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Systematic Contagion Effects of the Global Finance Crisis: Evidence from the World's Largest Advanced and Emerging Equity Markets

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† We dedicate this paper in memory of our co-author Mardi Dungey, who passed away unexpectedly in January 2019. With her we have lost not only a great researcher with unique expertise in economics and finance, but also an inspiring mentor, colleague and great friend. Earlier version of the paper was titled "Identifying Contagion Using a Conditional Factor Model". Dinesh Gajurel acknowledges research support from the Faculty of Management, the University of New Brunswick.

Abstract: This paper examines the systematic contagion effects of the global financial crisis of 2007–2009 on the world's largest advanced and emerging equity markets, using the conditional factor model of Dungey and Renault (2018) and and the adjusted correlation coefficient approach of Forbes and Rigobon (2002). Our findings indicate that when applying the Forbes and Rigobon approach, no evidence of contagion is found, while using the conditional factor model, we observe significant evidence of contagion in the aggregate equity markets of both advanced and emerging markets. Furthermore, the results from the conditional factor model suggest that the structural relationship across the financial sectors of advanced and emerging markets was significantly disrupted during the crisis period.

Keywords: financial contagion; financial sector; generalized method of moments

JEL Classification: F30; G01; G12; G15; G20

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1. Introduction

Financial contagion is a crisis phenomenon associated with high market volatility and stronger co-movement of markets than during normal periods. To measure financial contagion empirically, researchers typically focus on quantifying the interdependence of markets during highly volatile periods using correlation measures such as correlation coefficients or beta coefficients (Bekaert et al. 2005; Dungey et al. 2005; Forbes and Rigobon 2002; Hwang et al. 2013; Kasch and Caporin 2013). A limitation of conventional correlation measure is that it tends to be biased upwards when series experience high volatility (Forbes and Rigobon 2002). Suppose that we specify a bivariate relationship in a market model that captures all shared risk (systematic risk) for a group of assets and that the idiosyncratic components are uncorrelated for all assets; an illusion of excess correlation may arise if we ignore time-varying volatility (Polson and Scott 2011). This happens because cross-market correlations are conditional upon aggregate market volatility.

A number of authors have attempted to correct this bias while testing for contagion. For instance, to correct the upward bias in cross-market correlation, Forbes and Rigobon (2002) propose taking into account the heightened volatility of the source market during the crisis period, whereas Corsetti et al. (2005) suggest modifying the correlation coefficient by analyzing the shifts in the variance ratios of common and idiosyncratic factors during the same period. The Forbes and Rigobon (2002) approach has some drawbacks, such as underestimating the adjusted correlation coefficient and the possibility of a break or a shift in the true underlying relationship during the crisis period due to factors such as policy initiatives that restrict cross-border capital flows, changes in exchange rates, central bank liquidity support, and fiscal support.[1] The Corsetti et al. (2005) approach relaxes the assumption of a constant underlying relationship between two markets but assumes that the variance within sub-sample periods remains constant—which is not necessarily true. Dungey and Renault (2018) offer a latent factor volatility model that accounts for heteroskedasticity and considers the potential source of contagion through a common factor or systematic risk.

In this paper, we apply the Dungey and Renault (2018) model and examine the financial contagion in equity markets for the eight largest advanced and emerging economies for the global financial crisis (GFC) of 2007–2009, focusing on contagion through the common factor. More specifically, we test for a change in common factor loading during the crisis period. In this sense, contagion here refers to "fundamentals based contagion" as in Kaminsky and Reinhart (1998) and "systematic contagion" as in Baur (2012) and Dungey and Gajurel (2015). The results reveal that most of the sample aggregate equity markets experienced a significant change in the structural relationship with the U.S. aggregate equity market, suggesting contagion through a systematic channel. However, the structural relationship between the U.S. financial sector and the financial sectors' other economies has broken completely during the crisis period indicating the potential impact of policy initiatives to shield domestic financial sectors from a crisis in the U.S. financial sector. Interestingly, when we apply the adjusted correlation coefficient approach of Forbes and Rigobon (2002), we do not find any evidence of contagion in the overall equity market and the financial sectors of the markets under investigation.

This paper contributes to the growing body of literature on the global financial crisis and contagion effects and is closely related to Dungey and Gajurel (2014). However, this paper differs in two major aspects. First, this paper differs in its definition of contagion as it emphasizes fundamental-based contagion, while Dungey and Gajurel (2014) concentrate on "idiosyncratic contagion," which involves the propagation of idiosyncratic shocks from a crisis-originating market to other markets. Second, this paper uses a conditional factor volatility model whereas the work of Dungey and Gajurel (2014) is based on an unconditional factor model. The results from this paper are, therefore, complementary to Dungey and Gajurel (2014) in understanding different aspects of financial contagion during the global financial crisis.

The rest of the paper is organized as follows. Section 2 provides the literature review. Section 3 presents the modeling framework for contagion tests including a description of the conditional factor model of Dungey and Renault (2018) and also describes the sample, data, and empirical implementation of the conditional factor model. The results and discussion are presented in Sections 4 and 5 to conclude the paper.

2. Literature Review

2.1. Definition of Financial Contagion

Financial contagion has multiple definitions. Eichengreen et al. (1996) define contagion as a heightened likelihood of a crisis in a country after a crisis in an origin country. Hamao et al. (1990) view it as a spillover of crisis-caused volatility to other countries. Jeanne (1997) defines it as cross-country asset price co-movements not explained by economics. Forbes and Rigobon (2002) and Dungey et al. (2005), among others, refer to contagion as a significant increase in the co-movements of prices across markets conditional on a crisis occurring in one market or a group of markets. Bekaert et al. (2005) define contagion as an increase in the correlation between the model residuals that cannot be explained by shifts in the common risk factors. In this paper, following Dungey and Gajurel (2014); Dungey et al. (2005, among others); and Dungey and Gajurel (2015), we define contagion as a significant change in cross-market co-movements during the crisis period which is above and beyond the co-movement during the pre-crisis period.

2.2. Crisis Transmission Mechanisms and Contagion Effects

There is a debate regarding the reasons and mechanisms behind the international propagation of financial crises. One group of theories focuses on economic interdependence, where interconnected economic fundamentals, such as trade and financial linkages among or between the countries, can create avenues to transmit a crisis across borders, and early empirical studies show that countries with weak economic fundamentals are prone to contagion (Kaminsky and Reinhart 1998; Kaminsky and Schmukler 1999; Kaminsky et al. 1998; van Rijckeghem and Weder 2001). The considerable changes in the financial markets over the last few decades, due to financial globalization, including the removal of restrictions on the cross-border flows of goods and services, have been associated with exposure to contagion (Bekaert et al. 2005; Kalemli-Ozcan et al. 2013). The other group of theories postulates that market idiosyncrasies, which are often attributed to the behavior of market participants, play important roles in propagating a crisis internationally (Calvo and Mendoza 2000; Dornbusch et al. 2000; Dungey et al. 2005; Kyle and Xiong 2001; Moser 2003; Yuan 2005). Information asymmetries can cause uncertainty about a country's economic fundamentals, and a crisis in one country may give a "wake-up call" to international investors to reassess risks in other countries, leading to market co-movement (Goldstein 1998; Pasquariello 2007; Yuan 2005). Market confidence and expectations can also cause contagion (Masson 1999; Mondria and Quintana-Domeque 2013). While the studies on crisis and contagion focused on fundamentals-based mechanisms and aimed to develop early warning systems (Eichengreen et al. 1996; Kaminsky et al. 1998; van Rijckeghem and Weder 2001), later studies have identified investor behavior-based mechanisms (Bekaert et al. 2014; Dungey and Gajurel 2014, 2015; Dungey et al. 2005).

