Journal of International Money and Finance 97 (2019) 57–69

Contents lists available at ScienceDirect

Journal of International Money and Finance

journal homepage: www.elsevier.com/locate/jimf

What drives European Union stock market co-movements?

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ARTICLE INFO

Article history:
Available online 29 June 2019

JEL classification:
G01
G11
G15

Keywords:
Stock market co-movements
Contagion
Crisis
Determinants

ABSTRACT

This paper analyses the co-movements and contagion between 24 European Union stock markets. We apply a Dynamic Conditional Correlation - Mixed Data Sampling model to extract short and long-run correlations. We use short-term correlations to detect contagion. Finally, we employ a gravity-type regression to investigate the determinants of long-term correlations. First, we find significant differences between the stock market co-movements, which seem to depend on economic development and market deepening. Moreover, the time varying correlations emphasize different phases of development, i.e. integration, contagion, and divergence. Second, the contagion estimates reveal that, during some crisis episodes, the contagion is temporary, while for other periods the contagion becomes more persistent, indicating a herding behavior. Third, the co-movements determinants show that global factors and economic similarities are important in explaining correlations. Finally, our findings on long-term correlations drivers in contagion times are mixed, revealing, on the one hand, a pure contagion that is not explained by fundamentals, and, on the other hand, a wake-up call in terms of cross-border bank flows.

1. Introduction

The global financial crisis (GFC) and the European sovereign debt crisis (ESDC) accentuated the changing nature of the financial markets. Moreover, in European Union (EU), the measures implemented by authorities to strengthen the single market and the presumed integration paths have influenced the financial markets. Given that the financial markets became very fickle over the last decade, we consider of great relevance to study the patterns and determinants of the co-movements and contagion in EU stock markets.

In this paper, our objective is threefold. First, we document the time varying nature of the pairwise dynamic conditional correlation (DCC) for 24 stock markets. We group the markets into developed, emerging, and frontier and we intend to identify integration paths and crisis effects. Second, we investigate the contagion incidence during the turmoil period. The definition and the measurement of contagion are widely debated in the literature (Forbes and Rigobon, 2002; Bekaert et al., 2014; Caporin et al., 2013; Dungey and Gajurel, 2014). In our approach, we follow Forbes and Rigobon (2002) who define contagion as a significant increase in the level of co-movements between two markets after a crisis. Moreover, if investors from different markets show a simultaneous behavior when the markets co-movements coefficients are high, then this is a sign of herding behavior (Chiang et al., 2007). Therefore, we interpret the significant co-movements increases as contagion

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https://doi.org/10.1016/j.jimonfin.2019.06.004
0261-5606/

and the tendency of these increases to persist as herding. Third, we are interested in the factors that drive the DCCs during both normal and crisis periods, and in contagion times.

Considering the above objectives and the related studies, we contribute to the literature in several ways. First, even if there is a significant number of studies in the literature that investigate the nature of the stock market DCC, we differ from these by using a Dynamic Conditional Correlation - Mixed Data Sampling model (DCC-MIDAS) that enables the extraction of a high and low-frequency component for the pairwise DCC. To our knowledge, the empirical literature that uses DCC-MIDAS for examining European stock markets is limited. Virk and Javed (2017) analyzed the integration patterns of seven European stock markets, while Mobarek et al. (2016) examined the determinants of 20 international stock market co-movements. Both studies extracted the long-run correlation component by means of a DCC-MIDAS model. Second, we contribute to the contagion literature through the varying nature of the estimated contagion indicator over time and across country pairs. To our knowledge, only Buchholz and Tonzer (2016) followed a similar approach for the CDS market. Third, despite the important body of literature, the number of papers that investigate the drivers of EU stock market co-movements, especially in the light of the GFC and ESDC, is not significant. Furthermore, we contribute to the literature by studying the wake-up call hypothesis in contagion times and the nexus between banking flows and pairwise stock market dynamic correlations. Under this hypothesis, country fundamentals are likely to be significant vehicles in the propagation of shocks (Bekaert et al., 2014).

To address our goals, we formulate some research questions and we summarize the results as follows. *How did the stock market co-movements evolve over time?* We find that co-movements varied significantly over time, highlighting stages of integration, contagion, herding behavior, and divergence. *Are there major differences in cross-country DCCs?* We notice disparities across sample markets, especially in the case of emerging markets and frontier markets. *Is there evidence of contagion in EU stock markets in crisis times?* We document contagion effects during both GFC and ESDC, more obvious during the most severe crisis episodes. *What is the time varying nature of contagion during turmoil?* Our findings show that contagion is temporary for all markets, while during other periods contagion becomes more persistent, exhibiting herding behavior. *What drives stock market co-movements during normal and crisis period?* In general, our analysis reveals that excess volatility and higher credit risk lead to an increase of the co-movements. Furthermore, in both normal and crisis times, economic, institutional, and financial variables play an important role in explaining the pairwise dynamic correlations. *What are the drivers of long-term correlations in contagion times?* The findings are mixed. On the one hand, the estimates indicate pure contagion, that cannot be explained by fundamentals. On the other hand, we notice a wake-up signal in terms of cross-border bank flows, highlighting the nexus between stock markets and the banking sector.

There is a broad literature on time varying stock market co-movements, contagion, and determinants of pairwise correlations. Due to space constraints, we will not review it here (for more details, see Mobarek and Mollah, 2016; Christoffersen et al., 2012; Gjika and Horvath 2013; Syllignakis and Kouretas, 2011; Dungey and Gajurel, 2014; Tabak et al., 2016).

The remainder of the paper is structured as follows. Section 2 presents the methodology framework. Section 3 describes the data. Section 4 details and discusses the results. Section 5 concludes.

2. Methodology

To study the pairwise time varying patterns of stock returns co-movements, we use the DCC-MIDAS model of Colacito et al. (2011). The main advantage of this model is that it allows extracting a short- and long-run component specification for the DCC. Briefly, if Q_t is the conditional correlation matrix with the typical element $q_{ij,t}$, then the conditional covariance between returns of asset i and asset j can be expressed as:

$$q_{ij,t} = \rho_{ij,t}(1 - a - b) + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{ij,t-1} \tag{1}$$

where $\varepsilon_{i,t-1}$ and $\varepsilon_{j,t-1}$ are the standardized residuals of the previous period, obtained from the GARCH-MIDAS model. The long-run component $\rho_{ij,t}$ does not vary at daily frequencies and it is a MIDAS weighted sum of K lags of sample correlations matrices $c_{ij,t-1}, c_{ij,t-2}, \cdots, c_{ij,t-k}$:

$$\rho_{ij,t} = \sum_{k=1}^{K} \psi_k(\omega) c_{ij,t-k} \tag{2}$$

where $c_{ij,t}$ is determined by the standard formula of the sample correlation matrix and $\psi_k(\omega)$ is the weight in the beta function:

$$\psi_k = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}} \tag{3}$$

The final correlation matrix R_t is then given by:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{4}$$

To facilitate the estimation of the model, we have to set the number of lags that we should use in the MIDAS equation (K in Eqs. (2) and (3)). We follow Colacito et al. (2011) and Engle et al. (2013) and compare different DCC-MIDAS models with different K lags via maximum profiling of the likelihood function. We notice that the highest maximum likelihood value is achieved around 12 lags for most of the DCC-MIDAS models. Therefore, we set $K = 12$, which corresponds to a so called three MIDAS years period. Finally, for estimating the DCC-MIDAS lower frequency component, we run two set of estimations. First, we fix t to a week, in order to obtain weekly DCC-MIDAS for the contagion tests. Second, we fix t to a quarter, for obtaining quarterly DCC-MIDAS for the gravity-type regression model.

