian distribution and is calculated as follows:

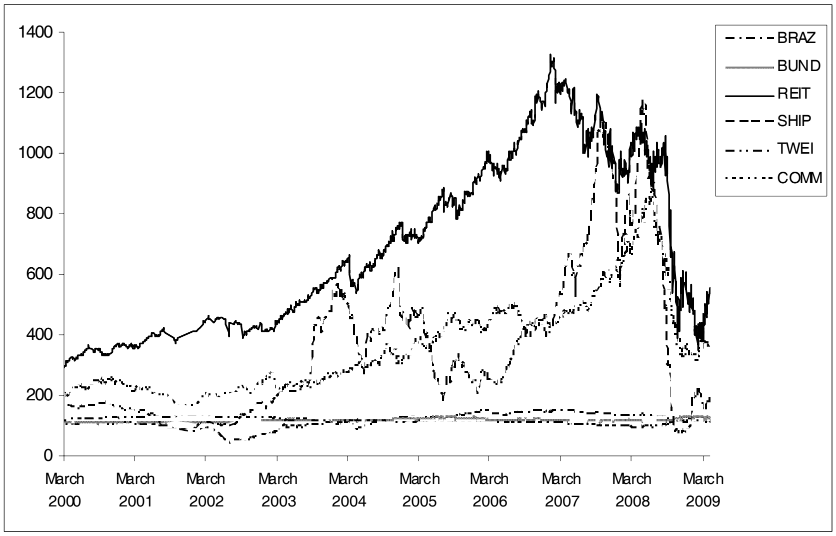

FIGURE 2.— Asset Market Indices 2000-2009

Note: The graph shows the evolution of six aggregate asset indices (2 bond indices, real estate, shipping, foreign exchange and commodities) during the full sample period (29/02/2000 - 5/05/2009). The correspondence between asset classes and indices is: BRAZ: Brazilian twenty-year bond index; BUND: German ten-year Bund index; REIT: MSCI U.S. Real Estate Investment Trust index; SHIP: Baltic Dry Index; TWEI: Trade Weighted Exchange index; COMM: S&P Goldman Sachs Commodity Index. The closing prices of the shipping index have been divided by 10 in order to have all indices expressed in hundred points.

From table 3, the results show an increase in the correlations among developed and emerging markets during the crisis period at different significance levels. However, the pairwise correlations among S&P500 and each of the other equity market indices do not increase during the

$t = \frac{|\bar{X}_A - \bar{X}_B|}{S_{AB}\sqrt{\frac{1}{n_A} + \frac{1}{n_B}}}$, where $\bar{X}_A$ is the average correlation among two markets during the crisis period and $\bar{X}_B$ is their average correlation during the pre-crisis (stable) period, S_{AB} is the pooled estimate of standard deviation of turmoil correlation series (A) and pre-crisis correlation series (B), while n_A and n_B are the number of observations of A and B, respectively. The t–value is compared with critical (theoretical) values of t_{th}, corresponding to the given degree of freedom N (in the present case $N = n_A + n_B - 2$) and the confidence level chosen. If $t > t_{th}$, then H_0 is rejected.

TABLE 3. Unconditional Average Correlations among Equity Returns

Equity market		Crisis period (1/8/2007-5/5/2009)	Stable period (29/2/2000-31/7/2007)	t-stat.
S&P500	DEUR	–0.015	0.249	–3.155
	DPAC	0.004	0.082	–0.815
	EMASIA	0.021	0.115	–1.675
	EMEUR	0.042	0.070	–0.587
	EMLAMER	–0.001	0.149	–2.175
	BRIC	–0.021	0.050	–2.124
DEUR	DPAC	0.508	0.380	6.324***
	EMASIA	0.535	0.442	2.251**
	EMEUR	0.723	0.412	4.124***
	EMLAMER	0.744	0.533	3.019***
	BRIC	0.029	0.003	1.706*
DPAC	EMASIA	0.673	0.439	3.578***
	EMEUR	0.452	0.297	3.412***
	EMLAMER	0.379	0.255	5.165***
	BRIC	–0.049	0.003	–1.741
EMASIA	EMEUR	0.531	0.485	2.286**
	EMLAMER	0.507	0.539	–2.056
	BRIC	0.041	–0.062	1.699*
EMEUR	EMLAMER	0.681	0.534	3.017***
	BRIC	–0.040	–0.056	0.985
EMLAMER	BRIC	–0.003	–0.027	0.914

Note: This table reports unconditional correlations among equity markets during crisis and stable (pre-crisis) periods. To check whether the estimated unconditional correlations are significantly different across the two periods, t-test statistics are employed. The rejection of the null hypothesis against the one-sided alternative that the turmoil correlation is greater, at the 10%, 5%, 1% significance levels, is denoted by *, **, ***, respectively.

crisis period, and in some cases are reversed from positive to negative (–0.021 for S&P500-BRIC, –0.015 for S&P500-DEUR, and –0.001 for S&P500-EMLAMER, during the crisis period). A switch to negative correlation during the crisis period is also observed among the Developed Pacific (DPAC) and BRIC equity market indices (–0.049).

