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Financial Contagion During Stock Market Bubbles

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JEL: F30; G15

Keywords: Financial contagion; Stock markets; Bubbles; Dynamic correlations, Dynamic panels

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We investigate the role of bubbles on financial contagion using a set of developed economies. First, using the recursive flexible window right-tailed ADF-based procedure, we date stamp bubble periods in stock index series. Second, we capture contagion with a DCC multivariate GARCH framework. In a third step, we construct a panel by pooling across the time-series dynamic conditional correlations and bubbles to estimate various dynamic panel specifications that consider the endogenous nature of bubbles. We find statistically significant decreases in the dynamic correlations during periods of bubbles, which shows that the financial contagion between pair of countries diminishes when any of the two countries in the pair is going through a bubble period. This implies that during bubble periods investors are looking for an investment opportunity within their economy and rely less on international diversification. However, decrease in contagion between two economies could provide ample diversification opportunities for portfolio managers.

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1. Introduction

Stock markets are a fascinating example of an integrated world with complex financial systems whose advancements are closely monitored by investors and governments around the globe. Among many factors contributing to the movement and interconnectedness of the global financial markets, 'contagion' is perhaps the least well understood. This study investigates the role of price bubble on financial market contagion. Bubbles are an important aspect of financial markets, as we have repeatedly seen connection between asset price bubbles, systematic risk, and the macroeconomy. Such link was recently observed during the financial crisis of 2007-2009, which most economist agree erupted from bursting of the U.S. housing bubble. The global magnitude of the 2007-2009 U.S. recession and the potential consequences of being affected by financial crisis contagion continuously attract attention from wide array of economists and policymakers. The transmission of shocks to global financial markets and the cross-countries co-movements, beyond the fundamental link, has long been an issue of importance to investors and policy makers, as it has significant implications for asset allocation and portfolio management.

Financial contagion refers to the spread of financial instabilities from one economy to others. Forbes and Rigobon (2002) define contagion as a significant increase in cross-market linkages after a shock to one country (or group of countries), while a continued market correlation at high levels is not contagion, but the interdependence between a pair of economies. The central theme around contagion study is correlation analysis, i.e., a substantial increase in correlation during the crash period (Chiang et al., 2007). For example, Kenourgios et al. (2011) confirms a contagion effect from the crisis country to all others in sample of countries, while Baig and Goldfajn (1999) support the contagion phenomenon during the East Asian crisis. In similar study, Hon et al. (2007) find dot-com bubble burst in the U.S. resulted in an increase in correlation between the U.S. and other foreign financial markets. In this study, we examine these concerns by modeling time varying correlations and bubble periods to disentangle bubble impact on financial market contagion in six developed economies. This is in addition to simple stock market contagion and interdependence study, which typically proceeds by simply obtaining and analyzing dynamic correlations.

This paper provides a three-fold contribution to the existing literature. First, we detect bubble periods in all six stock index series. To do so, we implement bubble detection method proposed by Phillips, Wu, and Yu (hereafter, PWY, 2011) for identification of a single bubble episode and later extended by Phillips, Shi, and Yu (hereafter, PSY, 2015) for identification of multiple bubble episodes. From bubble detection analysis, we notice that shocks from dot-com bubble and burst as well as shocks from 2007-2009 U.S. recession are mostly captured in almost all countries in our sample. This provides preliminary evidence of financial contagion among developed economies during periods of crises. Second, to obtain time varying correlations we use the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model proposed by Engle (2002), which is appropriate for measuring time varying conditional correlations and addresses the heteroskedasticity issue raised by Forbes and Rigobon (2002). In addition, we use lagged U.S. stock returns as an exogenous global common factor and estimate all dynamic correlations simultaneously to resolve the omitted variable problem. Third, to test for the effect of bubbles on financial market contagion we pool the dynamic correlation coefficients and bubble periods across six countries to obtain a panel of correlations. Finally, we estimate various dynamic panel models that allow for dynamic feedbacks between bubble periods and conditional correlations, in addition to allowing bubble periods to be potentially endogenous. Date-stamping the initiation and termination points of bubbles follows the GSADF approach on the stock price series. In addition, the bubble itself is a function of actual stock price and stock price fundamentals (for e.g., dividends); therefore, it is well justified to model bubble periods as potentially endogenously to explain financial market contagion.

Our sample of six developed economies (France, Germany, United Kingdom, Japan, United States, and Canada) from January 1, 1999 to December 29, 2017, shows statistically significant evidence of a decrease in contagion between financial markets. Our panel definition of bubbles is if any of the two countries in the correlation is going through bubble periods. The results show strong evidence of regional and global financial market contagion. Moreover, the dynamic panel estimates show that financial contagion diminishes when any of the two countries in the pair is going through bubble periods.

Our work is motivated by a gap in the contagion literature. Studies prior to the 2007-2009 financial crisis find that contagion is mainly concentrated on the impact of crises in emerging markets. Forbes and Rigobon (2002) find some weak evidence of contagion in developed financial markets. Many other studies support the idea of contagion being important to emerging markets but agree on developed economies being largely immune (Bae et al., 2003; Lee et al., 2007; Chevapatrakul and Tee, 2014). It is a well-known fact that the U.S. being major financial market is considered at least in casual terms as a source of contagion for the 2007-2009 crisis (Dooley and Hutchison, 2009; Dimitriou et al., 2013). However, this paper not only finds regional and global financial market contagion but also provides empirical evidence to support the hypothesis of diminishing financial market contagion during periods of the price bubbles in developed economies.

Various studies on financial contagion (e.g., Dungey et al., 2006; Bekaert et al., 2005; Baur, 2012) follow a correlation breakdown approach in which substantially significant increases in financial market correlations during and after the shock from the crisis indicate contagion. Studying contagion through correlation analysis has three main limitations. Chiang et al. (2007) provides detail discussion of these limitations and drawbacks in the empirical studies. First, the issue of heteroskedasticity when measuring correlations, caused by increase in volatility during the crisis period. We address the heteroskedasticity problem raised by Forbes and Rigobon (2002) using the methods in Engle (2002). Second, a problem of an omitted variable while estimating a cross-country correlation. To address the omitted variable issue, we use lagged U.S. stock returns. Third, Forbes and Rigobon (2002) defines contagion as significant increases in cross-market co-movements, while any continuous market correlation at high levels is considered interdependence. Therefore, the time-varying correlation analysis is needed to address concerns of substantially increasing cross-market co-movements. In addition, we report in Appendix B (Table B1), tests of significant increase in dynamic conditional correlation coefficients by adopting the Fisher *Z*-transformation as our testing framework, where we identify U.S. 2007-2009 recession as the source of contagion.[1]

The rest of the paper is organized as follows. Section 2 presents the data. The empirical strategy and estimation methods are presented in Section 3, while Section 4 discusses empirical results. Finally, Section 5 concludes.

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[1] Morrison (1983) suggests the test statistic for a null hypothesis of no increase in correlation, given as: $T = (Z_0 - Z_1)/\sqrt{[1/(N_0 - 3) + 1/(N_1 - 3)]}$, where $Z_0 = 1/2 \ln[(1 - \rho_0)\,/(1 - \rho_0)]$ and $Z_1 = 1/2 \ln[(1 - \rho_1)\,/(1 - \rho_1)]$ are Fisher *Z*-transformation of correlation coefficients before (Z_0) and after (Z_1) the crisis; $N_0 = 2325$ and $N_1 = 2630$ are the number of observations, while ρ_0 and ρ_1 are dynamic conditional coefficients before and after the crisis in this paper. The test statistics is approximately normally distributed and is robust to the non-normality of correlation coefficients. Basu (2002) and Corsetti et al. (2005) have employed this test.

2. Data

Our time series daily data contains six developed countries value-weighted stock indexes. We use Antoniou et al. (2005) and Chelley-Steeley (2005) as our benchmark for the selection of developed European economies (i.e., France, Germany, United Kingdom), in addition to Japan, United States, and Canada. These six developed economies have the largest and most developed financial markets measured in term of market capitalization. According to the 2016 World Federation of Exchange statistics, the North American stock exchanges account for over 40%, European for over 19%, and Asian for over 33% of world's total stock market capitalization. We overcome the difficulty in the estimation of multivariate GARCH models with various series by focusing on a representative set of countries from these three regions. Table 1 presents the descriptive statistics of our series. We obtained country specific stock markets data from Thomson Reuters Datastream, while the country specific Consumer Price Index (CPI) data are retrieved from the Federal Reserve Economic Data (FRED). To adjust for inflation, we divide nominal country specific stock market index by their respective CPI. The data period covers nineteen years of daily data from January 1, 1999 to December 29, 2017.

