



## Interconnectedness in the interbank market<sup>☆,☆☆,★</sup>

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### ABSTRACT

We study the behavior of the interbank market around the 2008 financial crisis. Using network analysis, we study two network structures, *correlation networks* based on publicly traded bank returns and *physical networks* based on interbank lending transactions, among these public and also private banks. While the two networks behave similarly pre-crisis, during the crisis the correlation network shows an increase in interconnectedness, while the physical network highlights a marked decrease in interconnectedness. Moreover, these networks respond differently to monetary and macroeconomic shocks. Physical networks forecast liquidity problems, while correlation networks forecast financial crises.

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## 1. Introduction

The breakdown of liquidity in normally robust financial markets presents one of the enduring questions from the recent financial crisis. During the crisis, central bank intervention failed to enhance liquidity and, over short intervals, crowded out private liquidity (Brunetti et al., 2011). In addition, precautionary hoarding by relatively weak banks during the crisis appeared to exacerbate market liquidity problems.<sup>1</sup> Given the central role that banks play in providing valuable liquidity to many markets, the interbank market plays a significant role in facilitating market liquidity in the wholesale funding market.<sup>2</sup> As the Bank for

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<sup>1</sup> See, for instance, Acharya et al. (2010); Heider et al. (2015); Ashcraft et al. (2011); Acharya and Skeie (2011), and Acharya and Merrouche (2013).

<sup>2</sup> Interconnectedness is one of the five (equally important) characteristics used by the European Union to determine globally systemic important banks (Bank for International Settlements, 2011).

International Settlements<sup>3</sup> notes, during the recent crisis “a market run on an institution whose illiquid assets were financed by short-term liquid liabilities ... spread quickly and widely to other institutions and markets,” i.e., physical network interconnectedness plays an important role in identifying a bank’s systemic importance.

In this paper, we study interconnectedness in the European interbank market to explore whether, and how, bank interconnectedness evolved during the crisis using two different network structures—the correlation (Granger-causality) network of bank stock returns (Billio et al., 2012) and the physical interbank trading network. We study how interconnectedness in these networks is affected by monetary and macroeconomic shocks related to the European Central Bank (ECB) interventions and announcements of both conventional and unconventional ECB operations (see Rogers et al., 2014). Further, we explore whether interconnectedness metrics help to forecast financial and economic activity.

We show that during the crisis, physical network connectedness drops significantly, reflecting hoarding behavior among banks, which impairs interbank market liquidity. Conversely, and similar to results in Billio et al. (2012) and Diebold and Yilmaz (2014), we find that European bank correlation networks reveal increased connectedness during the crisis. These findings show that correlation and physical networks evolve differently and reflect different economic content. While the physical trading network reveals the breakdown between banks, the correlation network reveals that banks equity returns were moving closely together during the crisis.

We further explore the source of these interconnected changes by utilizing information on the country of origin for each bank, by core Europe (those from Austria, Belgium, France, Germany, Luxemburg, and the Netherlands), peripheral countries (those from Greece, Ireland, Italy, Portugal, and Spain), and others (those from Denmark, Great Britain, Norway, and Switzerland). Within correlation networks, banks from peripheral countries consistently contribute most to changes in interconnectedness. However, within the physical network, banks from both peripheral and core European countries are important at different times, with the importance of banks from core countries bottoming out immediately following the failure of Lehman Brothers on September 15, 2008.

We also find that correlation and physical networks respond differently to monetary and macroeconomic shocks. Early in the crisis central banks intervened heavily to promote funding and market liquidity. Interconnectedness in physical networks adjusts strongly and quickly to these central bank operations and announcements, revealing important market characteristics related to interbank trading at short (daily) horizons. Conversely, interconnectedness in correlation networks changes little in response to these events, presumably since these announcements and interventions have little impact on the factors driving stock

returns.<sup>4</sup> In this light, monitoring the response of the interbank market to announcements and interventions is more valuable to policy makers interested in monitoring and enhancing interconnectedness among banks.

We further compare networks to test whether interconnectedness measures might serve to forecast short-term (daily) economic conditions. We show that correlation and physical networks can identify (and forecast), at the daily horizon, hard information like industrial production and retail sales. Complementarily, physical interbank trading networks serve to identify weakening interconnectedness in the interbank system that may lead to liquidity problems in the wholesale funding market.

