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Full Length Article

On systemic risk contagion in the euro area: Evidence from frequency connectedness and the DY approaches

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Abstract

This study analyzes systemic risk contagion across the euro area by employing the Diebold-Yilmaz and the frequency connectedness methodologies with data from January 1, 1999, to January 25, 2021. We use the daily Composite Indicator of Systemic Stress (CISS) series for 11 countries in the euro area developed by Holló et al. (2012) and calculate the overall connectedness between the series by employing two pioneering approaches. Additionally, we estimate the short-, medium-, and long-cycle connectedness of systemic risk over the study period that covers three financial burst periods: the global financial crisis (GFC), the European sovereign debt crisis (ESDC), and the COVID-19 pandemic. Overall, spillover indexes notably rise around well-known financial/geopolitical events over the study period. Finally, we examine the network connectedness of systemic risk spillovers during the GFC, the ESDC, and COVID-19 periods and thereby compare them. Our results highlight an efficient regulatory mechanism to control systemic risk contagion.

JEL classification: C58; F37; G10

Keywords: Connectedness network; Financial connectedness; Frequency connectedness; Spillovers; Systemic risk

1. Introduction

Throughout the twentieth and twenty-first centuries, the global economic system has experienced severe and acute financial/political imbalances. The world economy has recovered from them but with massive wounds, and the system remains prone to financial crises due to its nature. Globalization has yielded tightly interconnected financial markets, which exacerbates rapid risk spillovers through them. For example, the contagious repercussions of the 2007−2009 global financial crisis (GFC) quickly spilled from the US to the rest of the world. The world economy has confronted several upheavals since then, and the most severe ones are the European sovereign debt crisis (ESDC) and the COVID-19 pandemic.

Since the foundation of the European Union (EU), the eurozone states have withstood adverse macroeconomic/financial shocks. Financial/external imbalances and surging public debt levels appear to be looming problems of the mid-2000s, particularly for states on the periphery of the EU. Because of the detrimental effects of the GFC and the failure to tighten fiscal policy, the euro area had one of the most severe financial upheavals in its history (Lane, 2012). Although the debate over the reasons for the ESDC continues, the adverse effects of the crisis are still being felt, and the economy of the EU is fragile even almost a decade later.

In the post-ESDC period, the turbulence in the EU financial system rose around events such as the Brexit referendum, but the COVID-19 pandemic hit the European economy even harder. The novel coronavirus first emerged in Wuhan, China, in December 2019 and rapidly spread around the world. The first European case was identified in France on January 24, 2020, and the EU implemented policy responses after the

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World Health Organization (WHO) officially declared COVID-19 a pandemic (Goniewicz et al., 2020). By the third week of 2021, the number of cases in Europe had reached 18, 849, 065 and the number of deaths totaled 449,395.[1] Despite the economic rescue packages implemented by the EU member states, the devastating effects of the COVID-19 pandemic have spread across the euro area (Austermann et al., 2020).

Since the GFC, one of the hot topics in financial economics has been the contagion of financial imbalances. However, no consensus has been achieved in the literature on financial contagion despite numerous studies about it. For example, some studies label financial contagion as excessive cross-market correlations after a shock to one country (Bekaert & Harvey, 2003; Forbes and Rigobon, 2000). At the same time, some studies link financial contagion with return/volatility comovements in financial markets (Connolly & Wang, 2003; Phylaktis and Xia, 2009).

As extensively reported in the extant literature, the connectedness between financial indicators is prone to increases around financial/political crises or global imbalances (Akhtaruzzaman et al., 2020; Bekiros, 2014; BenSaïda & Litimi, 2020; Gkillas et al., 2019; Park and Shin, 2020; Rizvi et al., 2015). The COVID-19 pandemic is an example for this, and contagion in financial markets noticeably spread after the COVID-19 outbreak in early 2020 (Chevallier, 2020; Corbet et al., 2020; Guo et al., 2021; Okorie and Lin, 2020; So et al., 2020).

In view of the rise in interdependence after the COVID-19 outbreak, this study investigates systemic risk contagion across the euro area. For this purpose, we use daily financial stress indexes (FSIs) known as a Composite Indicator of Systemic Stress (CISS) developed by Holló et al. (2012) for 11 countries in the eurozone between January 1, 1999, and January 25, 2021.[2] The CISS consists of 15 financial stress measures, reflecting five main components of the financial system: financial intermediaries, money markets, equity markets, bond markets, and foreign exchange markets. We implement the Diebold-Yilmaz connectedness (DY) and the frequency connectedness (BK) approaches to estimate connectedness between daily FSIs. In doing so, we calculate directional spillovers between FSIs during periods of financial tranquility and distress employing two seminal approaches. Furthermore, we analyze network topologies of systemic risk across the euro area in three distinct periods: the GFC, the ESDC, and the COVID-19.

