International Review of Financial Analysis 83 (2022) 102273

Contents lists available at ScienceDirect

International Review of Financial Analysis

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

Static and dynamic liquidity spillovers in the Eurozone: The role of financial contagion and the Covid-19 pandemic

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ARTICLE INFO

Keywords:
Liquidity spillovers
Static
Dynamic
Financial contagion
COVID-19 pandemic

ABSTRACT

This paper investigates static and dynamic liquidity spillovers for a pool of ten Eurozone countries for the period 2000–2021. We estimate a generalised vector autoregressive (VAR) model based on Diebold and Yilmaz (2009, 2012). We find evidence for static and dynamic transmission of shocks through the liquidity channel. We propose a static measure of liquidity spillovers which captures total and pairwise average spillovers across Eurozone countries. Our measure shows strong evidence of interconnection within the Eurozone through the liquidity channel. We investigate the dynamic intensity and direction of liquidity spillovers, finding significant evidence of contagion during crisis periods. Our results indicate that most of the shocks during periods of financial uncertainty arise from leading economies within the Euro area.

1. Introduction

In spite of the twin impacts of the Covid-19 pandemic and the departure of the UK from the European Union ('Brexit'), the world continues to be characterised by significant globalisation and integration within financial markets, as well as the ongoing prevalence of highly mobile capital. As such, understanding the nature and consequences of financial contagion remains of fundamental importance (Longstaff, 2010). In the relatively recent past there have been a number of significant events both at the international level, such as the Global Financial Crisis (GFC) (2007–2009), as well as at more regional level, including the Irish banking crisis and the Greek sovereign debt crises. These events triggered prolonged periods of uncertainty and higher volatility across financial markets. Similarly, the spread of the Covid-19 pandemic, which originated in China and subsequently spread to the rest of the globe, triggered significant economic and health related measures internationally, as well as uncertainty surrounding the potential duration and consequences of the Covid-19 pandemic. In contrast to the global financial crisis of 2007–2009 which caused structural changes in the global economy with persistent downward pressure on the equity market, the equity market sell off in February 2020 was sudden and pervasive, as Covid-19 began emerging globally. Subsequently, there has been a V-shaped recovery that ultimately brought stock markets more-or-less to pre-pandemic levels. There exists ample evidence that those as well as previous crises (see, e.g. Amihud et al., 1990; King & Wadhwani, 1990) were driven by liquidity shortages, causing significant challenges to Eurozone stability, as well as requiring policy makers to deal with possible contagion and impacts that arose, especially in relation to economies with fundamental structural weaknesses. Sudden and pervasive liquidity drops are acknowledged as key drivers in otherwise puzzling market episodes (Chordia et al., 2000).

This paper investigates contagion across equity markets within the euro area through the liquidity channel. Contagion can be interpreted as a significant increase in cross-market linkages following a shock experienced by a particular country (Forbes & Rigobon, 2002; Longstaff, 2010). This definition leads to two significant implications. First, interdependence is not a sufficient condition since contagion requires increased co-movements between markets. Second, interdependence does not reveal the source and intensity of the shock. For example, interdependence does not disentangle the origin of a shock, such as a shock emerging in the US that subsequently spreads to the UK and then to Japan. The existing literature identifies four channels for contagion (Guidolin et al., 2015; Longstaff, 2010; Smimou & Khallouli, 2015). The first is the information channel, which emerges when a shock in one market signals economic news that directly or indirectly impacts security prices in other markets (King & Wadhwani, 1990). Another vector of transmission arises via the liquidity channel. As outlined by Smimou and Khallouli (2015), liquidity shocks may be internal, or those driven by economic fundamentals, or they may be

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https://doi.org/10.1016/j.irfa.2022.102273
Received 31 January 2022; Received in revised form 25 May 2022; Accepted 27 June 2022
Available online 8 July 2022

exogenous. Brunnermeier and Pedersen (2009) propose that investors who suffer losses in one market may experience funding constraints in other markets also, so that overall market liquidity deteriorates. Furthermore, internal liquidity shocks in one market may increase uncertainty and episodes of investors' withdrawal from other markets, as was the case during the 19th October 1987 market crash (Amihud et al., 1990). Another channel emerges via the flight-to-quality whereby investors switch to safer securities from riskier investments. A typical example is represented by the switch from stocks to bonds. Lastly, another route for contagion can be realised through specific risk channels, whereby a shock in one market is followed by an increase in the risk premia within other markets (Acharya & Pedersen, 2005). Consequently, contagion occurs when negative returns in the distressed market affect subsequent returns in other markets, which also provides supporting evidence for the time-varying nature of risk premia (Amihud et al., 2015). While there is ample evidence suggesting that liquidity has been a key driver for spreading uncertainty, leading to contagion effects during the GFC (Andrikopoulos et al., 2014; Longstaff, 2010; Smimou & Khallouli, 2015), the role of liquidity during the ongoing pandemic is yet to be investigated. For example, there is ample evidence of commonality in liquidity at a regional and global level (Brockman et al., 2009) as well as illiquidity in returns premia (Amihud et al., 2015).

We are interested in the transmission of liquidity spillovers, especially within the Euro area, for the following reasons. First, shocks in market liquidity and volatility have been shown to be driven by regional and international factors (Amihud et al., 2015; Andriosopoulos et al., 2014; Brockman et al., 2009). Second, since shared monetary policy and the single currency (the Euro) aim to further enhance policy synchronisation, the Eurozone possesses particular characteristics (Glick & Rose, 2016) that lend support to a strong degree of interconnection between Eurozone economies. Lastly, our sample includes leading global economies such as Germany and France, as well as peripheral countries such as Portugal and Spain, thereby providing an empirical investigation of a diverse range of economic entities regulated by a single institution responsible for monetary policy, the European Central Bank. This is a relatively neglected aspect, for example Andrikopoulos et al. (2014) limit their analysis to G7 stock markets only. Furthermore, the literature is predominantly US-centric suggesting wider benefits that arise from investigation of other contexts that can help improve our understanding of this phenomenon. We focus on the stock market, due to its importance for economic growth and socio-political implications (Andriosopoulos et al., 2014) and given ample evidence that the financial channel constitutes the primary route for spillovers across economies (Forbes & Rigobon, 2002; Longstaff, 2010; Smimou & Khallouli, 2015).

In our paper, we empirically assess the following: (i) Is there a spillover effect through the liquidity channel among Eurozone countries?; (ii) What is the intensity and direction of spillovers during both turbulent as well as calm periods (i.e. is it time varying)?; and (iii) Is there evidence of contagion during the Covid-19 pandemic as well as during the global financial crisis, and what countries transmit it? Our empirical analysis presents two key components: first, static spillovers tables and second, dynamic spillovers plots. Our plots include a graphic for the entire Eurozone, which in our view is highly informative and essentially provides key evidence for contagion within the Eurozone. One key research question that emerges is: is there contagion across countries and what are the key transmitters of this contagion? To answer this question, our analysis presents both an aggregated measure of "gross" spillover as well as country-specific "net" spillovers. In particular, net spillover shows the total contribution transmitted *net* of the spillover received, and this can therefore more clearly highlight who transmits contagion to whom.

We analyse the spillovers dimension of illiquidity shocks across Eurozone markets and our research makes three main contributions. First, we introduce a novel measure that captures average pairwise and total spillover effects, which we define as the illiquidity spillover index (ISI). We construct the ISI by adapting the models of Diebold and Yilmaz (2009, 2012) which relate to volatility spillovers using a vector autoregressive (VAR) framework. These have received growing interest and applications within recent financial literature, but these methods have not previously been applied to analysis of liquidity transmission channels (e.g. see Antonakakis & Vergos, 2013; Gong et al., 2021; Magkonis & Tsopanakis, 2016; Magkonis & Tsouknidis, 2017). Previous research employing VAR models mainly investigates contagion in terms of returns and volatility spillovers to estimate the degree of causal relationships between countries through pairwise analysis (see,e.g. Beirne & Gieck, 2014). While popular, VAR models suffer from limitations due to econometric issues such as the ordering of variables which leads to different results from Cholesky factorisation. An alternative approach is proposed by Diebold and Yilmaz (2009, 2012) who introduce an innovative measure of volatility spillovers that captures interconnections within a more dynamic setting. Diebold and Yilmaz (2009) report evidence of return and volatility spillovers across nineteen global equity markets. While their first model is also based on Cholesky factorisations, in their second paper, they overcome this limitation. Diebold and Yilmaz (2012) focus on volatility spillovers across asset classes within the US, rather than across markets. Antonakakis and Vergos (2013) implement the methodology of Diebold and Yilmaz (2009, 2012) for the context of bond yield spillovers within the Euro area, finding that shocks originating in peripheral countries have substantially greater destabilising force, compared to shocks from core economies. Gong et al. (2021) show spillover effects across natural gas and future markets, while Chuliá et al. (2020) estimate the relationship between volatility and commonality in liquidity.

Second, we find evidence for contagion across Eurozone countries showing, in particular, that leading economies such as Germany, France and Italy are dominant transmitters of shocks through the liquidity channel, especially during periods of financial uncertainty. We do this by using a dynamic version of the spillover index obtained by employing a two hundred week rolling window estimation, which captures the time-varying behaviour of the transmission of shocks. Lastly, we extend previous research in this field by including a measure for the direction and intensity of illiquidity spillovers (see,for example Andrikopoulos et al., 2014; Smimou & Khallouli, 2015). Our findings provide important implications both for investors and regulators. Our results provide a handy measure for signalling through provision of early warning for emerging crises, as well as enabling monitoring of existing crises. Our measure, obtained from vector autoregressive (VAR) models, is similar to that proposed by Diebold and Yilmaz (2012), and our measure provides supporting evidence of strong interconnection among economies. The spillover table that we derive includes information relating to the source and intensity of spillovers also. We show that spillovers are time-varying and they tend to increase alongside the introduction of the euro and the onset of the GFC. One notable finding is that much of the spillover effect during the global financial crisis originates from the leading economies within the euro area including France. In contrast, we note that peripheral countries are mostly receivers of shocks, except when the source of shocks is internal, in which case they become transmitters to other markets, as seen for the case of the Greek sovereign debt crisis.

To the best of our knowledge, our paper is the first to provide evidence of liquidity contagion within the Eurozone during the Covid-19 pandemic. Our paper applies the methodology of Diebold and Yilmaz (2009, 2012) to five different liquidity measures that describes both pairwise as well as total spillovers across Eurozone countries. Second, we test a dynamic version of spillovers to investigate the existence of contagion through liquidity channels including the recent Covid-19 pandemic, as well as the GFC and other regional crises. We find robust evidence of contagion in conjunction with noteworthy events, but the magnitude varies with respect to the liquidity measure employed. For instance, while we are the first to show evidence of contagion during the Covid-19 pandemic, this is captured by direct liquidity measures more than through price impact-based proxies. Third, we show the direction and intensity of spillovers to uncover new evidence that identify leading transmitters and receivers within the Eurozone. We find that Germany was the leading transmitter of shocks around the beginning of the Covid-19 pandemic.

The answers to these research question have important implications both for practitioners and regulators. Portfolio and risk managers may benefit from the identification of sources of risk that affect equity returns for purposes of risk mitigation and diversification strategies. Regulators and policy makers would find significant benefit from the identification of periods characterised by liquidity contagion when setting monetary policy initiatives, such as those implemented in the aftermath of the global financial crisis, some of which are still in place. Furthermore, within the Eurozone, identifying the transmitters of shocks could result in the implementation of bespoke policy initiatives, targeting countries more responsible for the spread of contagion, as well as measures to mitigate against any adverse consequences. Our empirical investigation extends the recent literature in this field (Andrikopoulos et al., 2014; Smimou & Khallouli, 2015) by facilitating a better understanding of the nature of contagion within financial markets and the fundamental importance of this phenomenon for regulators and policy makers who are engaged in continuing efforts to promote stability within the Euro area. Given previous inconclusive evidence relating to potential channels of transmission among Eurozone economies (MacDonald et al., 2018), our research sheds further light on the liquidity spillover effect across these economies.