[Table 1, about here]

From Panel A we observe that Germany and Canada are the best performing markets. Stock index daily return averages 1.36 basis points, while adjusting daily return to a yearly basis accounts to a 3.43% annual return for Germany's stock market (Column 3).[2] Similarly, daily return for the Canadian stock index is 1.19 basis points, with an approximate annual return of

[2] We assume 252 days in a year after approximately excluding weekends and holidays.

3%. On the other hand, the French stock index daily return is 0.07 basis points, which averages to a 0.18% annual return.

In addition, Panel B reports correlation statistics, which serve as a preliminary evidence of financial market contagion. All countries in our sample are highly correlated with each other, except for Japan, which displays a relatively low correlation. Ranaldo and Soderlind (2010) document that the Japanese yen has significant safe-haven characteristics and typically moves inversely with international equity markets and FX volatility. Investments are expected to flow into Japan's financial market during period of bearish global economy, while during bullish global economy investors are more willing to take risk and tend to invest in high yield investment markets. As expected, France, Germany, and the UK, being regional counterparts from the European continent show high correlations, while similar regional linkages are observed in the North American continent between the United States and Canada.

3. Empirical Strategy

The empirical strategy involves three steps. We first present the DCC GARCH framework to capture time varying contagion between different equity markets. In the second step, we detail the GSADF approach that allow us to identify and date-stamp stock market exuberances and collapses. In the third step, we use dynamic panels and combine the dynamic correlation from step one and the identified bubble periods from step two to test if contagion is affected by bubbles.

3.1 Modeling Financial Contagion

To capture contagion across financial markets, we employ the Dynamic Conditional Correlation (DCC) GARCH model of Engle (2002). Let the stock market index of a country τ in period t be denoted by P_t^τ. We use the country specific stock price index and the consumer price index to calculate real stock market return as $r_t^\tau = [\log\left(\frac{P_t^\tau}{P_{t-1}^\tau}\right) - \log\left(\frac{CPI_t^\tau}{CPI_{t-1}^\tau}\right)] \times 100\,\%$. Working with returns also helps to make sure all series are stationary.

Chiang et al. (2007) discusses three advantages of the DCC-GARCH model. First, the model allows including additional explanatory variables in the mean equation to allow for common factors. Our estimation includes U.S. stock returns as an exogenous global factor that potentially affects global financial markets. Second, the DCC-GARCH model estimates time-varying correlation coefficients of the standardized residuals and hence accounts for heteroscedasticity in the model. Third, the DCC-GARCH model allows including multiple returns without having to overparameterize the model. In other multivariate GARCH models, the estimation of the dynamic correlation coefficients is particularly difficult due to large number of coefficients in the variance-covariance matrix, as noted in Engle and Kroner (1995). In addition, the DCC-GARCH model adjusts the volatility overtime, so it does not have any bias from volatility clustering. Given the flexibility of DCC-GARCH, the parsimonious parameter setting allows us to model our 15 pairwise dynamic correlation coefficient series in a single representation. The resulting estimates provide us with a behavioral representation of country specific stock index returns in a multivariate setting. The resulting time varying correlation coefficients will assist us in studying the roles of financial bubbles on the contagion.[3]

We use the following AR(1) process to model our mean equations of stock returns:

$$r_t = \mu + \varphi r_{t-1} + \gamma r_{t-1}^{USA} + \varepsilon_t, \tag{1}$$

[3] Previous studies used the DCC-GARCH, for example, to capture the association between risk and return (see, e.g., Engle, 2004; and Cifarelli and Paladino, 2010).

where, r_t the vector of stock market return calculated from daily closing prices, $r_t = (r_{i,t}, r_{j,t}, \dots, r_{n,t})'$ for $n = 6$. Moreover, $\varepsilon_t = (\varepsilon_{i,t}, \varepsilon_{j,t}, \dots, \varepsilon_{n,t})'$ with $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$, where Ω_{t-1} is the information set available at the end of period $t-1$. The autoregressive term in Equation (1) will allow us to capture momentum effects, while the lagged U.S. stock returns serves as a control factor that can potentially impact other financial markets returns (Dungey et al., 2003) and allows agents to have an alternative investment opportunity (Chiang et al., 2007). We next model the conditional variance-covariance matrix H_t, using following specification:

$$H_t = D_t R_t D_t \tag{2}$$

where R_t is a $n \times n$ dynamic correlation matrix, whereas D_t is a diagonal matrix of conditional standard deviations for stock returns obtained from univariate GARCH estimation with $\sqrt{h_{\tau,t}}$, where τ = ($i, j, \dots, n$), represents respective countries in our sample. D_t and R_t both are time varying. We implement two-step estimation approach to model variance-covariance matrix H_t. First, $\sqrt{h_{\tau,t}}$ estimates are obtained using univariate volatility models for each country. Second, the residuals from the first step are adjusted using $\delta_{\tau,t} = \varepsilon_{\tau,t}/\sqrt{h_{\tau,t}}$, these transformed residuals are then used to estimate the conditional correlation coefficients. Following Engle (2002) the time varying conditional correlations is given by:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha\delta_{t-1}\delta_{t-1}' + \beta Q_{t-1}, \tag{3}$$

where $Q_t = q_{ij,t}$ is a (n×n) time-varying covariance matrix of standardized residuals (δ_t) and $\overline{Q} = E(\delta_t\delta_t')$ is the (n×n) unconditional correlations matrix of δ_t. α and β are nonnegative scalars following $(\alpha+\beta)<1$ restriction. Now in order to obtain the correlation matrix R_t, we rescale Q_t as follows:

$$R_t = \left(\mathrm{diag}(Q_t)\right)^{-\frac{1}{2}} Q_t \left(\mathrm{diag}(Q_t)\right)^{-\frac{1}{2}}, \tag{4}$$

where $\left(\mathrm{diag}(Q_t)\right)^{-\frac{1}{2}} = \mathrm{diag}\left(1\Big/\sqrt{q_{i,t}}, \dots, 1\Big/\sqrt{q_{n,t}}\right)$ and q_t are the main diagonal elements of Q_t. If Q_t is positive definite, R_t is a correlation matrix with ones on diagonal and less than one in absolute value off-diagonal elements. A typical expression of R_t in a bivariate case follows the form: $\rho_{ij,t} = {q_{ij,t}}\Big/{\sqrt{q_{i,t}, q_{j,t}}}$, $i, j = 1, 2, \dots, n,$ and $i \neq j$. Expressing the correlation coefficient in a bivariate case, we have:

$$\rho_{ij,t} = \frac{(1-\alpha-\beta)\overline{q}_{ij} + \alpha\delta_{i,t-1}\delta_{j,t-1} + \beta q_{ij},_{t-1}}{\left[(1-\alpha-\beta)\overline{q}_i + \alpha\delta_{i,t-1}^2 + \beta q_{i},_{t-1}\right]^{\frac{1}{2}} \left[(1-\alpha-\beta)\overline{q}_j + \alpha\delta_{j,t-1}^2 + \beta q_{j},_{t-1}\right]^{\frac{1}{2}}}, \tag{5}$$

where $\overline{q}_{ij}$ and $q_{ij},_t$ are the single off-diagonal elements of $\overline{Q}$ and Q_t respectively. We will estimate this model using a two-stage approach to maximize the log-likelihood function. Let $\theta = (\mu, \varphi, \gamma)$ denote vector of parameters to be estimated in D_t and let ϑ denote the parameters in R_t, then the log-likelihood function to be maximized is given by:

$$L_t(\theta, \vartheta) = -\frac{1}{2}\sum_{t=1}^{T}[(n\log(2\pi) + \log|D_t|^2 + \varepsilon_t' D_t^{-2}\varepsilon_t) + (\log|R_t| + \delta_t' R_t^{-1}\delta_t - \delta_t'\delta_t)] \tag{6}$$

The first term on the right-hand side is the sum of individual GARCH likelihoods. The second term represents the function to be maximized to obtain the correlation coefficients. Engle (2002) explain that in this two-step procedure, the first step estimates the diagonal elements θ

corresponding to D_t by maximizing the first term on the right-hand side of Equation (6). In the second step the estimates of ϑ are obtained by maximizing the second term.