In their seminal study, King and Wadhwani (1990) examine the correlation between U.S., U.K., and Japanese equity markets during the stock market crash in 1987. They find evidence of an increased correlation between the U.S., U.K., and Japanese equity markets during the crash but such increased co-movement cannot be explained by the economic fundamentals. Baig and Goldfajn (1999) use a similar approach to examine financial contagion in Asian markets during the Asian crisis. Their results show that the correlation across the countries increased significantly across the major asset classes during the crisis period. While King and Wadhwani (1990) and Baig and Goldfajn (1999) use unconditional correlation coefficient(s) to measure the contagion effects, Forbes and Rigobon (2002) offer an adjusted correlation coefficient approach to test for contagion in equity markets during the 1997 Asian crisis, the 1994 Mexican devaluation, and the 1987 U.S. market crash. Based on their findings, they conclude that the observed increase in correlation during the crisis period is due to increased interdependence among the markets, not contagion. Dungey and Martin (2001), Bekaert et al. (2005), and Corsetti et al. (2005) take the factor model approach for testing contagion during different episodes of financial crises.[2] For example, Dungey et al. (2005), using the factor model approach, show significant evidence of contagion effects during the 1997 Asian crisis. Bekaert et al. (2005) find an increased return correlation between two countries during the Latin American and Asian crises and argue that the increased co-movements could simply be the consequence of their exposure to a common factor.

There is a large body of empirical literature that examines financial contagion during the GFC. The existing empirical literature highlights the contagion effects in equity markets during the GFC. Baur (2012) finds that many advanced and emerging equity markets experienced significant contagion effects coming from the global equity market and that the global financial sector had a significant impact on real economy sectors. Bekaert et al. (2014) and Rose and Spiegel (2010), however, find little evidence of crisis shock effects from the U.S. to other countries during the GFC. Bekaert et al. (2014) find that the impact of the crisis in highly integrated economies is less pronounced than in economies with a lower level of global integration, which is contrary to the globalization hypothesis, which claims that financial markets with a high level of global integration are affected the most by the crisis (Kalemli-Ozcan et al. 2013). Dungey and Gajurel (2015) examine contagion effects in the banking sector of 54 economies and find evidence for most of the economies. Regarding the contagion effects in BRIC countries, there are limited studies. Kenourgios et al. (2011) find contagion between the BRIC countries, the U.S., and the U.K. for five historical crisis events using weekly data. Hwang et al. (2013) find evidence of contagion in China, Russia, and India (but omit Brazil from their study). On the other hand, Samarakoon (2011) finds no evidence of contagion from the U.S. to China or Russia in the GFC and shows that in the case of India shocks from the U.S. exacerbated the difference between U.S. and Indian returns (that is, contagion operated in the opposite direction than expected). The author finds identifiable contagion effects only for Brazil and, in general, concludes that the evidence is stronger for contagion to Latin America than other markets. The U.S.–Brazil contagion linkage is also strongest in Aloui et al. (2011). The authors also find that the commonality between the U.S. and Brazil and the U.S. and Russia is stronger than that for the U.S. and China and the U.S. and India. Wang et al. (2017) use the Forbes and Rigobon (2002) approach and a multiscale correlation coefficient to test for stock market contagion during the global financial crisis (GFC) from the U.S. to the other six G7 and BRIC countries. They find contagion effects mainly in the G7 markets. Dungey and Gajurel (2014) test for the existence of equity market contagion originating from the U.S. to advanced and emerging markets during the crisis period. Using the latent factor model approach of Dungey et al. (2005), they provide strong evidence of idiosyncratic contagion effects in both advanced and emerging equity markets. In the aggregate equity market indices, contagion from the U.S. explains a large portion of the variance in stock returns in both advanced and emerging markets. However, in the financial sector indices, there is less evidence of contagion than in the aggregate indices, and this is particularly the case for the advanced markets. Kangogo et al. (2022) show that Asian markets (both emerging and advanced) are vulnerable to spillovers and contagion from the U.S. equity market.

During the GFC, financial markets worldwide experienced substantial losses. Nevertheless, there is a lack of consensus regarding the international transmission of the crisis and the mechanisms behind it. The disagreement centers around whether the transmission of the crisis was due to interconnected global markets, both real and financial, or due to idiosyncratic factors, such as the behavior of market participants during the crisis period. The varying results of contagion tests largely depend on how the transmission channel is defined and applied in an empirical setting (Dungey et al. 2005). Detecting contagion effects necessitates a formal definition and measurement of the underlying shocks. Some approaches suggest that contagion is noticeable only during extreme (tail) events of market returns. In such cases, researchers may examine the convergence of tail returns across different markets or assets, as completed by Bae et al. (2003) or Boyson et al. (2010), or the effects of outliers in one market on those in another, as in Favero and Giavazzi (2002). The non-linear modules of measuring contagion effects use the copula, DCC, or GARCH frameworks, as shown in studies such as Aloui et al. (2011), Busetti and Harvey (2011), Hwang et al. (2013), Gurdgiev and O'Riordan (2021), and Bago et al. (2021).[3] Dungey and Renault (2018) demonstrate how a latent conditional factor model of the entire sample includes the coincident tail and outlier approaches and quantifies the systematic contagion.

The existing empirical literature on financial contagion during the GFC provides mixed results regarding the transmission of the crisis and its impact on various markets. While some studies find evidence of significant contagion effects from the U.S. equity market, others show limited evidence or none. The disagreement in findings highlights the complexity of measuring contagion effects and the need for a formal definition and measurement of underlying shocks. Nonetheless, recent advancements in contagion detection methodologies offer promising approaches to better understanding the mechanisms of financial contagion during extreme market events. In this paper, we take the Dungey and Renault (2018) approach to detect the contagion via a common factor, or the "systematic contagion" in the world's largest advanced and emerging equity markets.

3. The Modeling Framework

3.1. Motivation

There are several issues with identifying financial contagion empirically, particularly in the correlation-based approach. The most difficult of these is related to the issue of time-varying volatility. Here, we start with the conventional Forbes and Rigobon (2002) approach.

Suppose that one has specified the relationship between returns on two equity markets (r_x and r_y) in a bivariate regression framework as follows:

$$r_{y,t} = \alpha + \beta r_{x,t} + \epsilon_t \tag{1}$$

where $E[\epsilon_t] = 0$, $E[\epsilon_t^2] = c < \propto$(where c is a constant), and $E[r_{x,t}, \epsilon_t] = 0$. Consider a normal period (l), which is likely to be less volatile, and a crisis period (h), which is likely to be more volatile, and assume that the underlying relation between the two markets remains constant in both normal and crisis periods, that is, $\beta^h = \beta^l$ which implies:

$$\beta^h = \frac{Cov[r_x, r_y]^h}{Var[r_x]^h} = \frac{Cov[r_x, r_y]^l}{Var[r_x]^l} = \beta^l. \tag{2}$$

By construction, $Var[r_x]^h > Var[r_x]^l$, which implies that $Cov[r_x, r_y]^h > Cov[r_x, r_y]^l$. The second-order moment condition for Equation (1) can be expressed as

$$Var[r_y] = \beta^2 Var[r_x] + Var[\epsilon]. \tag{3}$$

Since the variance of the residual is positive, the increase in the variance of r_y across periods is less than proportional to the increase in the variance of r_x (see Forbes and Rigobon (2002) for further detail and proof). In other words,

$$\left(\frac{Var[r_x]}{Var[r_y]}\right)^h > \left(\frac{Var[r_x]}{Var[r_y]}\right)^l. \tag{4}$$

Now, consider the standard definition of the correlation coefficient (ρ):

$$\rho_{xy} = \frac{Cov[r_x, r_y]}{\sqrt{Var[r_x]Var[r_y]}} = \beta\sqrt{\frac{Var[r_x]}{Var[r_y]}} \tag{5}$$

where its standalone statistical significance (null hypothesis of $\rho_{xy} = 0$) can be tested using the conventional t-test with the test statistic:

$$t = \rho_{xy} * \sqrt{n-2}/\sqrt{1-\rho_{xy}^2}. \tag{6}$$

When we substitute Equation (2) into Equation (5) and consider the relationship expressed in Equation (4), we obtain

$$\rho_{xy}^h > \rho_{xy}^l. \tag{7}$$

Therefore, Equation (7) implies that the estimated correlation between r_x and r_y increases when the variance in r_x increases. Therefore, ignoring the effect of time-varying volatility can lead to spurious findings of excess correlation.