The rest of the paper is organised as follows. Section 2 reviews the existing literature and formulates our hypotheses. Section 3 explains the methodology and Section 4 describes the data. The last two sections present our empirical analysis and concluding remarks.

2. Literature review

Extant literature provides alternative, as well as complementary, definitions of contagion. Kyle and Xiong (2001) define contagion as the result of declining asset prices, the tightening of liquidity and the rise in volatility that spread from one market to another. Forbes and Rigobon (2002) describe contagion as an episode of increasing cross-market linkages arising from a shock to one market (see also Longstaff, 2010). As a result, if two markets are highly correlated both during periods of stability and after a shock in one of them, this may not necessarily be contagion, but only interdependence. Forbes and Rigobon (2002) show that cross-market correlation is time-varying and dependent on volatility, which implies that linkages across countries vary over time (see also Bae et al., 2003; King & Wadhwani, 1990).

Regardless of the formal definition of contagion, it is widely accepted that the main route for transmission is the financial channel (Smimou & Khallouli, 2015), mainly due to the high degree of financial connectedness across leading stock exchanges worldwide. The literature classifies four distinct spillover channels: correlated-information, liquidity, flight-to-quality and risk channels. Under the information channel, a shock to one market is interpreted as economic news that affects price equilibria in other markets. In other words, after a price shock in one market, investors adjust their expectations about future cash flows in other markets. Empirical evidence supporting this channel are provided, among others by King and Wadhwani (1990). Shocks can also be transmitted through the flight-to-quality channel (Caballero & Kurlat, 2008). This mechanism regards the shift in preferences from more volatile securities, such as stocks, to safer assets, i.e. bonds (Baur & Lucey, 2010; Gonzalo & Olmo, 2005), as well as studies related to cross-assets contagion. Longstaff (2010) reports episodes of spillover across asset classes within-country, rather than across economies. He observes a transmission mechanisms from subprime asset-backed collateralised debt obligations (CDO) to stock and bond markets during the GFC. A third mean of contagion takes place via the risk premium channel. A negative shock in one market is associated with greater risk premia in other markets, implying time-varying nature of risk premia. Investors who suffer losses in one market may be more risk averse in other markets also as a result of a shock (see also Acharya & Pedersen, 2005). The liquidity channel refers to the liquidity shock in one market that propagates to other markets. Brunnermeier and Pedersen (2009) describe "liquidity spirals" as the dynamic relationship between market and funding liquidity. While market liquidity relates to ease of trading and is concerned with the cost of buying and selling a security, funding liquidity is associated with both securities and agents that trade. A security is considered to have a good funding liquidity if it is easy to borrow using the security as collateral. An agent has good funding liquidity if he has plenty of capital or has considerable access to financing with low margin requirements. With significant availability of funding liquidity, market makers can satisfy even large orders with low margins and increase overall liquidity. This situation creates a positive effect on market liquidity due to favourable funding conditions. Similarly, market liquidity also affects funding. Periods of higher liquidity and lower volatility make it easier to finance traders' positions with lower margins. Liquidity spirals work in reverse during market downturns and this interaction is potentially more violent (Brunnermeier & Pedersen, 2009). Funding liquidity constraints force market makers to reduce liquidity and increase transaction costs, which hampers the availability of liquidity further. These dynamics also underpinned the GFC of 2007–2009, in which liquidity shocks generated declines in the amounts of funding available to leveraged individuals in other markets (Brunnermeier & Pedersen, 2009). Longstaff (2010) reports evidence of contagion primarily propagated through liquidity and risk-premium channels during the GFC, while Eross et al. (2016) show spillover effects in the interbank market between bond and swap spreads. We build on this solid theoretical foundation to further analyse the liquidity channel in relation to transmission of shocks within the Eurozone. This analysis includes the investigation of spillover effects from countries with liquidity constraints to other countries, with findings providing evidence for flight-to-liquidity.

Despite an extensive literature aiming to investigate contagion and spillovers across leading stock exchanges, evidence relating to the Eurozone is limited and inconclusive. Andrikopoulos et al. (2014) provide evidence for liquidity, returns and volatility spillovers among G7 stock markets. Even though their sample is made up of leading global stock markets and provides interesting insights for the presence of spillovers, the Euro area has particular features related to economic and monetary union, and market integration. In contrast to other currency unions, European regulators consistently aim to promote integration and synchronicity across countries. Furthermore, the presence of core, semi-core and peripheral countries within the same currency union allows us to assess which economies work as transmitters and which as receivers of liquidity and volatility shocks. Similar evidence are provided by Chuliá et al. (2020) who investigate the relationship between commonality in liquidity and volatility combining total static spillovers following Diebold and Yilmaz (2012) and Granger causality test. Differently from Chuliá et al. (2020), we focus on liquidity levels rather than commonality. Moreover we specifically seek to provide evidence of contagion via dynamic liquidity spillovers and we test the robustness of our results using several liquidity measures. Smimou and Khallouli (2015) analyse illiquidity spillovers in the Eurozone, finding pairwise causal relationships during the GFC. However, similarly to Andrikopoulos et al. (2014), they employ Granger causality tests on VARs. As a result, their methodology can only capture pairwise time-invariant causality. In addition, Granger causality suffers from a series of methodological limitations.[1]

[1] One formal discussion regarding possible drawbacks of this test is provided by Granger (1988) himself.

Table 1
Variable definitions.

Quoted spread (QS)	$P_a - P_b$, where P_a is the ask price and P_b is the bid price
Proportional quoted spread (prop. QS)	$(P_a - P_b)/P_m$, where P_m is the mid price obtained as $(P_a + P_b)/2$
Effective spread (ES)	$2\|P_t - P_m\|$, where P_t is the adjusted closing price
Proportional effective spread (Prop. ES)	$2\|P_t - P_m\|/P_t$
Illiquidity (illiq)	$\frac{\|R_{i,t}\|}{Vol_{i,t}}$, where $R_{i,t}$ is the daily return and $Vol_{i,t}$ is the daily volume

3. Methodology

We investigate channels of transmission for liquidity and volatility within the Eurozone, using a sample of ten countries, namely Austria, Belgium, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal and Spain. These countries constitute 96% of the total gross domestic product (GDP) and 95% of the total market capitalisation of the Eurozone thus providing a fuller picture of the Eurozone.[2] The sample we analyse is similar to other studies in this field (Amihud et al., 2015; Smimou & Khallouli, 2015). We collect data on weekly adjusted closing prices, bid and ask prices, and volumes from Thomson Reuters Datastream, in relation to virtually all stocks listed in our ten identified exchanges from 01/01/2000 to 15/03/2021. All data for prices and volumes for the period preceding the introduction of the euro are denominated in euros. Datastream converts all historical data from the time new currency came into effect for monetary transactions. The resulting twenty-one year time window permits us to obtain reliable estimates and also includes major market downturns that took place since the introduction of the euro.

3.1. (Il)liquidity measures

Several measures exist to proxy liquidity, both direct and indirect, which are mostly based on bid and ask prices, and volumes. Since all facets of liquidity cannot be captured by a single measure (Amihud et al., 2012), we employ five different proxies widely applied in the microstructure literature for our analysis (e.g. see Acharya & Pedersen, 2005; Amihud, 2002; Chordia et al., 2000; Foran et al., 2014). Liquidity is measured using the following: quoted spread, proportional quoted spread, effective spread, proportional effective spread and Amihud (2002) ILLIQ, which is a specific measure of illiquidity. A detailed description of the measures we employ is provided in Table 1.

While spread proxies are considered direct measures, volume-based proxies are indirect measures of liquidity. Amihud (2002) captures the response of price to order flows, through the absolute price change per dollar of trading volume, based on a measure defined as λ (Kyle, 1985). Kyle (1985) proposes that prices are an increasing function of the imbalance in the order flow, caused by the fact that market makers cannot distinguish between the order flow generated by informed and uninformed traders. Amihud (2002), using his illiquidity proxy, analyses the cross-sectional and time varying aspects of illiquidity, finding that expected stock returns are an increasing function of expected illiquidity and that illiquidity is persistent over time. Goyenko et al. (2009) compare several liquidity measures in order to test whether they are actually appropriate to measure liquidity. They provide two important findings. First, $ILLIQ$ constitutes the best trade impact measure that proxies liquidity among those tested in their study. Second, the use of lower frequency data (e.g. weekly or monthly) can enable estimation of high-frequency measures so that the effort involved in obtaining and making use of high-frequency data is not worth the cost (and in addition has further econometric drawbacks). Indirect proxies are also often employed since other direct measures, such as those based on bid and ask prices, may not be available for a large data set or for long time periods. Further support comes from Sadka (2006) who find the highest pairwise correlation between $ILLIQ$ and the fixed and variable components of its time-varying liquidity decomposition model. In results not reported here for reasons of brevity, we find that the correlation across liquidity measures for each country is generally low, providing further support for the inclusion of different measures in our analysis.

We obtain a measure for market liquidity as the equally-weighted average of the individual stock-specific measures for each stock in each market on a weekly basis. This estimation, performed at a weekly frequency, is in line with past studies (e.g., see Smimou & Khallouli, 2015), thus offering a useful means for comparison.

3.2. Static and dynamic spillovers

The literature that investigates cross-asset and cross-market linkages often employs vector autoregressive (VAR) models. Vastly popularised since the work of Sims (1980), these models provide a useful way to model complex multivariate relationships across time-series. In its simplest form, a bivariate VAR with one lag can be represented as follows:

$$\begin{aligned} y_{1,t} &= \beta_{1,0} + \beta_{1,1} y_{1,t-1} + \alpha_{1,1} y_{2,t-1} + u_{1,t} \\ y_{2,t} &= \beta_{2,0} + \beta_{2,1} y_{2,t-1} + \alpha_{2,1} y_{1,t-1} + u_{2,t} \end{aligned} \tag{1}$$

where the error terms are assumed to be white noise with $E(u_{i,t}) = 0$ and $E(u_{1,t}, u_{2,t}) = 0$. A general $VAR(k)$ model for n variables and k lags can be formalised as:

$$y_t = B_0 + B_1 y_{t-1} + B_k y_{t-k} + u_t \tag{2}$$

where y_t is a $N \times 1$ vector of endogenous variables, B_0 is a $N \times 1$ vector of intercepts, B_i are the $N \times N$ matrix of vector autoregressive coefficients and u_t is a N-dimensional white noise process, with $E(u_t) = 0$, constant variance $E(u_t u_t\prime) = \Sigma_u$ and $E(u_t u_s\prime) = 0$ for $s \neq t$. Coefficients can be estimated using multivariate least squares. However, an important condition that the VAR model needs to meet is that of stationarity, which implies that the process has time-invariant first and second moments.

However, time-invariant parameters may not be sufficient to capture the time-varying behaviour of financial time-series, particularly when the relationship is dynamic (Ang & Timmermann, 2012; Guidolin et al., 2015). Several examples in the literature report the unstable behaviour of financial time-series e.g. bull and bear markets which involve cycles of financial expansion and contraction. Volatility clustering, whereby periods of high (low) volatility are followed by periods of high (low) volatility (Bollerslev, 1986) also represent such instability. Further, liquidity itself is time-varying (Acharya & Pedersen, 2005; Amihud, 2002; Grillini et al., 2019). To account for time-varying characteristics of financial markets and to adjust for the dynamic relationship, static VAR models may not be adequate, instead they should be complemented by a dynamic version that accounts for such time-varying relationships. For example, King and Wadhwani (1990) argue that links between stock markets change over time.