3.2. Identifying Bubble Periods

The identification of price bubbles initially follows PWY to test for the existence of a single episode of explosive behavior. PWY uses rolling windows in a recurring estimation of the Augmented Dickey–Fuller (ADF) regression on a forward expanding sample sequence. To identify more than one explosive behavior we further employ the methods in PSY. The estimation in PSY uses a double recursive approach that involves ADF regressions that shift both, the start and end date of the rolling windows. PWY and PSY start with the following ADF regression:

$$\Delta y_t = a_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \varphi_{r_1,r_2}^{i} \Delta y_{t-i} + \varepsilon_t \tag{7}$$

where $y_t, \Delta y_t$, and ε_t represents the real stock indexes, the first differences of real stock indexes, and the error term ε_t, respectively.[4] In order to control for the serial correlation the k lagged difference terms are included in equation (7). r_1 and r_2 are the starting and ending points of a subsample period. The estimates and the error term variance depend on r_1 and r_2.

We primarily use PWY procedure of testing the unit null hypothesis against the alternative of mildly explosive behavior in y_t using right-sided unit root tests. Right-sided unit root tests are beneficial to date stamp the exuberance and mispricing in the data. ADF test statistics evolves as:

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[4] ε_t is expected to follow a normal distribution, i.e., $\varepsilon \sim iidN\,(0, \sigma^2_{r_1,r_2})$

$$ADF_{r_1}^{r_2} = \frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})} \quad (8)$$

where ADF is a standard form of unit root test statistics obtained by setting $r_1 = 0$ and $r_2 = 1$. To successfully detect the occurrences of explosive behavior, PWY propose a recursive procedure on the estimation of $ADF_{r_1}^{r_2}$ using different subsamples of data. This technique implements the forward recursive regression to obtain the supremum value of the $ADF_0^{r_2}$:

$$SADF\ (r_0) = \sup_{r_2 \in [r_0,1]} ADF_0^{r_2}. \quad (9)$$

If the SADF test statistics exceeds the right tale critical value, then the unit root null hypothesis of explosive behavior is rejected. SADF test have a greater power compared to methods proposed in Bhargava (1986), Kim (2000), and Busetti and Taylor (2004). This method shows mildly explosive behavior when an exuberance is detected in an asset series. The major shortcoming of SADF is that this method successfully identifies a single explosive episode but may not successfully detect the multiple episodes of exuberance. An improvement proposed by PSY addresses this issue with Generalized SADF (GSADF), which efficiently deals with multiple episodes of exuberance in a series. While the SADF method only allow changes in the initial observation following the recursive process, the GSADF allow variation in initial (r_1) and final (r_2) observation following the double recursion over all feasible ranges of (r_1) and (r_2). The GSADF statistics takes following form:

$$GSADF\ (r_0) = \sup_{\substack{r_1 \in [0, r_2 - r_0] \\ r_2 \in [r_0,1]}} ADF_{r_1}^{r_2}. \quad (10)$$

If the GSADF statistics exceeds the right tail critical value, we reject the null in favor of explosive alternative hypothesis. Evans (1991) finds that previously proposed unit root and cointegration-based tests may show a pseudo stationary behavior and is normally less successful in identifying subsequent bubbles after the first. Hence, we follow PSY methodology to date stamp the initiation and termination of bubbles using Backward Sup ADF (BSADF) statistic,

$$\mathrm{BSADF}_{\mathrm{r}_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2}. \tag{11}$$

The distributions of the $\mathrm{GSADF}(r_0)$ and the $\mathrm{BSADF}_{\mathrm{r}_2}(r_0)$ test statistics in Equations (10) and (11) are non-standard.[5] The beginning bubble date is stamped when the BSADF statistics exceeds the corresponding critical value. This is given by,

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \{r_2 \colon \mathrm{BSADF}_{\mathrm{r}_2}(r_0) > \mathrm{scv}_{\mathrm{r}_2}^{\alpha}\}. \tag{12}$$

Similarly, the termination date of a bubble is calculated as the first observation after $\hat{r}_e + \frac{n}{T}$ in which the BSADF falls below its critical value, where T represents the total sample size,

$$\hat{r}_f = \inf_{r_2 \in \left[\hat{r}_e + \frac{n}{T}, 1\right]} \{r_2 \colon \mathrm{BSADF}_{\mathrm{r}_2}(r_0) < \mathrm{scv}_{\mathrm{r}_2}^{\alpha}\}. \tag{13}$$

In Equation (12) and (13), $\mathrm{scv}_{\mathrm{r}_2}^{\alpha}$ denotes the $100(1-\alpha)\%$ critical value of the SADF based on $\lfloor r_2 T \rfloor$ observations and at a significance level α. The notation $\lfloor . \rfloor$ is the floor function that represents the integer part of $r_2 T$. In Equation (13), $\frac{n}{T}$ is selected randomly to make sure that bubbles last at least n days.

[5] Under the assumption of Gaussian innovation processes, the exact finite sample critical values for SADF and GSADF tests are obtained using a Monte Carlo simulation.

3.3. The Effect of Bubbles on Contagion

In this section, we present the framework to test how bubbles in stock market has affected financial market contagion. We begin by pooling the time series dynamic correlation coefficients to obtain a panel of correlations. Keeping the same notation as before, let ρ_t^{ij} be the time-varying correlation between countries *i* and j. We aim at estimating the following dynamic panel specification:

$$\rho_t^{ij} = \lambda \rho_{t-1}^{ij} + \kappa \mathrm{Z}_t^{ij} + \eta^{ij} + \nu_t^{ij}, \tag{14}$$

where λ and κ are coefficients of interest. In addition, Z_t^{ij} is defined as the dummy variable equal to one if a bubble period exists in one of the two countries in the bivariate pair *i* or *j*, but not in both, zero otherwise. Periods of bubble differ not only over *t*, but also by country. For bivariate pair of countries, Z_t^{ij} is equal to one if the GSADF statistics is greater than its corresponding 95% critical value for one of the two countries, otherwise zero. The disturbance term has two orthogonal components, i.e., $\varepsilon_t^{ij} = (\eta^{ij} + \nu_t^{ij})$; η^{ij} captures the country specific time-invariant effect, while ν_t^{ij} is the remaining stochastic term.

In Equation (14), the lagged dependent variable is not of direct interest, but its inclusion allows us to obtain consistent estimates of the effect of the bubbles on the dynamic correlations because a correlation between Z_t^{ij} and ρ_t^{ij} may be reflecting a common force behind the dynamic adjustment process. We also maintain that the ν_t^{ij} disturbances are serially uncorrelated by modeling bubble periods Z_t^{ij} as potentially endogenous in the sense that they may be correlated with ν_t^{ij} and earlier shocks, but Z_t^{ij} is uncorrelated with ν_{t+1}^{ij} and subsequent shocks,

$$\left.\begin{array}{ll} E(Z_s^{ij}\nu_t^{ij} \neq 0, & s \leq t \\ E(Z_s^{ij}\nu_{t+1}^{ij} = 0, & s > t \end{array}\right\}, \quad \forall ij. \tag{15}$$

From investment perspective dynamics of either Z_t^{ij} or ρ_t^{ij} may still hold significant future financial market return predictability, despite of endogenous Z_t^{ij}. Our estimation methods are consistent with investor's rational expectations and only assume that the disturbance element of the dynamic correlations ν_t^{ij} cannot be predicted.