In order to ensure the normal distribution of the conditional correlation coefficients, we apply Fisher-Z transformation:

$$\bar{\rho}_{ij,t} = (1/2)\ln\left[\left(1+\rho_{ij,t}\right)/\left(1-\rho_{ij,t}\right)\right] \tag{5}$$

For identifying the contagion episodes, we use the approaches proposed by Buchholz and Tonzer (2016) and Chiang et al. (2007). Following Buchholz and Tonzer (2016), we do not divide the sample into specific periods for generating dummy variables and we do not specify a source crisis country. Moreover, considering that the arbitrary selection for the crisis dummy may suffer from the limitation described in Billio and Pelizzon (2003), we use monthly dummy variables and estimate the contagion for each pairwise conditional stock returns. This will allow us to obtain contagion indicators that are time-varying and differ across country pairs. In order to detect contagion incidence, we estimate the following regression model:

$$\bar{\rho}_{ij,t} = \alpha + \sum_{p=1}^{P} \varphi_p \bar{\rho}_{ij,t-p} + \delta_q Dum_q + \varepsilon_{ij,t} \tag{6}$$

where $\bar{\rho}_{ij,t}$ is Fisher-Z adjusted conditional correlations of stock returns and Dum_q is a dummy variable taking value *1* for a given month and *0* otherwise. Considering that ARCH and serial correlation tests reveal significant heteroscedasticity and serial correlation in the series, the conditional variance equation follows a GARCH(1,1) specification. Since daily data is affected by non-synchronous trading hours and short-term correlations due to noise, we choose to estimate the contagion by using weekly conditional correlations. Weekly DCC are extracted from DCC-MIDAS model.

For checking the results robustness, we also investigate the contagion episodes following Chiang et al. (2007). We define dummy variables for different sub-samples periods. Since our sample period covers both the GFC and the ESDC, we estimate separately the following equation for each of these turmoil periods:

$$\bar{\rho}_{ij,t} = \alpha + \sum_{p=1}^{P} \varphi_p \bar{\rho}_{ij,t-p} + \sum_{q=1}^{Q} \delta_q Dum_{q,t} + \varepsilon_{ij,t} \tag{7}$$

where $Dum_{q,t}$ is a dummy variable for different phases of the crisis periods.

For identifying the determinants of the stock market co-movements, we estimate a gravity type model. In general, gravity type regressions have been extensively used in the empirical literature on bilateral trade. However, they became increasingly employed in explaining financial markets co-movements. The specification of the model has the following form:

$$\bar{\rho}_{ij,t} = \alpha + X'_{ij,t}\beta + \varepsilon_{ij,t} \tag{8}$$

where α is the overall constant, $X'_{ij,t}$ represents a vector of variables that can be specific to country pair and constant over time, time-and-country pair varying or common to all country pairs and time-varying. In order to control country pair fixed effects, we also estimate the following model:

$$\bar{\rho}_{ij,t} = \alpha + X'_{ij,t}\beta + \delta_{ij} + \gamma_t + \varepsilon_{ij,t} \tag{9}$$

where δ_{ij} and γ_t represent country pair fixed effects and, respectively, time fixed effects, while $X'_{ij,t}$ denotes a vector of variables that can be only time-and-country pair varying.

3. Data

The data set comprises the daily closing prices of stock market indices from 24 EU countries for the sample period of January 8, 2001 to July 1, 2016. The first three years correspond to the so called three MIDAS years period. The countries included in our study are: Austria, Belgium, Bulgaria, the Czech Republic, Denmark, Estonia, Spain, Finland, France, the United Kingdom, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Latvia, the Netherlands, Poland, Portugal, Romania, Sweden, and Slovakia. The data is collected from Thomson Reuters Datastream. In order to mitigate the impact of exchange rates, the data is denominated in U.S. dollars. For estimating stock market co-movements, we first calculate the logarithmic rates of return for each market index. Table A1 in Appendix presents some descriptive statistics of the daily index returns. The returns follow a non-normal distribution, are autocorrelated, and show signs of heteroscedasticity. These findings support the use of a DCC-GARCH model.

An important aim of our paper is to examine the determinants of stock market co-movements and to see what lies behind the contagion episodes. Forbes and Rigobon (2002) and Wälti (2005) highlight several mechanisms that explain contagion and synchronization of stock market co-movements: (i) common disturbance; (ii) country-specific shocks that affect other countries; (iii) shocks that cannot be explained (i.e. pure contagion). Bekaert et al. (2014) underline that trade, financial openness, and banking channels play an important role in explaining spillovers and contagion. Hence, in our estimates, we consider a set of variables regarding global and common factors, economic, institutional development, and financial indicators. Further, we briefly discuss these variables, while Table A2 in Appendix details them.

Global and common factors include VIX index, Euribor-Eonia spread, and a dummy variable for countries with common border. Changes in VIX index are proxy for investors' risk-aversion, while Euribor-Eonia spread is a measure for liquidity and credit risk. Risk-aversion and liquidity measures play an important role in assets co-movements (Bekaert et al., 2014, 2011; Buchholz and Tonzer, 2016). The dummy variable for countries with common border is included in the analysis in order to capture the regional proximity.

Economic integration and institutional variables refer to factors that account for similarities in economic area, such as: GDP, inflation and public debt differential, bilateral trade, and institutional development. Intuitively, countries with similar economic policies exhibit higher stock market co-movements. GDP differential is a measure of the economic cycle pattern, while inflation differential is a proxy for monetary convergence. Public debt allows us to asses a country's indebtedness and its sovereign risk. Although public debt has not been widely used to explain stock market co-movements, we consider it of major importance given the incidence of sovereign debt crisis in euro area. Bilateral trade is an important variable which reflects the nature of trade relationships between countries and for estimating it, we follow Pretorius (2002) and Beine and Candelon (2011). Institutional development refers to differences in governments' effectiveness, regulatory, and open market policies.

Financial variables include differences in cross-border banking flows and market size. On the one hand, cross-border banking inflows emphasize the integration, especially in periods of economic growth. On the other hand, the cross-banking outflows, that were significant during global GFC and ESDC, increased tensions in financial markets. Market size influences returns through information costs, transaction costs, and liquidity (Bracker and Koch, 1999).

