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# DISEQUILIBRIA AND CONTAGION IN FINANCIAL MARKETS: EVIDENCE FROM A NEW TEST

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This paper provides an analysis of contagion by measuring disequilibria in risk premium dynamics. We propose to test financial contagion using an econometric procedure where we first estimate the preference parameters of the consumption-based asset pricing model (C-CAPM) to measure the equilibrium risk premia in different countries and then we consider the difference between empirical and equilibrium risk premia to test cross-country disequilibrium episodes due to contagion. Disequilibrium in financial markets is modeled by the multivariate DCC-GARCH model including a deterministic crisis variable. Our approach allows to identify the disequilibria generated by increases in volatility that is not explained by fundamentals but is endogenous to financial markets and to evaluate the existence of contagion effects defined by exogenous shifts in cross-country return correlations during crisis periods. Our results show evidence of contagion from the U.S. to U.K., Japan, France, and Italy during the crisis started in 2007-08.

*JEL classification codes*: G10, G15
*Key words*: financial contagion, risk premium disequilibrium, cross-country return correlations, financial crises, DCC-GARCH model, C-CAPM

## I. Introduction

The investigation of the relationships among financial markets and the identification of financial contagion episodes are preferred topics in the econometric literature, especially after the recent global financial crises. Moreover, the dynamics of

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returns in international financial markets have been characterized by increases in volatilities and asset price synchronicity in the last decades and this has raised even further the scientific interest in the discrimination between interdependence and contagion effects. As a consequence, many different tests for detecting the existence of financial contagion have been developed (see, among many others, Corsetti et al. 2001; Forbes and Rigobon 2001; Dungey et al. 2005; Allen and Gale 2005; Rodriguez 2007; Cipriani et al. 2013). However, conclusions on both theoretical and empirical analyses of financial contagion are far from unique. Furthermore, there is not even a shared scientific definition of contagion (see Pericoli and Sbracia 2001 for a discussion).

In this paper, we propose a new econometric approach for the evaluation of contagion based on the extent of disequilibria in financial dynamics. In particular, using a step-wise procedure, we define an innovative test for the detection of contagion which specifically identifies the disequilibrium originated by the international transmission of financial crises and their relationships with the behaviors of market participants. In this framework, contagion effects are separated from the transmission processes of endogenous nature which have their genesis in the pricing process system and in investor's behaviors and which are responsible for the amplification of cross-market interdependence. In particular, our proposal is able to discriminate between contagion and interdependence among international financial markets and thus provides a powerful technique for testing for the existence of contagion.

In Section II of the paper, we discuss the theoretical framework underlying our approach. Section III illustrates the econometric model and details the proposed three-step procedure for evaluating contagion among countries. In Section IV, we estimate the model and present the results of the analysis. Finally, Section V concludes.

## II. Theoretical framework

Correlation shift is the criterion generally chosen in contagion literature to separate "normal" from contagious periods (e.g., Corsetti et al. 2001, 2005; Forbes and Rigobon 2002; Chiang et al. 2007, among many others). However, the adequacy of this approach is still questioned since it does not take into account the correlation endogenously and independently generated by phenomena different from contagion. This drawback has become increasingly serious in recent years because of the dramatic increase in the number of market participants, financial innovation, and the reform of financial regulations. The opening of international markets, the diffusion of sophisticated financial engineering and products, and the growing importance of behaviors described by cognitive psychology have increased uncertainty and have generated processes of amplification of the financial dynamics. These processes are endogenous to investment decision-making of market participants and have significantly increased volatilities and correlations between returns in international financial markets. Thus, in order to identify the cross-country transmission of the effects of country-specific events, we need econometric models able to separate the increased correlation in returns and volatilities originated by endogenous uncertainty from that due to exogenous transmission of idiosyncratic shocks among different regions. In fact, amplification processes, spillover effects, and correlation shifts can be either effects of financial contagion or processes endogenously generated inside the markets. By discriminating between the endogenous and the exogenous nature of the processes of amplification, we can separate contagion phenomena from other correlation shifts.[1] Specifically, the measurement of the shifts requires the discrimination between the endogenously generated correlation (interdependence) and that due to the transmission of exogenous shocks (contagion). Limiting the notion of contagion to the processes of disequilibrium amplification having exogenous nature, we are able to clearly separate the two classes of phenomena and to define powerful tests for financial contagion.