We use the methods described in Arellano and Bond (1991) and Blundell and Bond (1998) to obtain consistent estimates of the coefficients λ and κ. Arellano and Bond (1991) involve taking first differences in Equation (14) to eliminate country specific time-invariant effect η^{ij},

$$\Delta\rho_t^{ij} = \lambda\Delta\rho_{t-1}^{ij} + \kappa\Delta\mathrm{Z}_t^{ij} + \Delta\nu_t^{ij}. \tag{16}$$

We then use Generalized Method of Moments (GMM) based on the moment conditions $E\left(\Delta\nu_t^{ij}\mathrm{W}\right) = 0$, where we use lagged correlations ρ_{t-1}^{ij} and lagged bubble periods Z_t^{ij} for the set instruments W. These moments are valid under the assumption that the error term ν_t^{ij} is serially uncorrelated. The results section provides specification test for the serial correlation assumption and for the validity of the instrument list. Moreover, following Blundell and Bond (1998) we use the additional moments $E[\left(\eta^{ij} + \nu_t^{ij}\right)\mathrm{M}]$ from the equation in levels. For the instruments M, we use lags of first difference of correlation coefficients and bubble periods, $\Delta\rho_{t-1}^{ij}$ and $\Delta\mathrm{Z}_t^{ij}$. These additional moment conditions are important when the series are persistent as lagged levels might be weak instruments in W.

4. Empirical Results

4.1. Dynamic Correlation Estimates

Table 2 reports the DCC-GARCH estimation results. From the mean equations in Panel A, we observe that the regression constants μ are all positive and highly significant. As expected, these estimates are relatively close, but are greater in magnitude, to the respective means of the dependent variable r_t^τ, reported in Table 1. We further observe that the autoregressive coefficients φ^τ are all negative and highly significant. We interpret these negative estimates as negative momentum and as a partial adjustment for mean reverting behavior in stock markets (see, e.g., Fama and French, 2000). When the lagged dependent variable is negative, this can indicate a reversion towards an equilibrium value, i.e., any price movement today partly reverts the following day. In addition, we further observe that coefficients γ, capturing the effect of the U.S.'s S&P 500 index on other stock indexes, are all statistically significant at the 1% level. That is, the U.S. stock market significantly affect the stock price dynamics in global financial markets.

[Table 2, about here]

When examining the variance equations reported in Panel B, we observe that the coefficients on the ARCH terms b are statistically significant across all countries in our sample, supporting this specification that allows for time varying volatilities. We also find statistically significant lagged conditional volatility, captured by a, which further justifies the appropriateness of the GARCH specification. The measure of volatility persistence, $a + b$, reports values close to unity across all countries, implying high level of persistence in the conditional variances. Furthermore, following the second step proposed in Engle (2002), we report in Panel C the estimates of the mean-reverting process (α and β) in the multivariate DCC equation. The statistically significant α and β coefficients at 1% level are strong evidence of time varying co-movement across all countries in our sample. The Wald test against the null hypothesis that both coefficients are zero, i.e., $\alpha = \beta = 0$, provide strong evidence against the null at 1% level.

[Table 3, about here]

The DCC-GARCH estimation allows us to obtain time-varying correlations ρ_t^{ij} for all the pairwise combinations of the six countries in the sample. We report average dynamic correlations in Table 3, which are consistent with static correlations presented in Table 1. From Table 3 we observe that European countries (France, Germany, and the United Kingdom) have high time-varying correlation coefficients with each other, while similar is true for both North American countries, Canada and the United States. This shows strong and statistically significant regional financial market contagion. Japan, on the other hand, has small average dynamic correlations with all other developed nations, while the United States exhibits moderate to high correlation coefficients with all developed nations except for Japan. During the periods of global risk aversion or bearish global economy, money is expected to flow-in into Japan's stock market as Japan is considered as safe-haven economy, while during bullish global economy, investors are more willing to take risk and tend to invest in high yield investment markets. Our assessment of financial market contagion is well justified not just at the regional level but also at the global level.

4.2.Bubble Periods Results

Following Equations (9) and (10) we report on Table 4, Panel A, the SADF and GSADF statistics for our six value-weighted indexes. In addition, Panel B presents the 90%, 95%, and

99% critical values obtained via Monte Carlo simulations with 2,000 replications. When looking at the SADF statistics in column 1, we find that there is a strong evidence of single bubble periods in three of the series. However, when considering the more flexible GSADF, the relatively high-test statistics reported in column 2 support the existence of multiple episodes of explosive behavior in all six developed countries. As illustrated in Equations (9) and (10), the SADF test statistics are obtained from the forward recursive regression, while GSADF test statistics is more flexible as it allows a double recursive regression over all feasible range of sub-samples.[6]

[Table 4, about here]

For the stock index from France, both SADF (1.1566>0.7071) and GSADF (3.1545>3.1224) statistics exceed their 5% and 1% right-tail critical values, respectively. We find similar evidence of explosive behavior in Germany (SADF: 1.3594>1.1989 and GSADF: 3.1640>3.1224) and for the Canadian stock index (SADF: 1.4916>1.1989 and GSADF: 2.8379>2.6135), where both SADF and GSADF statistics show statistically significant evidence at least at the 5% level. On the other hand, Japan and the United States show statistically significant evidence (Japan, GSADF: 3.7048>3.1224; USA, GSADF: 3.1808>3.1224) at the 1% level, while for the United Kingdom (UK, GSADF: 2.3100>2.3035), we find significance at the 10% level.

[Figure 1, about here]

[Figure 2, about here]

[6] Sharma and Escobari (2018) present a framework to use these methods on commodity prices.

[Figure 3, about here]

Figures 1, 2, and 3 plot the recursive BSADF test statistics against their corresponding 95% critical value sequences to identify bubble episodes in the value weighted inflation-adjusted stock index series of France, Germany, and the United Kingdom. Following Equations (12) and (13) to datestamp the beginning and end of bubble periods, the results show evidence of at least five statistically significant bubble periods in these European countries. All three indexes exhibit similar periods of explosive behavior. Moreover, we notice that all European countries in our sample exhibit statistically significant explosive behavior prior to the dot-com bubble period, i.e., late 1999 to early 2000, while another explosive behavior is observed during stock market downturn of 2002 or "the internet bubble bursting." Bacchetta and Van Wincoop (2016) show that a business cycle panic will synchronize across countries if there is a minimum level of economic integration. Moreover, they showed that factors such as tight credit, the zero-lower bound, unresponsive fiscal policy, and increased economic integration contributed to a global crisis of 2007-2009. August 2011 bear stock market, where there was a sharp drop in stock prices in stock exchanges across the United States, Europe, Asia, and Middle East, are effectively date stamped in our GSADF graphs. This bearish stock market movement resulted due to fears of contagion of the European sovereign debt crisis to the rest of the global economy, also mounting concerns over the slow economic growth in the United States and U.S. credit rating being downgraded, as well as concerns over Frances's AAA rating status.

[Figure 4, about here]

Likewise, Figure 4 plots the recursive BSADF statistics against the corresponding 95% critical values to identify episodes of bubbles in inflation-adjusted Japan stock index. Unlike

European countries, Japan shows three statistically significant bubble episodes in its stock index. The figure documents significant evidence of bubble periods, e.g., when Japan's industrial production reached its peak in 2005. Nonetheless, soon after 2005 Japan had to deal with a major challenge spurring out of the United States, administering contagion effects in global financial markets when global demand weakened during the 2007-2009 credit crisis. Our BSADF sequences are consistent with those events. In addition, a statistically significant bubble episode is recorded in the Nikkei during 2013, a time characterized with market friendly economic policies, since December 2012, and aggressive monetary easing in 2013.

[Figure 5, about here]

[Figure 6, about here]

Figures 5 and 6 report the results for the inflation-adjusted North American stock indexes by plot the recursive BSADF statistics for the United States and Canada against their corresponding 95% critical values. The United States stock market only shows a couple of statistically significant episodes of bubbles, while the Canadian stock market shows five statistically significant bubble episodes. In both North American stock markets, explosive behavior is observed during the stock market downturn of 2002 (i.e., during the internet bubble bursting). The most prominent among all GSADF identified bubbles is observed during the 2007-2009 global recession. In addition, the recursive BSADF plot for Canada (Figure 6) captures the bullish financial market trend due to the dot-com bubble around late 1999 to early 2000. During 2003-2004 and 2005-2006, the Canadian financial market rebounded primarily driven by the demand for commodities.

Overall, Figures 1 to 6 show that all country-specific stock indexes supported the existence of bubble during the 2007-2009 recession. In addition, the existence of bubble periods that coincide across indexes suggests the possibility of a contagion effect in financial markets during bubble episodes. We now turn to explain the empirical approach to formally test the hypothesis that financial contagion is greater during bubble periods.