Since the (US based) Lehman Brothers failure appears to have altered the dynamics of how European physical and correlation networks react to shocks, we also explore the lead-lag relations between interconnectedness in the correlation networks for the two continents. Consistent with these altered dynamics, we find that US network variables (such as degree, clustering coefficients, etc.) significantly Granger-cause the European network variables in the two sub-periods leading up to the Lehman failure, but European network variables more commonly Granger-cause US network variables in the post-Lehman periods.

From a policy perspective, understanding both types of networks can be useful. Correlation networks constructed from equity market returns rely on publicly traded equity prices and so cannot identify problem banks that are privately held. Likewise, correlation networks cannot distinguish between common exposures and transmission among banks, nor can they identify the different channels of transmission, a precondition for preventive and palliative actions by policy makers and regulators. While correlation networks might better identify systemic risk,<sup>5</sup> physical networks respond to smaller exogenous shocks and are useful in identifying both systemically important and problem banks on an ongoing basis. Physical networks are therefore more useful when exogenous shocks are not large enough to threaten systemic risk (i.e., most of the time). Since market liquidity depends crucially on the connectedness between banks, regulators would be well suited to monitor the interbank market for early signs of liquidity problems.

Our work contributes to the literature on networks in finance, which, broadly speaking, distinguishes between correlation networks, where edges are based on asset return correlations (e.g. Billio et al., 2012; Diebold and Yilmaz, 2014), and physical networks, where links result from agent choices (e.g., banks *A* and *B* contract to exchange overnight funds as in Cont et al. (2012)). We demonstrate that the two types of networks capture related, but differing information sets, with correlation networks capturing both direct and indirect linkages and physical networks capturing more specific direct linkages among

<sup>3</sup> Bank for International Settlements, 2011. Global systemically important banks: assessment methodology and the additional loss absorbency requirement.

<sup>4</sup> Similarly, Fiordelisi et al. (2014) and Ricci (2015) find that standard ECB interventions more effectively restore the interbank market, while nonstandard interventions register stronger reactions in stock prices.

<sup>5</sup> See Puliga et al. (2014).

banks.<sup>6</sup> To guide this intuition, we develop an accounting framework that helps to illuminate the different nature of the two network structures. We then utilize the direct nature of our trading data to empirically compare and contrast correlation and physical networks.

The paper proceeds as follows. In [Section 2](#), we provide a review of the main literature. In [Section 3](#), we provide an accounting framework that helps in understanding the two different network formations. [Section 4](#) describes our data, while [Section 5](#) describes the interconnectedness metrics from the correlation and physical networks we construct. In [Section 6](#), we study how central bank announcements and interventions and traditional financial variables affect network topology in a forecasting exercise. We explore evidence of transmission between the US and Europe correlation networks in [Section 7](#) and conclude with a brief discussion in [Section 8](#).

## 2. Network interconnectedness literature

A number of research papers highlights how common holdings can drive interconnectedness within correlation networks. Much of the finance literature on networks concentrates on how network structures are important for the propagation of shocks. [Allen and Gale \(2000\)](#) and [Upper \(2006\)](#) shows that the network structure may exacerbate or attenuate contagion effects. In this literature, linkages (interconnectedness) between financial institutions may occur either as a result of common holdings or as a result of direct contractual agreements.

[Braverman and Minca \(2014\)](#) describe how common asset holdings among banks can transmit financial distress. If two banks,  $A$  and  $B$ , hold the same and an exogenous shock forces  $A$  to liquidate the asset, the price of the asset will decline and therefore change the value of  $B$ 's portfolio. While links in the network of common asset holdings are not readily specified in bank balance sheets, they may be estimated by stock market price linkages. [Braverman and Minca \(2014\)](#) show that the severity of contagion depends on both common holdings and the liquidity of these common holdings, with the higher the number of common assets, the higher is the possibility of contagion (a point first introduced by [Shaffer, 1994](#)).