We make three main contributions to the extant literature. First, we calculate systemic risk connectedness across the euro area using two pioneering approaches, the DY and the BK, over the period encompassing the GFC, the ESDC, and the COVID-19 outbreak. By doing so, we analyze these three episodes of turmoil in terms of the magnitude of pairwise spillovers among European economies and hence compare them. Second, we estimate the connectedness of FSIs on different frequency bands ($(\pi,\pi/4)$, $(\pi/4,\pi/10)$, and $(\pi/10, 0)$, respectively) and thereby calculate the short-, medium-, and long-cycle connectedness of systemic risk. This type of analysis provides valuable insights on temporal, medium-term, and permanent systemic risk interdependence across the euro area. Third, because a vast amount of systemic risk spreads in the short run, particularly during financial crises, we focus on the short-term network structure of pairwise FSI connectedness reflecting the GFC, the ESDC, and the COVID-19 periods. The short-term network structure allows us to capture temporary risk spillovers among the EU member countries during these three financial crises. To our knowledge, this work is the first to examine systemic risk connectedness in the euro area on different frequency bands using the CISS indexes and to concentrate on the short-term network structure of pairwise spillovers indicating prominent episodes of financial distress.

The paper is organized as follows. Section 2 reviews the literature on the contagion of financial crises and financial connectedness. Section 3 provides the methodology and reports the data on the study. Section 4 continues with a discussion of our empirical findings. Section 5 gives our concluding remarks on the study.

2. Literature review

The term “contagion” was originally used to refer to the spread of disease and pertains to medical science. However, this changed after the emergence of the Asian financial crisis in 1997 and severe economic downturns in the late 1990s and early 2000s. Since then, scholars have used “financial contagion” to indicate the transmission of financial crises (Claessens & Forbes, 2001). After the GFC, it gained further prominence, and subsequent studies have extensively focused on financial contagion.

Following the early study of King and Wadhwani (1990), which examined the contagious effects of the 1987 stock market crash, other initial studies modeled financial contagion using correlation analysis (Baig & Goldfajn, 1999; Calvo & Reinhart, 1996; Edwards and Susmel, 2001; Karolyi and Stulz, 1996; Lang and Stulz, 1992; Lee and Kim, 1993). Studies in this stream define “contagion” as an abrupt and monumental shift in the degree of correlation. Some of the earlier studies employ the autoregressive conditional heteroscedasticity (ARCH) or the generalized autoregressive conditional heteroscedasticity (GARCH) models and estimate the variance-covariance propagation (Chou et al., 1994; Edwards, 1998; Hamao et al., 1990; Susmel and Engle, 1994) or focus on changes in the long-run linkages between markets (Longin and Solnik, 1995) to understand the nature of financial contagion. Nevertheless, Forbes and Rigobon (2001) argue that “standard tests” for detecting contagion might produce insignificant results because of heteroskedasticity, endogeneity, or omitted-variable problems. They state that studies that address these problems find interdependence, not

[1] See https://www.ecdc.europa.eu/en/cases-2019-ncov-eueea/.

[2] The EU member states are selected based on data availability as follows: Austria, Belgium, Germany, France, Finland, Ireland, Italy, the Netherlands, Portugal, Spain, and the UK.

contagion. Along similar lines, Forbes and Rigobon (2002) fail to detect contagion during the 1987 stock market crash, the 1994 Mexican peso devaluation, and the 1997 Asian crisis. In this vein, Corsetti et al. (2005) find only excessive interdependence, not contagion, during the 1997 Asian financial crisis.

A vast number of studies focus on comovements between financial markets to capture the dynamics of financial contagion. For example, Caporale et al. (2005) investigate the contagion in the East Asian region within the framework of comovement analysis by taking into account heteroskedasticity, endogeneity, and omitted-variable problems between January 1, 1990, and July 31, 1998, and find evidence of contagion. Likewise, Connolly and Wang (2003) examine the return comovements in international equity markets and argue that foreign market returns play an essential role in influencing domestic market returns. Gravelle et al. (2006) concentrate on comovements between international currency and bond markets in terms of "shift contagion" and argue that the shocks are transmitted mainly via long-term links. Huyghebaert and Wang (2010) investigate comovements in stock markets in East Asia before, during, and after the Asian financial crisis and find strengthened linkages during the crisis, except in China. More recent studies have also employed comovement analysis to detect contagion in various financial markets (Das et al., 2018; Ftiti et al., 2016; Loh, 2013; Yuan et al., 2020).

One strand of literature focuses on mean or volatility spillovers across global financial markets and thereby analyzes financial contagion. In this vein, Baur (2003) investigates mean and volatility spillovers among 11 Asian stock markets in April 1997 and October 2001, highlighting the existence of mean and volatility contagion during the Asian financial crisis. Likewise, Chancharoenchai and Dibooglu (2006) examine volatility spillovers between Southeast Asian emerging stock markets using a multivariate-GARCH model and detect prevalent and strong spillovers during the crisis. Beirne et al. (2013) analyze volatility spillovers from advanced to emerging stock markets employing a tri-variate GARCH-BEKK model and report changes in volatility during times of turbulence. Choudhry and Jayasekera (2014) calculate volatility and leverage spillovers among major economies (Germany, the UK, and the US) and PIIGS (Portugal, Italy, Ireland, Greece, Spain) countries employing the GARCH-GJR model in 2002 and 2014. Their findings indicate that both mean and volatility spillovers were amplified during the global financial crises (2007−2014). More recent studies in this category estimate mean or volatility spillovers based on GARCH models and report evidence of strong contagion in turbulent times (Sarwar et al., 2020; Wang et al, 2018).