The Forbes and Rigobon (2002) approach tests for a significant difference between the unconditional correlation coefficient (after adjusting for increased variance) during a crisis period and the correlation coefficient during a non-crisis period. The crisis period unconditional correlation coefficient is given as:

$$\tilde{\rho}^h_{xy} = \frac{\rho^h_{xy}}{\sqrt{1+\delta\left[1-\left(\rho^h_{xy}\right)^2\right]}} \tag{8}$$

where $\delta = \left[Var[r_x]^h - Var[r_x]^l\right] / Var[r_x]^l$, the proportional change in variance during the crisis period. Therefore, the null hypothesis is:

$$H_0 : \tilde{\rho}^h_{xy} \le \rho^l_{xy} \tag{9}$$

against the alternative hypothesis of:

$$H_1 : \tilde{\rho}^h_{xy} > \rho^l_{xy} \tag{10}$$

A rejection of the H_0 is consistent with the presence of contagion.[4] Considering the finite sample properties and distribution of the correlation coefficient (bounded between +1 to -1), Forbes and Rigobon (2002) suggest using Fisher's transformation where the resulting t-stat is given by:

$$\frac{\frac{1}{2}ln\left(\frac{1+\tilde{\rho}^h_{xy}}{1-\tilde{\rho}^h_{xy}}\right) - \frac{1}{2}ln\left(\frac{1+\rho^l_{xy}}{1-\rho^l_{xy}}\right)}{\sqrt{\frac{1}{T_1-3}+\frac{1}{T_2-3}}} \tag{13}$$

where T_1 and T_2 refer to the sample size for the pre-crisis and crisis periods, respectively.

A limitation of the correlation coefficient approach of Forbes and Rigobon (2002), even with this correction, is that it assumes constant variance within sub-sample periods, which is less likely in cases of financial return series.[5]

Dungey et al. (2005) show that the variance adjustment in the correlation coefficient can be equivalently implemented in a regression framework such as Equation (1) for the crisis period as

$$r^h_{y,t} = \alpha + \tilde{\beta}^h \tilde{r}^h_{x,t} + \epsilon^h_t \tag{15}$$

where

$$\tilde{r}^h_{x,t} = r^h_{x,t} / \sqrt{(1+\delta\tilde{\rho}^h_{xy})/(1+\delta)}; t = 1, ..., T_2 \in T_2. \tag{16}$$

The test of the contagion equivalent to Equation (9) is:

$$\tilde{\beta}^h = \beta^l \tag{17}$$

which can be tested using the conventional t-test with the test statistic:

$$t = (\tilde{\beta}^h - \beta^l) / \sqrt{(SE(\tilde{\beta}^h)/T_2 + SE(\beta^l)/T_1}. \tag{18}$$

Dungey and Renault (2018) argue that Forbes and Rigobon (2002)'s approach of adjustment in the correlation coefficient may overestimate the spurious component of the correlation coefficient so that their proposed test tends towards an erroneous conclusion of "no contagion". This is the most likely case when the volatility of the recipient market increases more than the volatility of the source market during the crisis period.[6] Considering this heteroskedasticity issue and potential time-varying structural relationship between a crisis-originating market and recipient markets, Dungey and Renault (2018) provide a conditional factor model which is explained next.

3.2. The Conditional Factor Model

Consider a simple latent factor model of asset pricing where the return on risky assets $(r_1, r_2, ..., r_n)$ is a function of a common factor and can be represented as:

$$r_{i,t+1} = \lambda_i F_{t+1} + \varepsilon_{i,t+1} \; i = 1, ..., n \tag{19}$$

where r_i, F, and ε_i are the excess return of risky asset i, the common factor, and the model residual, respectively; all of which have a zero conditional expectation at time t. λ_i is the factor loading of asset i. Dungey and Renault (2018) show multiple factors are possible, but, in practice, most financial data confirms the existence of one common factor.

Equations (19) can be identified through the structure of conditional moment conditions given by

$$Cov_t[F_{t+1}, \varepsilon_{i,t+1}] = 0, \;\; i = 1, ..., n \tag{20}$$

$$Cov_t[\varepsilon_{i,t+1}, \varepsilon_{j,t+1}] = \omega_{i,j}, \;\; i, j = 1, ..., n. \tag{21}$$

Equation (20) and (21) suggest that the conditional variance of the common factor is the only source of time variation of conditional variances and covariances of asset returns (Dungey and Renault 2018).

To characterize financial contagion within such a factor model, consider the asset return on the crisis-originating country and r_n as a mimicking factor. Then,

$$r_{i,t+1} = b_i r_{n,t+1} + \epsilon_{i,t+1}; \; i = 1, ..., n-1 \tag{22}$$

where a structural break in the coefficient b_i for the crisis period can be considered evidence of contagion. As covered in Section 2.1, ignoring the potential changes in the variance of r_n over time may result in spurious changes in b_i during the crisis period. To overcome this issue, Dungey and Renault (2018) suggest expressing the data-generating process of the mimicking asset return as:

$$r_{n,t+1} = F_{t+1} + \varepsilon_{n,t+1} \tag{23}$$

with variances

$$Var(r_{n,t+1}) = Var(F_{t+1}) + Var(\varepsilon_{n,t+1}). \tag{24}$$

and

$$Var(F_{t+1}) = \alpha Var(r_{n,t+1}). \tag{25}$$

The choice of the normalization constant α is limited by the constraint to ensure positivity:

$$\alpha \geq 1 - \frac{MinVar_t(r_{n,t+1})}{Var(r_{n,t+1})} = \bar{\alpha} \tag{26}$$

where $MinVar_t(r_{n,t+1})$ is the minimum of $Var_t(r_{n,t+1})$. Since the $E[Var_t(r_{n,t+1})] = Var(r_{n,t+1})$, we have $1 > \bar{\alpha} \geq 0$, indicating that the return $(r_{n,t+1})$ is conditionally heteroskedastic (Dungey and Renault 2018). Assigning $\bar{\alpha} Var(r_{n,t+1})$ amount of variance to the factor captures the time-varying part of the conditional variance (Dungey and Renault 2018). The normalization parameter α can be derived from a univariate GARCH process of the mimicking factor, where the implied conditional variance path provides $MinVar_t(r_{n,t+1})$, and the unconditional variance from the sample provides $Var(r_{n,t+1})$. Equation (25) hence implies that if the unconditional variance of the mimicking asset, r_n, increases, the variance of the common factor should increase in the same ratio to keep the underlying relation between them unchanged.

Dungey and Renault (2018) suggest a generalized method of moments (GMM) to estimate the parameters of the model, where the moment condition restrictions are:

$$E_t[r_{j,t+1}(r_{i,t+1} - b_i r_{n,t=1})] = c_{ij, \; j=1,...,n; i=1,...,n-1} \tag{27}$$

and

$$E[r_{i,t}r_{n,t} - b_i \alpha r_{n,t-1}^2 - w_{i,n}] = 0. \tag{28}$$

where (b_i, c_{ij}, w_{in}) are the unknown parameters. Equation (27) is the conditional moment restriction, whereas Equation (28) is the unconditional moment restriction.