Finally, we consider that it is important to investigate which are the factors that influence stock market co-movements during contagion period. Moreover, given the wake-up call hypothesis, we consider it is important to study the domestic factors that drive contagion. Hence, we link the contagion indicator to some economic and financial integration variables. In general, strong financial links and bilateral trade are responsible for the spread of contagion from one country to another (Kaminsky and Reinhart, 2000; Van Rijckeghem and Weder, 2001; Tong and Wei, 2010; Bekaert et al., 2014). Therefore, we selected bilateral trade, cross-border banking flows, and market size to explain the contagion between stock market. Futhermore, considering the magnitude of sovereign debt crisis, we also include public debt ratio in the contagion analysis.

Our data is quarterly data, except for VIX index and Euribor-Eonia spread, for which daily data is aggregated to quarterly values, and institutional development indices, for which annual data is converted to quarterly values. Also, the contagion indicator has a monthly frequency. The indicator is aggregated to the quarterly frequency and equals *1* if at least one of the monthly dummies showed evidence for contagion and *0* otherwise.

4. Results

4.1. Co-movements between EU stock markets

Using the DCC-MIDAS model, we obtained 276 ($24 \times 23/2$) country pairwise stock market co-movements. Table 1 shows the means of the pairwise dynamic correlations. There is a significant range of values in the co-movements means. When studying closely these values, we notice homogeneity across some groups of countries. First, except for Greece, all co-movements between old EU countries are high, reflecting a significant level of integration. The highest pairwise correlation is between Germany and France, while the lowest is between Denmark and Portugal. Second, there is a group of three countries, the Czech Republic, Hungary, and Poland, for which the pairwise dynamic correlations with the old EU countries and among these countries are lower, i.e. between 0.70 and 0.52. Greece would fit better to this group of countries. Third, we have the group of Estonia, Latvia, Lithuania, Bulgaria, Croatia, and Romania, for which the co-movements with the first two groups of countries and between them are within a range of 0.57 and 0.28. Last, Slovakia has very low values of pairwise correlations, i.e. around 0.25. Although Slovakia is economically more similar to the Czech Republic, Hungary, and Poland, we consider that the low value of co-movements is determined by the poor development of the stock market. Considering the results, it is reasonably to think that the values of the pairwise dynamic correlations decrease according to economic development and market deepening. While the co-movements between developed countries with high market capitalization are in the upper tail of the range, in less developed countries or in countries with low market capitalization the indices returns are determined by endogenous factors. Consequently, the pairwise correlations between them and with other countries are lower.

Fig. 1 plots the weekly and quarterly dynamic correlations based on the DCC-MIDAS estimates for the sample period from January 5, 2004 to July 1, 2016. Our sample period includes the events that stressed the financial markets, particularly the GFC and the ESDC. In order to highlight the effects of these episodes, we introduced cut-off lines for some of the most important shocks.

Given the significant number of pairwise correlations, we chose to synthesize the results by grouping the countries into developed, emerging, and frontier markets, based on the classification suggested by S&P Dow Jones Indices. The developed markets (DMs) include Belgium, Germany, France, the Netherlands, Austria, Finland, Ireland, Spain, Italy, Portugal, Denmark, Sweden, and the United Kingdom. The emerging markets (EMs) sample is represented by the Czech Republic, Greece,

Table 1
Average country pairwise DCC-MIDAS.

	DE	FR	NL	AT	FI	IE	EL	ES	IT	PT	DK	SE	UK	CZ	HU	PL	SK	EE	LV	LT	BG	HR	RO
BE	0.86	0.89	0.88	0.75	0.81	0.74	0.54	0.83	0.85	0.74	0.70	0.77	0.79	0.64	0.58	0.63	0.25	0.46	0.34	0.42	0.35	0.45	0.44
DE		0.94	0.91	0.69	0.81	0.71	0.49	0.85	0.86	0.68	0.68	0.82	0.82	0.61	0.57	0.64	0.22	0.40	0.30	0.37	0.31	0.41	0.40
FR			0.93	0.72	0.82	0.74	0.52	0.89	0.90	0.71	0.70	0.83	0.85	0.62	0.58	0.64	0.22	0.41	0.30	0.37	0.31	0.41	0.40
NL				0.72	0.82	0.73	0.52	0.85	0.86	0.70	0.70	0.82	0.85	0.62	0.57	0.65	0.22	0.43	0.31	0.39	0.31	0.41	0.41
AT					0.74	0.66	0.54	0.72	0.73	0.68	0.64	0.67	0.69	0.70	0.59	0.61	0.24	0.46	0.34	0.43	0.33	0.42	0.45
FI						0.71	0.51	0.77	0.78	0.69	0.71	0.83	0.75	0.63	0.58	0.63	0.22	0.42	0.30	0.37	0.31	0.41	0.41
IE							0.49	0.69	0.70	0.64	0.63	0.67	0.70	0.56	0.50	0.54	0.21	0.42	0.33	0.37	0.30	0.37	0.39
EL								0.53	0.53	0.51	0.48	0.47	0.46	0.50	0.41	0.45	0.20	0.34	0.26	0.32	0.26	0.34	0.34
ES									0.88	0.74	0.66	0.77	0.78	0.61	0.56	0.61	0.23	0.40	0.29	0.37	0.32	0.40	0.40
IT										0.73	0.66	0.77	0.79	0.62	0.56	0.61	0.23	0.42	0.31	0.37	0.32	0.41	0.40
PT											0.62	0.63	0.64	0.58	0.52	0.54	0.28	0.47	0.37	0.44	0.38	0.43	0.43
DK												0.69	0.66	0.59	0.52	0.55	0.23	0.42	0.31	0.39	0.33	0.40	0.42
SE													0.77	0.58	0.55	0.61	0.21	0.38	0.30	0.35	0.30	0.39	0.36
UK														0.58	0.52	0.60	0.19	0.36	0.28	0.34	0.27	0.37	0.38
CZ															0.62	0.63	0.24	0.46	0.35	0.45	0.35	0.44	0.46
HU																0.65	0.22	0.38	0.29	0.37	0.28	0.38	0.41
PL																	0.22	0.38	0.28	0.37	0.31	0.42	0.40
SK																		0.27	0.25	0.29	0.24	0.28	0.20
EE																			0.42	0.57	0.39	0.41	0.40
LV																				0.45	0.33	0.35	0.31
LT																					0.37	0.41	0.38
BG																						0.42	0.35
HR																							0.35