From the estimated unconditional correlations reported in table 4, the correlations across stable and turmoil periods do not increase between the Baltic Dry index (SHIP) and S&P500 (from 0.161 to –0.123) and for the pairs of REIT-SHIP (from 0.082 to –0.098) and S&P500-TWEI (from 0.353 to –0.011). On the other hand, the historical inverse relationship between equities and commodities does work during the crisis period, since a statistically significant increase in

TABLE 4. Unconditional Average Correlations among Asset Markets' Returns

Asset markets		Crisis period (1/8/2007-5/5/2009)	Stable period (29/2/2000-31/7/2007)	t-stat.
REIT	S&P50	0.775	0.349	10.894***
	BRAZ	0.079	–0.063	0.987
	BUND	–0.333	–0.059	–1.697
	COMM	0.212	–0.098	2.189**
	SHIP	–0.098	0.082	–1.731
	TWEI	–0.203	–0.091	–2.297
S&P500	BRAZ	0.121	0.105	2.167**
	BUND	–0.388	–0.389	2.094**
	COMM	0.252	–0.027	1.724*
	SHIP	–0.123	0.161	–1.689
	TWEI	0.011	0.353	–1.701
BRAZ	BUND	0.034	0.057	–1.699
	COMM	0.057	0.036	1.678*
	SHIP	0.046	0.081	–1.712
	TWEI	–0.141	–0.092	–1.700
BUND	COMM	–0.252	–0.017	–2.297
	SHIP	–0.055	–0.214	1.745*
	TWEI	0.131	–0.192	2.189**
COMM	SHIP	–0.003	0.081	–1.724
	TWEI	–0.499	–0.198	–2.194
SHIP	TWEI	–0.064	0.066	–0.784

Note: This table reports unconditional correlations among asset markets during crisis and stable (pre-crisis) periods. To check whether the estimated unconditional correlations are significantly different across the two periods, t-test statistics are employed. The rejection of the null hypothesis against the one-sided alternative that the turmoil correlation is greater, at the 10%, 5%, 1% significance levels, is denoted by *, **, ***, respectively.

correlations is observed between S&P500 (and REIT) and S&P GSCI (COMM). The larger increase in correlations across the stable and turmoil periods is observed for the pairs of REIT-S&P GSCI (from –0.098 to 0.212) and REIT-S&P500 (from 0.349 to 0.775, the largest increase of correlation across the two periods). Finally, correlations among equities (S&P500) and the two bond indices also increase during the crisis period.

B. Estimates of Dynamic Conditional Correlations

Tables 5 and 6 report average conditional correlations among equity

TABLE 5. Estimates of Conditional Average Correlations among Equity Returns

Equity markets		Crisis period (1/8/2007-5/5/2009)	Stable period (29/2/2000-31/7/2007)	t-stat.
S&P500	DEUR	0.054	0.256	–8.654
	DPAC	0.052	0.089	–1.721
	EMASIA	0.091	0.122	–7.894
	EMEUR	0.048	0.079	–1.734
	EMLAMER	0.075	0.168	–6.147
	BRIC	–0.054	0.080	–1.681
DEUR	DPAC	0.516	0.391	5.164***
	EMASIA	0.539	0.413	5.741***
	EMEUR	0.753	0.419	4.953***
	EMLAMER	0.752	0.539	6.141***
	BRIC	0.088	0.010	1.710*
DPAC	EMASIA	0.680	0.440	6.419***
	EMEUR	0.469	0.305	5.358***
	EMLAMER	0.387	0.260	5.146***
	BRIC	–0.068	0.055	–1.679
EMASIA	EMEUR	0.540	0.494	3.128***
	EMLAMER	0.511	0.548	–3.984
	BRIC	0.117	–0.080	2.213**
EMEUR	EMLAMER	0.540	0.538	3.617***
	BRIC	–0.059	–0.068	1.690*
EMLAMER	BRIC	–0.035	–0.039	1.722*

Note: This table reports conditional correlations among the stock markets during crisis and stable (pre-crisis) periods. Estimates are obtained using the AG-DCC GARCH model (equations 5 and 6). To check whether the estimated conditional correlations are significantly different across the two periods, t-test statistics are employed. The rejection of the null hypothesis against the one-sided alternative that the turmoil conditional correlation is greater, at the 10%, 5%, 1% significance levels, is denoted by *, **, ***, respectively.

indices and among asset classes, respectively, across the stable (pre-crisis) and crisis periods by using the AG-DCC model [equations (5) and (6)]. Again, t-test statistics are performed in order to check the statistical significance of the estimated conditional correlations across the two periods.