In this paper we analyse illiquidity spillovers across Eurozone's markets employing a modified version of Diebold and Yilmaz (2012, 2015). This methodology is based on a VAR modelling technique which involves a subsequent estimation of variance decomposition. This approach, built on previous work by Koop et al. (1996) and Pesaran and Shin (1998), allows us to measure directional illiquidity spillovers within a generalised VAR framework that overcomes possible limitations related to variable ordering. Previous evidence for

[2] The figures refer to 2015.

financial contagion using the liquidity channel yields limited findings due to severe methodological constraints. For instance, Andrikopoulos et al. (2014) find evidence of Granger causality based relationship between G7 stock markets for returns, volatility and illiquidity. A similar methodology is employed in Smimou and Khallouli (2015) for liquidity spillovers for a set of Eurozone countries. Although both studies adopt variance decomposition as robustness tests, they are both limited by the ordering of variables and are only able to capture pairwise causation.

This paper differs from previous contributions for a number of reasons. First, we employ an innovative illiquidity spillover index (ISI) which is able to capture the contribution of spillovers to illiquidity shocks across markets. Secondly, distinct from approaches based on variance decomposition and Cholesky factorisation, our results are invariant to ordering of variables, as shown in Diebold and Yilmaz (2009). Lastly, we estimate both the intensity and direction of gross and net spillovers. In contrast, models based on Granger causality and variance decomposition can only capture pairwise correlations, which is assumed to be constant over the full sample. Recent economic events, characterised by turbulence, growing economic integration and impacts of worldwide shocks, make it unlikely that fixed-parameter models applied over the entire sample are an appropriate way to carry out empirical analysis, thus requiring a more dynamic approach to estimation. For these reasons, we calculate a dynamic model of spillover analysis using rolling-window estimations that take into account the time-varying component of liquidity, consistently with the theoretical literature (Brunnermeier & Pedersen, 2009; Chordia et al., 2000).

Consider a covariance-stationary N-variable $VAR(p)$ with p lags, of the form:

$$X_t = \sum_{k=1}^{p} a_k X_{t-k} + \varepsilon_t \tag{3}$$

where X_t is a vector of log illiquidity measures, $\sum_{k=1}^{p} a_k$ is the matrix of the autoregressive parameters and ε_t is a vector of iid error terms $\varepsilon \sim (0, \sigma^2)$ for each equation in the system. The moving average representation of the covariance-stationary VAR(p) is $X_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$, where the A_i is a $N \times N$ matrix of coefficients that follows the recursion $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \cdots + \varphi_p A_{i-p}$, with A_0 being a $N \times N$ identity matrix with $A_i = 0$ for $i < 0$. We follow Diebold and Yilmaz (2012) by specifying a generalised VAR model with four lags based on Koop et al. (1996) and Pesaran and Shin (1998), in which variance decomposition is invariant to variable ordering. This results in an h-step-ahead forecast error variance decomposition $\theta_{ij}^{g}(H)$ with $H = 1, 2, \ldots$. Consequently, we have:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e\prime A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i \prime A_h \sum A_h \prime e_i)} \tag{4}$$

where $\sum$ represents the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation and $e\prime$ is a selection vector, with one as the ith element and zeros otherwise. The entries of the variance decomposition matrix are normalised based on the row sum, in order to satisfy the condition $\sum_{i,j}^{N} \tilde{\theta}_{i,j}^{g}(H) = 1$, where the superscript $\tilde{\theta}$ indicates the normalised error variance. The total illiquidity spillover index is then constructed as:

$$ISI = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1}^{g} \tilde{\theta}_{i,j}^{g}(H)} * 100 \tag{5}$$

and, under the above condition of normalisation, it is equal to:

$$ISI = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{i,j}^{g}(H)}{N} * 100 \tag{6}$$

This measure describes the average contribution of illiquidity spillovers from shocks due to all variables arising from the total forecast error variance and constitutes a sufficient tool to estimate how much of the shocks come from liquidity spillovers within Eurozone markets. However, the normalised elements of the matrix provide further information on the direction of spillovers, transmitted from market i to all other markets:

$$ISI_{i\to j} = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{j,i}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{j,i}^{g}(H)} * 100 = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{j,i}^{g}(H)}{N} * 100 \tag{7}$$

We can also estimate spillovers received by market i from all other markets:

$$ISI_{i\leftarrow j} = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{i,j}^{g}(H)} * 100 = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{i,j}^{g}(H)}{N} * 100 \tag{8}$$

A further interesting feature is the computation of the net spillover measure, which shows whether a market is a net receiver or transmitter. The net illiquidity spillover from market i to all other markets j is obtained as:

$$NISI_i = ISI_{i\to j} - ISI_{i\leftarrow j} \tag{9}$$

The measures above capture total and net directional spillovers using a simple but effective and robust measure. While this analysis provides valuable information for transmission of illiquidity shocks, it is not limited to a static representation of spillovers. Given the time-varying nature of illiquidity and the market-wide events that characterise recent economic and financial events, it is necessary to include more dynamic models for such analysis. Further, single fixed-parameters may omit valuable information relating to the illiquidity transmission mechanism. To address this issue, we estimate illiquidity spillovers within a dynamic setting, using a 200-week rolling window.

The VAR model specified only accounts for the transmission of illiquidity shocks and, as such, the spillover effect is assumed to take place only through the illiquidity channel. Although such a specification is robust to the different illiquidity measures employed, it may have two potential limitations. First, the assumption that shocks are transmitted through the illiquidity channels may lead to over-specification and excludes other channels of transmission such as the information and risk channels. Therefore, the VAR model is not likley to capture all possible sources of transmission of shocks, but only those related to stock market liquidity. Second, the VAR model does not account for the underlying source of the shock that determines the level of country-specific illiquidity. Market-specific characteristics have been partially addressed by Claeys and Vašíček (2014), who employ a factor analysis to capture country-specific heterogeneity in their augmented VAR model to estimate transmission of shocks for government bond yields across Eurozone countries. Although this is an improvement, it can be argued that such an empirical approach is more meaningful in the particular analysis carried out by Claeys and Vašíček (2014), given that government bond yields incorporate several different sources of country risk as compared to stock market liquidity, which may result in more serious issues of over-estimation of the spillover effect. Our empirical approach aims to address such methodological limitations. In addition to the spillovers based analysis that we have described above, we also present preliminary results and graphics based on use of suitable Pearson correlation heatmaps, cluster based analysis using dendrograms employing appropriate Euclidean distances, as well as use of Minimum Spanning Trees. Further details follow in the next section.

4. Data and descriptive statistics

We employ data on adjusted closing prices, bid and ask prices and volumes from Thomson Reuters DataStream for the period between 01/01/2000 to 15/03/2021. In order to minimise the risk of data errors as argued by previous literature when equity data from Thomson Datastream are employed (Andrikopoulos et al., 2014), we follow the procedure of Ince and Porter (2006). We include only domestic stocks recorded as equity in DataStream and listed in the main stock exchange for which data are available. Data are cleaned to remove possible biases also using the following filters: (i) zero daily returns are coded as

Table 2
Summary statistics.

	Austria	Belgium	Finland	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain
Returns:										
Mean	0.124	0.116	0.008	−0.054	−0.083	−0.072	−0.116	−0.07	0.031	−0.032
Median	0.342	0.309	0.202	0.206	0.216	0.128	0.264	0.215	0.103	0.295
SD	2.205	1.982	2.385	2.236	2.564	3.174	2.698	2.596	2.76	2.557
Min	−19.06	−17.03	−17.658	−21.024	−16.233	−20.12	−18.56	−20.292	−19.45	−22.661
Max	8.726	9.745	10.497	8.231	13.642	13.68	8.177	9.312	9.495	9.175
Kurtosis[a]	11.115	9.587	6.432	10.846	4.342	5.712	4.568	6.164	3.355	7.393
Skewness	−1.625	−1.36	−0.877	−1.758	−0.866	−0.914	−1.08	−1.22	−0.456	−1.196
Illiquidity										
Mean	1.614	1.399	−0.548	1.58	1.607	−0.854	−1.503	−0.226	1.057	−1.865
Median	1.582	1.416	−0.603	1.583	1.593	−0.911	−1.511	−0.249	1.105	−1.91
SD	0.481	0.585	0.937	0.382	0.339	1.183	0.694	0.869	1.124	0.639
Min	−0.031	−0.179	−3.164	0.595	0.606	−5.117	−3.814	−2.619	−4.22	−3.819
Max	3.45	3.753	1.957	2.623	2.681	3.063	1.672	2.651	3.668	0.938
Kurtosis[a]	0.361	−0.204	−0.419	−0.532	−0.104	0.397	0.363	−0.400	0.395	0.453
Skewness	0.312	−0.085	0.121	0.007	0.135	0.048	0.215	0.07	−0.45	0.427
Pr. quoted spread										
Mean	0.037	0.03	0.02	0.043	0.098	0.042	0.016	0.018	0.057	0.013
Median	0.03	0.028	0.016	0.04	0.068	0.039	0.013	0.017	0.051	0.011
SD	0.031	0.01	0.01	0.012	0.188	0.017	0.008	0.007	0.029	0.008
Min	0.008	0.009	0.006	0.014	0.027	0.01	0.003	0.006	0.012	0.004
Max	0.75	0.089	0.058	0.086	1.953	0.144	0.049	0.051	0.224	0.061
Kurtosis[a]	259.155	2.027	1.174	0.965	46.423	4.294	2.246	0.743	2.296	5.059
Skewness	12.049	1.168	1.293	1.09	6.551	1.479	1.616	0.859	1.277	2.241
Pr. effective spread										
Mean	0.046	0.03	0.018	0.039	0.489	0.037	0.013	0.017	0.564	0.011
Median	0.03	0.027	0.016	0.037	0.145	0.034	0.012	0.016	0.048	0.01
SD	0.056	0.026	0.008	0.011	2.546	0.016	0.004	0.007	11.39	0.005
Min	0.006	0.007	0.007	0.012	0.031	0.01	0.006	0.005	0.01	0.004
Max	0.909	0.759	0.058	0.083	32.778	0.119	0.029	0.118	277.8	0.056
Kurtosis[a]	64.438	560.369	2.019	0.599	84.080	3.116	1.080	33.263	542.247	8.468
Skewness	6.065	20.843	1.413	0.994	8.777	1.444	0.99	3.032	23.3	2.033

Notes: The table presents summary statistics (mean, standard deviation, minimum and maximum values, skewness and kurtosis) for each country. The sample runs from January 1, 1990 to December 31, 2015. Each observation corresponds to a weekly average.
[a]Excess kurtosis is reported here.

missing; (ii) daily returns are coded as missing if they are greater than 200% and if $(1 + r_{i,d}) * (1 + r_{i,d-1}) - 1 \leq 50\%$; (iii) daily returns are coded as missing if their drop in value is greater than 97%; (iv) stocks with daily volume greater than their number of outstanding shares are deleted; (v) daily volumes are coded as missing if their value is smaller than 100€; (vi) market days in which more than 90% stocks have zero returns are excluded.

Table 2 reports some statistical properties of our data set in relation to returns and liquidity measures for each market within the sample. We report statistics for returns, $ILLIQ$, proportional quoted and effective spreads to proxy for the indirect and direct impacts of liquidity. Our other liquidity variables are not reported in Table 2, but they generally confirm the features of the data reported. Statistics refer to equally-weighted weekly averages of individual stocks in each market. As shown in Table 2, more than half of the countries report average negative returns, with Austria showing the highest average returns and Italy the lowest. The logarithm of illiquidity indicates Austria, Germany and France as the most illiquid countries, while Spain and Italy are the least illiquid. Germany is also the country with the widest average proportional quoted spread, while Spain and Italy show the narrowest, in line with such measures for average illiquidity. Portugal and Germany lead rankings for average proportional effective spread, followed by Austria and France. Similar to the other measures, Spain and Italy are the most liquid, i.e. they show the narrowest average proportional effective spread. Other features of the data, such as skewness and kurtosis, expressed as excess kurtosis, show that the nonnormality is observed for our variables. Values for skewness and kurtosis are consistent with the existing findings within the literature for the characteristics of liquidity, characterised by sudden and pervasive drops (see, e.g. Grillini et al., 2019).