Risk premium is a sensitive indicator of return amplification and financial market disequilibrium and thus can be used to discriminate between the exogenous amplification derived from contagion and those generated by endogenous processes. In this paper, disequilibria are identified comparing equilibrium risk premia, determined by preference parameters and the consumption dynamics, with empirical risk premia. Precisely, the deviation between the equilibrium level

[1] The main focus of the paper is on conditional correlations. However, higher conditional moments may also play an important role in the detection of contagion. In particular, conditional co-skewness might well characterize contagion. In a recent work, Yang et al. (2010) show that stock and bond conditional co-skewness negatively affects stock and bonds risk premia, thus providing important implications for portfolio management. Moreover, Dodge and Rousson (2001) show that higher moments aid in sorting out exogeneity, which is impossible to determine when using correlation coefficients due to its symmetric nature. Hence, a promising focus for future research would be to investigate the potential of approaches based on higher conditional moments to detect contagion.

and the observed risk premium measures financial market disequilibrium. The estimates of risk premium obtained within a consumption-based asset pricing model (C-CAPM) automatically reflect the dynamics of fundamentals influenced by endogenous processes of amplification. Therefore, the comparison between the empirical risk premium and the one inferable from the C-CAPM provides an approximation of disequilibrium which is extremely useful for contagion tests. By modeling dynamic conditional correlations in risk premia disequilibrium we can discriminate between endogenous and exogenous processes, where the latter can be ascribed to financial contagion.[2] To test the existence of exogenous shocks which generate contagion, we analyze the dynamics of time-varying conditional correlation coefficients including a deterministic variable which denotes the idiosyncratic shock. Hence, we test the potential impact that such shock had in regions different from where it originally occurred. The procedure proposed for testing contagion can be summarized in three steps. The first step consists in determining the disequilibria in risk premium for each country, defined by the difference between empirical risk premia and the risk premia predicted by the C-CAPM. In the second step, we model disequilibria in risk premia using a dynamic conditional correlation (DCC) multivariate GARCH model. In the third step, we test for contagion between markets by analyzing the exogenous shifts in the conditional correlation coefficients estimated in the second step. Specifically, the test is defined by modeling the estimated conditional correlation coefficients with autoregressive models including dummy variables corresponding to crisis periods. In this framework, the (positive) dummy coefficients measure the correlation shifts due to the transmission of idiosyncratic shocks from one country to another which denotes contagion.

[2] Note that the asymmetric nature of this relationship removes any risk of mixing contagion episodes with business cycle co-movements which are symmetric. Moreover, the two situations are empirically distinct, since the latter is driven by productivity (see, e.g., Crucini et al. 2011 and references therein), whereas the former is driven by monetary and financial factors.

## III. The econometric procedure

In this section we briefly outline the three steps of the procedure proposed to evaluate financial contagion.

### A. Step 1: Disequilibrium of risk premia

In the first step, we estimate the preference parameters (risk aversion and intertemporal substitution rate) of agents who rationally maximize their expectations using a power utility function. The parameters are estimated by the first order conditions through the generalized method of moments (GMM; Hansen and Singleton, 1982). The estimation of the model allows the evaluation of the behavior of the representative consumer-investor in each country with respect to macroeconomic fundamentals.

Considering the constant relative risk aversion (CRRA) utility function, we specify the Euler equations which allow the estimation of the parameters of intertemporal substitution rate $\delta$ and risk aversion $\gamma$ using GMM:

$$E\left[\delta\left(\frac{c_{t+1}}{c_t}\right)^{-\gamma}\mathbf{r}_{t+1}-\mathbf{1}\,|\,\mathbf{Z}_t\right]=0\,, \tag{1}$$

where $\mathbf{r}_{t+1}=[r_{m,t+1},\ r_{f,t+1}]'$ is the vector of asset returns and $\mathbf{1}=[1,\ 1]'$. The model is thus specified as a system of equations which, in addition to the consumption growth rate $w_t=c_t/c_{t-1}$, considers the stock market return $r_m$, and the risk-free asset return $r_f$ (approximated by the interest rate of Treasury Bills). Furthermore, we also evaluate the information set that the representative consumer-investor has at time $t$. This set of instrumental variables is collected in the information matrix $\mathbf{Z}_t$. In order to address the weak identification problem (Stock and Wright 2000), we define matrix $\mathbf{Z}_t$ including a wide set of lagged macroeconomic variables.

Furthermore, with the attempt of ensuring a certain level of homogeneity in our analysis, we consider the same variables for all the countries under investigation.[3]

For country $i$, the estimated risk aversion rate allows the measurement of the equilibrium risk premium, denoted as *ERP*, which also depends on the dynamics of the consumption growth rate:

$$ERP_{i,t} = \hat{\gamma}_i w_{i,t} . \tag{2}$$

Therefore, the C-CAPM estimation allows the rigorous measurement of the development of risk premia by considering the dynamic pattern of consumption as the main reference of macroeconomic fundamentals.

Let *ORP* denote the risk premium empirically measured as the excess return with respect to the risk-free asset, i.e., $ORP_{i,t} = r_{m,i,t} - r_{f,i,t}$. The disequilibrium in each financial market is then measured as the distance between *ORP* and the (theoretical) equilibrium risk premium obtained on the basis of the preferences estimated by the model, i.e., *ERP* in equation (2):

$$X_{i,t} = ORP_{i,t} - ERP_{i,t} . \tag{3}$$

$X_{i,t}$ represents the variable of interest in our analysis since it measures the differential between the risk premium of rational equilibrium and the one actually observed for country $i$. These measures of disequilibria, which include both endogenous and exogenous factors, are then investigated in the second step of our analysis.