From table 5, turmoil conditional correlations are substantially greater than unconditional correlations in most cases, supporting the presence of asymmetric responses to negative shocks. The signs of the pairwise conditional and unconditional correlations among the equity indices across the stable and crisis periods are the same. Exceptions are the pairs of S&P500-DEUR (from 0.256 to 0.054) and

TABLE 6. Estimates of Conditional Average Correlations among Asset Markets' Returns

Asset markets		Crisis period (1/8/2007-5/5/2009)	Stable period (29/2/2000-31/7/2007)	t-stat.
REIT	S&P50	0.799	0.383	7.984***
	BRAZ	0.086	–0.067	4.112***
	BUND	–0.390	–0.071	–4.461
	COMM	0.243	–0.115	3.894***
	SHIP	–0.129	0.145	–3.636
	TWEI	–0.223	–0.095	–2.150
S&P500	BRAZ	0.121	0.106	1.713*
	BUND	–0.393	–0.393	0.894
	COMM	0.279	–0.036	3.446***
	SHIP	–0.135	0.183	–2.109
	TWEI	–0.028	0.368	–1.706
BRAZ	BUND	0.045	0.067	–1.691
	COMM	0.069	0.040	0.914
	SHIP	0.045	0.081	–1.015
	TWEI	–0.128	–0.092	–0.841
BUND	COMM	–0.252	–0.017	–0.922
	SHIP	–0.056	–0.229	2.271**
	TWEI	0.132	–0.192	3.991***
COMM	SHIP	–0.001	0.084	–1.143
	TWEI	–0.499	–0.200	–4.436
SHIP	TWEI	–0.066	0.067	–0.769

Note: This table reports conditional correlations among the asset markets during crisis and stable (pre-crisis) periods. Estimates are obtained using the AG-DCC GARCH model (equations 5 and 6). To check whether the estimated conditional correlations are significantly different across the two periods, t-test statistics are employed. The rejection of the null hypothesis against the one-sided alternative that the turmoil conditional correlation is greater, at the 10%, 5%, 1% significance levels, is denoted by *, **, ***, respectively.

S&P500-EMLAMER (from 0.168 to 0.075). In general, turmoil conditional correlations among equity markets (developed and/or emerging) are statistically significant and greater than "stable" correlations. Exceptions are the pairs of S&P500-DPAC (from 0.09 to 0.05), S&P500-EMASIA (from 0.12 to 0.09), S&P500-EMEUR (from 0.08 to 0.05) and S&P500-EMLAMER (from 0.17 to 0.07).

Figure 3 illustrates the evolution of the estimated dynamic conditional correlations dynamics among BRICs and the other six regional equity indices. According to this graph and the estimates in table 5, a significantly increase in turmoil conditional correlations is

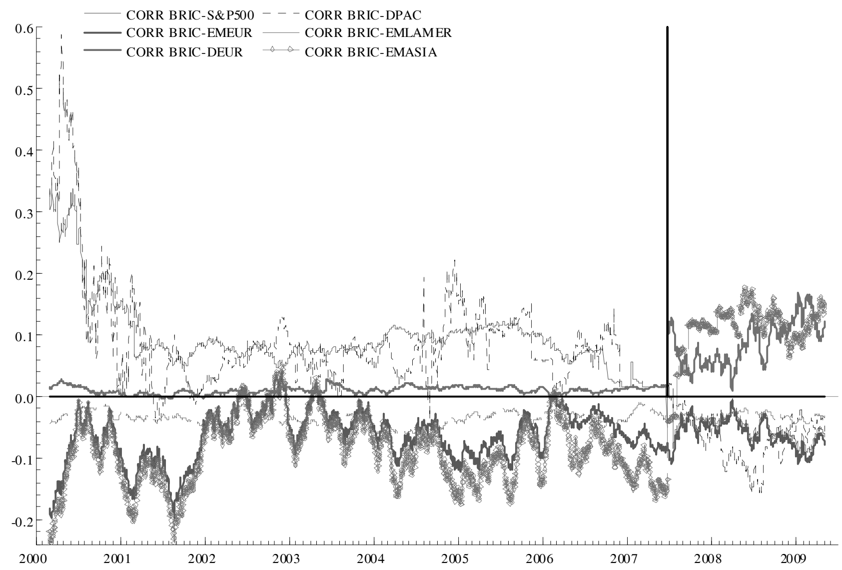

FIGURE 3.— Dynamic Conditional Correlations among BRICs and the other Regional Equity Indices 2000-2009

Note: The graph shows the evolution of the estimated dynamic conditional correlations (CORR) dynamics among BRIC stock index and the other six regional aggregate stock indices. A statistically significant decrease in turmoil correlations is observed among BRIC equity index and the stock indices of S&P500 and DPAC. The black vertical line indicates the start of the Global Financial Crisis (1/8/2007). The correspondence between regions and stock indices is: EMLAMER: Emerging Latin America; EMEUR: Emerging Europe; EMASIA: Emerging Asia; DPAC: Developed Pacific; DEUR: Developed Europe; SP 500: U.S. S&P 500; BRIC: Brazil, Russia, India and China.

observed for the pairs of BRIC-DEUR, BRIC-EMASIA, BRIC-EMLAMER and BRIC-EMEUR. On the contrary, BRICs seems to decouple from the developed stock indices of S&P500 and DPAC, since their conditional correlations are decreased during the crisis period. This finding supports the decoupling of BRIC equity markets and implies that those markets may provide diversification benefits to international investors. This is not consistent to Dooley and Hutchison (2009) and Aloui, Ben Aossa and Nguyen (2011), who find strong evidence of time-varying dependence between each of the BRIC equity markets and the U.S. stock market.