4.3.Role of Bubbles on Financial Contagion

After pooling the dynamic correlations to form a panel, we report on Table 5 the OLS and country fixed effects regression estimates of the static version of Equation (14). The estimates of the constant reported in column 1 of Table 5 imply that on average the pairwise time-varying correlations is about 0.638. The main result in this table is the statistically significant point estimates for the bubble dummies. For example, from column 1 the negative point estimate of -0.062 reads that during bubbles the contagion is smaller. We observe that the average correlation decreases from 0.638 outside bubble periods to 0.576 during bubbles. This is evidence of impact of bubble periods on financial market contagion. Contagion among markets has become a prominent constraint while analyzing investment and portfolio diversification. Consistent with the estimates in column 1, column 2 presents estimates while controlling for months fixed effects.

[Table 5, about here]

Similarly, the within country point estimates reported in columns 3 and 4, indicate that bubble periods have a negative effect on conditional correlations. Column 3 shows that correlations outside bubbles are on average 0.636, while they are about 0.605 during bubbles. The difference is statistically significant at the 1% level.

When comparing columns 1 and 2 with the country fixed effects estimates in columns 3 and 4, we notice that the magnitude of the bubble coefficient decreases after controlling for country time-invariant characteristics. The estimates in columns 1 and 2 are likely to be biased due to the omitted country-pair effects.

[Table 6, about here]

One concern in the estimates reported in Table 5 is that the origin and end of bubbles is assumed to be exogenous. Moreover, the assumed data generating process rules out any dynamic adjustments. The dynamic panel estimates reported in Table 6 are aimed at relaxing both assumptions. The lagged dependent variable and the bubbles are treated as endogenous in all specifications. Consistent with the point estimates reported in Table 5, the bubble periods have a negative effect on contagion with the magnitude of the coefficient being smaller. All system GMM specifications in columns (1) through (4) pass both specification tests. The relatively large p-values associated with AR(2) serial correlation test support the assumption of no second order serial correlation in the difference error term. Moreover, the Hansen test of over-identifying instrument restrictions, which examines the sample analogs of the moment conditions implemented in the GMM estimation, validates the instrument set W. In addition, the difference Hansen test validates the additional instruments M used in the level equations.

5. Conclusion

International financial contagion refers to a spread of market changes from one country to another. In this paper, we test whether financial contagion changes during bubble periods using data from six developed economies. To test this hypothesis, we first build a framework to model financial contagion. In a second step we identify financial bubbles, and in the third step we assess the role of bubbles in financial contagion.

The framework to capture international financial contagion builds on Engle (2002) and uses dynamic conditional correlations. The correlations obtained in this step show evidence of regional and global financial market contagion consistent with Chiang et al. (2007) and contrasting the 'no contagion' conclusion offered by Forbes and Rigobon (2002). For the identification of financial bubbles, we employ the recursive flexible window right-tailed ADF-based procedure proposed in Phillips et al. (2011) and further extended in Phillips et al. (2015). We successfully identify and date-stamp the initiation and termination dates of bubble episodes. Pooling the time-series dynamic correlations and combining them with the identified bubble periods we run various dynamic panel specifications that allow us to directly test the hypothesis that financial bubbles affect international financial market contagion.

The results from the dynamic panel regressions, that pass both specification tests, show that financial contagion decreases during bubble periods. We find a statistically significant decrease in the correlations during bubble periods, which suggests that the financial contagion between a pair of countries diminishes when any of the two countries in the pair is going through a bubble period. This finding is robust to various specifications, including when we allow for dynamics in the nature of the correlations and potential endogeneity of bubbles booms and bursts.

Our findings have important implications for portfolio managers and international investors, as different diversification strategy is required during bubble periods in multi-market investment settings. During bubble periods investors are looking for an investment opportunity within domestic economy and rely less on international diversification. However, a decrease in contagion between two economies during bubble periods could provide ample diversification opportunities for investors and portfolio managers. Our analysis could be extended to other financial markets or different asset classes.

Appendix A

The key benefit when using the SADF and GSADF statistics to test for an explosive behavior is that we do not need to observe market fundamentals. However, critics state that the empirical evidence of explosive behavior may not certainly imply the existence of bubbles. For example, if the production is growing unexpectedly faster than previously the techniques may mistakenly lead to conclude growth trend as bubble. To formalize this notion, we define a bubble B_t as the difference between the after-dividend price P_t of an asset and the market fundamentals P_t^f, i.e., $B_t = P_t - P_t^f$. Then the market basics simply follow the asset pricing equation:

$$P_t^f = \sum_{i=0}^{\infty} \left(\frac{1}{1+r_f}\right)^i E_t(D_{t+i} + U_{t+i}), \qquad \text{A1}$$

where, r_f is the risk-free interest rate, D_t is the payoff amount or dividend received from the asset, and U_t signifies the unobserved fundamentals. In absence of bubbles, the degree of stationarity of P_t is completely determined by the degree of stationarity of P_t^f, i.e., following the Equation (A1), it would depend on the characteristics of the dividend series and the overlooked fundamentals. For instance, if the dividend series and fundamentals are either stationary or integrated of order one, then most likely the asset price is also integrated of order one. Asset prices show explosive behavior in the presence of bubbles, if the series fulfill the sub-martingale property $E_t(B_{t+1}) = (1 + r_f)B_t$. We can then conclude that empirical evidence of explosive behavior, as obtained with the SADF and GSADF statistics, is evidence of bubbles in the series.

Appendix B

Test of significant increase in dynamic conditional correlation coefficients (U.S. 2007-2009 recession as the source of contagion)

Table B1. Test for an increase in dynamic conditional correlation coefficients (U.S. 2007-2009 recession as the source of contagion)

	DCC Before Crisis			**DCC After Crisis**			
Variable	n	Mean	SD	n	Mean	SD	Z-statistics
$\rho^{\mathrm{France-USA}}$	2,325	0.6706	0.0794	2,630	0.6979	0.0839	-1.8073**
$\rho^{\mathrm{Germany-USA}}$	2,325	0.6592	0.0850	2,630	0.6974	0.0931	-2.4833***
$\rho^{\mathrm{Japan-USA}}$	2,325	0.3179	0.1416	2,630	0.4009	0.1111	-3.3504***
$\rho^{\mathrm{UK-USA}}$	2,325	0.7589	0.0851	2,630	0.7870	0.0796	-2.4586***
$\rho^{\mathrm{Canada-USA}}$	2,325	0.8803	0.1358	2,630	0.8969	0.0873	-2.7725***

Morrison (1983) suggests the test statistic for a null hypothesis of no increase in correlation, given as: $T = (Z_0 - Z_1)/\sqrt{[1/(N_0 - 3) + 1/(N_1 - 3)]}$, where $Z_0 = 1/2\ln[(1 - \rho_0)\,/(1 - \rho_0)]$ and $Z_1 = 1/2\ln[(1 - \rho_1)\,/(1 - \rho_1)]$ are Fisher Z-transformation of correlation coefficients before (Z_0) and after (Z_1) the crisis; $N_0 = 2325$ and $N_1 = 2630$ are the number of observations, while ρ_0 and ρ_1 are dynamic conditional coefficients before and after the crisis in this chapter. The null hypothesis is no increase in correlation. 1%, 5%, and 10% statistical significance are represented by ***, **, and *, respectively, whereas the respective critical values for a one-sided test of the null are -2.32, -1.64, and -1.28. The test statistics is approximately normally distributed and is robust to the non-normality of correlation coefficients. Basu (2002) and Corsetti et al. (2005) have employed this test.

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Table 1. Descriptive Statistics & Correlations

***Panel A*:**	Stock Index	Index Mean	Obs.	Return Mean	Return SD.	Return Min.	Return Max.
		(1)	(2)	(3)	(4)	(5)	(6)
France	France CAC 40	4546.75	4,956	0.0007	1.4323	-9.4715	10.5946
Germany	DAX 30 Performance	6913.38	4,956	0.0136	1.4752	-8.8747	10.7975
Japan	Nikkei 225 Stock Average	13324.54	4,956	0.0099	1.4661	-12.1110	13.2346
UK	FTSE All Share	3057.33	4,956	0.0016	1.1070	-8.7099	8.8107
Canada	S&P/TSX Composite Index	11449.43	4,956	0.0119	1.0777	-9.4524	9.3703
USA	S&P 500 Composite Index	679.54	4,956	0.0074	1.1872	-9.4695	10.9572

***Panel B*:**	France	Germany	Japan	UK	Canada	USA
	(1)	(2)	(3)	(4)	(5)	(6)
France	1					
Germany	0.8890	1				
Japan	0.2801	0.2492	1			
UK	0.8782	0.8052	0.3050	1		
Canada	0.5266	0.5218	0.1994	0.5340	1	
USA	0.5530	0.5876	0.1198	0.5276	0.7169	1

Notes: Table 1 reports the descriptive and correlation statistics. The nominal stock price indexes are obtained from Datastream on daily basis from January 1, 1999 to December 29, 2017. The real stock indexes are obtained by dividing the nominal price series by country specific Consumer Price Index (CPI). Country specific CPI are obtained from the Federal Reserve Bank of St. Louis.