Before investigating the degree of spillover across liquidity measures in depth, we provide a graphical analysis of correlations between countries for each liquidity measure. Figs. 1 and 2 show the heat map of Pearson correlations across countries for our full sample. Fig. 1 shows the heat map for illiquidity. These figures show that there exists a positive correlation across most variables, with France generally exhibiting the highest pairwise correlation with other countries, with the highest pairwise correlation shown for its correlation with Finland at 0.55. Interestingly, Germany is generally uncorrelated with other variables and the highest pairwise correlation for Germany can be seen with the Netherlands at 0.11. The correlation heat maps for the other liquidity measures generally show a more heterogeneous degree of correlations. For instance, Germany tends to be uncorrelated with other countries, while the magnitude of linear dependence for e.g. for France and Finland is stronger using direct liquidity measures. Mixed evidence arises for example for the case of Portugal and Spain, which are uncorrelated with core Eurozone countries while they are both more correlated with Italy.

Next, we perform a cluster based analysis on our liquidity measures. We provide a graphical representation of observed hierarchical clustering using Euclidean distance between each correlation pair by employing the average linkage algorithm. This algorithm computes distances between each pair of observations in each cluster. The observations are then added up and divided by the number of pairs to obtain an average inter-cluster distance. The resulting visual tool is called a dendrogram and it presents us with a hierarchical cluster analysis using a set of dissimilarities for the n objects being clustered. The algorithm proceeds iteratively by assigning each element to its own cluster and then joining the two most similar clusters for each stage until there is only a single cluster that emerges.

In addition to the dendrogram, we illustrate within-system dependencies using an appropriate mapping strategy. From the correlations between liquidity variables shown in Figs. 1 and 5, we model

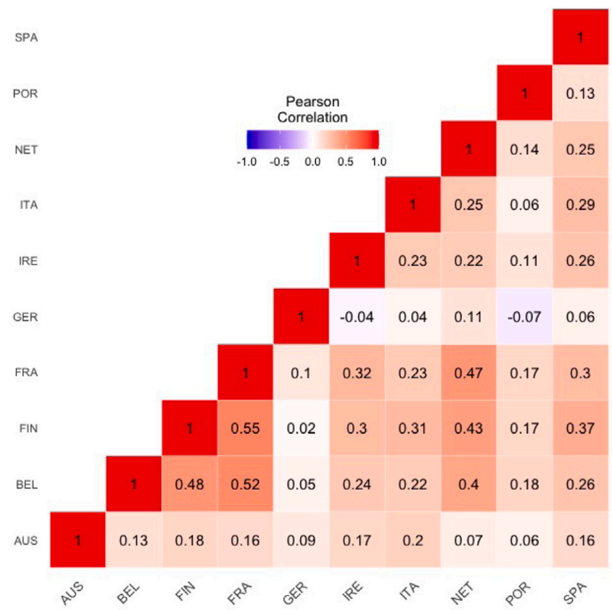

Fig. 1. Pearson correlation heat map: Illiquidity.

the relationship between variables using a simple distance function following Mantegna (1999) as follows:

$$d(i,j) = \sqrt{2(1-\rho_{ij})} \tag{10}$$

where $d(i,j)$ is the pairwise distance between variables (countries in our case) and $\rho_{i,j}$ is the correlation coefficient. Mantegna (1999) shows that this specification satisfies the key properties of a metric distance and he provides full proof of the three key axioms underpinning this method. From the matrix of pairwise distances, we build a connected graph of "nodes" with the minimum possible total edge width, which is obtained from a transformation of correlation coefficients, similar to the approach implemented in Samitas et al. (2022). We do so using the distance matrix obtained from correlation coefficients and we compute the Minimum Distance Spanning Tree (MST). In this paper, the MST problem is solved employing the Kruskal (1956) algorithm following (Samitas et al., 2022).

Figs. 3–5 show the results of our graphical analysis employing dendrograms and MSTs for illiquidity, proportional quotes spread and proportional effective spread, respectively. Fig. 3 illustrates the hierarchical clusters for our illiquidity measure, where the y-axis measures the distance between the two merging countries. The key to interpreting a dendrogram is to focus on the height at which any two countries are joined together as well the number of clusters. In Fig. 3 we can see three distinct clusters, as well as Germany, forming an independent cluster. This result is also highlighted by the general lack of correlation with other countries, as shown in Fig. 1. The distance obtained from correlation coefficients is minimised for Finland and France, since the link that joins them together is the lowest. This evidence is consistent with the correlation matrix shown in Fig. 1. However, in Fig. 3 we observe that Finland and France form a cluster with Belgium and the Netherlands. Italy and Spain are found to be similar to each other as well as to Ireland. The evidence obtained from the MST shows that France is the central node and connects to most of the other nodes.

Graphical clustering using direct proxies of liquidity provide further supporting evidence as well as some new features from the data. The dendrogram shown in Fig. 4 is similar to the one shown in Fig. 3 in relation to the cluster obtained by minimising Euclidean distance, i.e. that formed by France, Finland, Belgium and the Netherlands. However, for this instance, Austria constitutes an independent cluster, while Germany forms a cluster with two peripheral countries, Spain

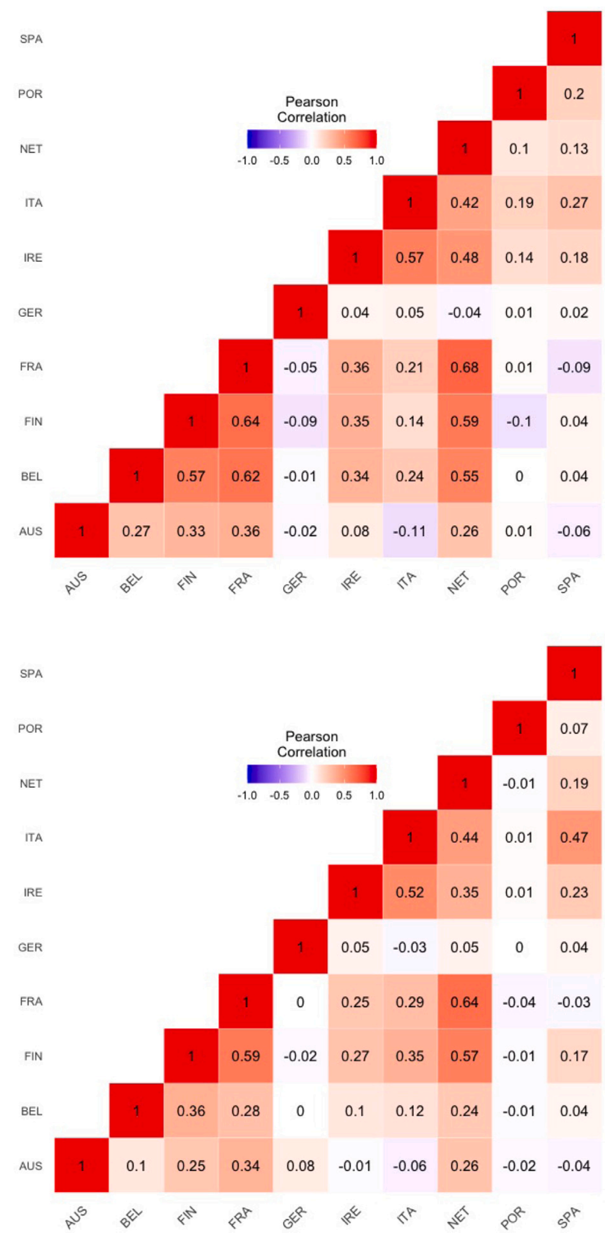

Fig. 2. Pearson correlation heat map: Liquidity.

and Portugal. The MST confirms France as the most connected node, followed by Italy. Italy and France are also the most connected nodes in the MST shown in Fig. 5 using proportional quoted spread. This time, however, Belgium does not belong to the same cluster as other liquidity measures have shown. Samitas et al. (2022) find that countries that are physically close to each other tend to be reflect the composition of the financial network using daily returns for a significantly larger sample as compared to ours spanning four continents. We do not find similarly striking results with regard to physical closeness. On the other hand, France constitutes a central node across European countries both in Samitas et al. (2022) model using daily returns as well as in our model using weekly liquidity measures. One of the main limits of the correlation-based distances employed here is that they assume correlation is constant over time, which is an assumption which is unlikely to hold when using financial data. In order to overcome this limitation, we estimate dendrograms and MSTs for three sub-sample:

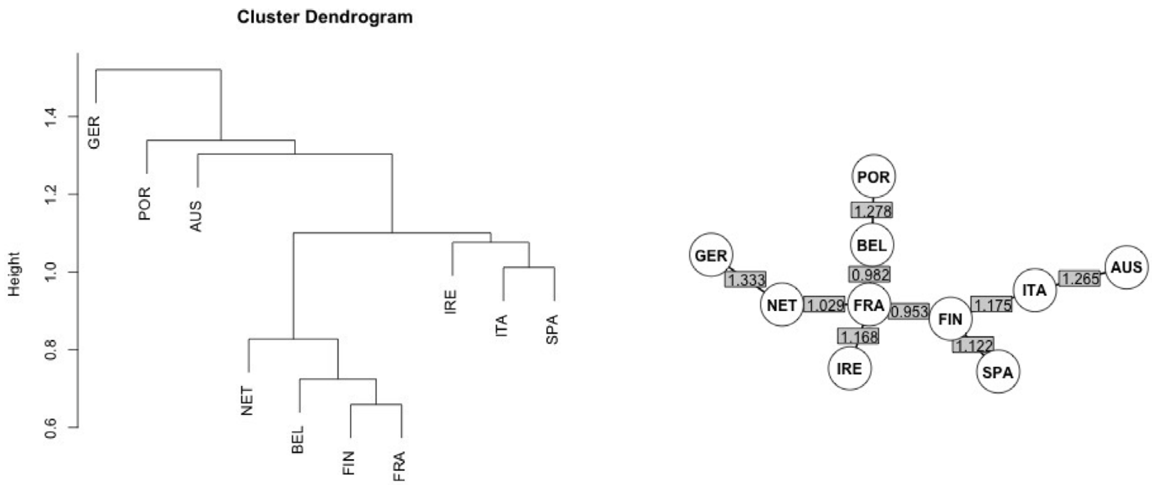

Fig. 3. Illiquidity dendrogram and minimum spanning tree.

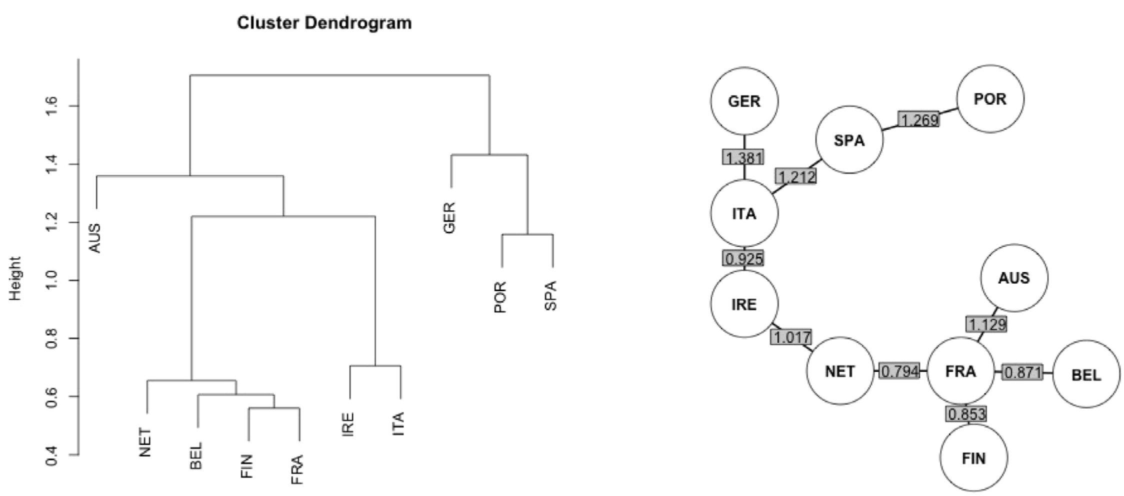

Fig. 4. Pr. Quoted spread dendrogram and minimum spanning tree.