The results reported in table 6 show that average conditional correlations among U.S. stock market (S&P500), commodities (S&P GSCI) and real estate (MSCI REIT) are significantly positive and higher

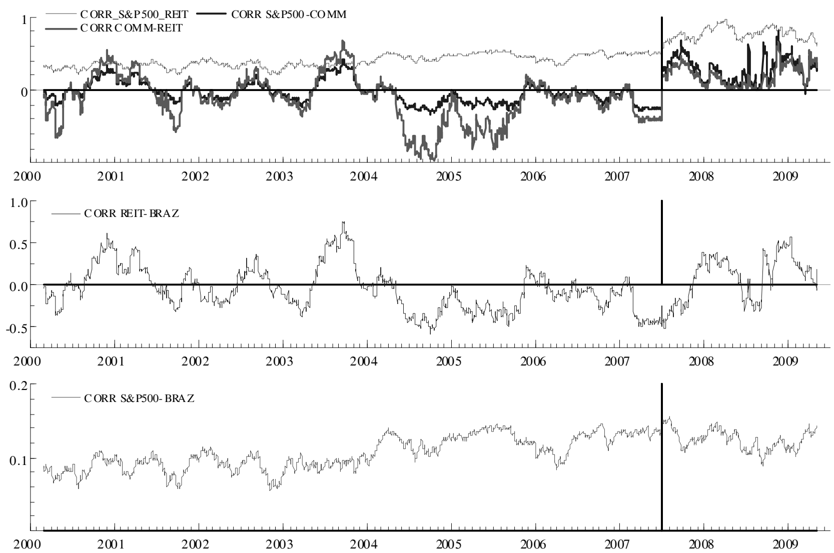

FIGURE 4.— Dynamic Conditional Correlations among the U.S. Markets and other Asset Market Indices 2000-2009

Note: The graph shows that the average conditional correlations (CORR) among the U.S. stock market (S&P500), commodities (S&P GSCI), real estate (MSCI REIT) and emerging Brazilian bond index (BRAZ) are positive and higher during the crisis period than the pre-crisis period, supporting the contagion phenomenon. The black vertical line indicates the start of the Global Financial Crisis (1/8/2007).

during the crisis period than the pre-crisis period, supporting the contagion phenomenon (from 0.383 to 0.799 for REIT-S&P500, from –0.115 to 0.243 for REIT-COMM and from –0.036 to 0.279 for S&P500-COMM). All three indices show strong evidence of asymmetries in their pair-wise conditional correlations, suggesting that real estate and commodities provide reduced hedging potential against the stock market downturn. This finding is in line with the results of Guo, Chen and Huang (2011) and Chan et al. (2011). A statistically significant increase in turmoil conditional correlations is also observed among the emerging Brazilian bond index and the two U.S. markets (0.086 for REIT-BRAZ and 0.121 for S&P500-BRAZ), confirming the existence of a contagion mechanism. The dynamic condition correlations behavior among the above four asset indices over time is displayed in figure 4.

Figure 5 displays the evolution of the dynamic conditional

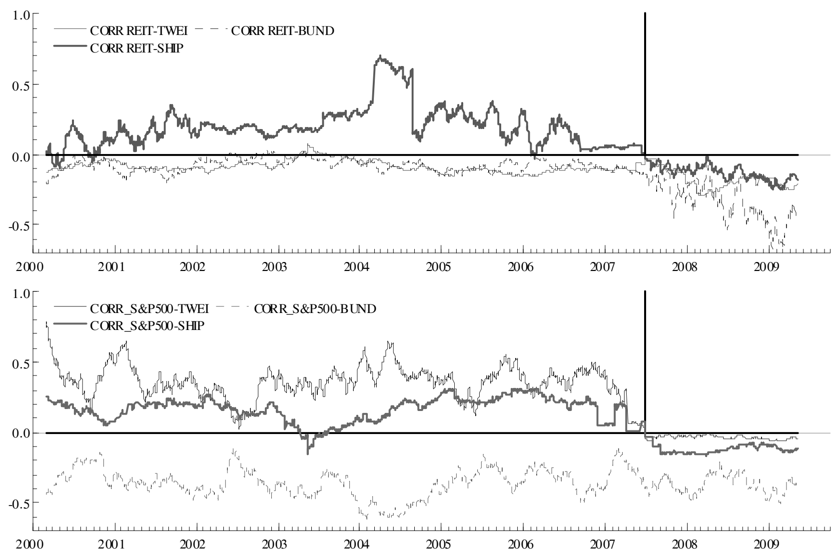

FIGURE 5.— Dynamic Conditional Correlations among the U.S. Markets, BUND, SHIP and TWEI 2000-2009