Connectedness between financial markets tends to grow in times of spreading contagion. In this context, several studies are devoted to measuring connectedness between financial assets to detect contagion. Diebold and Yilmaz (2009) construct an approach to measure financial connectedness known as DY, which is based on an H-step-ahead forecast error decomposition of a Vector Auto Regressive (VAR) model. The authors calculate return and volatility spillovers among 19 global stock markets with the DY method for the periods 1992−2001 and 2007−2011. However, the proposed method relies on a Cholesky decomposition of the VAR, and hence the estimations are dependent on the order of variables in the VAR. To overcome this drawback, Diebold and Yilmaz (2012) propose the DY measures within a framework of generalized VAR, which produces estimations that are invariant to the VAR ordering. Furthermore, they introduce directional spillovers, which are not addressed in the previous approach. Following this study, Diebold and Yılmaz (2014, 2015) calculate connectedness across various markets.[3]

Scholars have extensively employed the DY framework to estimate connectedness among global financial markets. For example, more recent studies calculate return or volatility spillovers between stock markets (Abbas et al., 2019; Caloia et al., 2018; Chow, 2017; Wu, 2020), currency markets (Huynh et al., 2020; Salisu et al., 2018), debt markets (Ahmad et al., 2018; Cronin & Dunne, 2019; Mensi et al., 2020), the banking sector (Demirer et al., 2018; Hernandez et al., 2020), and cryptocurrency markets (Aslanidis et al., 2021; Ji et al., 2019; Koutmos, 2018). Table S1 (in the Supplementary Material available online) summarizes recent financial connectedness studies that use the DY approach.

Aiming to measure connectedness between financial variables on different frequency domains, Baruník and Křehlík (2018) define the frequency connectedness approach known as BK, which relies on the spectral representation of variance decomposition of the VAR. This methodology uses the Fourier transforms of the impulse-response functions (frequency responses) and estimates connectedness in short-, medium-, and long-term connectedness. This innovative approach has attracted overwhelming attention from scholars, and studies have calculated connectedness between financial assets by implementing the BK framework (Baruník & Kocenda, 2019; Ferrer et al., 2021; Jiang et al., 2020; Luo and Ji, 2018; Mensi et al., 2019 Naeem et al., 2020; Polat, 2019).

Systemic risk is inherent in the entire financial system, related to economic, geopolitical, or market-related events, and therefore scholars have explored systemic risk connectedness, particularly during times of financial turmoil. For example, Davydov et al. (2021) examine the linkage between bank liquidity creation and systemic risk using quarterly data on US banks between 2003 and 2016. They argue that liquidity creation strengthens the systemic linkage of individual banks to acute financial shocks. Because of the noteworthy impact of the COVID-19 pandemic on financial markets, recent studies have analyzed the interdependence of financial markets during the COVID-19 era. Among them, Shahzad et al. (2021) analyze the connectedness between 95 US firms between 2018 and 2020 and detect a spike in the level of risk contagion during the COVID-19 pandemic. Likewise, Bouri et al. (2021) investigate return interconnectedness across various assets by employing a Time-Varying

[3] See http://financialconnectedness.org.

Parameter (TVP)-VAR-based connectedness approach and report evidence of a dramatic change in the time-varying patterns of return connectedness around the COVID-19 outbreak. In a similar vein, Naeem et al. (2021) estimate time-frequency connectedness among six financial assets by employing both the DY and BK approaches. Their findings indicate amplified return connectedness between financial markets due to the COVID-19 pandemic. Along similar lines, Shahzad et al. (2021) investigate return spillovers by building networks within the framework of the quantile VAR-based DY between October 29, 2001, and October 27, 2020. Their empirical results show that the connectedness network and the spillovers depend considerably on the market state, and the dominant clusters in the network become more intensified with the emergence of the COVID-19 pandemic. Belaid et al. (2021) examine the impacts of the COVID-19 crisis on the connectedness between 22 emerging and advanced economies by using the DY methodology, as well as the Toda-Yamamoto, Dolado, and Lütkepohl causality approaches. The study reports excessive transmission of stress and uncertainty between emerging and developed economies during the COVID-19 era.

3. Empirical model and data

3.1. Empirical model

3.1.1. The Diebold-Yilmaz connectedness

Diebold and Yilmaz (2012) present the DY connectedness approach, which relies on a covariance stationary M-variable $VAR(p)$ model:

$$x_t = \sum_{i=1}^{p} \theta_i x_{t-1} + \varepsilon_t \tag{1}$$

where $\varepsilon_t \sim (0, \Lambda)$ are independently and identically distributed error terms. The moving average (MA) representation of the $VAR(p)$ is specified as. $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$

The H-step-ahead forecast error variance decomposition by $\phi_{ij}^g(H)$, for $H = 1, 2, \ldots$ is

$$\phi_{ij}^g(H) = \frac{\rho_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Lambda e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Lambda A_h' e_i\right)} \tag{2}$$