In the GMM framework, these moment restrictions are implemented via an $(n+1)$ vector of instruments $z_t = [1, r_{1,t}, r_{2,t}, ..., r_{n,t}]'$. The estimation of Equation (27) for a vector of returns, r_i, and instruments can be written as:

$$\underbrace{r_{i,t+1}[r_{t+1} \otimes z_t]}_{Y_{i,t+1}} = \underbrace{b_i[r_{n,t+1} \otimes (r_{t+1} \otimes z_t)] + c_i[I_n \otimes z_t]}_{X_{t+1}\theta_i} + u_{i,t+1} \tag{29}$$

where r_{t+1} is a set of n assets that yields an $n(n+1)$ column matrix for $[r_{t+1} \otimes z_t]$, and the notation $\otimes$ denotes the Kronecker product. I_n is the identity matrix of dimension n; u_i is residual; and $\theta = \{b_i, c_i\}$ contains unknown parameters of interest. The unconditional moment restriction

$$E[u_{i,t+1}] = 0 \tag{30}$$

helps to identify these unknown parameters in Equation (29). The starting values for the parameters are obtained by running an ordinary least square (OLS) in the univariate regression by averaging Equation (29) over time, that is:

$$\theta_{i,T,(OLS)} = \left[\overline{X}_T \overline{X}_T^{'}\right]^{-1} \overline{X}_T^{'} \overline{Y}_{i,T} \tag{31}$$

where $\overline{Y}$ and $\overline{X}$ refer to the average over time, t = 1,...,T.

Equation (29) does not take into account the arguments provided in Equations (23)–(25). As shown in Dungey and Renault (2018), the extension of Equation (29) considering Equation (25), can be written as:

$$\begin{bmatrix} r_{i,t+1}[r_{t+1} \otimes z_t] \\ r_{i,t+1}r_{n,t+1} \\ r_{n,t+1} \odot r_{n,t+1} \end{bmatrix} = \begin{bmatrix} b_i[r_{n,t+1} \otimes (r_{t+1} \otimes z_t)] + c_i[I_n \otimes z_t] \\ b_i[e \otimes (\alpha \odot r_{n,t+1} \odot r_{n,t+1})] + w_i \\ (1-\alpha)^{-1} w_n \end{bmatrix} + \begin{bmatrix} \tilde{u}_{iz,t+1} \\ \tilde{u}_{in,t+1} \\ \tilde{u}_{nn,t+1} \end{bmatrix} \tag{32}$$

or

$$\underbrace{\begin{bmatrix} r_{i,t+1}[r_{t+1} \otimes z_t] \\ r_{i,t+1}r_{n,t+1} \\ r_{n,t+1} \odot r_{n,t+1} \end{bmatrix}}_{\widetilde{Y}_{i,t+1}} = \underbrace{\begin{bmatrix} r_{n,t+1} \otimes (r_{t+1} \otimes z_t) & I_n \otimes z_t & 0 & 0 \\ e_n \otimes (\alpha \odot r_{n,t+1} \odot r_{n,t+1}) & 0 & 1 & \\ 0 & 0 & 0 & (1-\alpha)^{-1} \end{bmatrix}}_{\widetilde{X}_{t+1}} \underbrace{\begin{bmatrix} b_i \\ c_i \\ w_i \\ w_n \end{bmatrix}}_{\theta} + \begin{bmatrix} \tilde{u}_{iz,t+1} \\ \tilde{u}_{in,t+1} \\ \tilde{u}_{nn,t+1} \end{bmatrix} \tag{33}$$

where $\odot$ refers to the component-wise product, or the Hadamard product, and $e_n =$ is a vector of ones. The first row in Equation (32) is the same as in Equation (29). The second and third rows in Equation (32) add the linear expression of covariance and variance. Now, for the test of contagion, the parameter of interest, b_i can be estimated with the moment restrictions specified in Equations (27), (28), and (30) for the pre-crisis period and crisis period.

3.3. Sample and Data

With the U.S. equity market as the source of the crisis, we investigate the contagion effects on the equity markets of four major advanced economies—France, Germany, Japan, and the U.K. —and the four largest emerging economies—Brazil, China, India, and Russia. These markets were selected based on the size and nature of their respective economies. We collect the daily aggregate equity market price index and the financial sector equity index data for each of these sample markets from the Thomson Reuters Datastream. The price (P) series are transformed into return (r) series by taking the first log difference., i.e., $r_t = ln(P_t) - ln(P_{t-1})$ where t refers to time. Table 1 shows the Datastream tickers for the respective markets. Our sample period covers the time period from August 2, 2004 to May 30, 2009, with the corresponding crisis period from July 19, 2007 to May 30, 2009, as identified in Dungey and Gajurel (2014).

Table 1. Ticker of the equity indices in Datastream.

Country	Aggregate Equity Market	Financial Sector
U.S.	TOTMKUS	FINANUS
France	TOTMKFR	FINANFR
Germany	TOTMKBD	FINANBD
Japan	TOTMKJP	FINANJP
U.K.	TOTMKUK	FINANUK
Brazil	TOTMKBR	FINANBR
China	TOTMKCA	FINANCA
India	TOTMKIN	FINANIN
Russia	TOTMKRS	FINANRS

Augmented Dickey–Fuller (ADF) Test

The empirical literature on financial time series suggests that the stock return series are generally stationary (Bhuiyan and Chowdhury 2020; Gajurel and Chawla 2022). For our confirmation, we perform an augmented Dickey and Fuller (1979) (ADF) test for each of the return series in our sample. Here, we briefly outline the ADF test process.

Let r_t be a return time series. Deriving from an autoregressive order one representation, the ADF test with an intercept involves the following regression:

$$\triangle r_t = c + \lambda r_{t-1} + \delta \triangle r_{t-1} + u_t \tag{34}$$

where $\triangle$ is the difference operator and u_t is a white-noise innovation. Now, the parameter of interest is λ. Under the null hypothesis that the series r_t has a unit root, we t-test for $\lambda = 1$. MacKinnon (1994) provides approximate p-values for the t-test. The rejection of the null hypothesis confirms that the return series is stationary.

3.4. *Tests of Contagion*

In this paper, we implement three other tests of contagion along with a test of contagious based on the Dungey and Renault (2018) conditional factor model. We briefly outline the implementation strategies for each of these tests' procedures.

3.4.1. Unadjusted or Naive Correlation Test

In a naive or unadjusted correlation coefficient-based test of contagion, we estimate the pairwise correlation coefficient between the U.S. market and each of the other markets in the sample for the pre-crisis and crisis periods. We then perform a t-test for a significant difference in the pairwise correlation coefficient. The null hypothesis is:

$$H_0 : \rho^h_{(US,i)} - \rho^l_{(US,i)} = 0 \tag{35}$$

where the superscripts h and l refer to the crisis and pre-crisis period, respectively, and i refers to non-U.S. markets in our sample. The rejection of null at a 5% level of significance provides evidence of contagion effects from the U.S. market to the market i.

3.4.2. Adjusted Correlation Test of Forbes and Rigobon (2002)

In the Forbes and Rigobon (2002) test of contagion, the null hypothesis is:

$$H_0 : \tilde{\rho}^h_{(US,i)} \leq \rho^l_{(US,i)} \tag{36}$$

against the alternative hypothesis of:

$$H_1 : \widetilde{\rho}^h_{(US,i)} > \rho^l_{(US,i)} \tag{37}$$

where $\widetilde{\rho}$ is the heteroskedasticity corrected correlation coefficient, as shown in Equation (8). Therefore, this test of contagion is a one-tailed t-test, and the rejection of the null provides evidence of a significant contagion effect (Forbes and Rigobon 2002).

3.4.3. Adjusted Beta Test of Dungey et al. (2005)

Since the Dungey et al. (2005) approach to the contagion test is based on a simple regression framework, the test of contagion will be a test of the equality of the slope or the beta of regression for the pre-crisis period and crisis period. The null of the contagion test based on a naive or unadjusted beta is:

$$H_0 : \beta^h = \beta^l \tag{38}$$

and the null for the adjusted beta is:

$$\widetilde{\beta}^h = \beta^l, \tag{39}$$

respectively, where $\beta = Cov(US, i)/Var(US)$. Using the t-test provided in the Equation (18), rejection of the null hypothesis is considered evidence of contagion. However, if we define contagion as a significant increase in the beta during the crisis period, as in Forbes and Rigobon (2002), the null hypotheses in Equations (38) and (39) should be adjusted as in Equation (36).