Note: The graph shows that the average conditional correlations (CORR) among the U.S. stock and real estate markets (S&P500 and MSCI REIT), foreign exchange value of U.S. dollar index (TWEI), shipping index (SHIP) and German bond index (BUND) are decreased or turn to be negative during the crisis period. The black vertical line indicates the start of the Global Financial Crisis (1/8/2007).

correlations among the U.S. stock and real estate markets (S&P500 and MSCI REIT) and the other three asset indices (TWEI, SHIP and BUND). The shipping index may provide diversification benefits for U.S. stocks and real estate, since their average conditional correlations (see table 6) do not increase during the crisis period and turn to be negative (–0.129 for REIT-SHIP and –0.135 for S&P500-SHIP). A similar pattern is also observed for the foreign exchange value of U.S. dollar index (TWEI), which also seems to constitute a diversification vehicle for U.S. real estate (turmoil correlation –0.223) and, to a lesser extent, for U.S. stocks (–0.028). Furthermore, the reported conditional correlations among German Bund, U.S. stocks and real estate do not increase and are negative during the crisis period (–0.390 for REIT-BUND and –0.393 for S&P500-BUND). This finding indicates a flight to quality from risky U.S. assets to the European bond benchmark and is in line with Fleming, Kirby and Ostdiek (1998) and

Connolly, Stivers and Sun (2005), who find that government bonds are a safe haven for investors in times of financial turmoil. Finally, the turmoil correlations among BUND-SHIP and BUND-TWEI are significantly increased, while this is not the case for the pairs of BUND-BRAZ (0.045) and COMM-TWEI (–0.499).[8]

C. Statistical Analysis of Dynamic Conditional Correlations during the Crisis Period

In order to assess the impact of the GFC, the evolution of the dynamic conditional correlations (DCCs) is also examined by using a regression with a constant and a crisis dummy. In this set up, we test for an increase in DCCs during the crisis period by employing a dummy variable as follows:

$$D\hat{C}C_t = \delta_0 + \xi_1 DM_{1,t} + \lambda_t \tag{7}$$

where δ_0 is a constant term, $D\hat{C}C_t$ is the estimated conditional correlation among each pair of market indices during the full sample period, while $DM_{i,t}$ is the dummy variable which is equal to unity during the crisis period (1/8/2007-5/5/2009) and zero otherwise (pre-crisis period). Based on equation (7), this analysis tests whether the GFC significantly alter the dynamics of the estimated conditional correlations among the markets under examination. In other words, a positive and statistically significant dummy coefficient indicates that the correlation during the GFC is significantly different from that of the stable period, supporting the existence of a contagion effect.

Tables 7 and 8 report the estimated results. Overall, the results based on the dummy coefficients estimates support the findings of the average conditional correlations analysis provided in the previous subsection. Specifically, the coefficients of the dummy variable ξ_1 among S&P500 and all other regional equity indices are statistically significant and negative, indicating that the GFC lowered the dynamic conditional

---

8. In order to check the robustness of the estimated average conditional correlations, we also conduct a sensitivity analysis of variations in the start date of the crisis with a fixed crisis period length and of variations in crisis and stable periods' length with a fixed start date of the crisis. The outcome of this analysis demonstrates that period definition (tranquil and turbulent periods) does not affect the central results, while any observed changes in average conditional correlations estimates among markets are rather small and insignificant.

TABLE 7. Tests of Changes in Estimated DCCs among Equity Markets

Equity markets	δ_0	t-stat.	ξ_1	t-stat.
S&P500-DEUR	0.0042***	3.193***	–0.0092	–4.252***
S&P500-DPAC	–0.0136***	–3.841***	–0.0163	–3.513***
S&P500-EMASIA	0.0078***	3.645***	–0.0374	–5.014***
S&P500-EMEUR	0.0225***	3.381***	–0.0639	–5.787***
S&P500-EMLAMER	0.0098**	2.297**	–0.0021	–4.282***
S&P500-BRIC	0.0001	0.931	–0.0019	–2.187**
DEUR-DPAC	0.0341***	7.113***	0.0128	3.006***
DEUR-EMASIA	0.0068***	4.236***	0.0095	3.339***
DEUR-EMEUR	0.0211***	3.541***	0.0035	3.998***
DEUR-EMLAMER	0.0261***	5.134***	0.0091	2.294**
DEUR-BRIC	0.0017*	1.729**	0.0078	3.069***
DPAC-EMASIA	0.0261***	3.541***	0.0036	2.286 **
DPAC-EMEUR	0.0874***	9.321***	0.0097	5.214***
DPAC-EMLAMER	0.0099***	6.979***	0.0112	3.769**
DPAC-BRIC	–0.0169**	–2.217**	–0.0022	–2.198**
EMASIA-EMEUR	0.0159***	7.647***	0.0246	3.618***
EMASIA-EMLAMER	0.0016*	1.732*	–0.0068	–3.694***
EMASIA-BRIC	–0.0089**	–2.263**	0.0139	4.854***
EMEUR-EMLAMER	0.0184***	5.316***	0.0139	2.253**
EMEUR-BRIC	0.0036*	1.684*	0.0049	2.182**
EMLAMER-BRIC	0.0194***	12.897***	0.0079	2.275**