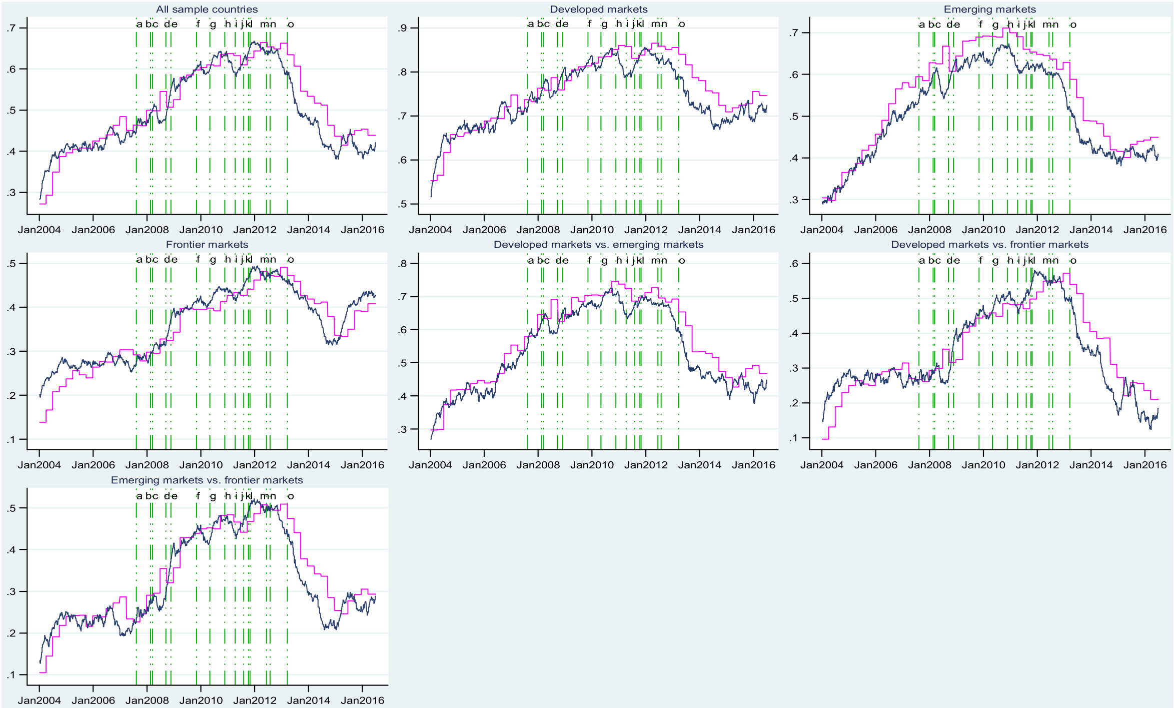

Fig. 1. Weekly and quarterly DCC-MIDAS estimates for developed, emerging, frontier, and all markets. Notes: (a) BNP Paribas suspended three investment funds. (b) Northern Rock is nationalized. (c) Bear Stearns is bought out by JP Morgan. (d) Lehman Brothers files for bankruptcy. (e) U.S. authorities rescue Citigroup. (f) Greece's 12.7% budget deficit announcement. (g) First rescue package for Greece. (h) Ireland requests financial assistance. (i) Portugal requests financial assistance. (j) Financial tensions spread to Italy and Spain. (k) Dexia is nationalized. (l) Greek haircut. (m) Spain requests financial assistance. (n) Draghi's "whatever it takes to preserve the euro" (o) Capital controls in Cyprus.

Hungary, and Poland, while the frontier markets (FMs) consist of Slovakia, Estonia, Latvia, Lithuania, Bulgaria, Croatia, and Romania. The plots from Fig. 1 show some similar patterns in time varying correlations, but significant differences with respect to their values. Intuitively, the weekly co-movements are more volatile than the quarterly estimates.

We notice considerable variance in time varying DCCs. Broadly, a visual examination of the graphs highlights different stages in the dynamic of the time varying correlations. For most of the plots, there is a mild upward trend in market co-movements at the beginning of the sample period up to the middle of 2007, implying higher co-movements dependence. Considering Bekaert et al. (2005) and Goetzmann et al. (2005) who reveal an increase in market dependence due to market integration, it is likely that the integration process has been a main determinant for the paths of the co-movements within this period. The subsequent period, late 2007 to late 2012, is characterized by a strong upward trend with frequent short-lived ebbs, more obvious in the high frequency correlations series. The sharp increase in dynamic correlations seems to occur in correspondence with the crisis episodes, implying a more news-driven behavior among investors. This observation is consistent with Forbes and Rigobon (2002), Ang and Bekaert (2002), and Baele (2005) who emphasized that the correlations among markets tend to rise when the stock returns fall sharply. The magnitude of the co-movements increases could be a sign of contagion, while the tendency of these increases to persist could be a sign of herding. This hypothesis is confirmed by the findings presented in the second sub-section of the results. It is important to note that, intuitively, contagion is more obvious in the high frequency dynamic correlations series, where the sudden jumps in co-movements around the crisis episodes are quite evident. Also, the herding behavior is more visible in the low frequency DCCs series, where the co-movements persist at higher levels, particularly during ESDC. After 2012, there is an intensive downward trend, where the co-movements paths dipped for both weekly and quarterly DCCs, revealing a significant divergence between the sample markets. Therefore opportunities in terms of portfolio diversification can be exploited.

In what concerns the group of DMs we notice that the pairwise correlations are higher and less volatile compared to the correlations inside the groups of EMs and FMs. The findings are in line with Christoffersen et al. (2012) and Mobarek et al. (2016) who reported similar results for developed and emerging markets. In the same vein, until late 2007, the patterns of correlations display a mild rising trend. After late 2007, the paths start to increase significantly. This is consistent with the previous findings of Virk and Javed (2017) who emphasized similar paths for seven leading European stock markets during December 2007 and December 2013. The signal point for the surging DCCs was when BNP Paribas suspended three investment funds. We notice some peak points around the most severe shocks of the GFC and ESDC, more pronounced during the latter. This period is dominated by numerous short-lived V-shaped correlations. There is a downward pattern from early 2012, which tends to stabilize around the tail end of the sample period. The paths for the EMs are quite similar. However, we notice that, until late 2007, the upward trend is more intense, indicating probably a stronger integration pattern for these markets. For the group of FMs, the bankruptcy of Lehman Brothers has been the signal point that triggered the rise of the co-movements. Also, the correlations across FMs started to increase at the tail end of the sample period, compared to DMs and EMs. We notice higher peak points during the ESDC for both the EMs and FMs.

Irrespective of their level of development, the stock markets in our sample fell sharply during crisis episodes, leading to higher co-movements. However, we notice that the surge in DCCs was stronger and more persistent during ESDC than during GFC. This observation is reasonable if we consider that the increases in DCCs during GFC were more exogenously determined. This is consistent with the findings of Virk and Javed (2017) who documented that European markets responded more dramatically to ESDC compared to the GFC.

Broadly, the mixed correlations between developed, emerging, and frontier markets are in line with the previous remarks. However, we emphasize some specific patterns. The correlations between DMs and EMs are higher than the other two. The DCCs between all three mixed markets display severe divergence after late 2012, more deeply for the DMs and FMs. Moreover, the co-movements between DMs and EMs and between EMs and FMs at the end of the sample tail tend to stabilize, while the DCCs between DMs and FMs continue to vanish, reaching some of the lowest levels. We consider that this pattern emphasizes two important observations. First, the divergence proves that the significant increases in the DCCs between late 2007 and late 2012 were not consistent, but rather driven by market contagion and herding. Second, the intensive dissimilarity in returns after 2012 between DMs and FMs show that even the integration period at the beginning of the sample period was not entirely driven by fundamentals.