### B. Step 2: Measurement of disequilibrium amplification

We distinguish between episodes of contagion (exogenous amplification processes) and other situations in which the financial dynamics is (endogenously) amplified

[3] Is not easy to answer the question of whether there is a set of homogenous instruments that holds between different countries. However, by considering a large number of common instruments we not only ensure international comparability but, from a theoretical viewpoint, we also think that the instrumental variables we find in Section IV.A constitute the main factors that contribute to the definition of the preference parameters of the representative agent.

with respect to the fundamentals by investigating the dynamics of disequilibria in equation (3). In particular, we aim to evaluate two directions: (i) the relevance that financial crises have in cross-country transmission of negative tendencies which are not justified by fundamentals; (ii) the persistence of these irrational processes which cause the transmission and the amplification of the dynamics during a financial crisis. We address both aspects by modeling the irrational amplifications identified by $X_{i,t}$ using a multivariate ARCH-type model able to evaluate the volatility processes of risk premia and their interrelations both in the level and in persistence. In particular, the test for assessing contagion effects is based on the analysis of the dynamic conditional correlations between two countries, one of which is assumed to be the originator of the crisis. Therefore, we assess whether an (exogenous) shift in the correlation coefficient value is due to the spillover effect of a crisis originated in the other country. This analysis is based on the multivariate GARCH model with dynamic conditional correlations (DCC MV-GARCH) proposed by Engle (2002). A limitation which virtually affects all the tests for evaluating the presence of contagion is that such tests suffer from the arbitrary choice of two fundamental factors: (i) which country has to be considered as the originator of the crisis and (ii) what should be the time window length for the crisis periods (Billio and Pelizzon 2003). Moreover, the definition of sub-samples on the basis of high and low levels of volatility is a further arbitrary process subjected to a selection bias (Boyer et al. 1999). The DCC MV-GARCH model is particularly suitable for overcoming these limitations. In particular, this methodology allows us to face the heteroskedasticity problem raised by Forbes and Rigobon (2002) without arbitrarily splitting the time series into two sub-samples according to its volatility levels.

The DCC MV-GARCH model assumes that random variables $X_{i,t}$ are distributed as conditional multivariate normals with zero means and time-varying covariance matrix $\Sigma_t$, i.e., $X_t \mid I_{t-1} \sim N(0, \Sigma_t)$. In this specification, the covariance matrix is decomposed in three matrices, namely $\Sigma_t = D_t R_t D_t$, where $D_t$ is the diagonal matrix of conditional standard deviations and $R_t$ is the time-varying conditional correlation matrix, and is estimated using a two-stage procedure. In the first stage, each conditional variance included in matrix $D_t = \mathrm{diag}[\sigma_{i,t}]$ is estimated using univariate GARCH($p$,$q$) processes as

$$\sigma_{i,t}^2 = \omega_i + \sum_{p=1}^{P_i} \alpha_{i,p} X_{i,t-p}^2 + \sum_{q=1}^{Q_i} \beta_{i,q} \sigma_{i,t-q}^2 .$$

Matrix $R_t = [\rho_{ij,t}]_{i \neq j}$ is computed in the second stage using maximum likelihood estimator for the dynamic correlation structure

$$Q_t = (1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n)\overline{Q} + \sum_{m=1}^{M} a_m (\varepsilon_{t-m} \varepsilon'_{t-m}) + \sum_{n=1}^{N} b_n Q_{t-n} ,$$

which is used to compute $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$, where $\overline{Q} = \frac{1}{T} \sum_{m=1}^{T} \varepsilon_{t-m} \varepsilon'_{t-m}$ is the unconditional covariance of standardized residuals obtained in the first stage of the estimation procedure and $Q_t^*$ is a diagonal matrix containing the square roots of elements on the diagonal of matrix $Q_t$, namely $Q_t^* = \mathrm{diag}[\sqrt{q_{ii,t}}]$. Thus, the general element in matrix $R_t$ is given by $\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}$ , for $i \neq j$ .These estimates are modeled to test for the existence of contagion between pair of countries.

### C. Step 3: Test for contagion between countries

Once estimated the series of dynamic conditional correlations between different countries, we assess the existence of contagion between countries $i$ and $j$ by investigating the dynamics of the estimated $\rho_{ij,t}$. This allows the identification of the shift in correlation coefficients ascribed to contagion phenomena, having controlled for all the endogenous amplification factors in the previous steps. Thus, we evaluate the estimated coefficients of the following (autoregressive) regression model

$$\rho_{ij,t}^* = c + \sum_{p=1}^{P} \phi_p \rho_{ij,t-p}^* + \sum_{l=1}^{C} \delta_l DM_{l,t} + e_{ij,t} , \qquad (4)$$

where $\rho^*_{ij,t} = \frac{1}{2}\ln\left(\frac{1+\rho_{ij,t}}{1-\rho_{ij,t}}\right)$ is the Fisher transformation of the dynamic correlation coefficient between countries $i$ and $j$, and $DM_{l,t}$ denotes the dummy variable for crisis $l$, for $l$ = 1, .., $C$ and where $C$ denotes the number of detected crises. For each pair-wise correlation coefficient, the order $P$ of the autoregressive component is identified according to the well-known Akaike, Schwarz, and Hannan-Quinn information criteria (AIC, BIC, and HQC).