Λ is the variance vector of ε, ρ_{ii} is the standard deviation of ε_t for the ith equation, and e_i is the selection vector, with 1 as the ith element, and 0 otherwise. Each element of the variance decomposition matrix is normalized as:

$$\tilde{\phi}_{ij}^g(H) = \frac{\phi_{ij}^g(H)}{\sum_{j=1}^{N} \phi_{ij}^g(H)} \tag{3}$$

The total volatility spillover is constructed as:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\phi}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\phi}_{ij}^g(H)}{N} \cdot 100 \tag{4}$$

The directional volatility spillover received by market i from all markets j is:

$$S_{i.}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ij}^g(H)}{N} \cdot 100 \tag{5}$$

The directional volatility spillover propagated by market i to all markets j is:

$$S_{.i}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ji}^g(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ji}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ji}^g(H)}{N} \cdot 100 \tag{6}$$

The net volatility spillover from market i to all markets j is:

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{7}$$

The net pairwise volatility spillover is:

$$S_{ij}^g(H) = \frac{\tilde{\phi}_{ji}^g(H) - \tilde{\phi}_{ij}^g(H)}{N} \cdot 100 \tag{8}$$

3.1.2. The frequency connectedness

Baruník and Křehlík (2018) introduce the frequency connectedness approach, which relies on the spectral representation of variance decompositions of an M-variable $VAR(p)$ model given in Equation (1).

The MA representation of the $VAR(p)$ model is given as $x_t = \Omega(\mathrm{L})\varepsilon_t$, where $\Omega(\mathrm{L})$ is the matrix of infinite lag polynomials and can be identified as $\theta(L) = [\Omega(\mathrm{L})]^{-1}$.

Henceforth, the frequency response function is outlined as $\Omega(e^{-iw}) = \sum e^{-iwh}\Omega_h$ is the Fourier transform of the coefficients Ω_h^h.

The spectral density of x_t at frequency w is described as the Fourier transform of $MA(\infty)$ filtered series as follows:

$$S_X(W) = \sum_{h=-\infty}^{\infty} E\left(x_t x_{t-h}'\right) e^{-iwh} = \Omega(e^{-iw}) \Lambda\, \Omega'(e^{+iw}) \tag{9}$$

The generalized causation spectrum over frequencies $w \in (-\pi, \pi)$ is defined as:

$$(\eta(w))_{j,k} = \frac{\rho_{kk}^{-1} \left|(\Omega(e^{-iw})\Lambda)_{j,k}\right|^2}{(\Omega(e^{-iw})\Lambda\Omega'(e^{+iw}))_{jj}} \tag{10}$$

where $\Omega(e^{-iw}) = \sum_h e^{-iwh}\Omega_h$, and $\rho_{kk} = (\Lambda)_{kk}$.

Scaled generalized variance decompositions on the frequency band $d = (a, b) : a, b \in (-\pi, \pi)$, and $a < b$ is defined as $(\tilde{\varphi}_d)_{j,k} = (\varphi_d)_{j,k} / \sum_k (\varphi_\infty)_{j,k}$, where

$$\left(\tilde{\varphi}_d\right)_{j,k} = \frac{1}{2\pi} \int_a^b \frac{(\Omega(e^{-iw})\Lambda\Omega'(e^{+iw}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi} (\Omega(e^{-i\lambda})\Lambda\Omega'(e^{+i\lambda}))_{jj} d\lambda} (\eta(w))_{j,k} dw \tag{11}$$

And

$$(\varphi_\infty)_{j,k} = \frac{1}{2\pi}\int_{-\pi}^{\pi} \frac{(\Omega(e^{-iw})\Lambda\Omega'(e^{+iw})_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\Omega(e^{-i\lambda})\Lambda\Omega'(e^{+i\lambda})_{jj}d\lambda} \tag{12}$$

The within connectedness on d is defined as:

$$C_d^w = 100.\left(1 - \frac{Tr\left(\tilde{\varphi}_d\right)}{\sum\tilde{\varphi}_\infty}\right) \tag{13}$$

The frequency connectedness on d is defined as:

$$C_d^f = 100.\left(\frac{\sum\tilde{\varphi}_d}{\sum\tilde{\varphi}_\infty} - \frac{Tr\left(\tilde{\varphi}_d\right)}{\sum\tilde{\varphi}_\infty}\right) = C_d^w\frac{\sum\tilde{\varphi}_d}{\sum\tilde{\varphi}_\infty} \tag{14}$$

where $Tr\{\}$ is the trace operator, and $\sum\tilde{\varphi}_d$ is the sum of all elements of the. φ_d.

3.1.3. VAR-LASSO

Tibshirani (1996) defined the least absolute shrinkage and selection operator (LASSO) regression as depending on Breiman's (1995) algorithm, which adds a penalty to the least squares minimization problem denoted by the L_1 norm of the model's coefficient vector, indexed by the multiplicative positive factor λ (penalty or tuning parameter), as follows:

$$Q(\beta) = (y_t - \beta_0 - X_t\beta)'(y_t - \beta_0 - X_t\beta) + \lambda\beta \tag{15}$$

where y_t is the explained variable, X_t is the vector of regressors, β_0 is a constant, and β is the vector of coefficients.