3.4.4. Conditional Factor Model-Based Test of Dungey and Renault (2018)

The implementation of the Dungey and Renault (2018) conditional factor model asks for a choice of the normalization parameter, (α), and instruments for the GMM estimation. We estimate the normalization parameter α from a univariate GARCH(1,1) process applied to the U.S. aggregate equity index returns' data as it is a mimicking factor in the model. The estimated value of α is 0.87.[7] In our sample, we have a total of nine markets $(n = 9)$ and represent the nine equity indices with the U.S. equity market index as r_n, considering the U.S. as the crisis-originating country. We choose constant and squared lagged returns as instruments. Because we have nine assets, we choose 10 $(= n + 1)$ instruments $[z_t = (1, r^2_{1,t}, ..., r^2_{9,t})]$. As we perform market-by-market estimation, for the pre-crisis period T_1 and the crisis period T_2 (where $T_1 + T_2 = T$), for each $Y_{i,t+1}$, we have 90 $(= n(n+1))$ columns. As we have two estimation windows (pre-crisis and crisis periods), we compute $Y_{i,}$ for each day (t) and average it over each estimation window. Computing this provides 90 mean observations for Y and one mean observation for (r_i, r_n), the second row of Equation (32).[8] The estimation of $\widetilde{X}_{t+1}$ follows a similar process. The GMM estimates for $\theta_{i,T}$ can be estimated as:

$$\widetilde{\theta}_{i,T,GMM} = \left[\overline{\widetilde{X}}_T \left(\widetilde{\Sigma}_{i,T}\right)^{-1} \overline{\widetilde{X}}'_T\right]^{-1} \overline{\widetilde{X}}'_T \left(\widetilde{\Sigma}_{i,T}\right)^{-1} \overline{\widetilde{Y}}_{i,T} \tag{40}$$

where $\left(\widetilde{\Sigma}_{i,T}\right)$ is the OLS consistent estimator of the covariance matrix:

$$\widetilde{\Sigma}_{i,T} = \frac{1}{T} \sum_{t=1}^{T} (\widetilde{u}_{i(\theta,OLS)})(\widetilde{u}_{i(\theta,OLS)})' \tag{41}$$

and works as a weighting matrix in Equation (40). As suggested in Dungey and Renault (2018), we choose five-day rolling moving averages for r_n to correct for the serial correlation.

Now, the test of contagion for market $i = 1, ..., n-1$, therefore, refers to significant differences between $\widetilde{\theta}^h_{(i,GMM)}$ and $\widetilde{\theta}^l_{(i,GMM)}$. More specifically, the null of t-test is:

$$b_i^h = b_i^l \tag{42}$$

where the standalone statistical significance of b_i^l and b_i^h indicates an underlying structural relationship between the equity market of country i and the U.S. equity market, the mimicking factor in the model (see Equation (33)). The rejection of null is considered evidence of contagion.

3.5. Testing Hypotheses about Model Identification and Structural Stability

3.5.1. Hansen's J-Test

In the GMM framework, the model identification can be tested using Hansen's J-test (Hansen 1982). We have implemented a single-factor model for the pre-crisis and crisis period estimates in each period. Therefore, we test the overall significance of the model specified in Equation (33) using Hansen's J-test for a number of over-identification restrictions in Equation (27) and Equation (28) where the J-statistic is:

$$J = T\theta \tag{43}$$

where T is the sample size, and θ is the value of the objective value function of the GMM estimator, which takes the form specified in Equation (40). The J-statistic is distributed asymptotically as χ^2 with ϑ (number of restricted parameters) degrees of freedom. There will be $(n+1)(n+2)$ moment restrictions that are used to identify the factor loading b_i. If the value of the J-statistic is below the χ^2 critical value at a 5 percent level of significance for a given level of the degrees of freedom, the null hypothesis of "the model is valid with restrictions" is not rejected. The J-test can also be applied to perform regardless of any break in the number of factors during the crisis period. In such a case, the J-statistic for model identification and breaks in the number of factors for the crisis period would be identical (See Hansen (1982), Hall (2005), and Dungey and Renault (2018) for further elaboration).

3.5.2. Ghysels–Hall Test

While Hansen's J-test determines whether a single-factor model is valid for each sample period, the factor loading may change during the crisis period. For this reason, we conduct the Ghysels and Hall (1990) test of structural change, where the null hypothesis is that neither the model specification nor the factor loadings have changed between the two periods. The Ghysels and Hall predictive statistic (PR) can be expressed as:

$$PR = g_l(\tilde{\theta}_l)'(S_h + D_h V_l D_h')^{-1} g_h(\tilde{\theta}_l) \tag{44}$$

where all the elements of the expression that depend on θ are computed at $(\tilde{\theta}_l)$; g_l and g_h represent the orthogonaility conditions computed over pre-crisis and crisis period, respectively; and S_l and S_h represent subsample estimators of the weighting matrix of orthogonality conditions. Let D_l and D_h be the derivatives of the subsample orthogonality conditions with respect to the paramers, and V_l is the consistent estimator of the variance of θ. The PR statistic follows the χ^2 distribution with $[(n+1)(n+2)+1]$ degrees of freedom (see Dungey and Renault 2018).

Hall (2005) states that when there is no change, the two J-test statistics and the Wald test statistics that compare parameter values are asymptotically independent. Our main focus will be on the Wald test, specifically on the test of null of no change in the factor loading between the pre-crisis and crisis periods. The Wald test statistic (W) will be:

$$W = (T_l + T_h)(\hat{b}_h - \hat{b}_l)' V^{-1} (\hat{b}_h - \hat{b}_l) \tag{45}$$

which follows asymptotically the $\chi^2_{(1)}$ distribution. See Hall (2005) for more detail on these tests.

4. Results and Discussions

4.1. Stylized Facts and Summary Statistics

Figure 1 provides aggregate equity market indices for each country in our sample. The vertical line splits the sample period into pre-crisis and crisis periods. While all the markets experienced a price plunge during the crisis period, the timing differs from market to market, especially between the advanced and emerging markets. The pattern of price movement of other advanced markets (excluding Japan) is similar to that of the U.S. market where prices started declining in July 2007. The emerging markets, however, started declining later, beginning in Jan 2008 in China and India, and in June 2008 in Brazil and Russia. From their peak around the pre-crisis period to their low during the crisis period, the loss for the advanced markets ranged between 49% (U.K.) and 60% (Japan) and, for the emerging markets, ranged between 59% (Brazil) and 72% (Russia), indicating the severity of the GFC on both advanced and emerging equity markets.[9]