In our framework, the model in equation (4) implies that the significance of the estimated coefficients for the dummy variables indicates structural breaks in the correlation coefficients during financial crises. Thus, the test for evaluating contagion between two countries with respect to crisis $l$ is based on the null hypothesis $\mathrm{H}_0 : \delta_l = 0$ which assumes the absence of contagion effects against the alternative $\mathrm{H}_1 : \delta_l > 0$ of presence of contagion.

## IV. Results

In this section, we show the results related to the three-step procedure for model estimation and the test for the evaluation of contagion outlined in Section III. In our analysis, we consider five countries, namely United States, United Kingdom, Japan, France, and Italy, using quarterly data series from Q2 1980 to Q2 2011 ($T$ = 125 observations). All the data are collected from Thompson Datastream.

### A. Step 1: Disequilibrium of risk premia

The first step of the analysis consists in estimating the C-CAPM via GMM to obtain, for each country, the values of the two parameters of interest: the intertemporal substitution rate $\delta$ and the relative risk aversion $\gamma$. The selection of the instrumental variables collected in matrix $\mathbf{Z}_t$, i.e., the choice of the information set available at time $t$ on which investor-consumers base their decisions, is based on two information criteria for GMM, namely the MMSC-BIC and the MMSC-HQ proposed by Andrews and Lu (2001). According to these model selection criteria, we have the following variables for each country: $r_{m,t}$, $r_{m,t-1}$, $r_{m,t-2}$, $r_{m,t-3}$, $r_{f,t}$, $r_{f,t-1}$, $r_{f,t-2}$, $r_{f,t-3}$, $\Delta prod_t$, $\Delta prod_{t-1}$, $\Delta prod_{t-2}$, $\Delta prod_{t-3}$, $\Delta gdp_t$, $\Delta gdp_{t-1}$, $\Delta gdp_{t-2}$, $\Delta gdp_{t-3}$, $spread_t$, $spread_{t-1}$, $spread_{t-2}$, $spread_{t-3}$, where:

- $r_m$ is the return of the market portfolio approximated by the Datastream index for the whole stock market in a given country;
- $r_f$ is the return of the risk-free asset defined as the average value of the redemption yield;
- $\Delta prod$ is the $\Delta$log of the industrial production series (seasonal adjusted);
- $\Delta gdp$ is the $\Delta$log of the gross domestic product series (seasonal adjusted);
- *spread* is the treasury bill interest rate spread computed as the difference between the long term T-Bill rate (7-10 years) and the short term T-Bill rate (1 month).

**Table 1. C-CAPM asset pricing models: coefficient estimates and J-tests**

| Country *i* | $\hat{\delta}_i$ | $\hat{\gamma}_i$ | J-test (p-value) |
|---|---|---|---|
| United States | 0.9835 | 0.1265 | 22.39 |
| | (0.0007) | (0.0153) | (0.9889) |
| United Kingdom | 0.9866 | 0.6411 | 21.30 |
| | (0.0016) | (0.0555) | (0.9933) |
| Japan | 0.9954 | 0.4227 | 20.28 |
| | (0.0011) | (0.0368) | (0.9960) |
| France | 0.9868 | 0.7323 | 20.02 |
| | (0.0012) | (0.0983) | (0.9965) |
| Italy | 0.9879 | 0.5481 | 19.51 |
| | (0.0009) | (0.0463) | (0.9974) |

Note: Standard errors in parenthesis.

Table 1 shows the estimates of coefficients $\delta$ and $\gamma$ for each country. The results in Table 1 show that all coefficients are significant and, according to the J-tests, the over-identifying restrictions implied by the model are not rejected for all countries. In particular, the similar values of the J-test statistics in Table 1 can be interpreted as evidence of, on the one hand, the effectiveness and accuracy of the GMM estimator and, on the other hand, the reliability of the obtained results. The estimated values of $\delta$ and $\gamma$ are plausible as we expect that parameter $\delta$ is close but less than 1 and the annualized value of $\gamma$ is smaller than 3 (see, e.g., Mehra and Prescott 1985; Brandt and Wang 2003). The estimation of the risk aversion rate allows the measurement of the equilibrium risk premium as in equation (2) for each country $i$. Then, using equation (3), we obtain the time series of risk premium disequilibria in each country, denoted as $X_{i,t}$, measured as the distance between equilibrium and actual observed risk premia.