The penalty parameter can be selected depending on the information criterion or cross-validation. However, the cross-validation generates a set of coefficients that are more robust, because the information criterion only minimizes the in-sample variance of a forecasting error adjusted by the number of parameters.

3.2. Data

We collect data on the CISS of ten EU member states (Austria, Belgium, Germany, France, Finland, Ireland, Italy, Netherlands, Portugal, and Spain) and the UK from the European Central Bank (ECB) Statistical Warehouse, and our data span the period January 1, 1999, to January 25, 2021.

4. Results

4.1. Characteristics of CISS series

Fig. 1 shows the daily CISS series for ten EU member countries and the UK for the study period.

As shown in Fig. 1, the FSIs for 11 countries surge around periods of financial turbulence, such as the GFC, the ESDC, the Brexit referendum, and the COVID-19 outbreak, and subside during periods of financial tranquility. All series had in common that they peaked during the GFC and escalated during the ESDC. The FSIs markedly rose in July 2016, which coincides with the Brexit referendum in the UK and have risen sharply since January 2020 because of the COVID-19 outbreak.

4.2. Connectedness analysis with the DY and the BK approaches

Following Diebold and Yilmaz (2012), we calculate the overall connectedness of the FSIs by implementing the DY method in 200-day moving windows with a 10-day forecast horizon.[4] Fig. 2 shows the overall connectedness of the FSIs with significant financial/geopolitical events.

As shown in Fig. 2, the overall spillover index oscillates between 58 percent and 90 percent over the study period. The index reached its trough on August 20, 2014, at 58.73 percent, and peaked on August 11, 2020, at 88.79 percent, which relates to the COVID-19 period. The index reached its first peak on May 3, 2002, at 85.81 percent, shortly after the 2002 stock market downturn. The overall spillover index skyrocketed on August 9, 2007, after the announcement by BNP Paribas that it was shutting down three investment funds, and was about 87 percent on September 15, 2007, after the collapse of Lehman Brothers. The index properly captures noteworthy events during the ESDC, such as the bailouts of Greece, Ireland, and Portugal, and the longer-term refinancing operations (LTRO) of the ECB. The overall spillover index markedly rose because of the Deutche Bank contingent convertibles (CoCo) bond trouble, and surpassed 85 percent during the period of the Brexit referendum. Overall connectedness of the FSIs soared around the troubles of the Financial Times Stock Exchange (FTSE) and the EU stock market indexes in February 2018. The index skyrocketed after the official announcement of the COVID-19 outbreak on March 11, 2020, and approached almost 90 percent.

Next, we calculate the overall connectedness of the FSIs on the $(\pi, \pi/4)$, $(\pi/4, \pi/10)$, and $(\pi/10, 0)$ frequency bands in a 300-day moving window with a 100-day-ahead forecast horizon employing the BK method.[5] Following Baruník and Křehlík (2018), we calculate connectedness measures by performing the VAR-LASSO method with automatic selection of the LASSO penalty using cross-validation. Fig. 3 presents the total connectedness of the FSIs estimated over short, medium, and long cycles.

[4] Before conducting a connectedness analysis, we perform the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP), and the Kwiatkowski−Phillips−Schmidt−Shin (KPSS) unit-root tests for CISS series. Unit-root tests results confirm the stationarity of all series at least at the 10% significance level. The unit-root test results are not included here to save space and are available from the author upon request. The optimal order of the VAR model determined by the Akaike information criterion (AIC) and Bayesian information criterion (BIC) is 14.

[5] $(\pi, \pi/4)$, $(\pi/4, \pi/10)$, and $(\pi/10, 0)$ reflect approximately one to four days, four to ten days, and ten days to infinity connectedness, respectively.

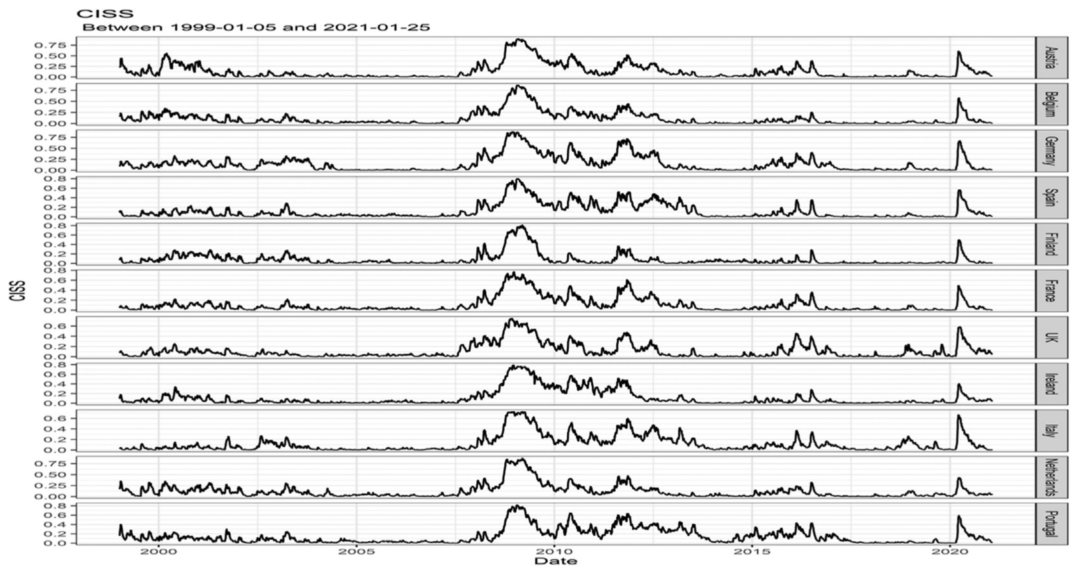

Fig. 1. CISS series between January 1, 1999, and January 25, 2021.