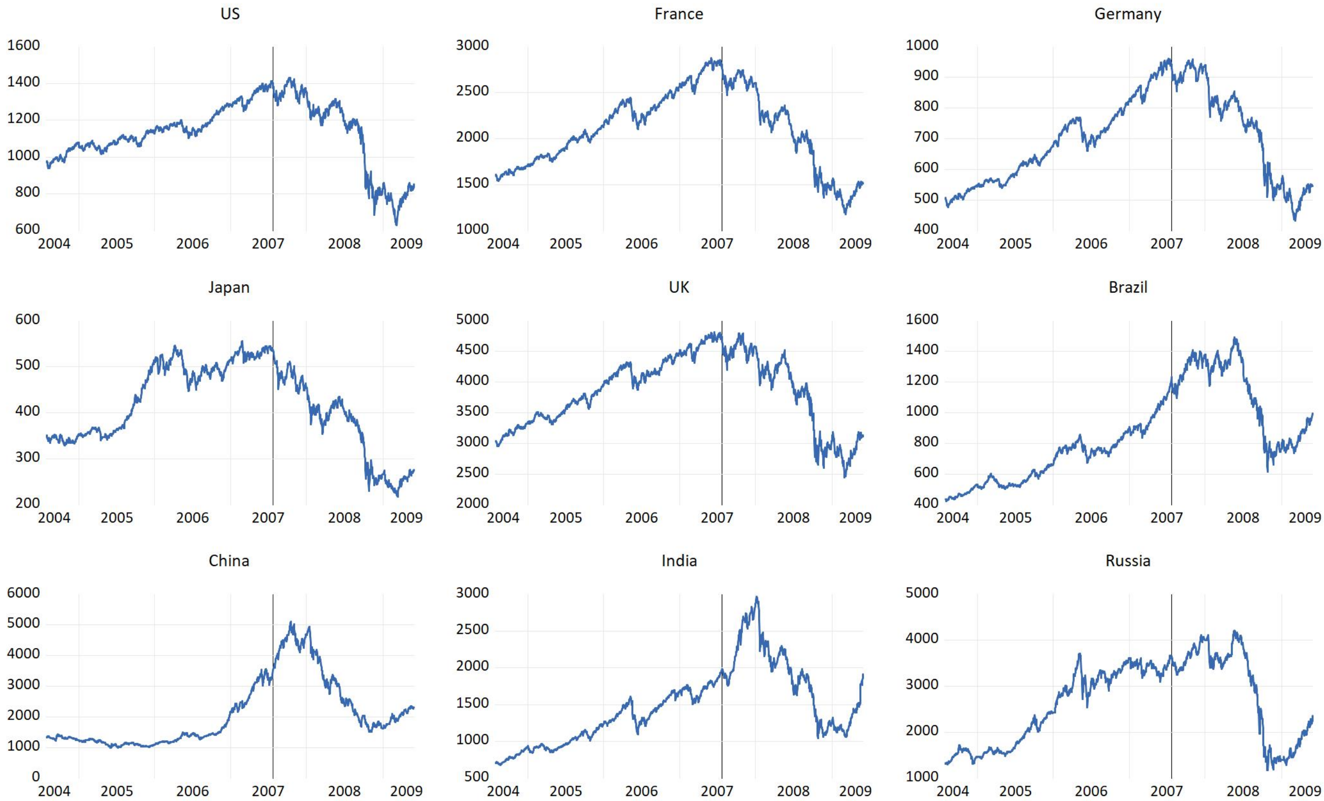

Figure 1. Aggregate equity market indices.

Table 2 provides the descriptive statistics of equity returns for the sample markets. Panel A shows the statistics for the entire sample period, while Panel B and Panel C display the statistics for the pre-crisis and crisis periods, respectively. The table highlights that the emerging markets not only have higher median daily returns but also possess a higher standard deviation of returns than the advanced markets. Furthermore, the augmented Dickey–Fuller unit root tests indicate that all the return series are stationary, as the test statistic was lower than the −2.86 critical value at a 5% level of significance.

Table 2. Summary statistics of daily return for aggregate equity market indices.

Statistics	Advanced Markets					Emerging Markets			
	U.S.	**France**	**Germany**	**Japan**	**U.K.**	**Brazil**	**China**	**India**	**Russia**
Panel A: Whole sample period (2 August 2004 to 30 May 2009)									
Mean	−0.0106	−0.0045	0.0057	−0.0192	0.0027	0.0656	0.0428	0.0793	0.0460
Median	0.0488	0.0432	0.0874	0.0000	0.0417	0.0780	0.0281	0.1390	0.0612
Maximum	10.9019	9.9199	16.0461	12.2917	8.8611	10.8596	9.0409	15.0785	23.1743
Minimum	−9.4087	−8.4287	−6.9133	−9.6851	−8.7142	−9.9400	−9.3062	−12.1159	−19.8503
Std. Dev.	1.4617	1.3285	1.2887	1.5316	1.3355	1.7157	1.9462	1.8383	2.4724
Skewness	−0.2748	0.0202	1.2866	−0.3039	−0.1890	−0.1886	−0.2103	−0.2509	−0.2540
Kurtosis	14.0983	12.4743	28.9023	11.0001	12.0579	8.6266	5.9864	10.3122	19.7653
ADF test	−29.7948 **	−17.1676 **	−37.5623 **	−27.2110 **	−17.3607 **	−35.2048 **	−35.8301 **	−32.8214 **	−34.9397 **
Observations	1260	1260	1260	1260	1260	1260	1260	1260	1260
Panel B: Pre-crisis period (2 August 2004 to 18 July 2007)									
Mean	0.0477	0.0721	0.0797	0.0545	0.0569	0.1300	0.1151	0.1304	0.1301
Median	0.0596	0.0910	0.1219	0.0144	0.0701	0.1144	0.0555	0.2108	0.1338
Maximum	2.2614	2.6220	2.7766	3.5518	2.8932	4.1818	8.0492	6.2996	9.2462
Minimum	−3.4177	−3.0584	−4.6597	−3.6684	−2.8766	−5.5808	−9.3062	−7.3263	−10.7884
Std. Dev.	0.6435	0.7368	0.7241	0.9513	0.6612	1.1264	1.5497	1.2813	1.7221
Skewness	−0.2474	−0.4725	−0.7768	−0.3647	−0.4476	−0.2487	−0.4860	−0.7565	−0.8911
Kurtosis	4.4435	5.0650	7.0114	4.7469	5.5629	4.5510	7.6762	7.3546	9.1114
Observations	773	773	773	773	773	773	773	773	773
Panel C: Crisis period (19 July 2007 to 30 May 2009)									
Mean	−0.1032	−0.1259	−0.1117	−0.1361	−0.0833	−0.0367	−0.0721	−0.0019	−0.0874
Median	0.0000	−0.0189	0.0021	0.0000	−0.0002	0.0000	0.0000	0.0161	−0.0008
Maximum	10.9019	9.9199	16.0461	12.2917	8.8611	10.8596	9.0409	15.0785	23.1743
Minimum	−9.4087	−8.4287	−6.9133	−9.6851	−8.7142	−9.9400	−8.0253	−12.1159	−19.8503
Std. Dev.	2.2052	1.9198	1.8565	2.1486	1.9783	2.3650	2.4445	2.4770	3.3310
Skewness	−0.0823	0.2220	1.3498	−0.1035	−0.0082	−0.0435	0.0061	−0.0274	0.0146
Kurtosis	6.9832	7.2817	17.4736	7.0402	6.3743	5.8098	4.2753	7.2795	14.5368
Observations	487	487	487	487	487	487	487	487	487

** indicate statistical significance at a 5% level.

4.2. Results from the Tests of Contagion

Table 3 provides the results for tests of contagion in our sample. Panel A of Table 3 provides the pairwise correlation coefficient between the U.S. equity market returns and the equity market returns for other sample countries along with the unadjusted and adjusted correlation-based tests of contagion. When we perform the t-test provided in Equation (6) to determine the standalone statistical significance of these pairwise correlation coefficients, we reject the null hypothesis of $\rho = 0$ at a 5% level of significance in all cases, except for the pre-crisis period correlation coefficient and the crisis period adjusted correlation coefficient between the equity markets of the U.S. and China.

Amongst the sample markets, a distinct pattern of co-movement with the U.S. equity markets is clearly evident. Most of the advanced equity markets (except for Japan) have a high degree of correlation with the U.S. equity market, which suggests a high level of equity market integration in advanced countries (Bekaert and Harvey 1995; Bekaert et al. 2005). The emerging equity markets (except for Brazil), however, have a comparatively low level of correlation with the U.S. equity market, indicating a low level of market integration. The results for Brazil, however, suggest a high level of regional integration of the Brazilian equity market with the U.S. equity market. The Chinese equity market has the lowest level of market co-movement with the U.S. equity market in the sample. Samarakoon (2011) also provides similar results for China, and Tan et al. (2008) indicate herding behavior in the Chinese stock markets.

Table 3. Tests of contagion in the aggregate equity market indices.