In a similar vein, [Lagunoff and Schreft \(1999\)](#) develop a model that shows that as economies increase in size, diversification opportunities also increase, which reduces network fragility. However, if the increase exceeds a given threshold, the high level of interconnectedness may increase financial fragility. Indeed, [Cont and Wagalath \(2013, 4\)](#) show that realized correlations in equity indices increased dramatically with the Lehman Brothers collapse and conjecture that the increased correlation resulted from the liquidation of large positions by market participants. Their model, in which returns are driven by both fundamentals and liquidity, shows that even without correlation among fundamentals, liquidity correlations can gen-

erate correlated asset returns, "thus losing the benefit of diversification exactly when it is needed".

[Cabral et al. \(2014\)](#) model contagion as the transmission of a pathologic disease, linking firms as they exchange assets to meet capital requirements and noting a trade-off between risk sharing and contagion. Similarly, [De Vries \(2005\)](#) claims that banks, by holding similar portfolios, are exposed to the same market risks so that bank equity returns are asymptotically dependent. Likewise, [Acharya and Yorulmazer \(2008\)](#) show that if banks hold stakes in the same companies, bank equities are necessarily interdependent.

A second burgeoning literature on financial networks examines contractual agreements similar to our physical network constructed from interbank trades. For example, [Acemoglu et al. \(2015\)](#) find that financial contagion is a function of the network structure—a network where all banks are connected is less fragile than an incomplete network for small exogenous shocks but is more fragile for large shocks. Similarly, [Gai et al. \(2011\)](#) present a theoretical framework to show shocks can have large consequences, and [Roukny et al. \(2016\)](#) show the structure of (credit market) networks can affect the capacity of regulators to assess the level of systemic risk.

Some works consider both correlation and physical networks. [Cifuentes et al. \(2005\)](#) construct a model that incorporates two channels of contagion: direct linkages through the interbank market and indirect linkages through common holdings. Similarly, [Caccioli et al. \(2013\)](#) analyze both the network of common holdings and the physical network and show that in a crisis, contagion is mainly driven by common holdings, but it is amplified by trading in the physical network—i.e., both networks contribute to systemic risk.<sup>7</sup>

Most of this literature highlights the fact that common asset holdings, reflected in correlation networks, are the main source of systemic risk ([Elsinger et al., 2006](#)) and that interbank lending (the physical network of bank connections) plays only a marginal role. Conversely, we analyze these networks from a different angle. We aim to quantify the information content of these two network structures to better understand how policy decisions might be more effective in ameliorating systemic risk and enhancing market liquidity in times of crisis.

## 3. An accounting framework

In order to highlight the two different network formations, we adopt a simple accounting framework (following [Shin, 2009a, b](#) and [Elliott et al. 2014](#)) in which banks connect lenders to borrowers as intermediaries, collecting deposits from households and firms and investing the deposits in a portfolio of assets, including loans to the household sector (via mortgages and consumer debt) and firms.

We now introduce some notation:

1.  $y_{i,k}$  denotes the market value of bank  $i$ 's assets—including loans to firms and households as well as  $k$  asset classes (equities, bonds, commodities, etc.).

<sup>6</sup> The linkages among our banks include, but are not limited to, interbank lending. Many are large banks, domiciled in a variety of European countries (see below), and likely interact with additional business relationships.

<sup>7</sup> See also [Allen and Babus \(2010\)](#) and [Allen et al. \(2010\)](#). In related work, [Roukny et al. \(2013\)](#) analyze bank network topology and find that topology matters only when the market is illiquid.

2.  $w_{i,k}$  is the weight invested in each of the  $k$  assets by bank  $i$ ;  $\sum_k w_{i,k} = 1$ .
3.  $x_i$  denotes the total value of liabilities of bank  $i$  held by other banks.
4.  $x_{i,j}$  is the value of bank  $i$ 's liabilities held by bank  $j$ .
5.  $\pi_{i,j}$  is the share of bank  $i$ 's liabilities held by bank  $j$ .
6.  $e_i$  indicates the market value of bank  $i$ 's equity.
7.  $d_i$  is the total value of liabilities of bank  $i$  held by non-banks.