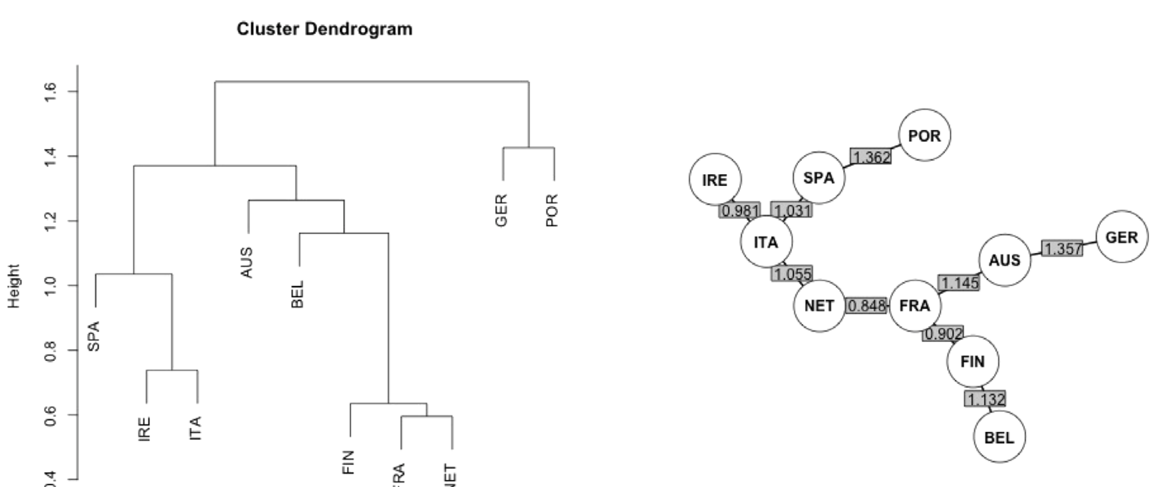

Fig. 5. Eff. Quoted spread dendrogram and minimum spanning tree.

the Global Financial Crisis, the Eurozone debt crisis and the outbreak of the Covid-19 pandemic.[3]

[3] These results are available in an online Appendix.

5. Empirical results

Next, we present our empirical results for static and dynamic channels of liquidity transmission for our pool of ten Eurozone countries. We implement our illiquidity spillover index (ISI) together with a dynamic

Table 3
Illiquidity spillover index.

	AUS	BEL	FIN	FRA	GER	IRE	ITA	NET	POR	SPA	From others
AUS	93.321	0.223	0.308	0.326	1.304	1.069	1.06	0.98	0.242	1.167	6.679
BEL	0.317	82.665	4.72	5.966	0.453	1.312	0.8	2.035	0.935	0.793	17.335
FIN	2.628	3.4	83.072	4.985	0.861	0.964	0.37	1.556	0.725	1.444	16.928
FRA	0.32	7.378	4.584	81.031	0.687	0.705	0.43	3.974	0.466	0.421	18.969
GER	1.369	0.17	0.691	1.895	91.35	0.259	0.42	1.144	2.505	0.2	8.65
IRE	1.668	0.589	2.096	1.367	0.355	90.323	0.85	1.157	0.398	1.199	9.677
ITA	4.366	0.909	2.102	0.832	0.908	0.681	85.8	0.673	0.193	3.53	14.194
NET	1.036	3.181	3.679	4.971	1.049	0.866	0.99	83.389	0.098	0.741	16.611
POR	0.097	1.432	1.619	0.815	0.556	0.136	0.16	0.257	94.111	0.815	5.889
SPA	1.409	0.261	3.009	0.295	0.665	1.174	1.81	1.4	0.368	89.605	10.395
To others	13.211	17.543	22.809	21.452	6.839	7.166	6.89	13.176	5.929	10.309	125.327
Net (from-to)	−6.532	−0.208	−5.881	−2.483	1.811	2.511	7.3	3.435	−0.04	0.086	12.53%

Notes: The table shows the illiquidity spillovers to and from each market in the sample, namely Austria, Belgium, Finland, France, Germany, Italy, Ireland, Netherlands, Portugal and Spain. The estimation is performed on weekly illiquidity averages from 01/01/2000 to 15/03/2021. Each ijth entry represents the estimated contribution to the forecast error variance and elements in the diagonal report the own contribution. The column "From others" reports the row sum and the row "To others" reports the column sum, both excluding own contribution. The number on the bottom right is the illiquidity spillover index and is reported in percentage.

approach, using a rolling estimation technique. The latter allows us to better understand the intensity and direction of spillovers in tranquil periods, as well as during periods of increased financial turmoil.

5.1. Static spillover analysis

We report the full-sample spillover analysis, which estimates the average spillover effect across Eurozone stock markets. Tables 3–5 present the results of illiquidity and liquidity spillovers indices, based on the 10-weeks ahead forecast error variance decomposition. Liquidity is proxied by proportional quoted and effective spreads.[4] Diebold and Yilmaz (2009, 2012) report a similar table that represents volatility spillovers across markets and asset classes. We employ a similar analytical framework to Diebold and Yilmaz (2009, 2012), but our measure specifically uses direct and indirect proxies of liquidity. Table 3, which we call the illiquidity spillover table, shows the average contribution of illiquidity shocks to and from each country. Every ijth entry represents the estimated contribution to the forecast error variance of country i coming from innovations to country j. Each entry, for $i \neq j$, represents pairwise directional connectedness. For example the 3,2 entry (3.4) indicates that shocks in illiquidity to Belgium are responsible for 3.4% of the 10-step-ahead forecast error variance in Finland. Similarly, the 7,10 entry indicates that 3.53% of the 10-ahead forecast error variance in Italy are caused by Spain. The last column of the table, labelled "From others" indicates the sum of the total contribution to country i from all other countries j. Similarly, the row labelled "To others" is the column sum of the total contribution from country i to all other countries j. For instance, the value of 18.969 in the fourth entry of the rightmost column of Table 3 denoting that France receives almost 19% of its variation from the other countries within the Euro area (which are included in our sample). Similarly, each entry in the row sum "Contribution to others" indicates the contribution of each country to the forecast error variance of the other economies. Finally, the main feature of this table is our new measure, ISI, shown in the lower right corner, which represents the average illiquidity forecast error variance in all 10 countries, coming from the observed spillovers. This is computed as a grand average, in all cases for $i \neq j$. The value of 12.53% is interpreted as the average connectedness of shocks across countries, while the remaining 87.47% is explained by idiosyncratic shocks.

From Table 3 it can be noted that the highest share of forecast error variance is explained by own country illiquidity spillovers. The elements on the diagonal are all above 80%, which is far greater than the off-diagonal elements. While these figure refer to average spillover effects, these finding are in line with the internal channel related to the notion of liquidity spirals (Brunnermeier & Pedersen, 2009). It can be seen that, on average, France and Finland are among the dominant transmitters as well as receivers of shocks to other economies. France and Finland are responsible for 21% and 23% of shock transmission to other countries respectively, while receiving 19 and 17% from all other countries. The Netherlands is also among the dominant receivers of shocks, an evidence in line with Antonakakis and Vergos (2013), who show that the Netherlands is the dominant receiver of bond yield spread spillovers from other Eurozone countries. In particular, France is responsible for 6%, 5% and 5% of the 10-weeks ahead forecast error variance in Belgium, Finland and the Netherlands, respectively. Andrikopoulos et al. (2014) report unexpected evidence of insignificant Granger causality between France and Italy. In contrast, we show that spillover effects do exist between these two economies also. France accounts for almost 1% of shocks in Italy, while Italy accounts for less than half within France.

The last row of the table, labelled "Net (From-To)" reports that France is one of the three countries with the lowest average negative net contribution, after Finland (−5.88%) and Austria being the lowest (−6.53%). These results are of great significance, not only to describe the interconnectedness amongst European countries, but also because they constitute an important indicator for regulators in order to understand future changes in illiquidity and the sources of shocks.

Table 4 presents similar evidence for the transmission of liquidity spillovers using proportional quoted spreads. The average connectedness measure (18.40%) shows that almost 20% of the total shocks across markets arise from liquidity spillovers. It can be seen that the diagonal elements of the matrix fluctuate between 66% for the Netherlands and 98% for Germany. The row sum "From Others" shows that the Netherlands and France are the highest receivers of liquidity spillovers. For instance, spillovers in France are mainly explained by the Netherlands and Belgium, with values of 9.38% and 7.3%, respectively. The row "To others" shows that while France and the Netherlands are also dominant transmitters, the highest transmitter is Italy, which accounts for more than 50% of shocks to other countries. This evidence is confirmed by the row labelled "Net", where Italy shows the highest difference in spillovers received and transmitted (−31), while both France and the Netherlands are net receivers of spillovers. We also notice that, in addition to the Netherlands and Belgium, peripheral economies, such as Portugal and Spain, are generally net receivers of spillovers on average, while being amongst the lowest contributors with values of 4.54% and 7.6%, respectively. This evidence is of great interest for regulators, particularly in the aftermath of a crisis that characterises peripheral economies, such as after the Greek sovereign bond crisis, that challenged the stability of the Eurozone. In fact, one would expect core economies in the Eurozone to absorb shocks coming from the periphery. If, however, peripheral countries tend to be net

[4] The spillover index for the other liquidity measures is provided in the online appendix.

Table 4
Liquidity spillover index: Proportional quoted spread.

	AUS	BEL	FIN	FRA	GER	IRE	ITA	NET	POR	SPA	From others
AUS	92.687	0.565	1.387	2.165	0.084	0.102	0.4	1.639	0.842	0.124	7.313
BEL	0.869	77.005	5.229	7.304	0.698	2.126	3.02	3.032	0.02	0.695	22.995
FIN	0.478	3.125	78.749	3.318	0.03	1.069	8.08	4.578	0.281	0.289	21.251
FRA	1.675	4.896	4.565	69.415	1.04	1.309	6.19	9.067	0.196	1.648	30.585
GER	0.151	0.364	0.229	0.463	97.713	0.446	0.16	0.166	0.171	0.135	2.287
IRE	0.328	0.55	2.368	1.073	1.656	79.039	11	2.881	0.787	0.318	20.961
ITA	0.277	0.754	3.429	3.219	0.659	5.424	80.5	2.834	0.359	2.58	19.536
NET	1.313	1.83	4.663	9.376	0.966	4.066	10.2	65.869	0.788	0.929	34.131
POR	0.556	0.21	0.773	1.465	0.279	0.774	2.53	1.157	91.37	0.885	8.63
SPA	0.684	0.158	1.486	1.61	0.21	0.27	8.86	1.937	1.099	83.685	16.315
To others	6.331	12.453	24.131	29.993	5.622	15.585	50.5	27.292	4.542	7.603	184.00
Net (from-to)	0.982	10.542	−2.88	0.592	−3.335	5.376	−31	6.839	4.088	8.712	18.40%

Notes: The table shows the liquidity spillovers to and from each market in the sample, namely Austria, Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Portugal and Spain. The estimation is performed on weekly liquidity averages of proportional quoted spread from 01/01/1990 to 31/12/2015. Each ijth entry represents the estimated contribution to the forecast error variance and elements in the diagonal report the own contribution. The column "From Others" reports the row sum and the row "To Others" reports the column sum, both excluding own contribution. The number on the bottom right is the liquidity spillover index and is reported in percentage.