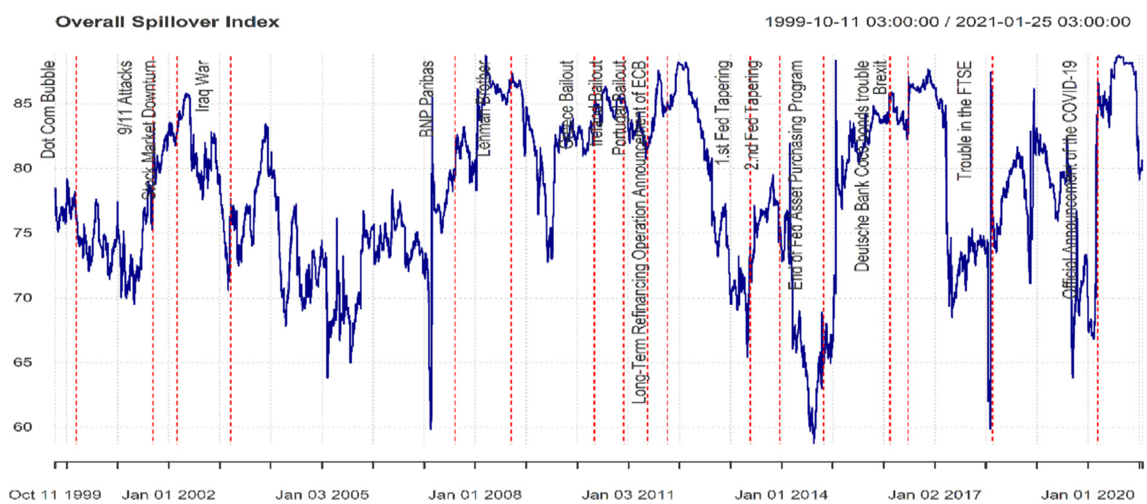

Fig. 2. Overall connectedness of the FSIs with the DY method.

Fig. 3. Overall connectedness of the FSIs over short, medium, and long cycles.

Fig. 3 indicates that the patterns in the connectedness of the FSIs over medium and long cycles overall are similar over the study period. Nonetheless, the short-cycle overall connectedness of the FSIs differs from the medium- and the long-cycle overall connectedness indexes over most of the period. The short- and medium-cycle overall connectedness indexes peak on January 28, 2008 (94.77%, and 91.12%, respectively), whereas the long-cycle overall connectedness of the FSIs peaks on December 11, 2018 (91.12%). The overall connectedness indexes estimated on different frequency bands fluctuate between 37 percent and 95 percent and surge around financial/geopolitical crises. The overall spillover indexes skyrocket during the GFC and COVID-19 periods and surpass 90 percent connectedness level because of worsening financial conditions.

4.3. Robustness check

We follow Yoon et al. (2019) and estimate spillover measurements in alternative N-day rolling windows and the alternative h-day forecast horizons. Fig. 4 shows the robustness check for DY spillover indexes in 200-day and 250-day rolling windows with two-, five-, and ten-day forecast horizons.

As depicted in Fig. 4, overall spillover indexes have similar patterns, confirming that the DY spillover estimations are insensitive to the window size or forecast horizons.

4.4. Network connectedness

In the network analysis, we concentrate on the short-cycle FSI connectedness because a significant amount of systemic risk is transmitted in the short run (Diebold & Yılmaz, 2014). In this context, we provide network graphs of pairwise FSI connectedness on the frequency band reflecting three periods of financial crisis, such as the GFC, the ESDC, and the COVID-19 pandemic. The Bank for International Settlements (BIS, 2009) and the Federal Reserve Board of St. Louis (2009) provide the official timeline for the GFC as between August 1, 2007, and November 1, 2009, but we choose the timeline as between November 5, 2009, and March 15, 2013, following Kenourgios (2014). Since the first case of COVID-19 was officially reported in December 2019 and quickly spread around the world, we define the timeline for the COVID-19 era as starting on January 1, 2020.[6] In the network analysis, we only consider pairwise spillovers that are larger than a threshold value to better illustrate the network connectedness.[7] Furthermore, the size of each node shows the magnitude of spillovers, reflecting total FROM spillovers. The thickness of the arrow indicates the strength of the spillover connecting a pair of nodes. Fig. 5 displays the network plot of euro FSI connectedness on the frequency band during the GFC.