Hence, banks  $i$ 's balance sheet is given by

Assets	Liabilities
$\sum_k w_{i,k} y_{i,k}$	$e_i$
$\sum_j x_j \pi_{i,j}$	$x_i$ $d_i$

(1)

and bank  $i$ 's balance sheet identity is

$$\sum_k w_{i,k} y_{i,k} + \sum_j x_j \pi_{i,j} = e_i + x_i + d_i. \quad (2)$$

The left hand side is the value of all bank  $i$ 's assets that is equal to the market value of bank  $i$ 's portfolio, first term, and to the funds lent by bank  $i$  to other banks (interbank lending), second term.<sup>8</sup>

From Eq. (2) we can express the vector of interbank debt as follows

$$\mathbf{X} = \boldsymbol{\Pi} \mathbf{X} + \mathbf{WY} - \mathbf{E} - \mathbf{D}, \quad (3)$$

and

$$(\mathbf{I} - \boldsymbol{\Pi})\mathbf{X} = \mathbf{WY} - \mathbf{E} - \mathbf{D}. \quad (4)$$

The left hand side is the interbank market that, according to Eq. (4), depends on the market value of the portfolio of assets held by banks, the market value of bank equities, and the value of bank liabilities held by non-banks. The interbank market is dynamic, with daily trading (overnight loans represent the overwhelming majority—92.3% of contracts in our e-MID data) in response to their funding needs, which is linked to minimum reserve requirements, margin calls, or shortages needed to fulfill contractual obligations—the first term of the right hand side of Eq. (4). Bank equity ( $\mathbf{E}$ ) changes over time may also drive interbank lending through the second term.

Following Shin (2009a), we assume that the debt liabilities to nonbanks are expected to be sticky—i.e.,  $\mathbf{D}$  will move very slowly.  $\mathbf{D}$  represents debt claims on the banking sector by households, mutual and pension funds, and other

nonbank institutions, so while  $\mathbf{D}$  varies over time, changes to  $\mathbf{D}$  are less likely to drive interbank lending.

Given the accounting identity that governs the full system of banks, we represent the adjacency matrix of the interbank lending market as follows.

	Bank 1	Bank 2	...	Bank $s$
Bank 1	0	$\pi_{1,2}$	...	$\pi_{1,s}$
Bank 2	$\pi_{2,1}$	0	...	$\pi_{2,s}$
...	...	...	...	...
Bank $s$	$\pi_{s,1}$	$\pi_{s,2}$	...	0

From Eq. (4) we build the consolidated balance sheet of the banking sector as a whole, where assets and liabilities are aggregated across banks. Given that  $x_{i,j}$  is a liability for bank  $i$  but an asset for bank  $j$ , the aggregated balance sheet does not include any interbank claims. Hence, Eq. (1) becomes

Assets	Liabilities
$\sum_i \sum_k w_{i,k} y_{i,k}$	$\sum_i e_i$
	$\sum_i d_i$

(5)

and the balance sheet identity is now<sup>9</sup>

$$\mathbf{E} = \mathbf{WY} - \mathbf{D}. \quad (6)$$

Eqs. (4) and (6) highlight how the two networks subsume different information sets which represent our main object of investigation. The main difference between the two networks emanate from the aggregation which is required in the correlation network and from the fact that the networks are driven by different agents. Correlation networks are inferred from market prices, driven by investors, whereas physical networks are driven by the actions of banks. The different drivers of connections in correlation and physical networks make intuitive sense, since investor behavior links to systemic risk, while interbank behavior more closely captures liquidity in the banking system.<sup>10</sup> To further explore the fundamental drivers of each network type and hence how these networks might also be connected, we also formally test whether and how economic fundamentals and shocks affect interconnectedness in the two network structures.

<sup>9</sup> Eq. (6) has an interpretation similar to that in Elliott, Golub, and Jackson (2014) and is based on the results in Brioschi et al. (1989) and Fedenia et al. (1994). De Vries (2005, 2) interprets Eq. (6) as “The fortunes of the banking sector as indicated by the balance sheet items, are sooner or later also reflected in the value of bank equity. This enables us to characterize systemic failure in terms of the joint bank equity price movements ... driven by the interdependent bank portfolios.”