Table 5
Liquidity spillover index: Proportional effective spread.

	AUS	BEL	FIN	FRA	GER	IRE	ITA	NET	POR	SPA	From others
AUS	91.324	0.135	1.11	2.944	0.829	0.698	0.31	2.176	0.14	0.331	8.676
BEL	0.048	92.716	4.27	1.042	0.05	0.222	1.12	0.342	0.008	0.187	7.284
FIN	0.178	4.544	75.208	1.669	0.231	2.661	10.8	2.679	0.138	1.897	24.792
FRA	1.664	0.553	6.73	71.066	0.364	1.702	7.66	9.134	0.133	0.995	28.934
GER	1.104	0.032	0.553	0.526	95.357	0.643	0.17	0.458	0.206	0.953	4.643
IRE	0.634	0.03	1.142	0.808	0.908	82.93	10.4	2.289	0.21	0.613	17.07
ITA	0.581	0.046	7.348	0.995	0.504	7.032	75.4	3.555	0.269	4.235	24.565
NET	1.815	0.503	6.455	9.316	0.254	2.891	10.2	65.957	0.347	2.232	34.043
POR	0.085	0.083	0.134	0.468	0.201	0.09	0.46	0.678	87.538	10.265	12.462
SPA	0.123	0.097	3.293	0.719	0.229	1.124	7.51	2.022	4.664	80.221	19.779
to others	6.232	6.023	31.035	18.486	3.57	17.064	48.7	23.332	6.115	21.709	182.248
Net (from-to)	2.444	1.261	−6.243	10.448	1.073	0.006	−24	10.711	6.347	−1.93	18.23%

Notes: The table shows the illiquidity spillovers to and from each market in the sample, namely Austria, Belgium, Finland, France, Germany, Italy, Ireland, Netherlands, Portugal and Spain. The estimation is performed on weekly illiquidity averages from 01/01/2000 to 31/12/2015. Each ijth entry represents the estimated contribution to the forecast error variance and elements in the diagonal report the own contribution. The column "From Others" reports the row sum and the row "To Others" reports the column sum, both excluding own contribution. The number on the bottom right is the illiquidity spillover index and is reported in percentage.

receivers, their internal instability could further jeopardise the stability of the whole European financial system, during periods of greater financial turmoil.

In Table 5 we present evidence of liquidity spillovers, using proportional effective spread as our direct proxy. We observe that more than 18% of the total shocks is transmitted across markets, similarly to our previously estimated value. Italy contributes to most of the transmission, with average contribution of 48.7%, followed by Finland with around 31%. However, neither Italy nor Finland are dominant receivers. Instead, the Netherlands and France are dominant receivers with 34.04% and 28.93%, respectively. This finding is also supported in the last row, where we notice that the greatest net transmitter is Italy (−24%). We find the surprising evidence that Germany, the most developed core country in the eurozone, is the least significant contributor to spillovers, both transmitted and received, to and from other countries.

Overall, we conclude that using our various measure yields estimates of average spillover effects of between 12 and 18% for all liquidity measure. Our findings extend previous evidence on liquidity spillovers among leading stock exchanges. Andrikopoulos et al. (2014) provide limited findings using Granger causality tests employing time series for volatility and illiquidity. They only report causation, which is not robust to the time-variation of the spillover and their sample focuses solely on the G7 markets. Smimou and Khallouli (2015) report similar evidence, also using sub-samples of time-series to highlight how the causation varies over time. Our paper makes a contribution to the literature in the following ways. First, we introduce a liquidity spillover index, implementing the methodology proposed by Diebold and Yilmaz (2009, 2012). We provide estimates for total spillovers received by and transmitted to each country and we investigate the dynamic spillover using rolling-windows (presented in the next section). Given that results based on the spillover index are sensitive to the inclusion of new observations, which helps in determining significant changes in the average spillover effect, our analysis highlights the need to investigate the dynamic evolution of connectedness to clearly understand the available evidence relating to contagion through the liquidity channel. The main benefit of our static analysis of liquidity spillovers using several measures relates to the multidimensional characteristics of liquidity. That is, by using only one liquidity measure, as in Chuliá et al. (2020), one could overemphasise the role played by some countries, underestimating the impact caused by others in the transmission of shocks.

5.2. Dynamic spillover analysis

Given a number of global and local macroeconomic events that have taken place within our sample period, including the global financial crisis, the euro crisis and the Covid-19 pandemic, it is reasonable to conclude that financial turbulence cannot be fully represented by a static model captured by a single parameter. In order to effectively analyse changes in liquidity spillovers, we estimate our model outlined in Eq. (3) using a 200-weeks rolling window based analysis, similar to Diebold and Yilmaz (2012) who employ daily data. A dynamic assessment of liquidity spillovers would also corroborate evidence of contagion through the liquidity channel. Differently from other studies that have attempted to capture time-varying spillovers using pre-determined time-windows (Andrikopoulos et al., 2014; Smimou & Khallouli, 2015), our dynamic models allows for internal and external channels that may impact on spillovers without coinciding with noteworthy events.

Fig. 6 shows the dynamic total spillovers for the three liquidity proxies, which correspond to the dynamic version of the total average spillover reported in the bottom right corner of Tables 3–5. We can clearly note large variability for the total spillover index for all our measures, suggesting strong evidence indicating time-varying connectedness across countries through the liquidity channel. For each graph, we report the main noteworthy events that characterised the last 17 years generating significant financial turmoil both internally, i.e. within the EU, and globally. Illiquidity decays from about 30% during the year 2006 to around 25% in the first part of the graph, being aligned to the bankruptcy of the New Century real estate investment trust (NC), which can be formally considered the prelude to the GFC. From the bankruptcy of NC until late 2009, illiquidity spillovers increase sharply and remain steady above 30%, which is also the case after the collapse of Lehman Brothers. Overall, the series reaches a peak by the end of 2009, remaining above 30% also in line with the Euro crisis. The transmission of shocks decays gradually between 2010 and 2014 before increasing again until the beginning of the European Central Bank's (ECB) quantitative easing programme towards the beginning of 2015. Graphical evidence suggests that increase in illiquidity led to policy intervention by the ECB and the downtrend following the quantitative easing provides supporting evidence for ECB policy effectiveness. After a general downtrend, spillovers rise again sharply in line with the February 2020 stock market sell-off that corresponds to the outbreak of the Covid-19 pandemic in the Eurozone. Nevertheless, this increase fades away quickly. It can be seen that not all crises have the same impact on the transmission of illiquidity shocks, whether they originate within or outside the EU. While there is a significant increase in spillovers in line with the GFC, the Covid-19 outbreak suggests only a temporary increase in illiquidity of slightly over 25%. Moreover, policy-induced changes in liquidity seem to have a positive impact on reducing turmoil.

Total liquidity spillovers using proportional quoted spreads show a similar pattern to illiquidity spillovers, in spite of some differences. While the magnitude of the transmission is larger than illiquidity spillovers until the beginning of the GFC and shortly after the collapse of NC, two peaks above 50% are noticeable. While the first peak suddenly disappears, the second peak, triggered by the collapse of Lehman Brothers, suggests a longer period of transmission of shocks. In the years immediately after the GFC, liquidity spillovers fall back rapidly, for instance regardless of domestic shocks that were related to the Irish banking sector collapse or the Greek sovereign debt crisis. While remaining steady for most of the remaining sample with a value around 30%–35%, the effect of the Covid-19 outbreak in contributing to the transmission of liquidity shocks is noticeably more pronounced. We can see a sharp increase in liquidity transmission in February 2020, which after a partial reduction remains at the same level as seen during the Euro crisis. Observed persistent illiquidity and its transmission across countries, particularly during the GFC and the Covid-19 pandemic, finds theoretical support in relation to the notion of liquidity spirals (Brunnermeier & Pedersen, 2009). The sudden peak corresponding to the Covid-19 pandemic, and following a long period of expansionary monetary policy, highlights the potential ineffectiveness of policy measures aimed at avoiding contagion across Eurozone countries after a Global shock.

We find similar results using proportional effective spread as our liquidity proxy but with some exceptions. While our evidence confirms periods of increasing connectedness during the GFC and the Covid-19 outbreak, this series is characterised by sudden and temporary shocks that are not strictly related to noteworthy events. We observe two spikes well above 40% that are not related to specific events. While surprising, this evidence is in line with existing findings around liquidity, which are characterised by sudden and pervasive drops (Amihud, 2002).

Overall, our graphical evidence provide some key insights. First, we provide strong evidence of time-varying interconnectedness leading to evidence of contagion within the Eurozone, driven by the liquidity channel. Furthermore, using different liquidity measures, we uncover new evidence of contagion during the Covid-19 pandemic, which would have not been captured using price impact proxies, such as that of Amihud (2002). Our findings corroborate the evidence that one single measure cannot fully capture all liquidity characteristics. Lastly, our results show important implications regarding effectiveness of policy measures. The expansionary monetary policy in the aftermath of the GFC played a crucial role in reducing instability and enhancing liquidity within the Eurozone, as shown by our illiquidity measure (in the main). However, once the benefit of liquidity-induced relief measures from Central Banks die out, further expansionary measures subsequent to shocks are not as effective. This is particularly evident for the Covid-19 pandemic, where the accommodating monetary policy has probably been in line with market expectations.

5.2.1. *Directional spillovers: transmitters and receivers*

The previous section reports the results of graphical analysis using total spillover plots. However, valuable pieces of information regarding the direction of shocks are not investigated therein. That information is contained in the row "Net" within Tables 3–5. The "Net" directional spillovers are obtained, for each table and for each country, as the difference between the row "From Others" and the row "To others". We investigate this aspect by iterating the 200-weeks rolling window estimation for data in this row. This allows us to have a fuller picture of the dynamic transmission between economies in the euro area. Furthermore, these results provide important implications for researchers and regulators interested in investigating which countries are net transmitters or net receivers of spillovers. We refer to these figures as "Net directional spillovers" and we report their evolution in plots shown in Figs. 7–9 for all our liquidity measures.

We group our ten countries in three categories, similar to Claeys and Vašíček (2014), i.e. we focus specifically on core, semi-core and peripheral countries. Core countries include Germany and France, which are also the largest stock markets by capitalisation within the Eurozone. Austria, Belgium, Finland and the Netherlands constitute semi-core countries, while peripheral countries include Ireland, Italy, Portugal and Spain. We observe that dynamic net spillovers vary hugely across time and across countries.

Fig. 7 shows that core economies behave differently over the period under consideration. For instance, we find evidence pointing towards opposite trends for France and Germany, whereby the former was a net transmitter of shocks mainly during and after the GFC, while the latter exhibits a clear peak of transmission corresponding to the Covid-19 outbreak, during which time illiquidity shocks increased sharply. Among semi-core countries Finland and the Netherlands are found to be among the major transmitters, while Belgium behaved as a receiver for most part of the period. This dynamic evidence is also in line with the static spillover shown in Table 3, where Belgium and France are found to be the dominant average transmitters. In contrast, Belgium, Germany and, in parts, Austria have been net receivers. In particular, Germany tended to absorb all shocks coming from other economies for the whole sample, except for the period covering the Covid-19 pandemic, during which time it has been the leading transmitter across core economies. In contrast, it can be seen that across peripheral economies, only Spain was a net transmitter, while Italy was the leading receiver of shocks.