Note: This table reports estimates based on equation 7 for the dynamic conditional correlations (DCCs) among equity indices using a dummy variable during the GFC. δ_0 is the constant, while ξ_1 is the crisis dummy variable coefficient. A positive and statistically significant dummy coefficient indicates that the correlation during the GFC is significantly different from that of the stable period, supporting contagion. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

correlations for these pairs (see table 7). Furthermore, coefficients ξ_1 are also negative and statistically significant among stock index of BRIC and S&P500 and DPAC, supporting the decoupling of BRIC equity markets. However, this is not the pattern among the other pairs of developed and emerging markets, since the dummy coefficients are positive and statistically significant.

The results of DCCs dynamics among asset markets are presented in table 8. The coefficients of the dummy variable ξ_1 among U.S. stock market (S&P500), commodities (S&P GSCI) and real estate (MSCI REIT) are positive and statistically significant, supporting the contagion effect. On the other hand, the GFC decreased the conditional correlations among the U.S. stock and real estate markets (S&P500 and

TABLE 8. Tests of Changes in Estimated DCCs among Asset Markets

Asset markets	δ_0	t−stat.	ξ_1	t−stat.
REIT-S&P500	0.0429	4.877***	0.0357	4.671***
REIT-BRAZ	–0.0198	–1.726***	0.0084	3.136***
REIT-BUND	0.0087	3.922***	–0.0091	–3.799***
REIT-COMM	–0.0053	–1.723*	0.0115	3.416***
REIT-SHIP	0.0092	4.841***	–0.0254	–3.397***
REIT-TWEI	–0.0018	1.691*	–0.0191	–2.293**
S&P500-BRAZ	0.0164	9.612***	0.0172	3.541***
S&P500-BUND	–0.0059	–1.722*	–0.0257	–2.204**
S&P500-COMM	–0.0317	–3.962***	0.0133	2.283**
S&P500-SHIP	–0.0098	–2.294**	–0.0077	–3.117***
S&P500-TWEI	0.0022	0.975	–0.0067	–3.282***
BRAZ-BUND	0.0288	1.716*	–0.0082	–3.668***
BRAZ-COMM	–0.0074	–0.947	0.0129	1.023
BRAZ-SHIP	0.0001	0.852	0.0094	1.153
BRAZ-TWEI	0.0145	4.659***	0.0051	0.894
BUND-COMM	–0.0155	–5.941***	0.0028	0.965
BUND-SHIP	0.0126	1.125	0.0087	2.266**
BUND-TWEI	0.0337	6.822***	0.0058	3.211***
COMM-SHIP	0.0082	25.639***	0.0005	1.132
COMM-TWEI	–0.0139	–29.354***	–0.0011	–3.644***
SHIP-TWEI	–0.0094	–2.236**	–0.0059	–1.129

Note: This table reports estimates based on equation 7 for the dynamic conditional correlations (DCCs) among asset markets using a dummy variable during the GFC. δ_0 is the constant, while ξ_1 is the crisis dummy variable coefficient. A positive and statistically significant dummy coefficient indicates that the correlation during the GFC is significantly different from that of the stable period, supporting contagion. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

MSCI REIT) and the other three asset indices (TWEI, SHIP and BUND), since the crisis dummy coefficients are negative and statistically significant.

The final step is to focus on the robustness of the changes in estimated DCCs presented in tables 7 and 8 by taking into account the effects of asynchronous trading across markets. Following the existing literature (Forbes and Rigobon, 2002), returns are calculated as rolling-average, two-day moving averages on each index. Appendix table A1 displays the estimates of equation (7) for equity markets, while table A2 for asset markets. The analysis finds no significant difference using daily vs. two-day returns.

VI. Conclusions

This study investigates the contagion effects of the GFC across multiple asset markets, borders and regions, using a data set of six different asset classes during the period 2000-2009. To provide a robust analysis of contagion, we estimate and compare average conditional correlations among markets, and especially between the two U.S. “crisis” indices (S&P500 and MSCI REIT) and all other markets, across the stable and crisis periods. The analysis is also extended by using a dummy variable for the crisis period in order to investigate the dynamic feature of the conditional correlation changes.

A good understanding of the linkages between different assets is an important consideration when designing investment portfolios. Any proposed benefits from portfolio diversification across assets depend on the relationships between their returns. The results show: i) increasing linkages among equity markets (developed and/or emerging) across the tranquil and turmoil periods; ii) the U.S. stock market shares the lower positive correlations with the other regional equity markets during the crisis period; iii) the decoupling of BRIC equity markets from the developed U.S. and Pacific equity markets; iv) the existence of a contagion mechanism among the U.S. stocks, real estate, commodities and emerging Brazilian bond index; v) shipping and foreign exchange value of the U.S. dollar indices may provide diversification benefits for U.S. stocks and real estate; and vi) a flight to quality from the risky U.S. assets (stocks and real estate) to the German Bund.