The results in Fig. 5 can be summarized as follows. First, Germany, France, and the Netherlands are at the epicenter of the network. Germany is the largest transmitter of total systemic risk (77%), whereas the UK transmits the least total systemic risk (34%). This result demonstrates the strong systemic risk transmission between Germany and European economies and is consistent with the findings of Magkonis and Tsopanakis (2017). The pairs Netherlands/Finland, Belgium/Finland, Germany/France, Germany/Netherlands, and France/Belgium have the strongest connectedness. This result indicates high transmission of systemic risk across the core EU states during the GFC, whereas the pairs UK/Austria, UK/Spain, and Ireland/Finland have the weakest connectedness.

Fig. 6 presents a network topology of euro FSI connectedness on the $(\pi, \pi/4)$ frequency band during the ESDC.

As clearly shown in Fig. 6, systemic risk connectedness substantially rises during the ESDC compared with the GFC period. Portugal is the largest transmitter of systemic risk. The highest systemic risk is transmitted from Portugal to Ireland (11.25%), and followed by the spillovers from Portugal to Italy (10.73%), from Spain to Italy (10.57%), and from Portugal to Spain (10.53%). The findings are consistent with the extant literature and signify the essential role of peripheral European economies in the ESDC (De Santis, 2012; Lane, 2012). Concurrently, the UK still transmits the least systemic risk, and the least systemic risk spreads from the UK to Spain (4.07%).

Fig. 7 illustrates the network topology of FSI connectedness on the $(\pi, \pi/4)$ frequency band during the COVID-19 period.

Fig. 7 reveals that the Netherlands, France, and Belgium are at the center of the network, with total TO directional spillover values of 83.4%, 83.1%, and 81.8%, respectively. This is probably because the first COVID-19 case was in France and rapidly spread to EU countries that were geographically nearby. Meanwhile, Ireland transmits the least total systemic risk (38%). Germany/Italy (15.64%), Portugal/Spain (15.52%), and France/Belgium (14.15%) are the most tightly connected, whereas Spain/Ireland (0.30%), Italy/Ireland (0.54%), and Ireland/Spain (0.63%) are the least connected. The COVID-19 connectedness network leads us to draw several conclusions. First, geographic proximity plays an essential role in the transmission of systemic risk across Europe during the COVID-19 period. Second, the core European states drive a higher level of spillovers than the peripheral EU states during the COVID-19 period. This finding is consistent with that of Karkowska and Urjasz (2021). Third, Ireland transmits the least systemic risk to the rest of the EU, which is in line with the finding of Aslam et al. (2021). Finally, the peripheral EU states, except Portugal, are characterized by the weakest systemic risk connectedness during the COVID-19 period.

[6] See https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200423-sitrep-94-covid-19.pdf#:~:text=The%20first%20human%20cases%20of,%2C%20in%20December%202019/.

[7] $\rho_x := (\max(\mathit{FROM\ directionalspillovers}) \times \alpha)$, where $\alpha = 0.2$. We provide spillover tables as Table S2, Table S3, and Table S4 in the Supplementary Material available online.

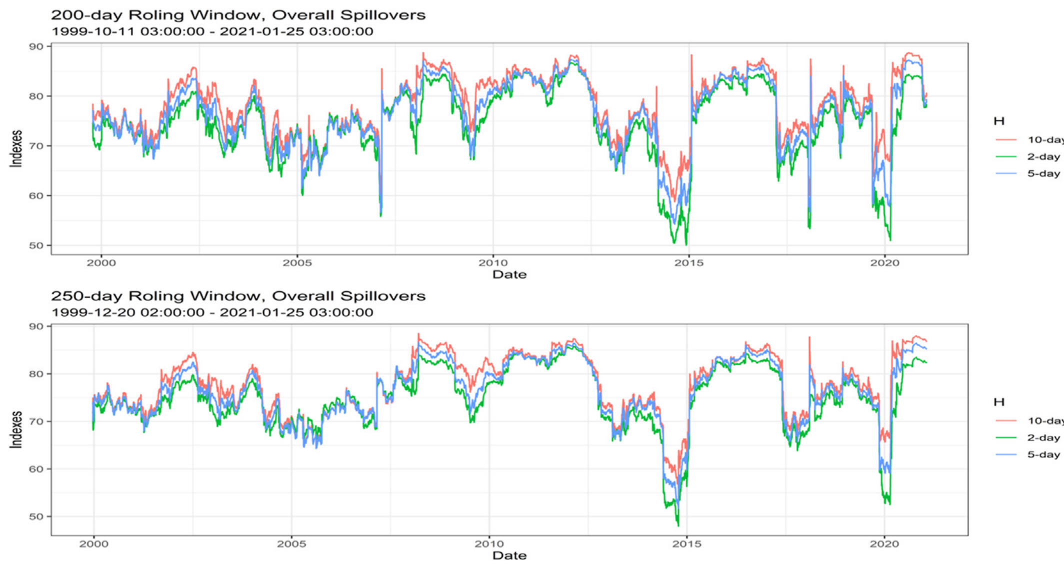

Fig. 4. Robustness check for DY estimations for the FSIs.