The DCCs for EMs, FMs, and for the mixed correlations show higher portfolio diversification benefits compared to DMs. This is in line with the findings of Christoffersen et al. (2012) who revealed lower portfolio diversification benefits for DMs compared to EMs.

4.2. Contagion incidence across EU stock markets

In the second step of our Results Section, we analyze the contagion effects during GFC and ESDC. In line with other studies (Forbes and Rigobon, 2002; Bekaert et al., 2014; Virk and Javed, 2017), we informally define the crisis period, i.e. the start date and duration, considering major events. The findings are presented in Fig. 2 and Table 2. Fig. 2 illustrates the number

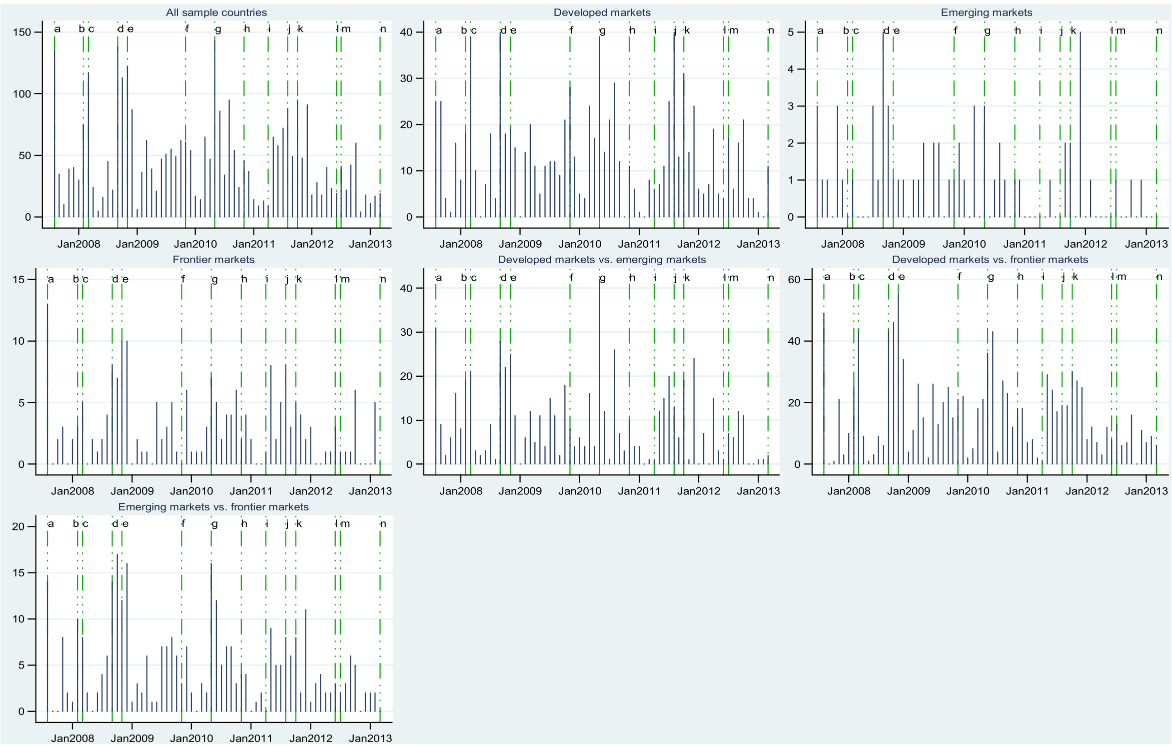

Fig. 2. Contagion episodes for developed, emerging, frontier, and all markets. Notes: A positive and significant coefficient for δ_q in Eq. (6) is interpreted as a contagion episode. Each episode takes the value of one. All estimates are computed separately and sequentially for each pairwise DCC. The number of contagion episodes (vertical axis) is summed up across country pairs. (a) BNP Paribas suspended three investment funds. (b) Northern Rock is nationalized. (c) Bear Stearns is bought out by JP Morgan. (d) Lehman Brothers files for bankruptcy. (e) U.S. authorities rescue Citigroup. (f) Greece's 12.7% budget deficit announcement. (g) First rescue package for Greece. (h) Ireland requests financial assistance. (i) Portugal requests financial assistance. (j) Financial tensions spread to Italy and Spain. (k) Dexia is nationalized and Greek haircut. (l) Spain requests financial assistance. (m) Draghi's "whatever it takes to preserve the euro" (n) Capital controls in Cyprus.

of contagion episodes summed up for each month across developed, emerging, frontier, and all markets obtained by using Eq. (6). All estimates are computed separately and sequentially for each pairwise DCCs. A positive and statistical significant coefficient at 5% level for the monthly dummy variable is interpreted as a contagion episode.

The results clearly support the hypothesis of increased contagion during most severe crisis episodes. Examining the plot for all markets, we notice a significant number of contagion episodes during August 2007, when BNP Paribas froze three investment funds. However, this contagion episode is not persistent. Temporary contagion can be found when Northern Rock was nationalized and Bear Stearns was bought by JP Morgan. Between September 2008 and December 2008, the contagion becomes more persistent, indicating a herding behavior. Similarly, frequent contagion episodes are detected from May 2010 to September 2010, when the ESDC started to build up and from July 2011 to December 2011, when the crisis spread to Italian, Spanish, and to other European banks. We consider that these periods are marked by a convergence of investors' sentiments, driven by bad news, which lead finally to herding behavior. The patterns for the DMs, EMs, and FMs are in line with the above findings.

Table 2 lists the results for the contagion estimates using Chiang et al. (2007) approach for developed, emerging, frontier, and all markets. Eq. (7) was estimated separately for GFC and ESDC and for each pairwise DCCs. With respect to the GFC, we defined three dummy variables. $Dum_{1,t}$ reflects the early stage of the financial crisis characterized by an increase in markets uncertainty. $Dum_{2,t}$ designates the second phase of the crisis marked by a severe decline of markets, by financial bankruptcies in U.S., and by increasing illiquidity in the markets. Finally, $Dum_{3,t}$ captures the third phase of the crisis, marked by central bank interventions (liquidity injections or bail-outs of financial institutions) and government fiscal stimulus. In order to analyze the ESDC we created five dummy variables. The first dummy describes the period when Greece began to confront with a confidence crisis caused by investors' concerns in meeting its debt obligations. The second dummy variable captures the period marked by the financial assistance programs activated in favor of Greece, Ireland, and Portugal. The third dummy variable is related to the period when the crisis spread through the European banking system and, especially, through Italian and Spanish banking system. The fourth dummy variable illustrates the period when Spain and Cyprus requested financial aid and when European Central Bank adopted a more aggressive policy in tackling the ESDC. The last dummy variable specifies the period when markets began to recover.