The findings have important implications for policy makers regarding the linkages among the markets during the GFC. In particular, they should carefully examine and uncover the underlying primary driving forces behind the crisis, and take precautions against the potential risk factors in making future policy decisions. It is critical for policymakers to guide investors to pay special attention to those unexpected factors arising from various markets. This study thus provides useful information about the behavior of asset markets through the crisis and can assist policy makers and investors to reduce the costs of a financial crisis in the future. Future research may include into the analysis the post crisis regime (from Q2 2009 onwards) and the investigation of the other two transmission channels appeared in the literature, since the correlated-information channel seems that does not fully work as a contagion mechanism in this study.

Accepted by: *Prof. P. Theodossiou*, *Editor-in-Chief*, *October* 2013

Appendix

TABLE A1. Tests of Changes in Estimated DCCs among 2-day Average Equity Market Returns

Equity markets	δ_0	t-stat.	ξ_1	t-stat.
S&P500-DEUR	0.0059	2.264**	–0.0089	–5.963***
S&P500-DPAC	–0.0189	–4.923***	–0.0093	–3.661***
S&P500-EMASIA	0.0138	2.243**	–0.0563	–6.778***
S&P500-EMEUR	0.0077	0.933	–0.0086	–3.863***
S&P500-EMLAMER	0.0084	3.088***	–0.0084	–4.874***
S&P500-BRIC	–0.0092	–1.132	–0.0074	–2.236**
DEUR-DPAC	0.0175	8.644***	0.0211	2.199**
DEUR-EMASIA	0.0094	6.225***	0.0184	3.367***
DEUR-EMEUR	0.0152	4.012***	0.0144	3.883***
DEUR-EMLAMER	0.0088	3.462***	0.0139	2.269**
DEUR-BRIC	0.0073	3.632***	0.0051	2.284**
DPAC-EMASIA	0.0184	5.684***	0.0084	4.117***
DPAC-EMEUR	0.0277	9.621***	0.0092	5.924***
DPAC-EMLAMER	0.0153	6.159***	0.0084	3.347***
DPAC-BRIC	–0.0042	–2.266***	–0.0081	–2.197**
EMASIA-EMEUR	0.0086	7.138***	0.0092	3.834***
EMASIA-EMLAMER	0.0174	2.286**	–0.0079	–3.926***
EMASIA-BRIC	–0.0083	–2.188**	0.0180	3.022***
EMEUR-EMLAMER	0.0519	6.521***	0.0377	6.558***
EMEUR-BRIC	0.0083	2.227**	0.0076	2.182**
EMLAMER-BRIC	0.0184	13.529***	0.0094	2.276**

Note: This table reports estimates based on equation 7 for the dynamic conditional correlations (DCCs) among 2-day moving average equity market returns with a dummy variable during the GFC. δ_0 is the constant, while ξ_1 is the crisis dummy variable coefficient. A positive and statistically significant dummy coefficient indicates that the correlation during the GFC is significantly different from that of the stable period, supporting contagion. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

TABLE A2. Tests of Changes in Estimated DCCs among 2-day Average Asset Market Returns

Asset markets	δ_0	t-stat.	ξ_1	t-stat.
REIT-S&P500	0.0185	3.511***	0.0086	3.965***
REIT-BRAZ	–0.0134	–5.824***	0.0247	3.855***
REIT-BUND	0.0246	6.215***	–0.0144	–4.899***
REIT-COMM	–0.0163	–1.097	0.0092	4.446***
REIT-SHIP	0.0336	6.954***	–0.0231	–3.922***
REIT-TWEI	–0.0166	0.963	–0.0195	–3.633***
S&P500-BRAZ	0.0076	3.746***	0.0063	2.299**
S&P500-BUND	–0.0082	–3.466***	–0.0164	–4.512***
S&P500-COMM	–0.0133	–2.239**	0.0086	3.111***
S&P500-SHIP	–0.0076	–4.199***	–0.0099	–4.057***
S&P500-TWEI	0.0378	0.859	–0.0078	–2.998***
BRAZ-BUND	0.0156	1.724*	–0.0060	–2.313**
BRAZ-COMM	–0.0097	–1.297	0.0163	1.198
BRAZ-SHIP	0.0006	0.755	0.0188	1.174
BRAZ-TWEI	0.0124	7.139***	0.0078	0.822
BUND-COMM	–0.0117	–6.685***	0.0090	1.093
BUND-SHIP	0.0283	1.078	0.0081	1.742*
BUND-TWEI	0.0177	6.911***	0.0078	1.771*
COMM-SHIP	0.0227	29.857***	0.0074	1.164
COMM-TWEI	–0.0286	–31.105***	–0.0096	–3.388***
SHIP-TWEI	–0.0129	–3.918***	–0.0199	–1.059

Note: This table reports estimates based on equation 7 for the dynamic conditional correlations (DCCs) among 2–day moving average equity market returns with a dummy variable during the GFC. δ_0 is the constant, while ξ_1 is the crisis dummy variable coefficient. A positive and statistically significant dummy coefficient indicates that the correlation during the GFC is significantly different from that of the stable period, supporting contagion. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

References

Acharya, V., and Pedersen, L. 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77: 375–410.