### B. Step 2: Measurement of disequilibrium amplification

The second step of the analysis starts with the identification of the financial crises in each country on the basis of the standardized values of variables $X_{i,t}$. In particular, we detect a crisis in country $i$ at time $t$ when the standardized value of the series is lower than the 5th percentile ($X_{i,t} < -1.64$). This procedure allows us to overcome the limitation of the arbitrary choice of the crisis periods raised by Billio and Pelizzon (2003). For each country, we report the quarters which are detected as turmoil periods in Table 2.[4] As validation, we also identify the turmoil periods using the algorithm proposed by Bai and Perron (2003) for endogenous simultaneous estimation of multiple break-points in time series. This efficient algorithm is based on the principle of dynamic programming which allows the computation of estimates of the break dates as global minimizers of the sum of squared residuals with at most operations of order $O(T^2)$ for any number of breaks. In particular, we use the endogenous break-point method of Bai and Perron (2003) to investigate the presence of breaks in the variance of the standardized series for the United States, $X_{US,t}$. Bai-Perron's (2003) method coupled with BIC identifies seven break dates for the squared standardized series for the United States, namely Q3 1987, Q1 1988, Q3 1998, Q1 1999, Q3 2003, Q3 2008, and Q1 2009. These break dates are depicted in Figure 1 as dashed vertical lines. Comparing these results with the ones reported in Table 2, we note that the break dates determined via Bai-Perron's (2003) method correspond or are very close to the turmoil periods identified by the adopted 5th percentile selection procedure. The only exception is Q3 2008 where we observe a shift from a period of high volatility to a period of low volatility and, therefore, this break-point can be hardly associated with a turmoil period (see Figure 1). From Figure 1 we also note that, despite no break dates being detected in 2001 and 2002, this period is characterized by high volatility

[4] The 5th percentile threshold may be viewed as 'too conservative' as it does not detect some well-known crisis periods such as the European Exchange Rate Mechanism crisis in 1992 and the beginning of the 2007-08 financial crisis in the U.K. In fact, if we consider a 'more liberal' threshold, e.g., 20th percentile, we identify 20 more quarters including Q3 1992 and Q4 1992 for all the European countries and Q3 2008 and Q2 2009 for the U.K. However, our definition of crisis as a rare extreme event is consistent with a strict threshold. Note also that the break dates determined via Bai-Perron's (2003) endogenous method line up well with the 5th percentile selection procedure we adopted.

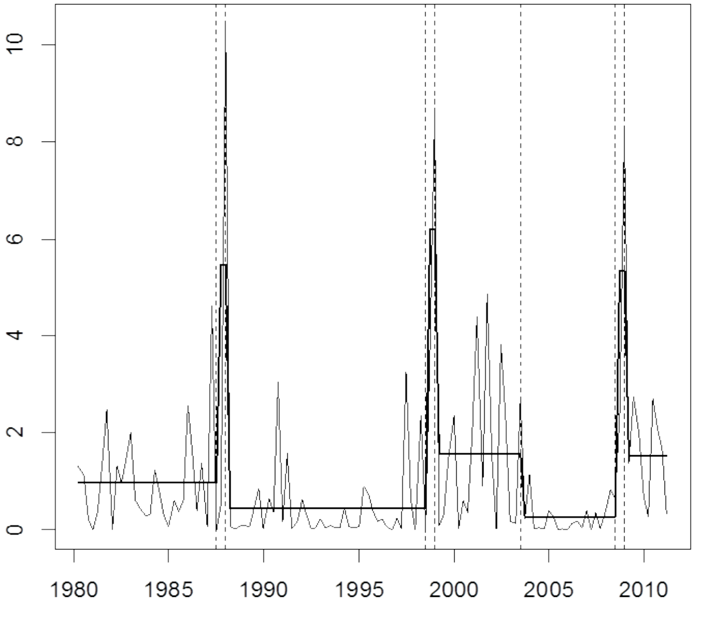
and, hence, can be interpreted as a turmoil period. The same holds for the period from Q1 2009 onwards.

Table 2. Identification of the quarters of financial turmoil

| | U.S. | U.K. | Japan | France | Italy |
|---|---|---|---|---|---|
| Q1 1988 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Q2 1990 | | ✓ | ✓ | | |
| Q4 1990 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Q2 1995 | | | ✓ | | |
| Q4 1998 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Q2 2001 | ✓ | ✓ | | | |
| Q4 2001 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Q4 2002 | ✓ | ✓ | | ✓ | ✓ |
| Q4 2008 | ✓ | | ✓ | | |
| Q1 2009 | ✓ | | ✓ | ✓ | ✓ |
| Q3 2010 | ✓ | ✓ | ✓ | | |

Note: Standardized $X_{i,t} < -1.64$.

Figure 1. Break dates for the squared standardized series of the United States




Note: Break dates determined by Bai-Perron's (2003) endogenous method. The break dates are Q3 1987, Q1 1988, Q3 1998, Q1 1999, Q3 2003, Q3 2008, and Q1 2009.