The results clearly support the hypothesis of contagion during GFC and ESDC. The findings for all markets show a significant number of contagion episodes during the second phase of the GFC, while for the ESDC, the contagion episodes are more prevailing for $Dum_{2,t}$, $Dum_{3,t}$, and $Dum_{4,t}$. Intuitively, the contagion is more visible for $Dum_{3,t}$, reflecting the spread of the crisis to the European banking system which is more connected to equity markets.

Our contagion estimates comply with other findings in the literature for different sample periods and markets during GFC and ESDC. For example, Tabak et al. (2016) highlighted contagion during both GFC and ESDC in CDS, banking, and equity markets. Baur (2012) emphasized strong contagion effects in developed and emerging stock markets during GFC. Syllignakis and Kouretas (2011) reported contagion effects due to herding behavior in CEE financial markets during GFC. Harkmann (2014) related the significant increase in correlations of CEE stock markets with the Eurozone proxy during GFC and ESDC to the contagion effects.

4.3. Explaining EU stock market co-movements in normal and turmoil periods

This section investigates the determinants of stock market co-movements for the full sample period and during turmoil period. Table 3 reports estimates of the gravity-type regressions for the full sample period and the turmoil period, i.e. from 2007.Q3 to 2013.Q1.

Table 2
Contagion episodes for developed, emerging, frontier, and all markets.

Variables	Period	All sample countries	Developed markets	Emerging markets	Frontier markets	Developed markets vs. emerging markets	Developed markets vs. frontier markets	Emerging markets vs. frontier markets
Global financial crisis estimates								
$Dum_{1,t}$	Aug. 8, 2007 – Sept. 5, 2008	(19)	(13)	(0)	(1)	(4)	(0)	(1)
$Dum_{2,t}$	Sept. 8, 2008 – Jan. 2, 2009	(208)	(45)	(6)	(17)	(33)	(81)	(26)
$Dum_{3,t}$	Jan. 5, 2009 – Apr. 3, 2009	(17)	(9)	(1)	(1)	(1)	(5)	(0)
European sovereign debt crisis estimates								
$Dum_{1,t}$	Oct. 5, 2009 – Apr. 23, 2010	(30)	(17)	(1)	(0)	(4)	(6)	(2)
$Dum_{2,t}$	Apr. 26, 2010 – July 15, 2011	(87)	(22)	(0)	(9)	(7)	(37)	(12)
$Dum_{3,t}$	July 18, 2011 – Dec. 30, 2011	(143)	(48)	(1)	(9)	(11)	(58)	(16)
$Dum_{4,t}$	Jan. 2, 2012 – Nov. 2, 2012	(85)	(21)	(0)	(4)	(12)	(36)	(12)
$Dum_{5,t}$	Nov. 5, 2012 – Mar. 29, 2013	(22)	(1)	(0)	(3)	(1)	(14)	(3)

Notes: A positive and significant coefficient for δ_q in Eq. (7) is interpreted as a contagion episode. Each episode takes the value of one. All estimates are computed separately for each pairwise DCC. The number of contagion episodes (in parentheses) is summed up across country pairs.

Table 3
Determinants of stock market dynamic correlations.

Dependent variable: pairwise DCC-MIDAS	All sample period				Turmoil period			
	I	II	III	IV	V	VI	VII	VIII
VIX Index	0.0458***		0.0459***		0.0180***		0.0180***	
	(0.0031)		(0.0031)		(0.0010)		(0.0010)	
Euribor – Eonia spread	0.728***		0.724***		0.723***		0.723***	
	(0.0194)		(0.0196)		(0.0406)		(0.0406)	
Regional proximity	0.0676		0.0613		−0.144		−0.146	
	(0.0924)		(0.0923)		(0.107)		(0.106)	
Q-o-Q GDP growth rate differential	−0.298***	−0.280***	−0.287***	−0.269***	−0.0363	0.0097	−0.0496	−0.0021
	(0.0820)	(0.0811)	(0.0819)	(0.0809)	(0.128)	(0.128)	(0.127)	(0.128)
Inflation rate differential	−0.0070***	−0.0066***	−0.0069***	−0.0066***	−0.0045***	−0.0040**	−0.0046***	−0.0041**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Public debt differential	−0.0013***	−0.0013***	−0.0013***	−0.0013***	−0.0011***	−0.0010***	−0.0011***	−0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Bilateral trade	0.720**	0.180	0.727**	0.181	2.045***	1.303**	2.081***	1.324**
	(0.346)	(0.418)	(0.344)	(0.419)	(0.381)	(0.542)	(0.382)	(0.546)
Institutional development differential	−0.0012***	−0.0012***	−0.0012***	−0.0011***	−0.0022***	−0.0023***	−0.0022***	−0.0023***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Cross-border banking inflows differential	−0.0005	−0.0005*	−0.0004	−0.0004*	−0.0014***	−0.0015***	−0.0013***	−0.0014***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Market size differential	−0.0039*	−0.0080**	−0.0042*	−0.0083***	−0.0068***	−0.0119***	−0.0067***	−0.0119***
	(0.0023)	(0.0032)	(0.0023)	(0.0032)	(0.0021)	(0.0029)	(0.0021)	(0.0029)
Public debt differential × Contagion indicator			−0.0001	−0.0001			0.0001	0.0001
			(0.0001)	(0.0001)			(0.0001)	(0.0001)
Bilateral trade × Contagion indicator			0.151**	0.149**			−0.0658**	−0.0610*
			(0.0655)	(0.0648)			(0.0303)	(0.0321)
Cross-border banking inflows differential × Contagion indicator			−0.0003**	−0.0003**			−0.0002*	−0.0002**
			(0.0002)	(0.0002)			(0.0001)	(0.0001)
Market size differential × Contagion indicator			0.0009*	0.0009*			−0.0001	−0.0002
			(0.0005)	(0.0005)			(0.0003)	(0.0003)
Constant	−0.240***	0.509***	−0.238***	0.5117***	0.773***	0.785***	0.777***	0.787***
	(0.0659)	(0.0423)	(0.0655)	(0.0422)	(0.0441)	(0.0546)	(0.0446)	(0.0549)
Country pair fixed (Fixed effects)	NO	YES	NO	YES	NO	YES	NO	YES
Time fixed (Time dummies)	YES	YES	YES	YES	YES	YES	YES	YES
No. of observations	12,972	12,972	12,925	12,925	6,348	6348	6,325	6,325
No. of clusters	276	276	275	275	276	276	275	275
R2 (overall)	0.6842	0.685	0.6850	0.686	0.6212	0.624	0.6210	0.623

Notes: *, **, *** denotes statistical significance at the 10%, 5% and 1% level, respectively. Robust standard errors (in parentheses) are used for all estimates.