<sup>10</sup> We thank our anonymous referee for bringing forward clarity on this point.

<sup>8</sup> We assume that banks have restrictions for cross holdings of equities. This assumption can be easily relaxed in our model.

For the correlation network, edges are a function of the variance-covariance matrix of bank equity returns. Following Billio et al. (2012), we first compute rate of returns of bank  $i$ 's equity,

$$r_{i,t} = \ln\left(\frac{e_{i,t}}{e_{i,t-1}}\right),$$

and then filter  $r_{i,t}$  using a standard GARCH(1,1) model. For each pair of bank returns,  $\mathbf{U}_t$ , we run the following vector autoregression model

$$\Phi(L)\mathbf{U}_t = \mathbf{V}_t, \quad (7)$$

where  $\mathbf{V}_t \sim N(0, \Sigma)$  and test the following null:

$$H_0 : \hat{\Phi}(L) = 0, \quad (8)$$

where  $\hat{\Phi}(L)$  refers to the off-diagonal terms of  $\Phi(L)$  estimated by ordinary least squares. This is a standard Wald test with covariance matrix equal to  $\mathbf{V}'\Sigma^{-1}\mathbf{V}$ . Rejecting the null in Eq. (8) produces an edge between the returns of the two banks in  $\mathbf{U}_t$ .<sup>11</sup>

#### 4. Data

The data required to construct correlation and physical networks highlight the unique composition of both networks. Our e-MID physical trading data includes 212 unique banks, with a diminishing number over time as the crisis progressed.<sup>12</sup> However, only 54 of these banks are publicly traded, so construction of correlation networks is limited to this smaller set of banks. Only in rare cases will a partial physical network of 54 banks fully capture how they trade with each other, since their trades with the other 158 banks would be excluded.<sup>13</sup> Therefore, we utilize all available data and construct the physical network using all 212 banks and construct the correlation network from the set of 54 publicly traded European banks in our e-MID dataset from January 2006 through December 2012.

<sup>11</sup> Barigozzi and Brownlees (2014) construct networks where edges are based on long run partial correlations. Lin and Michailidis (2017) construct systemwide Granger-causal networks assuming a sparse structure. Likewise, Diebold and Yilmaz (2014) propose several measures of interconnectedness based on the variance-covariance matrix and link these measures to connectedness used in the network literature. While the physical network of interbank trades is directly observable, the correlation network based on equity returns is the result of a testing procedure that, in addition to the classic type I and II errors, is a function of the model specification in Eq. (7). Moreover, Granger-causal networks require longer sample periods to establish connections.

<sup>12</sup> The e-MID platform is the only electronic market for interbank deposits in the Euro region, offering interbank loans ranging from overnight (one day) to two years in duration, with overnight contracts representing 90% of total volume during our sample period (see Brunetti et al. 2011).

<sup>13</sup> While recent work shows that metrics calculated from partial networks can have significant bias and loss of information (see, e.g., Achlioptas et al. 2009), Handcock and Gile (2010) show that partially observed network data can be used for valid statistical inference. Moreover, Chandrasekaran et al. (2012) show that for correlation networks, results based on a subset of nodes are valid as long as the unobserved nodes do not exert very strong influence on the observed nodes. This is definitely the case in our correlation network, where the largest (by assets) banks are included in our analysis—those exerting the largest influence. Similarly, for physical-type networks, Bliss et al. (2014) show that network statistics estimates are of good quality when based on random samples, a finding also in accordance with our analysis.

**Table 1**

Summary statistics of the daily rates of stock returns ( $\times 100$ ) for the different sub-periods.

Pre-crisis: 2-Jan-06 – 8-Aug-07		
Mean	Median	St. Dev.
0.0603	0.0000	14.236
	Crisis 1: 9-Aug-07 – 12-Sep-08	
-0.1457*	-0.0886	15.449
	Crisis 2: 16-Sep-08 – 1-Apr-09	
-0.5037**	-0.1986	19.706
	Crisis 3: 2-Apr-09 – 31-Dec-12	
-0.0439	0.0000	19.849

\* \*\*, and \*\*\* refer to significance levels of 10%, 5%, and 1% for testing the mean difference between each sub-period and the pre-crisis period that we use as benchmark. Standard errors are computed using bootstrapping.