Equity Market		France	Germany	Japan	U.K.	Brazil	China	India	Russia
Panel A. Correlation coefficients									
Pre-crisis period	ρ^l	0.64	0.69	0.28	0.62	0.65	0.07	0.27	0.31
Crisis period: naive	ρ^h	0.75	0.77	0.41	0.74	0.75	0.12	0.40	0.48
Crisis period: adjusted	$\tilde{\rho}^h$	0.34	0.37	0.14	0.34	0.34	0.04	0.14	0.17
Unadjusted correlation test: $(\rho^h - \rho^l)$	t-stat	3.63	3.20	2.64	3.89	3.36	0.82	2.63	3.42
	p-value	0.02	0.03	0.04	0.02	0.02	0.24	0.04	0.02
Adjusted correlation test: $(\tilde{\rho}^h - \rho^l)$	t-stat	−7.04	−7.99	−2.40	−6.62	−7.32	−0.60	−2.32	−2.58
	p-value	0.00	0.00	0.05	0.00	0.00	0.30	0.05	0.04
Panel B. Regression coefficients									
Pre-crisis period	β^l	0.74	0.78	0.41	0.64	1.17	0.19	0.55	0.81
	se	0.03	0.03	0.05	0.03	0.05	0.08	0.07	0.09
	t-stat	23.87	26.94	8.26	22.68	24.34	2.29	7.92	9.42
Crisis period: naive	β^h	0.69 †	0.68 †	0.43	0.70	0.86 †	0.15 †	0.51 †	0.81
	se	0.03	0.03	0.04	0.03	0.03	0.05	0.05	0.07
	t-stat	25.20	27.16	10.01	24.67	25.26	2.78	9.78	12.15
Crisis period: adjusted	$\tilde{\beta}^h$	0.26 †	0.26 †	0.16 †	0.26 †	0.32 †	0.06 †	0.19 †	0.31 †
	se	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.03
	t-stat	25.20	27.16	10.01	24.67	25.26	2.78	9.78	12.15
Panel C: Factor loadings									
Pre-crisis	b^l	2.03	1.92	2.73	1.84	3.00	0.90	4.36	4.99
	se	0.02	0.03	0.09	0.02	0.05	0.25	0.54	0.82
	t-stat	96.68	69.54	29.87	90.32	58.33	3.68	8.15	6.08
Crisis period	b^h	0.91	1.15	1.29	0.90	1.05	1.16	1.57	1.31
	se	0.15	0.39	0.56	0.33	0.49	0.35	0.75	1.66
	t-stat	6.31	2.94	2.30	2.76	2.15	3.36	2.11	0.79
T-test: $(b^h = b^l)$	t-stat	−170.53	−43.35	−56.83	−64.26	−88.89	14.56	−72.25	−45.74
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel D: Hansen's J-test for identification									
Pre-crisis	$\chi^2_{(80)}$	0.19	0.18	0.27	0.22	0.21	0.52	0.30	0.28
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Crisis	$\chi^2_{(80)}$	0.59	1.05	0.72	0.64	0.73	0.48	0.80	0.88
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel E. Tests for structural stability									
Ghysels–Hall test	$\chi^2_{(91)}$	110.90	108.47	88.99	121.95	106.39	84.90	106.60	109.65
	p-value	0.07	0.09	0.51	0.01	0.11	0.63	0.11	0.08
Break in factor loadings	$\chi^2_{(1)}$	195.86	102.28	111.27	153.25	158.50	72.79	109.34	75.09
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Break in number of factors	$\chi^2_{(80)}$	0.59	1.05	0.72	0.64	0.73	0.48	0.80	0.88
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note: † indicates significantly smaller than pre-crisis estimate based on the t-test provided in Equation (18).

The unconditional correlation coefficient for all of the markets in the sample (except China) increased significantly (at a 5% level of significance) during the crisis period, as shown in the row labeled "Unadjusted correlation test." However, when adjusted for heteroskedasticity as suggested in Forbes and Rigobon (2002), shown in the row labeled "Adjusted correlation test", the crisis period coefficient decreases significantly for all the markets (except for China). The correlation coefficients for China are insignificantly different using both measures. If we consider the one-tail test of the significant increase in correlation during the crisis period as evidence for contagion, as in Forbes and Rigobon (2002), the null of no contagion cannot be rejected. However, considering a decreased correlation against evidence of contagion may be misleading. The literature suggests that a crisis may have spillover effects in other countries, therefore, policymakers from other countries may impose restrictions to reduce the crisis effect that originated elsewhere. In such cases, the magnitude of the co-movement of these two markets may reduce. Similarly, when policymakers impose restrictions to reduce crisis effects, it may systematically distort the existing co-movement (linkages) of markets, which may lead to a decrease in the correlation.

The results from the regression-based approach of Dungey et al. (2005) are reported in Panel B of Table 3. The results are similar to the results reported in Panel A. However, the unconditional regression coefficients for the crisis period are generally smaller than the coefficients for the pre-crisis period, and the heteroskedasticity-corrected regression coefficients for the crisis period are even smaller. The significant change in the regression coefficient for the crisis period suggests that the true underlying relationship between the two markets has changed during the crisis period.

The results from the conditional factor model of Dungey and Renault (2018) are reported in Panel C of the table. The factor loadings for all the sample equity markets are significant for both the pre-crisis and crisis periods with the exception of the Russian equity market where the factor loading for the crisis period is not statistically significant at conventional levels. These statistically significant results suggest that the mimicking factor (aggregate U.S. equity market returns) can explain the returns of other sample markets—both advanced and emerging in both pre-crisis and crisis periods. When we perform a test for significant differences between the pre-crisis and crisis period loadings, the null of no difference is rejected for all the sample markets. As we are using the U.S. equity market return as a mimicking factor, the significant difference in common factor loadings provides evidence for contagion (from the US) during the global financial crisis. More specifically, this result suggests the transmission of a crisis through a common factor. In other words, the established relationship between the U.S. equity market and equity markets of other sample countries has changed at varying degrees but not broken completely during the crisis period. The extent of changes observed can be linked to the level of interdependence that these markets have with the U.S. market and the level of global integration (Bekaert and Harvey 1995; Samarakoon 2011). Consistent with these results, Fratzscher (2012) shows that the common shocks through capital flows (or portfolio re-balancing) affected both emerging and advanced economies during the GFC. Zhang et al. (2013) also provide evidence of change in co-movement between the U.S. equity market and equity markets of emerging economies (BRICS - Brazil, Russia, India, China, and South Africa) during the GFC.

In Panel D and E of the table, we report post-estimation tests. We first perform Hansen (1982)'s *J*-test for identification under the null of a single-factor specification across the pre-crisis and crisis periods. The results suggest that a single-factor model captures the data-generating process for each period in our sample. We then test for structural stability of the single-factor model using Hall (2005)'s test against the null of no break in the factor loadings. The null hypothesis is rejected for all of our sample markets, supporting our specification of a single factor across both periods and allowing for a break in the factor loadings in the pre-crisis and crisis periods. These results are further supported by Ghysels and Hall (1990)'s test of structural change where the joint null of no changes in either the model specification or the parameter loadings between the two periods is rejected in all of the countries, except for China and Japan.[10]

While the financial sector was the first and most affected sector during the GFC, Dungey and Gajurel (2014) provide more limited evidence of idiosyncratic contagion in the financial sector than in the aggregate equity market—the U.S. financial sector's shocks had limited power to explain the volatility of the financial sectors of other economies. We, therefore, apply the conditional factor model to the financial sectors of the sample countries and examine the systematic contagion effects in the financial sector of the sample economies. The results are provided in Panel A through E in Table 4. Although the results using correlation coefficients and the regression approach are similar to results for aggregate equity markets, the results from the single-factor model are interesting. For the pre-crisis period, the factor loadings are positive and statistically significant. Nonetheless, throughout the crisis period, with the exception of Germany, the factor loadings lack statistical significance. This suggests that the returns on the financial sector of other countries in the sample cannot be explained by the returns of the U.S. financial sector as the mimicking portfolio. There could be several reasons why a significant coefficient for the crisis period was not found. Firstly, many policy initiatives and market interventions in domestic jurisdictions were primarily directed towards the financial sector, with the aim of shielding the financial sector from the impact of the crisis in the U.S. financial sector. These measures included restrictions on cross-border mergers and acquisitions of financial institutions, as well as capital and liquidity support to local banks by central banks. Such actions helped to sever the existing linkages between financial sectors across different countries. For instance, Ait-Sahalia et al. (2012) find that policy interventions, especially in the financial sector, reduced the interbank credit and liquidity risks in advanced economies. Klyuev et al. (2009) also assert that policy initiatives contributed to a reduction in the risk of the financial system. Since our model is focused on the crisis effect (contagion) through common shocks (systematic channel), effective policy measures in domestic jurisdictions would most likely diminish or eliminate the crisis effects emanating from the U.S. financial sector.