Aloui, R.; Ben Aossa, M. S.; and Nguyen, D.K. 2011. Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking & Finance* 35: 130–141.

Baur, D. G. 2012. Financial contagion and the real economy. *Journal of Banking & Finance* 36: 2680-98.

Bekaert G.; Harvey, C. R.; Lumsdaine, R. L. 2002. Dating the integration of world equity markets. *Journal of Financial Economics* 65: 203-247.

Bekaert, G.; Ehrmann, M.; Fratzscher, M.; and Mehl, A. 2011. Global crises and equity market contagion. NBER Working paper, No. 17121.

Bank for International Settlements. 2009. The International Financial Crisis: Timeline, Impact and Policy Responses in Asia and the Pacific. Basle: Bank for International Settlements (August).

Boyer, B. H.; Kumagai, T.; and Yuan, K. 2006. How do crises spread? Evidence from accessible and inaccessible stock indices. *Journal of Finance* 66: 957-1003.

Brenner, M.; Pasquariello, P.; and Subrahmanyam, M. 2009. On the volatility and comovement of U.S. financial markets around macroeconomic news announcements. *Journal of Financial and Quantitative Analysis* 44: 1265-1289.

Brunnermeier, M., and Pedersen, L. 2009. Predatory trading. *Journal of Finance* 60: 1825–1863.

Cappiello, L.; Engle, R. H.; and Sheppard, K. 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics* 4: 537-572.

Chan, K. F.; Treepongkaruna, S.; Brooks, R.; and Gray, S. 2011. Asset market linkages: Evidence from financial, commodity and real estate assets. *Journal of Banking & Finance* 35: 1415-1426

Chiang, T. C.; Jeon, B. N.; and Li, H. 2007. Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance* 26: 1206–1228.

Connolly, R.; Stivers, C.; and Sun, L. 2005. Stock market uncertainty and the stock-bond return relation. *Journal of Financial and Quantitative Analysis* 40: 161-194.

Dooley, M., and Hutchison, M. 2009. Transmission of the U.S. subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis. *Journal of International Money and Finance* 28: 1331–1349

Dungey, M.; Fry, R.; González-Hermosillo, B.; and Martin, V. 2005. Empirical modeling of contagion: A review of methodologies. *Quantitative Finance* 5: 9–24.

Dungey, M; Fry, R.; González-Hermosillo, B.; Martin, V.; and Tang, C. 2008. Are financial crisis alike? Working paper Series 15. Centre for Applied Macroeconomic Analysis (CAMA).

Dungey, M.; Fry, R.; González-Hermosillo, B.; and Martin, V. 2011. Transmission of Financial Crises: A Latent Factor Approach. New York: Oxford University Press.

Engle, R. F. 2002. Dynamic conditional correlation - a simple class of multivariate GARCH models. *Journal of Business and Economic Statistics* 20: 339-350.

Engle, R. F., and Sheppard, K. 2005. Evaluating the specification of covariance models for large portfolios. Working paper. University of Oxford.

Federal Reserve Board of St. Louis. 2009. The Financial Crisis: A Timeline of

Events and Policy Actions. Federal Reserve Board of St. Louis.

Fleming, J.; Kirby, C.; and Ostdiek, B. 1998. Information and volume linkages in the stock, bond and money markets. *Journal of Financial Economics* 49: 111-137.

Forbes, K. J., and Rigobon, R. 2002. No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance* 57: 2223-2261.

Fry, R.; Martin, V.; and Tang, C. 2008. A new class of tests of contagion with applications to real estate markets. Working paper Series 1. Centre for Applied Macroeconomic Analysis (CAMA).

Guo, F.; Chen, C. R.; and Huang, Y. S. 2011. Markets contagion during financial crisis: A regime-switching approach. *International Review of Economics and Finance* 20: 95-109.

Kaminsky, G.; Reinhart, C.; and Vegh, C. 2003. The unholy trinity of financial contagion. *Journal of Economic Perspectives* 17: 51–74.

Kenourgios, D.; Samitas, A.; and Paltalidis, N. 2011. Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money* 21: 92-106.

Kenourgios, D., and Padhi, P. 2012. Emerging markets and financial crises: Regional, global or isolated shocks? *Journal of Multinational Financial Management* 22: 24-38.

Longstaff, F. A. 2010. The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics* 97: 436–450

Meric, I., and Meric, G. 1997. Co-movements of European equity markets before and after the 1987 crash. *Multinational Finance Journal* 1: 137-152.

Okimoto, T. 2008. New evidence of asymmetric dependence structures in international equity markets. *Journal of Financial and Quantitative Analysis* 43: 787-815.