Specifications I and II, estimated using Eqs. (8) and (9), reveal the impact of the global, economic, and financial determinants on stock market co-movements. Most of the variables are statistically significant and have the expected sign. The findings for global variables (I) show that global excess volatility, proxied by VIX, lead to higher stock market DCCs. The result is intuitive hence greater volatility is usually linked to higher risk aversion and to shocks that influence numerous markets. An increase of the liquidity risk, proxied by the Euribor–Eonia spread, which can be interpreted as a sign of stress in the markets, has a positive impact on pairwise co-movements. The findings are similar to those of Buchholz and Tonzer (2016) for the CDS markets. The regional proximity is not related to stock market pairwise correlations. This result contradicts the previous findings of Flavin et al. (2002) who showed that common borders are positively associated with co-movements.

In general, the estimates for the economic and institutional variables are in line with the expectations and quite similar for both specifications (I and II), with some minor exceptions. Countries with similar GDP growth rate and similar inflation have more integrated stock markets. The positive influence of similar economic fundamentals on stock market pairwise DCCs has also been documented by Johnson and Soenen (2002), Narayan et al. (2014), and Mobarek et al. (2016). Intuitively, the public debt differential is negative and statistically significant, implying that the higher the difference between two countries, the lower the DCC between the pair. Strong bilateral trade links are associated with an increase of the pairwise co-movement. However, when we include country-pair fixed effects in the estimations (II) the result is not robust. The effect of bilateral trade is also contradictory in the literature. On one side, Pretorius (2002), Wälti (2011), Alotaibi and Mishra (2015), and Mobarek et al. (2016) report a positive influence of bilateral trade on stock market co-movements. On the other side, Bracker and Koch (1999) and Beine and Candelon (2011) documented doubtful findings. In line with expectations, differences in institutional development are negatively related to stock market pairwise correlations.

In what concerns the financial variables, the cross-border banking inflows differential is not relevant in explaining the co-movements. However, when we include country-pair fixed effects (II), the result suggests that, as cross-border banking inflows diverge across two markets, stock returns also tend to diverge, resulting in a lower correlation. For the market size differential we obtain a robust result. Hence, when two stock markets diverge in terms of size, the pairwise correlation will be lower. The result is consistent with the findings of Bracker and Koch (1999) and Mobarek et al. (2016). Specifications III and IV allow us to investigate the factors that influence stock market co-movements during contagion periods. We highlight that the findings for the global, economic, and financial variables are similar with those observed in I and II.

The interaction of the variables with the contagion episodes reveals some interesting findings. The interaction between public debt differential and contagion is not relevant in explaining pairwise co-movements during contagion. A possible reasoning for this result is that, during contagion episodes, investors have treated similarly most of the countries in terms of sovereign risk. This argument is consistent with the findings of Gómez-Puig and Sosvilla-Rivero (2014) who emphasized the spread of sovereign risk from peripheral EMU countries to central EMU countries. The interaction between bilateral trade and contagion indicator support the hypothesis which relates trade intensity channel to financial contagion. Differences in the cross-border banking inflows lead to lower DCCs during contagion episodes, supporting a wake-up call hypothesis from the perspective of the banking fundamentals. This result shed light on the importance of the nexus between banking channels and stock markets during crisis times. It also shows that stronger prudential measures related to cross-border flows would have mitigated the contagion. Surprisingly, the findings reveal a positive impact of market size differential on pairwise DCCs during contagion times, implying higher co-movements between disparate markets in size.

Specifications V and VI show the results for the determinants of stock market co-movements, while VII and VIII include the interactions with the contagion indicator during turmoil period. The findings for the global, economic, and financial variables impact on pairwise correlations over the crisis period are quite similar with the results for normal times. We note that an increase of VIX index and of Euribor–Eonia spread lead to higher co-movements, while the common border effect is not significant. The inflation rate, public debt, institutional development, and market size differential are negatively associated with pairwise co-movements. The results for the bilateral trade and for cross-border banking inflows are robust in both specifications (V and VI). However, we see that the GDP growth rate is not relevant during crisis times. In general, the findings support the importance of economic and financial fundamentals for the stock market DCCs during both normal and crisis periods.

The estimates for the specifications that include the interactions with the contagion indicator (VII and VIII) reveal that public debt and market size are not relevant for the co-movements during contagion times. Surprisingly, the bilateral trade is negatively associated with pairwise correlations. The findings are a sign for the pure contagion hypothesis, which cannot be explained by fundamentals. However, we see that cross-border banking inflows differential is negatively associated with stock market co-movements, signaling a wake-up in terms of banking fundamentals.

To summarize, the estimates for the determinants of stock market pairwise DCCs are quite robust during both normal and crisis periods. In contagion times the findings are mixed, revealing pure contagion episodes and a wake-up call from the banking systems.

5. Conclusions

Our empirical results are summarized as follows. First, the results reveal a considerable range of values for the pairwise co-movements. However, the values of the pairwise dynamic correlations are decreasing in relation to economic development and market deepening. The time varying correlations emphasized different stages of development for all DMs, EMs, and FMs: integration, contagion, herding, and divergence.

Second, the contagion estimates support the hypothesis of increased contagion during most severe crisis episodes. However, the findings for DMs, EMs, FMs, and all markets reveal that during some crisis episodes the contagion is temporary, while for other periods the contagion becomes more persistent, indicating that investors adopt a herding behavior.

Third, the findings for the DCCs determinants show that excess global volatility and illiquidity in financial markets lead to an increase of the co-movements, while regional proximity is not relevant. In general, we find that in both normal and crisis times, economic, institutional, and financial variables play an important role in explaining the pairwise dynamic correlations. Therefore, similarities in terms of inflation, public debt, bilateral trade, institutional development, cross-banking inflows, and market size are positively associated with the pairwise stock market co-movements. Dissimilarities in GDP growth rate lead to lower dynamic correlations, but are not relevant during the crisis times. The results for the DCCs determinants during contagion are mixed, indicating, on the one hand, pure contagion, i.e. not explained by fundamentals, and, on the other hand, a wake-up flag in terms of cross-border bank flows.

The dependencies among stock markets are of major importance due to their impact on portfolio diversification, securities pricing, risk management, and assets allocation. Therefore, our findings have important implications for policy makers and investors. The integration patterns, the co-movements determinants, and the propagation of contagion provide insightful information for policy makers with respect to the measures required for increasing the real convergence in EU financial markets. The time varying dynamic correlations are important for investors and portfolio managers who can capitalize the returns asymmetries through portfolio diversification.

Acknowledgement

The second author acknowledges that this work was supported by a grant of the Romanian National Authority for Scientific Research and Innovation, CNCS – UEFISCDI, project number PN-II-RU-TE-2014-4-1827.

Appendix

Table A1
Descriptive statistics of the daily index returns.