Table 2. DCC-GARCH Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)
Countries:	France	Germany	Japan	UK	Canada	USA
Panel A. Mean Equations						
μ	0.0706***	0.0943***	0.0470***	0.0514***	0.0568***	0.0698***
	(0.0135)	(0.0139)	(0.0146)	(0.0102)	(0.00987)	(0.0108)
$\varphi r^{\text{France}}$	-0.138***					
	(0.00940)					
$\varphi r^{\text{Germany}}$		-0.101***				
		(0.0101)				
φr^{Japan}			-0.067***			
			(0.0131)			
φr^{UK}				-0.141***		
				(0.0101)		
$\varphi r^{\text{Canada}}$					-0.047***	
					(0.0141)	
γr^{USA}	0.320***	0.268***	0.560***	0.284***	0.0764***	-0.072***
	(0.0170)	(0.0175)	(0.0162)	(0.0133)	(0.0141)	(0.0142)
Panel B. Variance Equations						
c	0.0236***	0.0227***	0.0370***	0.0136***	0.00821***	0.0159***
	(0.00275)	(0.00260)	(0.00666)	(0.00169)	(0.00140)	(0.00214)
a	0.0688***	0.0675***	0.112***	0.0667***	0.0649***	0.0784***
	(0.00399)	(0.00384)	(0.00928)	(0.00430)	(0.00504)	(0.00596)
b	0.924***	0.926***	0.875***	0.924***	0.929***	0.911***
	(0.00435)	(0.00404)	(0.0101)	(0.00488)	(0.00538)	(0.00654)
Panel C. Multivariate DCC Equation						
α				0.0164***		
				(0.000833)		
β				0.970***		
				(0.00144)		
Obs.				4,955		
χ^2				1923		
χ^2 (p-value)				0		

Notes: The figures in parentheses are standard errors. For each countries the return Equations are: $r_t^{\tau} = \mu + \varphi r_{t-1}^{\tau} + \gamma r_{t-1}^{USA} + \varepsilon_t$, where $r_t = \left(r_{i,t}, r_{j,t}, \dots, r_{n,t}\right)'$, $\varepsilon_t = (\varepsilon_{i,t}, \varepsilon_{j,t}, \dots, \varepsilon_{n,t})'$, and $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$. The variance Equations: $h_t^{\tau} = c^{\tau} + \alpha^{\tau}(\varepsilon_{t-1}^{\tau})^2 + \beta^{\tau} h_{t-1}^{\tau}$ for countries $\tau = (i, j, \dots, n)$. The null hypothesis for the χ^2 test is H_0: $\alpha = \beta = 0$. * significant at 10%; ** significant at 5%; *** significant at 1% levels with critical values of 1.65, 1.96, and 2.58 respectively.

Table 3. Average Dynamic Correlations

	France	Germany	Japan	UK	Canada
	(1)	(2)	(3)	(4)	(5)
Germany	0.933***				
	(0.00418)				
Japan	0.268***	0.250***			
	(0.0286)	(0.0288)			
UK	0.886***	0.849***	0.254***		
	(0.00682)	(0.00884)	(0.0177)		
Canada	0.576***	0.561***	0.199***	0.582***	
	(0.0205)	(0.0210)	(0.0291)	(0.0203)	
USA	0.650***	0.651***	0.211***	0.623***	0.725***
	(0.0178)	(0.00884)	(0.0291)	(0.0188)	(0.0144)

Notes: The figures in parentheses are standard errors. *, **, and *** signifies significance at 10%, 5% and 1% levels. The average dynamic correlation coefficients are obtained from DCC GARCH models.

Table 4. Developed countries real stock indexes SADF and GSADF Test Statistics and Critical Values

Panel A. SADF test and the GSADF test statistics.			***Panel B. Finite sample critical values***		
	(1)	(2)		(3)	(4)
	SADF	GSADF		SADF	GSADF
France	1.1566**	3.1545***	99%	1.1989	3.1224
Germany	1.3594***	3.1640***	95%	0.7071	2.6135
UK	0.2861	2.3100*	90%	0.4833	2.3035
Japan	-0.0139	3.7048***			
Canada	1.4916***	2.8379**			
USA	0.1362	3.1808***			

Notes: The real stock indexes are calculated by dividing the nominal value-weighted index series (obtained from Datastream) by country specific Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). The sample spans from January 1, 1999 to December 29, 2017and the stock index prices are obtained on daily basis. SADF is Supremum Augmented Dickey–Fuller proposed by Phillips et al. (2011), and GSADF is Generalized SADF methodology proposed by Phillips et al. (2015). Critical values of both tests are obtained using Monte Carlo simulations with 2,000 replications. *** significant at 1%, ** significant at 5%, and * significant at 10%.

Table 5. Pooled and Fixed Effects Estimates

Periods of bubbles treated as:	Strictly Exogenous			
Estimator:	Pooled	Pooled	FE (Within)	FE (Within)
Dependent variable: $\mathrm{DCC}_{ij,t}$	(1)	(2)	(3)	(4)
$Bubble_t^{(i\,\Delta\,j)}$	-0.0616***	-0.0616***	-0.0313***	-0.0308***
	(0.00330)	(0.00333)	(0.0101)	(0.00983)
Constant	0.638***	0.638***	0.636***	0.635***
	(0.000796)	(0.00273)	(0.000680)	(0.00195)
Observations	71,715	71,715	71,715	71,715
Country fixed effect	No	No	Yes	Yes
Month fixed effect	No	Yes	No	Yes

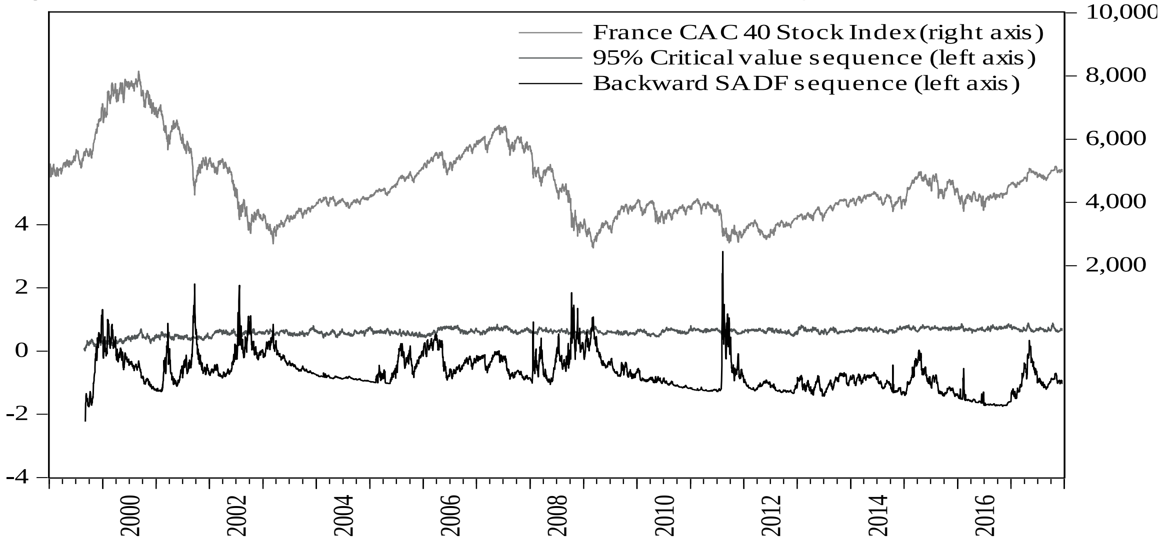
Notes: The dependent variable is $DCC_{ij,t}$. $Bubble_t^{(i\,\Delta\,j)} = \left\{Bubble_t^{(i-j)}\right\} \cup \left\{Bubble_t^{(j-i)}\right\} = \left\{Bubble_t^{i} - Bubble_t^{j}\right\} \cup \left\{Bubble_t^{j} - Bubble_t^{i}\right\}$, is a symmetric difference in bubble periods between two sets of countries *i* and *j*, excluding intersecting bubble periods in countries *i* and *j*. Column (2) and (4) are estimated with month fixed effect. *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors are reported in parentheses.