This evidence is particularly interesting for policy purposes because it reveals that core economies generally exhibit increased levels of transmission of shocks during periods of financial turmoil, with only Germany showing a sharp rise at during the period characterised by the Covid-19 pandemic. Instead, peripheral countries do not show significant peaks in illiquidity transmission. Our results are in line with previous studies. MacDonald et al. (2018) show that Ireland, France and Belgium contribute to volatility spillovers to the rest of the Euro area. They also find that Germany is immune to financial stress transmission

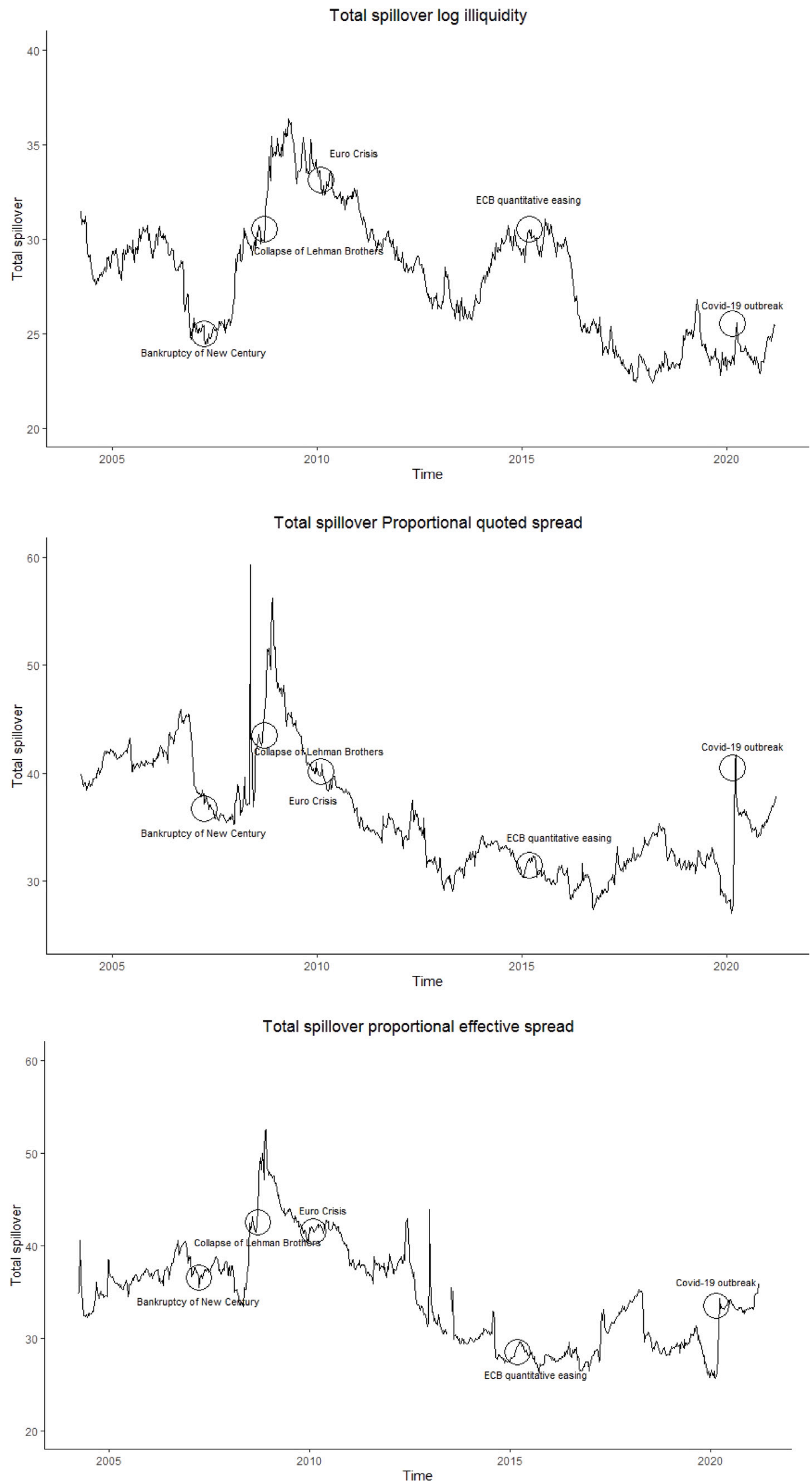

Fig. 6. Dynamic spillover plots.

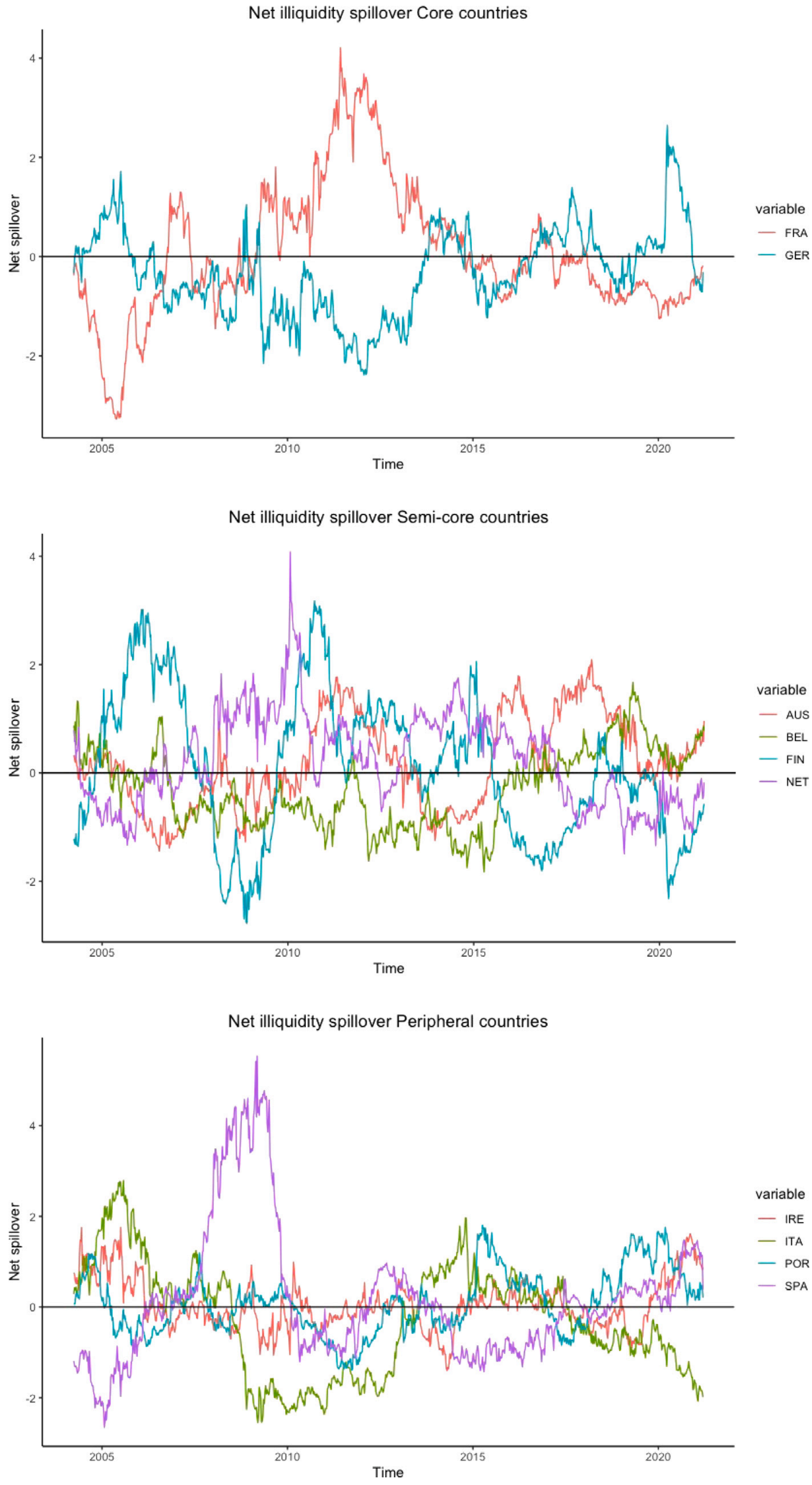

Fig. 7. Net directional illiquidity spillovers.

and that Greece is a receiver of volatility shocks. Furthermore, MacDonald et al. (2018) show that the French banking system is one of the major transmitters of shocks, together with Belgium.

Net directional liquidity spillovers, represented by Figs. 8 and 9, capture different characteristics of liquidity transmission. By examining proportional quoted spread for core economies (Fig. 8), it can be noted that earlier evidence showing France as leading transmitter in the period between 2008 and 2012 are substantially confirmed, with spillover reaching a peak at 10% of transmission. In contrast, Germany tends to be less volatile also at the beginning of 2020. Similarly, proportional quoted spread does not capture significant variation across semi-core economies, except for a noticeable spike of well above 30% reported by Austria, that quickly fades away. The benefit of using different liquidity measures becomes evident when comparing the evidence for peripheral countries between illiquidity (Fig. 7) and proportional quoted spread (Fig. 8). Three of the four countries, namely Ireland, Italy and Spain are net transmitters of shocks during the GFC. From 2013 onward Italy is the leading net transmitter. The intensity of spillovers is even greater during the Covid-19 outbreak, reaching a peak above 10%, which is a level that was reached only during the GFC by Ireland and Spain.

Net spillovers measured using proportional effective spread (Fig. 9) substantially confirm earlier evidence, but with some exceptions. First, the time-series are characterised by sudden, yet temporary, shocks (both positive and negative), mainly among semi-core countries. Second, the spillover effects do not consistently identify dominant receivers and transmitters for the period relating to the Covid-19 pandemic among core and semi-core countries, while such spillover effects identify Italy as the leading transmitter. This result can be explained if we consider that Italy was the first country to be severely hit by the first pandemic wave in Europe and also characterised by political instability. However, this series is characterised by a sharp, yet temporary, peak of spillovers from Portugal to all other countries of around 80%, by mid-2013. It is interesting to note that by the third quarter of 2013 the Portuguese bond market experienced a significant inflow of funds pointing to evidence supporting recovery from the sovereign debt crisis that took place between 2009 and 2012. This may have caused a shift of preferences from Portuguese equities to government bonds causing a temporary shock in stock market liquidity, which has been captured by our model.

Overall, our findings capture a number of features and peculiarities of time-varying spillovers that previous studies do not grasp. For example, Andrikopoulos et al. (2014) do not provide supportive findings of greater spillover effects using a dummy variable accounting for the GFC period (see Andrikopoulos et al., 2014, p. 123). Our results show that structural crises, such as the GFC, tend to last for some time, whereas shorter periods of market turmoil, e.g. the ongoing Covid-19 pandemic to date, may not be fully captured by all measures that are conventionally employed. More importantly, we provide evidence of contagion through the liquidity channel and we also make a further step by identifying the main stock market responsible for the transmission of shocks. Our findings enhance other studies in this field by providing a picture of which countries are, mainly, net transmitters and net receivers. Smimou and Khallouli (2015) report limited evidence of spillover effects across Eurozone economies. Using a smaller time frame as compared to our study, they report statistically significant pairwise Granger causation mainly during periods of greater turbulence which are primarily driven by small markets. In contrast, our methodological contribution is more sensitive to dynamic spillover effects and we show both their direction and intensity.

6. Conclusion

The financial globalisation of the last decades has led to a significant increase in linkages across stock markets at an international level. The degree of interconnection across stocks exchanges affects the transmission of shocks from one market to another. This generates a spillover effect that results in the phenomenon of contagion during periods of financial and macroeconomic distress. Contagion, which is defined as an increase in cross-market (or cross-asset) linkages after a shock in one market (Longstaff, 2010), has been found to be transmitted mainly through the financial channel. Among the different financial channels of transmission, the liquidity channel has received particular attention in recent years (see, e.g., Andriosopoulos et al., 2014; Smimou & Khallouli, 2015), due to its importance during the GFC and other major distress events.