We now model the endogenous process of risk premium disequilibria using the (standardized) $X_{i,t}$ obtained in Step 1 as the dependent variables of the DCC MV-GARCH model defined in Section III.B. In the first stage of the model estimation procedure, one univariate GARCH model is specified for each country. According to BIC, we consider a GARCH(1,1) model with Generalized Error Distribution, GED($\upsilon$), for all countries. The results for the univariate GARCH models, which are summarized in Table 3, show a high level of volatility persistence; i.e., $\alpha_{i,1} + \beta_{i,1}$ is very close to 1 for all countries. Moreover, coefficients $\hat{\beta}_{i,1}$ are all significant at least at a 5% level (except for Japan), thus highlighting the fact that the GARCH model is particularly suitable for analyzing risk premium disequilibria. The parameter estimation for the DCC(1,1) component are reported in the last rows of Table 3. Both coefficients $a$ and $b$ are found highly significant and the model detects a common pattern in the dynamics of the conditional correlations between the United States and the other four countries (see Figure 2). As in the case of univariate GARCH models, also the conditional correlation coefficients are characterized by a high level of persistence: the sum of the DCC parameters is close to 1.

### C. Step 3: Test for contagion between countries

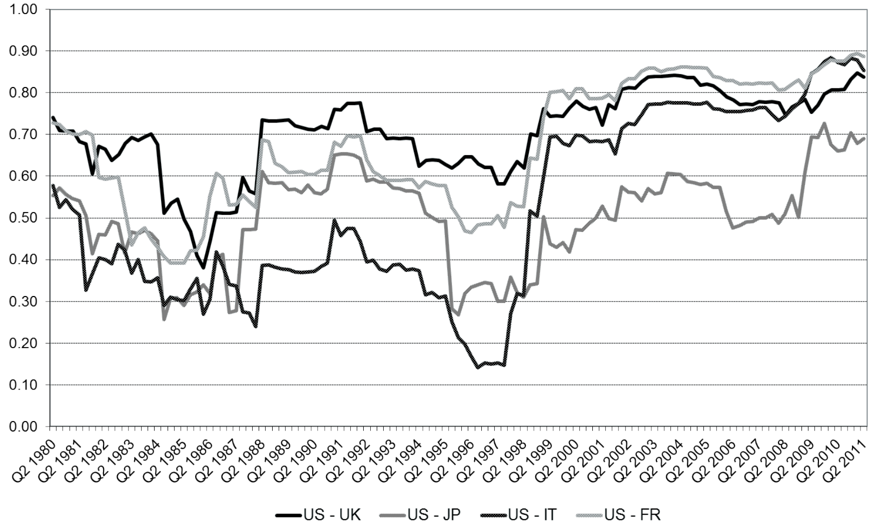
In the third step of our analysis, we analyze the exogenous shifts in the dynamics of the correlation coefficients estimated by the DCC MV-GARCH model in Step 2, with a specific focus on the relationships between United States and the other countries. This choice is based on the assumption that the U.S. market is the originator of both the 2000-01 turmoil period and the crisis started in 2007-08 and that U.S. financial-economic conditions have a strong influence on the financial mood in other countries. This assumption could be easily relaxed by investigating all the pair-wise correlation coefficients between countries.

From Figure 2 we can observe that, since mid-1998, correlations between the U.S. and the other countries have strongly increased. In order to evaluate whether this shift is exogenously determined and due to contagion phenomena, we analyze the dynamic conditional correlations using the autoregressive model specified in equation (4), where the dummy variables correspond to the detected crisis periods reported in Table 2. In particular, we investigate five recent financial turmoil periods: $DM_{1,t}$ represents the impulse dummy variable for Q4 1998, $DM_{2,t}$ and $DM_{3,t}$ identify Q4 2001 and Q4 2002, respectively, $DM_{4,t}$ is the dummy variable for Q1 2009, whereas $DM_{5,t}$ identifies Q3 2010. The results for the regression models illustrated in Table 4 show that, in addition to the autoregressive component coefficient which is highly significant for all the estimated models and close to one, the only significant dummy variable is $DM_{4,t}$ in the model which considers the correlation between the United States and Japan. The estimates of variables *DM* are non-significant in all the other cases, thus highlighting the absence of contagion between countries. The last two rows of Table 4 show the p-values related to the LM Breusch-Godfrey test for assessing residual autocorrelation up to four lags and the ARCH test which evaluates the presence of conditional heteroskedasticity. According to the p-values reported in Table 4, we do not reject the null hypotheses at a 5% significance level, stressing the fact that the AR(1) specification used is suitable and we do not need to specify an ARCH model.