Table 4. Tests for contagion in financial sectors of sample economies.

Equity Market		**France**	**Germany**	**Japan**	**U.K.**	**Brazil**	**China**	**India**	**Russia**
Panel A. Correlation coefficients									
Pre-crisis period	ρ^l	0.57	0.60	0.19	0.53	0.50	0.13	0.20	0.16
Crisis period: naive	ρ^h	0.63	0.68	0.33	0.65	0.62	0.09	0.35	0.40
Crisis period: adjusted	$\tilde{\rho}^h$	0.17	0.19	0.08	0.17	0.16	0.02	0.08	0.09
Unadjusted correlation test: $(\rho^h - \rho^l)$	t-stat	1.78	2.45	2.49	3.22	3.07	−0.76	2.99	4.64
	p-value	0.09	0.05	0.04	0.02	0.03	0.25	0.03	0.01
Adjusted correlation test: $(\tilde{\rho}^h - \rho^l)$	t-stat	−8.23	−8.74	−2.16	−7.18	−6.68	−1.98	−2.09	−1.18
	p-value	0.00	0.00	0.06	0.00	0.00	0.07	0.06	0.16
Panel B. Regression coefficients									
Pre-crisis period	β^l	0.73	0.68	0.37	0.57	0.99	0.34	0.47	0.51
	se	0.04	0.03	0.06	0.03	0.06	0.09	0.08	0.10
	t-stat	19.77	21.67	5.8	18.01	16.35	3.98	5.79	4.96
Crisis period: naive	β^h	0.52 †	0.44 †	0.28 †	0.56	0.47 †	0.07 †	0.36 †	0.49
	se	0.03	0.02	0.04	0.03	0.03	0.03	0.04	0.05
	t-stat	18.15	20.89	7.73	19.02	17.58	2.05	8.46	9.81
Crisis period: adjusted	$\tilde{\beta}^h$	0.12 †	0.10 †	0.07 †	0.13 †	0.11 †	0.02 †	0.08 †	0.11 †
	se	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	t-stat	18.15	20.89	7.73	19.02	17.58	2.05	8.46	9.81
Panel C: Factor loadings									
Pre-crisis	b^l	1.63	1.49	1.63	1.40	2.35	0.66	2.99	2.97
	se	0.06	0.05	0.15	0.04	0.19	0.46	0.42	1.98
	t-stat	26.1	30.22	10.62	38.59	12.31	1.43	7.05	1.5
Crisis period	b^h	0.91	0.87	1.17	0.99	0.62	0.75	1.18	1.15
	se	0.6	0.42	0.99	0.62	0.54	0.83	1.13	2.06
	t-stat	1.52	2.06	1.19	1.59	1.17	0.91	1.05	0.56
T-test: $(b^h = b^l)$	t-stat	−26.47	−32.44	−10.06	−14.62	−68.85	2.27	−33.89	−15.62
	p-value	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00

Table 4. *Cont.*

Equity Market		France	Germany	Japan	U.K.	Brazil	China	India	Russia
Panel D: Hansen's J-test for identification									
Pre-crisis	$\chi^2_{(80)}$	0.21	0.19	0.35	0.22	0.23	0.46	0.35	0.43
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Crisis	$\chi^2_{(80)}$	0.64	0.87	0.81	0.6	0.79	0.71	0.65	0.82
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel E. Tests for structural stability									
Ghysels-Hall test	$\chi^2_{(91)}$	117.31	111.19	98.09	127.19	119.28	112.23	111.62	123.49
	p-value	0.03	0.06	0.26	0.01	0.02	0.06	0.06	0.01
Break in factor loadings: Hall test	$\chi^2_{(1)}$	139.76	119.73	110.03	150.6	148.48	80.89	118.36	50.17
	p-value	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00
Break in number of factors	$\chi^2_{(80)}$	0.64	0.87	0.81	0.6	0.79	0.71	0.65	0.82
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note: † indicates significantly smaller than pre-crisis estimate based on the t-test provided in Equation (18).

5. Conclusions

This paper examines the systematic contagion in the equity markets of both advanced and emerging economies during the global financial crisis of 2007–2009 by using the adjusted correlation approach developed by Forbes and Rigobon (2002) and the conditional factor model proposed by Dungey and Renault (2018). The results obtained using the adjusted correlation approach do not provide any evidence of contagion in the market during the global financial crisis. However, the results from the conditional factor model suggest that there are significant structural relationships between the U.S. aggregate equity market and those of other advanced and emerging economies. These relationships experienced a structural shift during the global financial crisis, indicating potential contagion effects through a common factor. When focusing solely on the financial sectors, the results, however, suggest that the structural relationships between the U.S. financial sector and those of other sample countries that existed prior to the crisis were disrupted during the crisis period, perhaps due to the policy initiatives to mitigate the crisis effect in the financial sectors.

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Notes

1. See Billio and Pelizzon (2003), Corsetti et al. (2005), and Dungey et al. (2005) for limitations of the Forbes and Rigobon (2002) approach.
2. See Dungey et al. (2005) for a review of different correlation-based empirical methodologies.
3. See, for example, Phillips et al. (2015), Greenaway-McGrevy and Phillips (2016), Xu and Gao (2019), Mohti et al. (2019), and Samitas et al. (2020) for recent advancement in contagion detection methodologies.
4. In their actual empirical setting, Forbes and Rigobon (2002) test the following hypotheses:

$$H_0 : \rho_{xy} > \tilde{\rho}^h_{xy} \tag{11}$$

$$H_1 : \rho_{xy} \leq \tilde{\rho}^h_{xy} \tag{12}$$

where ρ_{xy} is the correlation coefficient based on full sample period indicating that any t-test value greater than t-test critical value at 5 percent indicates evidence of contagion while any t-test value less or equals to critical value indicates no contagion.

5 Corsetti et al. (2005) offer a similar approach to test for contagion. By relaxing the assumption in Forbes and Rigobon (2002) that the underlying relation between two markets remains constant, Corsetti et al. (2005) provide an adjustment in the unconditional correlation for changes in the variance ratios of the residuals (idiosyncratic factor) and the common factor during the non-crisis and crisis periods, (λ_j). More specifically, the adjusted correlation coefficient during the crisis period is:

$$\phi' = \frac{\rho^h_{xy}}{\sqrt{1+\delta\left[1-\left(\rho^h_{xy}\right)^2-\lambda_j\left(\rho^h_{xy}\right)^2\right]}} \tag{14}$$

Therefore, the null hypothesis of no contagion becomes $\phi' = \rho^h_{xy}$.

6 To overcome the heteroskedasticity issue, some recent studies compute the conditional correlation from the dynamic conditional correlation (DCC) GARCH approach (Engle 2002) and test for a significant increase in the conditional correlation during the crisis period (Chiang et al. 2007; Wang and Nguyen Thi 2012), under the null hypothesis of no contagion, $\rho_{y(DCC)} = \rho_{x(DCC)}$. The DCC approach overcomes the endogeneity issue and omitted variable issues of the Forbes and Rigobon (2002) approach by computing the conditional correlation coefficient from GARCH model residuals.

7 We have also performed sensitivity analyses for the different values of $\alpha[= 0.6, 0.7, 0.9]$. As postulated in Dungey and Renault (2018), the results are relatively insensitive to the choice of value for α.

8 The third row of $\widetilde{Y}_{i,t+1}$will have a constant term on the righthand side so it does not enter into the estimation process.

9 Note that the loss was computed as a percentage change in the price index with the highest and lowest values during the crisis period.

10 The p-values for the coefficients of Brazil and India are 0.11.

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