This paper investigates liquidity spillovers for a pool of ten Eurozone countries from January, 1 2000 to March 15 2021 and is the first empirical study to formally incorporate contagion via the liquidity channel during the Covid-19 pandemic. The sample also includes noteworthy events such as the GFC and the euro crisis. The purpose of this paper is to shed further light on the transmission of shocks through the liquidity channel, providing evidence of contagion. Liquidity has previously been investigated in relation to its time-varying dimension and the pricing of liquidity risk (see, e.g. Grillini et al., 2019; Watanabe & Watanabe, 2008). However, not much has been said with respect to its internal and external origin i.e. the direction, intensity and propagation channels relating to liquidity shocks.

Our main empirical findings can be summarised as follows. First, we introduce a new measure that captures interconnectedness, defined as the illiquidity spillover index (ISI) which is built following Diebold and Yilmaz (2009, 2012). This measure captures the forecast error variance received and transmitted from and to each country in the sample and over the entire time period. The ISI captures the average direction and intensity of liquidity shocks during the full time period being studied. The average direction and intensity of illiquidity shocks have not been previously investigated in similar studies within the euro area (Andrikopoulos et al., 2014; Smimou & Khallouli, 2015). Although the ISI represents a simple and handy measure to identify the average level of interconnection across countries, it does not consider other channels of transmission and it is invariant over time. This model exclusively analyses the transmission of shocks through the liquidity channel, even though other means of contagion have been found to be significant in the existing literature (Claeys & Vašíček, 2014; Longstaff, 2010).

The second contribution relates to the analysis of time-varying transmission of liquidity shocks. We test our ISI in a dynamic setting using weekly-rolling windows which enable us to obtain a total dynamic spillover index. We show a graphical representation of the total spillover index for the entire Eurozone and for each country. Our graphical analysis provides evidence supporting the existence of contagion within the Eurozone through stock market illiquidity. This evidence is particularly useful for policy makers and regulators since the total spillover index may be useful to signal illiquidity crises or to monitor ongoing crises that could jeopardise the stability of the financial system. Regulators are constantly seeking to implement micro-prudential, macro-prudential and monetary policies to reduce the effects of contagion, both when the shock is domestic, such as the Euro crisis or international, e.g. that seen during the GFC.

Policy institutions may also be interested in monitoring the spillover effects within individual countries in order to implement more targeted interventions. We observe significant variability of spillover effects across economies. We show that the three largest economies in terms of GDP viz. Germany, France and Italy are amongst the dominant transmitters of illiquidity shocks during a period of financial turmoil. This is particularly evident during the GFC. Germany and Italy show gross spillovers which reach a peak between 2007 and 2009. In contrast, we find that small and peripheral countries tend to be receivers of shocks, except when the source originates from spillovers.

The third and most interesting contribution of this paper, which we argue is new to this literature, relates to net directional spillovers which indicate the difference between shocks received and shocks transmitted to other countries. Our analysis extends previous studies in this field and complements the scarce and contrasting extant literature on contagion within the Euro area. Our results have direct implications for portfolio managers, who may be interested in understanding the sources of shocks and the dominant transmitters, in order to construct more diversified portfolios. Regulators may be interested in understanding the stability of individual countries emerging from impacts related

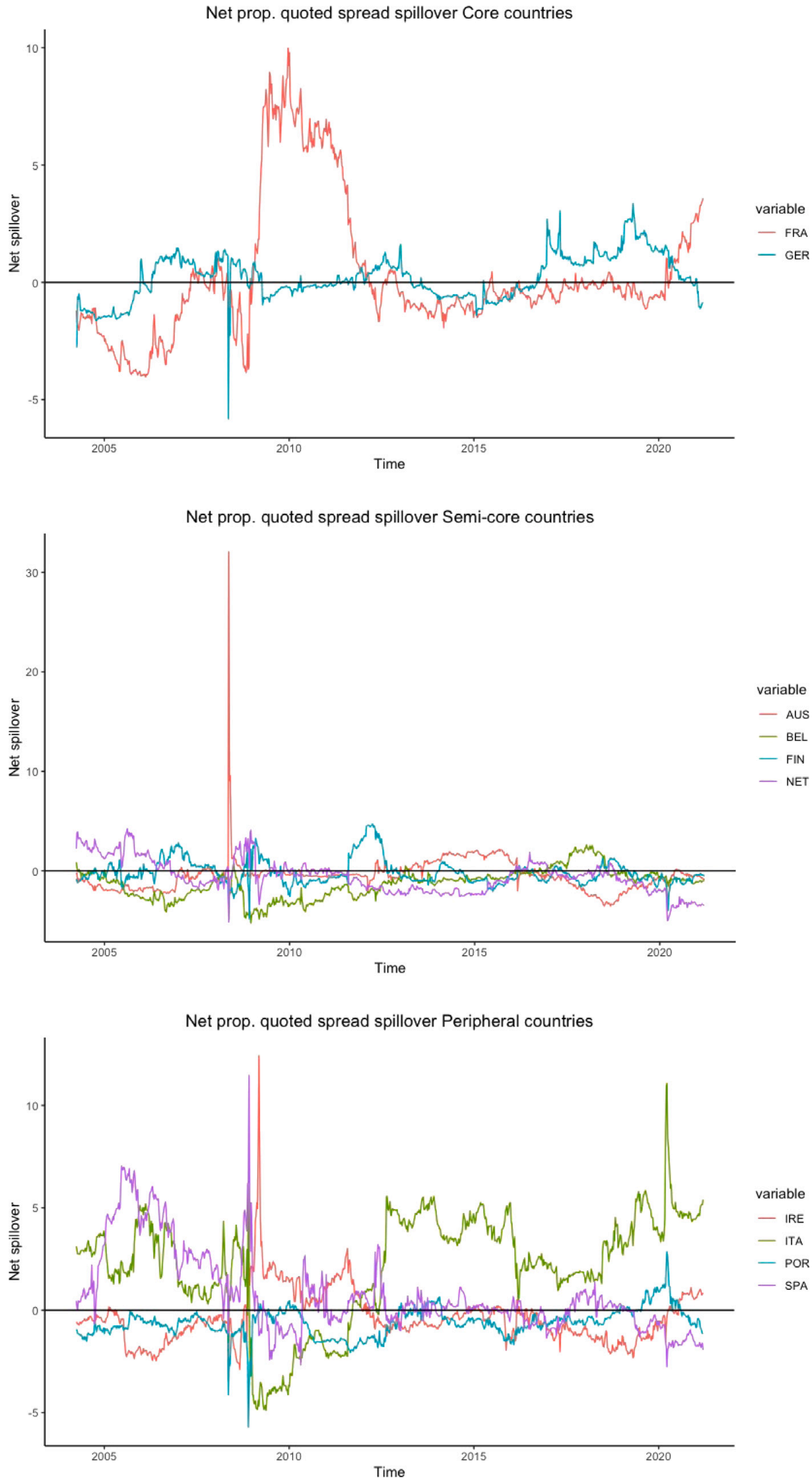

Fig. 8. Net directional Pr. Quoted Spread spillovers.

to local and external shocks. For instance, the monetary policy response to the Eurodebt crisis has often been perceived as inadequate and delayed. The extraordinary measure known as quantitative easing (QE) started in March 2015, six years after the beginning of the government debt challenges faced by peripheral economies such as Greece, Ireland, Cyprus and Portugal. Our results indicate that by the beginning of the

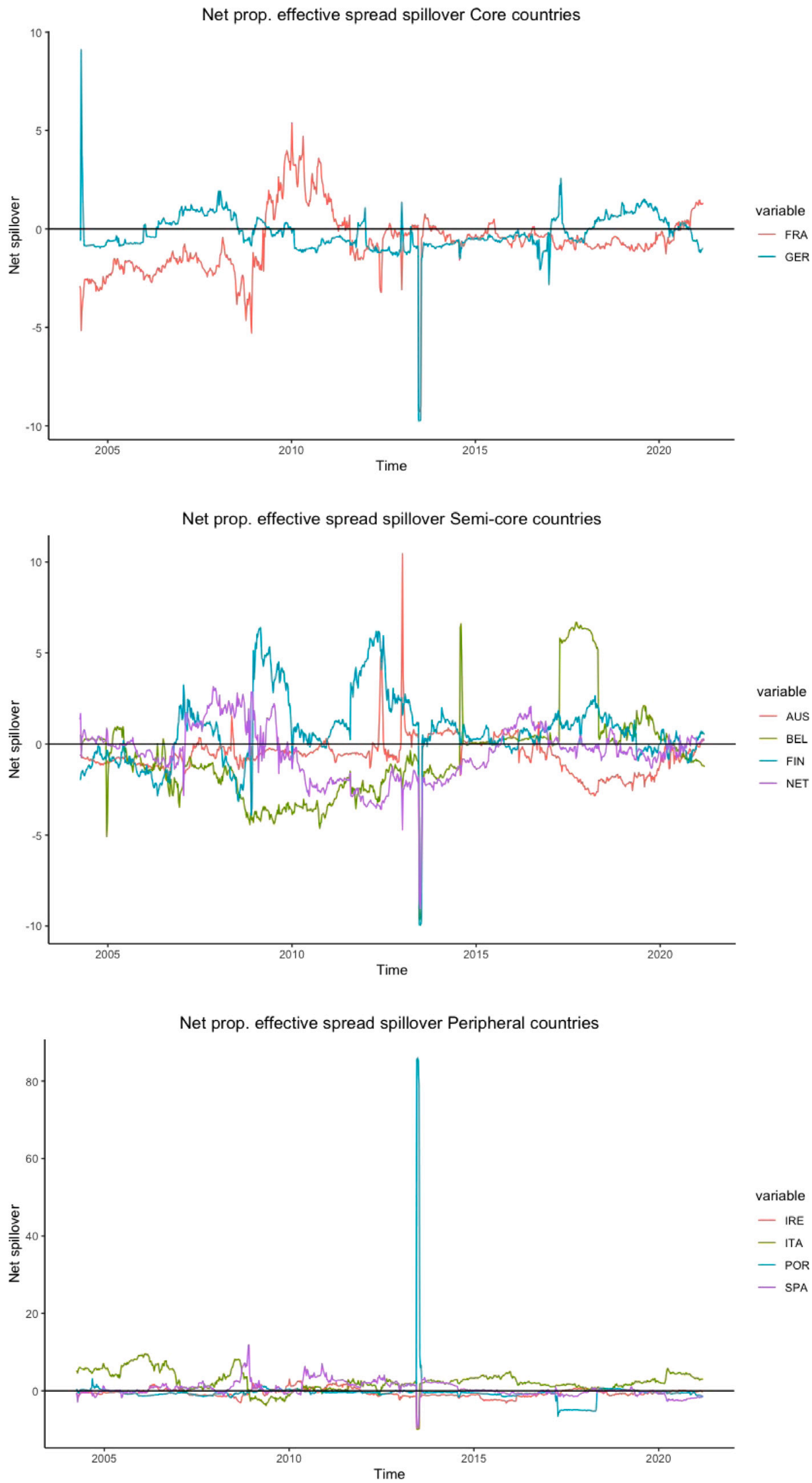

Fig. 9. Net directional Pr. Effective Spread spillovers.

implementation of QE, the transmission of shocks had reduced significantly. A deeper analysis of the various mechanisms of transmission may be useful for regulators interested in understanding these early warnings in order to implement appropriate monetary policies to stem the potentially devastating effects of persistent illiquidity shocks, and to get the timing of such policy decisions right. Future research can benefit from the findings presented here by investigating implications related to pricing of liquidity risk. In line with recent trends within this field (see, for example, Amihud et al., 2015), the inclusion of time-varying components and exogenous effects could shed further light on the illiquidity premia across countries, with important implications for both investors and regulators.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.irfa.2022.102273.

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