Table 6. System GMM with Month Fixed Effect Estimates

Instruments:	$t-2$	$t-3$	$t-2$	$t-3$
Dependent variable: $\mathrm{DCC}_{ij,t}$	(1)	(2)	(3)	(4)
$DCC_{ij,t-1}$			-0.012	-0.600
			(0.612)	(1.141)
$Bubble_t^{(i \Delta j)}$	-0.019**	-0.024***	-0.022**	-0.023**
	(0.008)	(0.006)	(0.009)	(0.011)
Constant	0.737***	0.721***	0.596*	1.466
	(0.068)	(0.065)	(0.360)	(1.148)
Observations	71,715	71,715	57,360	57,360
No. of instruments	19	21	19	21
Month fixed effect	Yes	Yes	Yes	Yes
AR2	-1.57	-1.64	0.22	-0.58
AR2 (p-value)	0.116	0.102	0.827	0.564
Hansen	0.1	1.25	2.56	4.12
Hansan (p-value)	0.980	0.975	0.634	0.661
Diff. Hansen test	4.51	8.73	0.92	3.61
Diff. Hansen test (p-value)	0.211	0.12	0.632	0.462

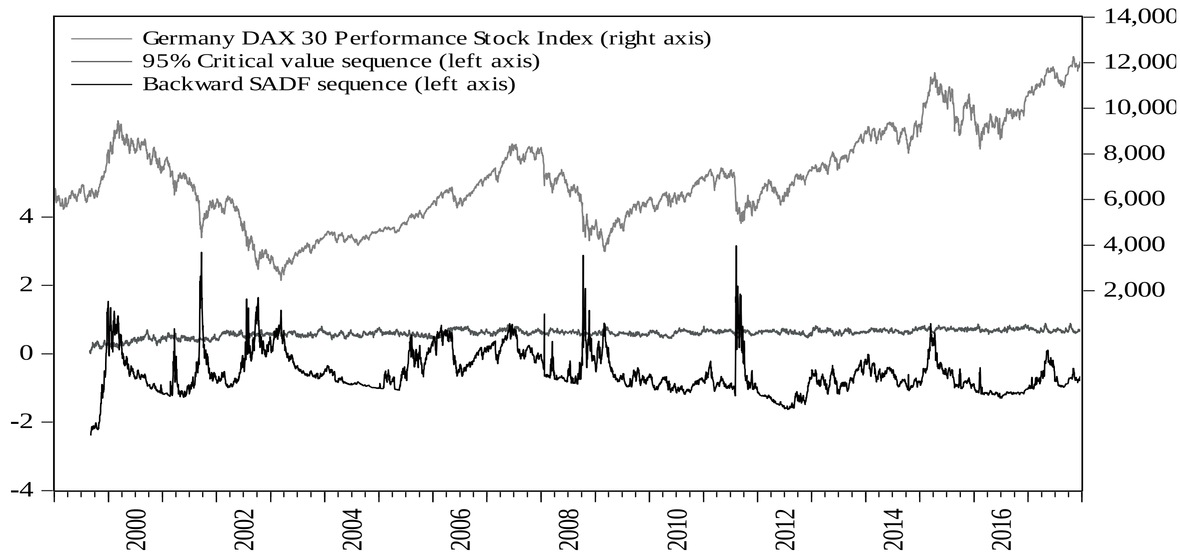
Notes: The dependent variable is $DCC_{ij,t}$. Please refer Table 5 notes for bubble periods explanation. For all endogenous variables in the System GMM, we use minimum lags of 2 and maximum lags of 4 (or 5) to complement daily data frequency. For the System GMM the Windmeijer finite sample corrected standard errors of the GMM two-step estimates are reported in parentheses and there are 15 contagion panels. For the SGMM, first, the null hypothesis is that the errors in the first-difference regression exhibit no second order serial correlation (valid specification). Second, the null hypothesis is that the instruments are not correlated with the residuals (valid specification). Third, the null hypothesis is that the additional instruments used in the levels Equations are not correlated with the residuals (valid specification). System GMM are estimated with month fixed effect. *** p<0.01, **p<0.05, * p<0.10.

Figure 1. GSADF: Bubble periods in the France CAC 40 Real Value-Weighted Stock Index.



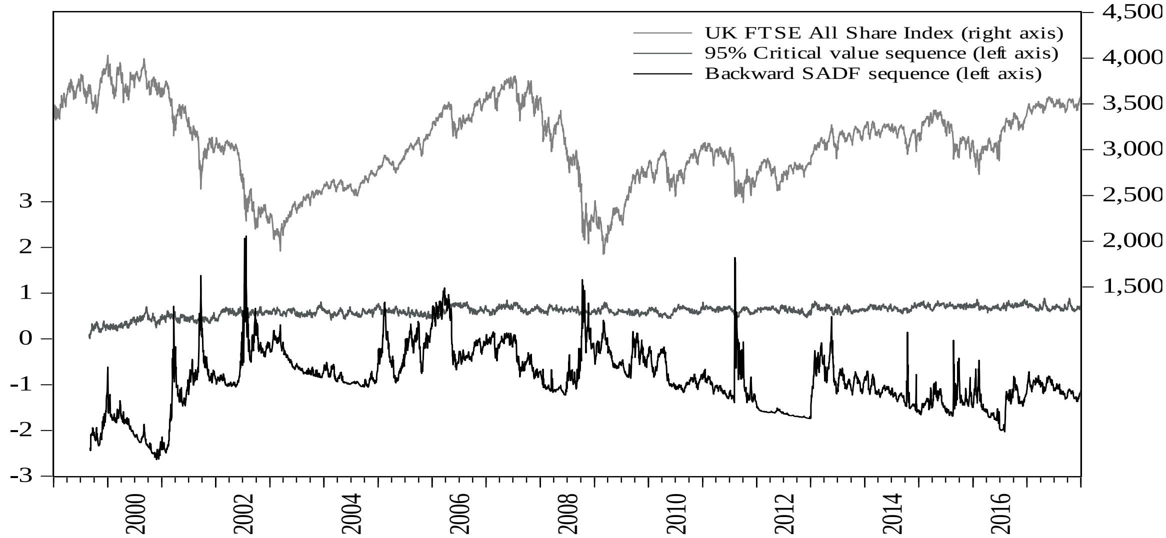
Notes: The France CAC 40 real stock index was obtained by dividing the nominal value-weighted stock index (obtained from Datastream) by the France's Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). The data spans from January 1, 1999 to December 29, 2017 on daily basis with the total number of observations being 4956. The Backward Supremum Augmented Dickey–Fuller (BSADF) follows Phillips et al. (2015) with the 95% critical values coming from Monte Carlo simulations with 2,000 replications.

Figure 2. GSADF: Bubble periods in the Germany DAX 30 Performance Real Value-Weighted Stock Index.