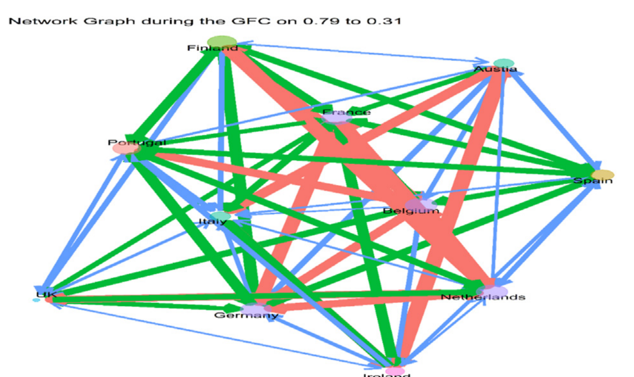

Fig. 5. Network of short-term euro FSI connectedness during the GFC

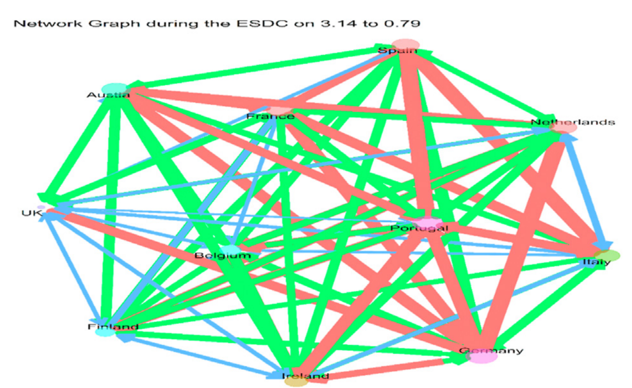

Fig. 6. Network of short-term euro FSI connectedness during the ESDC

5. Conclusion

The euro area has experienced severe and prolonged financial/geopolitical crises since the Great Depression in 1929, of which the most severe have been the GFC, the ESDC, and the COVID-19 pandemic. These financial upheavals have

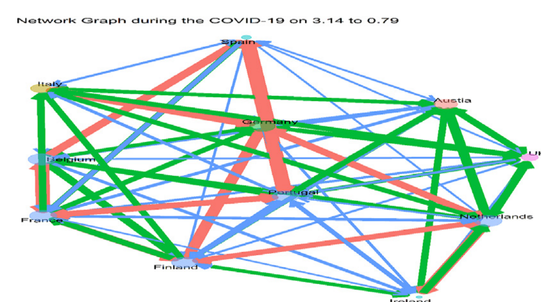

Fig. 7. Network of short-term euro FSI connectedness during the COVID-19 period.

had catastrophic impacts on the European economy, and connectedness/contagion across the eurozone countries has substantially risen accordingly (Lane, 2012). Additionally, the COVID-19 pandemic has acutely and adversely affected the global economy (Ashraf, 2020).

In the light of expansion in interdependence between financial markets during the financial/geopolitical crises, including the COVID-19 pandemic, in this study, we focus on systemic risk contagion across the euro area between January 1, 1999, and January 25, 2021. In this context, we use two pioneering approaches, known as the BK and the DY, to estimate the systemic risk connectedness between daily financial stress indexes, the CISS for 11 countries in the eurozone. Additionally, we analyze the network connectedness of systemic risk for the euro area in three distinct periods: the GFC, the ESDC, and the COVID-19 pandemic.

The total spillover index estimated with the DY approach notably rises around well-known financial/geopolitical events. The index reaches its peak on August 11, 2020, which is during the COVID-19 period. This finding shows the substantial impact of the COVID-19 pandemic on systemic risk contagion across the euro area. Total spillover indexes estimated in the short, medium, and long cycle with the BK methodology signal well-known financial/geopolitical crises. The indexes all rise sharply during the GFC and the COVID-19 periods, exceeding 90 percent connectedness.

In the final step, we illustrate the network topologies of systemic risk contagion across the euro area in the short cycle for the same three periods. The network analysis leads us to draw several conclusions. First, the main EU countries are at the epicenter of the network for the GFC and transmit the most systemic risk to the rest of the EU. Second, the magnitude of directional spillovers rose more during the ESDC than during the GFC period. Third, the largest systemic risk is spread throughout the peripheral EU states, and this finding is consistent with the extant literature. Finally, a modest amount of systemic risk spreads among states that are geographically nearby, indicating the key role of geographic vicinity in the connectedness network.

The suddenly enhanced systemic risk interdependence across the euro area during the COVID-19 pandemic highlights the acuteness of the crisis. Despite fiscal/monetary stimulus enacted by the governments in the aftermath of the outbreak and vaccination campaigns in early 2021, the devastating effects of the crisis continue to spread around the world. In view of this, policy makers should continue to extend fiscal/monetary stimulus, and high-income countries and international organizations should allocate funds for low- and medium-income countries to help them mitigate the worst impacts of the pandemic on real/financial and economic activity. Although financial investors and speculators might benefit from transitory intensified systemic risk contagion and minimize their risks using portfolio diversification, in the long term the global financial system is immune to the detrimental effects of the crisis. Accordingly, policy makers and central bank authorities should closely monitor the stability of the financial system and use modern risk management tools to determine the level of systemic risk to protect the financial system from an unprecedented financial shock.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2021.06.011.

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