**Table 3. DCC MV-GARCH model**

| Model | Parameter | Estimate | Std. Error | t-value | Prob. |
|---|---|---|---|---|---|
| U.S. GARCH(1,1) | $\omega_{US}$ | 0.1025 | 0.0669 | 1.533 | 0.1252 |
| | $\alpha_{US,1}$ | 0.3374 | 0.1471 | 2.294 | 0.0218 |
| | $\beta_{US,1}$ | 0.6102 | 0.1231 | 4.955 | < 0.001 |
| | $\upsilon_{US}$ | 1.6944 | 0.3244 | 5.223 | < 0.001 |
| U.K. GARCH(1,1) | $\omega_{UK}$ | 0.1180 | 0.1048 | 1.126 | 0.2602 |
| | $\alpha_{UK,1}$ | 0.2188 | 0.1577 | 1.388 | 0.1653 |
| | $\beta_{UK,1}$ | 0.7038 | 0.1243 | 5.664 | < 0.001 |
| | $\upsilon_{UK}$ | 1.3549 | 0.2555 | 5.303 | < 0.001 |
| Japan GARCH(1,1) | $\omega_{JP}$ | 0.2908 | 0.3111 | 0.935 | 0.3500 |
| | $\alpha_{JP,1}$ | 0.0295 | 0.0711 | 0.415 | 0.6782 |
| | $\beta_{JP,1}$ | 0.6938 | 0.3682 | 1.884 | 0.0595 |
| | $\upsilon_{JP}$ | 1.4515 | 0.2763 | 5.254 | < 0.001 |
| France GARCH(1,1) | $\omega_{FR}$ | 0.0013 | 0.1606 | 0.008 | 0.9937 |
| | $\alpha_{FR,1}$ | 0.0000 | 0.1043 | 0.000 | 1.0000 |
| | $\beta_{FR,1}$ | 0.9990 | 0.0607 | 16.46 | < 0.001 |
| | $\upsilon_{FR}$ | 1.1451 | 0.3302 | 3.468 | < 0.001 |
| Italy GARCH(1,1) | $\omega_{IT}$ | 0.2181 | 0.1602 | 1.362 | 0.1732 |
| | $\alpha_{IT,1}$ | 0.3292 | 0.2354 | 1.398 | 0.1620 |
| | $\beta_{IT,1}$ | 0.4913 | 0.2030 | 2.420 | 0.0155 |
| | $\upsilon_{IT}$ | 1.2727 | 0.1930 | 6.594 | < 0.001 |
| DCC(1,1) | $a$ | 0.0550 | 0.0067 | 8.195 | < 0.001 |
| | $b$ | 0.9446 | 0.0072 | 131.04 | < 0.001 |

**Figure 2. Dynamics of conditional correlation coefficients between United States and the other countries**




Note: Conditional correlation coefficients estimated by the DCC MV-GARCH.

**Table 4. Autoregressive model estimates with impulse dummy variables for crisis periods**

| $i-j$ | US − UK | US − JP | US − FR | US − IT |
|---|---|---|---|---|
| $c$ | 0.0390<br>(0.0263) | 0.0430*<br>(0.0219) | 0.0080<br>(0.0163) | 0.0049<br>(0.0110) |
| $DM_{1,t}$ | -0.0114<br>(0.0609) | -0.0129<br>(0.0629) | -0.0100<br>(0.0572) | -0.0224<br>(0.0578) |
| $DM_{2,t}$ | -0.0237<br>(0.0611) | -0.0062<br>(0.0625) | -0.0408<br>(0.0573) | -0.0688<br>(0.0579) |
| $DM_{3,t}$ | 0.0534<br>(0.0613) | -0.0238<br>(0.0625) | 0.0628<br>(0.0575) | 0.0477<br>(0.0580) |
| $DM_{4,t}$ | 0.0289<br>(0.0611) | 0.1569***<br>(0.0624) | -0.0646<br>(0.0575) | 0.0531<br>(0.0582) |
| $DM_{5,t}$ | 0.0119<br>(0.0613) | 0.0241<br>(0.0630) | 0.0004<br>(0.0579) | -0.0269<br>(0.0589) |
| $\rho^{*}_{ij,t-1}$ | 0.9586***<br>(0.0287) | 0.9244***<br>(0.0378) | 0.9958***<br>(0.0179) | 1.0002***<br>(0.0157) |
| P-value Test BG(4) | 0.4101 | 0.4120 | 0.1864 | 0.0594* |
| P-value Test ARCH(4) | 0.9205 | 0.8488 | 0.8464 | 0.1771 |

Note: Impulse dummy variables refer to the detected crisis periods: DM1,t = Q4 1998, DM2,t = Q4 2001, DM3,t = Q4 2002, DM4,t = Q1 2009, DM5,t = Q3 2010. Standard error in parenthesis; * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%; the hypothesis of the tests on the dummy variables is $H_0 : \delta_l = 0$ and $H_1 : \delta_l > 0$ ; BG denotes the Breusch-Godfrey autocorrelation test.