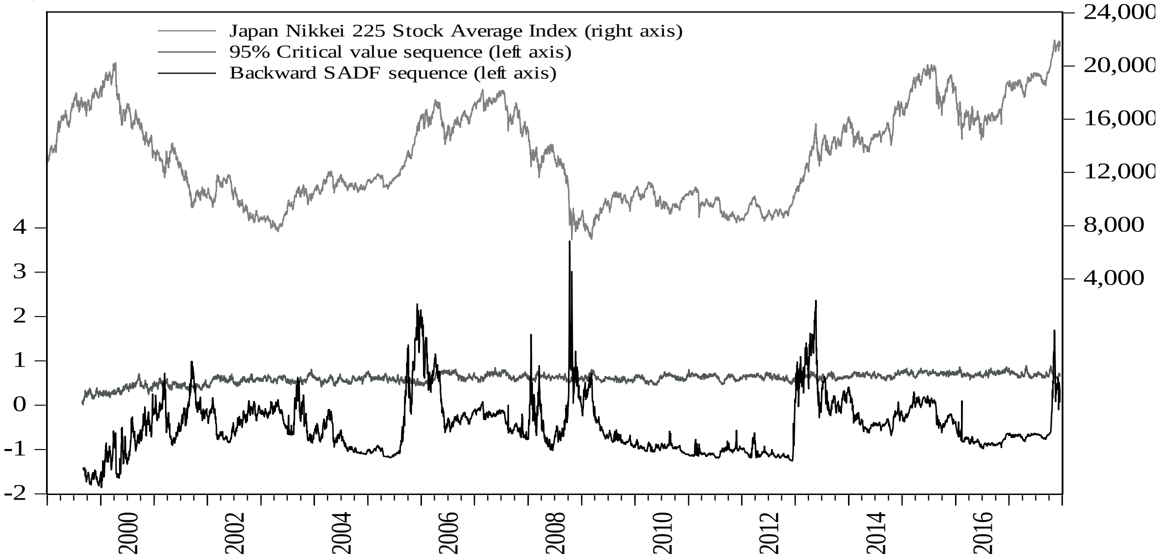
Notes: The Germany DAX 30 Performance real stock index was obtained by dividing the nominal value-weighted stock index (obtained from Datastream) by the Germany's Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). The data spans from January 1, 1999 to December 29, 2017 on daily basis with the total number of observations being 4956. The Backward Supremum Augmented Dickey–Fuller (BSADF) follows Phillips et al. (2015) with the 95% critical values coming from Monte Carlo simulations with 2,000 replications.

Figure 3. GSADF: Bubble periods in the UK FTSE All Share Real Value-Weighted Stock Index.



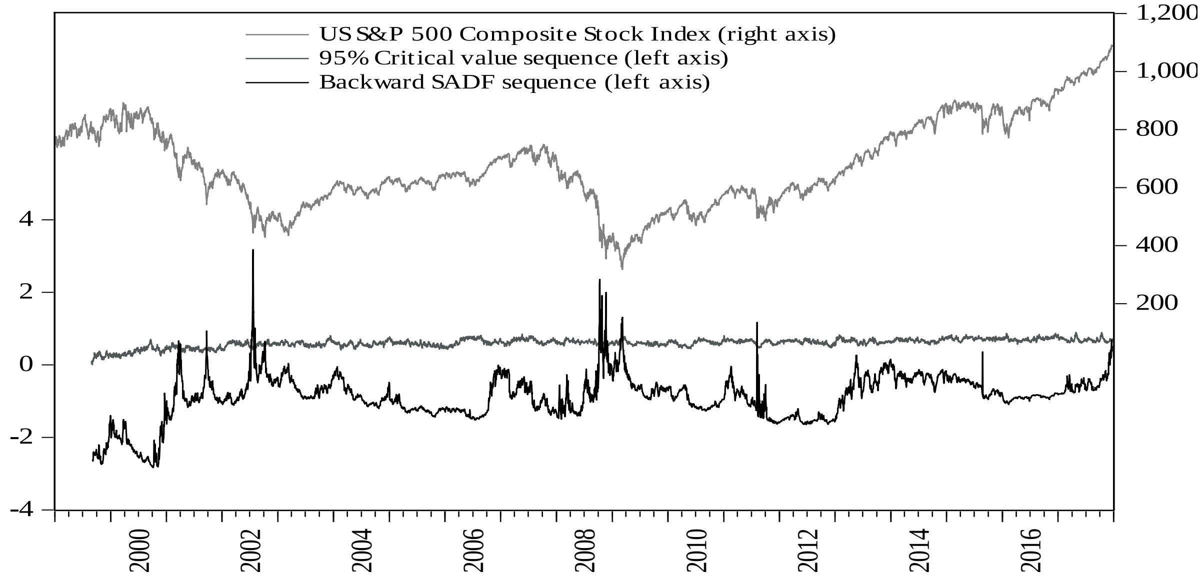
Notes: The UK FTSE All Share real stock index was obtained by dividing the nominal value-weighted stock index (obtained from Datastream) by the UK's Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). The data spans from January 1, 1999 to December 29, 2017 on daily basis with the total number of observations being 4956. The Backward Supremum Augmented Dickey–Fuller (BSADF) follows Phillips et al. (2015) with the 95% critical values coming from Monte Carlo simulations with 2,000 replications.

Figure 4. GSADF: Bubble periods in the Japan Nikkei 225 Real Value-Weighted Stock Index.



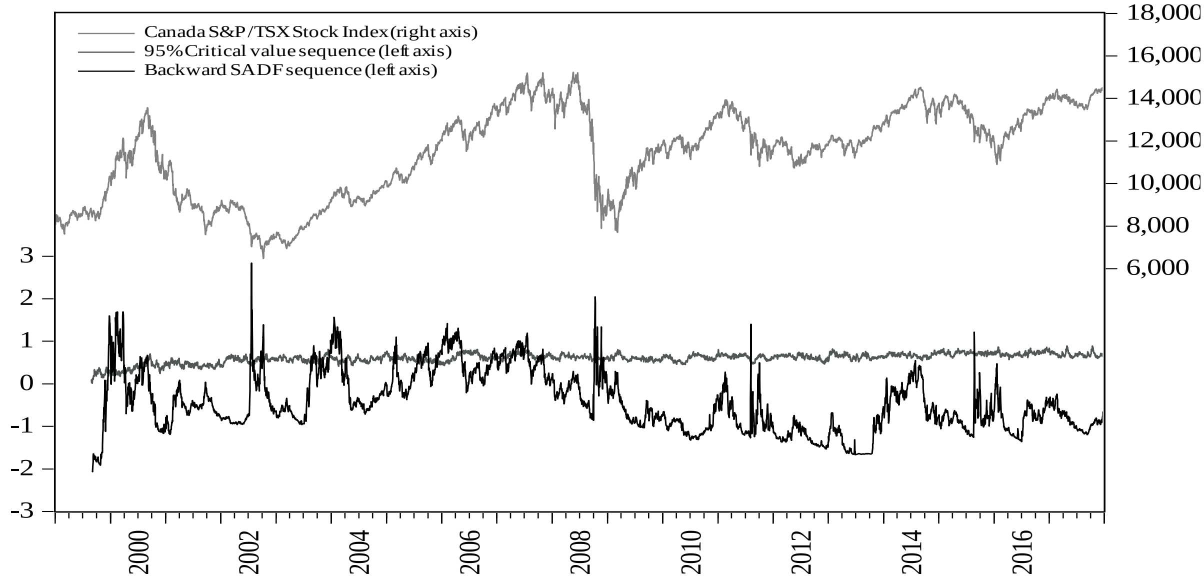
Notes: The Japan Nikkei 225 real stock index was obtained by dividing the nominal value-weighted stock index (obtained from Datastream) by the Japan's Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). The data spans from January 1, 1999 to December 29, 2017 on daily basis with the total number of observations being 4956. The Backward Supremum Augmented Dickey–Fuller (BSADF) follows Phillips et al. (2015) with the 95% critical values coming from Monte Carlo simulations with 2,000 replications.

Figure 5. GSADF: Bubble periods in the US S&P 500 Composite Real Value-Weighted Stock Index.



Notes: The US S&P 500 Composite real stock index was obtained by dividing the nominal value-weighted stock index (obtained from Datastream) by the USA's Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). The data spans from January 1, 1999 to December 29, 2017 on daily basis with the total number of observations being 4956. The Backward Supremum Augmented Dickey–Fuller (BSADF) follows Phillips et al. (2015) with the 95% critical values coming from Monte Carlo simulations with 2,000 replications.

Figure 6. GSADF: Bubble periods in the Canada S&P/TSX Real Value-Weighted Stock Index.



Notes: The Canada S&P/TSX real stock index was obtained by dividing the nominal value-weighted stock index (obtained from Datastream) by the Canada's Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). The data spans from January 1, 1999 to December 29, 2017 on daily basis with the total number of observations being 4956. The Backward Supremum Augmented Dickey–Fuller (BSADF) follows Phillips et al. (2015) with the 95% critical values coming from Monte Carlo simulations with 2,000 replications.