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Qz(10)	ARCH(5) Prob. F(5,4028)
Austria	0.0002	0.1235	−0.1113	0.0168	−0.3108	9.8421	28.2380***	201.5975***
Belgium	0.0001	0.0978	−0.0977	0.0146	−0.1850	8.4480	53.1180***	168.5505***
Bulgaria	0.0004	0.2087	−0.2134	0.0168	−0.5837	28.9816	77.3330***	57.3799***
Croatia	0.0002	0.1616	−0.1192	0.0150	0.2042	17.7218	28.1900***	179.7446***
Czech Republic	0.0002	0.1870	−0.1778	0.0170	−0.1644	15.8075	69.5100***	184.2430***
Denmark	0.0003	0.1162	−0.1370	0.0145	−0.2822	9.9625	27.2450***	221.4467***
Estonia	0.0005	0.1214	−0.0738	0.0128	0.0047	8.9555	95.1030***	89.9293***
Finland	0.0001	0.1086	−0.1156	0.0163	−0.1499	7.7284	25.7050***	118.7759***
France	0.0000	0.1235	−0.1145	0.0164	−0.0299	9.1180	59.9770***	131.2855***
Germany	0.0001	0.1257	−0.0931	0.0166	−0.1025	7.7608	28.7250***	140.6579***
Greece	−0.0006	0.1658	−0.1964	0.0231	−0.2376	9.3266	43.6650***	44.5868***
Hungary	0.0003	0.1839	−0.1824	0.0201	−0.0956	10.5742	63.8660***	103.8793***
Ireland	0.0000	0.1063	−0.1640	0.0162	−0.7685	11.9122	44.0250***	135.6033***
Italy	−0.0002	0.1278	−0.1499	0.0175	−0.2265	9.0579	71.4310***	106.3851***
Latvia	0.0004	0.1251	−0.1426	0.0157	−0.4152	16.4916	74.2260***	272.6966***
Lithuania	0.0005	0.1097	−0.1231	0.0123	−0.3869	14.4825	120.5200***	223.7060***
Netherlands	−0.0001	0.1252	−0.1157	0.0161	−0.1123	9.9736	66.5880***	202.7919***
Poland	0.0000	0.1430	−0.1274	0.0194	−0.1988	7.4019	25.3010***	132.4989***
Portugal	−0.0002	0.1102	−0.1235	0.0142	−0.2527	9.2910	48.7370***	111.4215***
Romania	0.0005	0.1445	−0.1351	0.0184	−0.2875	11.0590	39.0890***	103.6000***
Slovakia	0.0003	0.1086	−0.1528	0.0133	−0.6276	14.4563	27.4810***	3.2206***
Spain	0.0000	0.1431	−0.1485	0.0169	−0.1249	9.9547	37.0640***	95.4286***
Sweden	0.0001	0.1509	−0.1308	0.0184	−0.0195	8.5610	45.2660***	105.9749***
United Kingdom	0.0000	0.1299	−0.1057	0.0141	−0.1781	12.1332	78.7640***	196.8407***
Number of obs.	4040	4040	4040	4040	4040	4040	4040	4040

Note: *, **, *** denotes statistical significance at the 10%, 5% and 1% level, respectively.

Table A2
Variables description.

Variable	Description	Source
Daily stock market return indices	$R_{it} = ln(P_t/P_{t-1})$ for market *i* on day *t* The stock market indices are: FTSE 100 (the United Kingdom), OMXS30 (Sweden), OMXC20 (Denmark), CAC40 (France), AEX (the Netherlands), IBEX35 (Spain), ATX (Austria), DAX (Germany), WIG20 (Poland), PX (the Czech Republic), BUX (Hungary), BET (Romania), SOFIX (Bulgaria), FTSEMIB (Italy), BEL20 (Belgium), OMXH25 (Finland), OMXT (Estonia), PSI20 (Portugal), SAX (Slovakia), OMXR (Latvia), OMXV (Lithuania), ISEQ20 (Ireland), FTSE20 (Greece), CROBEX (Croatia).	Datastream
Pairwise dynamic conditional correlation	Estimated on weekly and quarterly basis using DCC-MIDAS model and converted to the Fisher-Z transformation.	Authors' estimates
Contagion indicator	Dummy variable takes value *1* if contagion is detected during a certain month, *0* otherwise. Related references: Buchholz and Tonzer, 2016	Authors' estimates
Global variables		
Volatility index	VIX Index Related references: Bekaert et al., 2014; Lehkonen, 2014	Datastream
Liquidity risk	Euribor – Eonia Related references: Caporin et al., 2013; Buchholz and Tonzer, 2016	ECB Statistical Data Warehouse
Regional proximity	Dummy variable takes value *1* for countries with common border, *0* otherwise. Related references: Flavin et al., 2002	CEPII Gravity Dataset
Economic integration and institutional development variables		
Q-o-Q GDP growth rate differential	$\lvert \Delta GDP_{it} - \Delta GDP_{jt} \rvert$, where i,j stand for country pair *i* and *j* during period *t* Related references: Johnson and Soenen, 2002; Beine and Candelon, 2011; Mobarek et al., 2016	Eurostat
Inflation rate differential	$\lvert \pi_{it} - \pi_{jt} \rvert$, where i,j stand for country pair *i* and *j* during period *t* Related references: Bracker and Koch, 1999; Beine and Candelon, 2011; Pretorius, 2002; Narayan et al., 2014; Mobarek et al., 2016	Eurostat
Public debt differential	$\left\lvert \frac{Public\_debt_{it}}{GDP_{it}} - \frac{Public\_debt_{jt}}{GDP_{jt}} \right\rvert$, where i,j stand for country pair *i* and *j* during period *t* Related references: Buchholz and Tonzer, 2016	Eurostat
Bilateral trade	$\frac{Z_{ij,t}+M_{ij,t}}{Z_{i,t}+M_{i,t}} + \frac{Z_{ji,t}+M_{ji,t}}{Z_{j,t}+M_{j,t}}$, where $Z_{ij,t}$ and $M_{ij,t}$ are exports and imports from country *i* to country *j* during period *t*. $Z_{i,t}$ and $M_{i,t}$ are the total exports and total imports of country *i* during period *t*. Related references: Pretorius, 2002; Wälti, 2011; Beine and Candelon, 2011; Mobarek et al., 2016	Eurostat
Institutional development differential	$\sqrt{\sum_{p=1}^{n}(F_{pi,t} - F_{pj,t})^2}$, where $F_{pi,t}$ is the score for the *p*th economic freedom indices. There are 10 economic freedom indices, respectively property rights, freedom from corruption, fiscal freedom, government spending, business freedom, labor freedom, monetary freedom, trade freedom, investment freedom, financial freedom. Related references: Lehkonen, 2014; Alotaibi and Mishra, 2015	The Heritage Foundation
Financial variables		
Cross-border banking inflows differential	$\left\lvert \frac{Bank\_inflows_{it}}{GDP_{it}} - \frac{Bank\_inflows_{jt}}{GDP_{jt}} \right\rvert$,where i,j stand for country pair *i* and *j* during period *t* Related references: Wälti, 2011	Bank for International Settlements Database
Market size differential	$\left\lvert \frac{Marketcapitalization_{it}}{GDP_{it}} - \frac{Marketcapitalization_{jt}}{GDP_{jt}} \right\rvert$, where i,j stand for country pair *i* and *j* during period *t* Related references: Bracker and Koch, 1999; Johnson and Soenen (2002); Mobarek et al., 2016	Datastream

Note: Related references lists studies that used similar measures.

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