Finally, we consider larger window lengths for the crisis periods than the single quarters reported in Table 2. In particular, we investigate three well-known turmoil periods associated to three new dummy variables: $DM^*_{1,t}$ identifies the Asian and Russian crises (Q4 1997 – Q2 1998), $DM^*_{2,t}$ denotes the dot-com bubble burst (Q1 2000 – Q4 2002), and $DM^*_{3,t}$ indicates the 2007-08 stock market crash (Q3 2008 – Q4 2010). Note that the three step dummies $DM^*_{l,t}$ include the five quarters which are identified by the impulse dummies $DM^*_{l,t}$ in the autoregressive model of Table 4. Dummy variables $DM^*_{l,t}$ enable us to detect potential exogenous structural breaks in the series of dynamic correlation coefficients for more extended time windows than dummies $DM^*_{l,t}$. The results related to the autoregressive models with dummies $DM^*_{l,t}$ reported in Table 5 show that $DM^*_{3,t}$ is significant at least at a 5% level for all the correlation coefficients between the U.S. and all the other countries. Therefore, considering larger window lengths for the crisis periods, we find evidence of contagion. Precisely, the financial crisis that started in 2007-08 in the United States infected all the countries we considered, causing a significant shift in the correlations after mid-2008.[5] Conversely, and in contrast with the findings in Corsetti et al. (2005), the Asian and Russian crises did not trigger contagion in international stock markets as found in Lee et al. (2007).

**Table 5. Autoregressive model estimates with step dummy variables for crisis periods**

| $i-j$ | US – UK | US – JP | US – FR | US – IT |
|---|---|---|---|---|
| c | 0.0443*<br>(0.0265) | 0.0590**<br>(0.0229) | 0.0167<br>(0.0171) | 0.0103<br>(0.0113) |
| $DM^*_{1,t}$ | 0.0348<br>(0.0427) | -0.0083<br>(0.0447) | 0.0277<br>(0.0405) | 0.0856**<br>(0.0398) |
| $DM^*_{2,t}$ | 0.0253*<br>(0.0192) | 0.0171<br>(0.0195) | 0.0130<br>(0.0187) | 0.0149<br>(0.0183) |
| $DM^*_{3,t}$ | 0.0342**<br>(0.0203) | 0.0569***<br>(0.0220) | 0.0384**<br>(0.0205) | 0.0573***<br>(0.0216) |
| $\rho^*_{ij,t-1}$ | 0.9471***<br>(0.0294) | 0.8872***<br>(0.0404) | 0.9799***<br>(0.0197) | 0.9797***<br>(0.0178) |
| P-value Test BG(4) | 0.5252 | 0.3987 | 0.5544 | 0.2308 |
| P-value Test ARCH(4) | 0.9114 | 0.9052 | 0.8354 | 0.4730 |

Note: Step dummy variables refer to the detected crisis periods: $DM^*_{1,t}$ Asian and Russian crises: Q4 1997 – Q4 1998, $DM^*_{2,t}$ dot-com bubble: Q1 2000 – Q4 2002, and $DM^*_{3,t}$ 2007-08 stock market crash: Q3 2008 – end. Standard error in parenthesis; * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%; the hypothesis of the tests on the dummy variables is $H_0: \delta_l = 0$ and $H_1: \delta_l > 0$; BG denotes the Breusch-Godfrey autocorrelation test.

[5] Note that we also find a mild evidence of contagion between the U.S. and the U.K. during the "dot-com bubble" as the dummy variable $DM^*_{2,t}$ in Table 5 is significant, but only at a 10% level. Moreover, quite surprisingly, $DM^*_{1,t}$ is found significant for the correlation coefficient between Italy and the U.S. (see Table 5). Since $DM^*_{1,t}$ identifies the Asian and Russian crises, this result is not easy to interpret and will require a more in-depth investigation.

## V. Conclusions

The dynamics of financial markets show synchronous amplification processes which can be easily misinterpreted as contagion. In this paper, we propose a new procedure for testing the existence of contagion effects between countries. Specifically, we develop an econometric approach that distinguishes between amplification processes endogenously generated and the exogenous transmission of shocks which can be attributed to financial contagion. We propose to model time-varying conditional correlations in risk premium disequilibria including deterministic variables representing crisis periods. In this way, we introduce a new test for contagion which is able to detect correlation shifts derived from idiosyncratic shocks originated in another country, ruling out the endogenous amplifications. Moreover, this approach allows us to test for contagion in forms which are rigorously consistent with the characteristics of modern financial markets where the behaviors of both professionals and less-experienced market participants play a crucial role in the amplification processes of volatility. In particular, we identify disequilibria by measuring the equilibrium risk premia and computing the distance between the equilibrium level and the risk premia actually observed for five countries. Focusing on the analysis of contagion phenomena between countries from mid-1998 onwards, we find evidence of significant contagion effects from the U.S. to the other countries for the 2007-08 financial crisis. This result is not surprising since the so-called "subprime crisis" has its own origin exactly in the U.S. financial system which, as we pointed out, is the generator of the amplification processes of volatility and, as a consequence, has easily affected worldwide financial markets. Comparing our results with the existing literature, we find that the transmission of idiosyncratic shocks across countries turns out to be essentially absent as found by, e.g., Forbes and Rigobon (2002), until 2008. However, we distinctly detect contagion effects for the latest financial crisis.

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