While European banks can also trade bilaterally via phone brokers and with the ECB directly, e-MID interbank activity accounts for 17% of total turnover in unsecured money market in the Euro area.<sup>14</sup> During our sample period, e-MID volume exceeds €18 trillion, and includes trades from every major European bank (spanning 15 different countries). Moreover, e-MID trades are also consequential—e-MID executed more large deals ( $> €100$ ) than standard-size (smaller) deals from 2005 to 2008.<sup>15</sup>

We examine daily and monthly data over four sub-periods: (1) a pre-crisis period from January 2, 2006 until August 7, 2007 (when the ECB noted worldwide liquidity shortages); (2) the first crisis period (pre-Lehman) from August 8, 2007 until September 12, 2008; (3) the second crisis period (post-Lehman) from September 16, 2008 through April 1, 2009 (when the ECB announced the end of the recession); (4) the third (post-recession) crisis period, from April 2, 2009 through December 31, 2012. This last period was characterized by a weak recovery in Europe—the recession officially ended in the third quarter of 2009, thanks largely to fiscal and monetary measures to stimulate the economy. The beginning and ending dates of our sample are limited by our access to e-MID data.<sup>16</sup>

Daily summary statistics for the rate of returns are reported in Table 1. In the pre-crisis period, rate of returns are positive and exhibit low volatility. In the crisis periods, returns are highly negative and exhibit very large volatility. Bank equity returns remain negative in the third crisis period albeit still very volatile, highlighting that the crisis continued to affect the banking system in post-recession Europe.<sup>17</sup>

<sup>14</sup> See European Central Bank, 2007. Euro money market study, 2006.

<sup>15</sup> See European Central Bank, 2009. Euro money market study, 2008.

<sup>16</sup> Other research analyzing e-MID data in the context of network analysis includes Hatzopoulos et al. (2014), Iori et al. (2014), Roukny et al. (2013), and Delpini et al. (2013).

<sup>17</sup> In 2011 and 2012 Euro area bank CDS premiums rose significantly and sovereign bond spreads widened appreciably for Greece, Ireland, Italy, Portugal, and Spain (relative to Germany).

To construct physical networks we employ e-MID trading data from the only electronic regulated interbank market in the world. Each e-MID transaction includes the time (to the second), lender, borrower, interest rate, quantity, and an indication of which party is executing the trade. The e-MID market is open to all banks admitted to operate in the European interbank market, and non-European banks can access the market through their European branches. As of August 2011, the e-MID market had 192 members from European Union countries and the US, including 29 central banks acting as market observers (Finger et al., 2013). We observe 212 unique banks and 464,772 trades in the data. At the beginning of our sample, internal estimates from e-MID reveal that this market covers about 20% of the interbank market in the Euro area. However, this percentage has been dropping since the crisis. Accordingly, we find a decline in the daily average number of banks in the data from 129 to 113 to 91 to 69 across our four sub-periods. The automated trade processing features in e-MID allow us to accurately assess and examine the interbank trading connections between banks in this market (at least those executed through the e-MID system).

**Table 2** reports daily e-MID market summary statistics, by sub-period, for price changes, effective spreads, volume, trade imbalances, market concentration (Herfindahl index), and signed volume. As shown, daily price changes are consistently negative, with greater negative changes during the two crisis periods. Volatility rises dramatically during the crisis, remains somewhat elevated through the crisis, with another dramatic rise at the end of 2011 during the third crisis sub-period as illustrated in **Fig. 1**.

Effective spreads, in **Table 2**, remain relatively stable across our sample period, suggesting that interbank market liquidity did not suffer appreciably during the crisis. On the other hand, average daily volume varies significantly and ranges from 927 to almost 42,000 contracts per day. The top right panel of **Fig. 1** shows clearly that volume drops substantially over time, resulting in third crisis period volume representing less than 20% of pre-crisis volume.

The lower left panel of **Fig. 1** plots trade imbalances (scaled by volume) over time and shows that imbalances increase over time, a result driven by the concurrent decline in volume. Market concentration, as measured by the Herfindahl index, also rises consistently over our sample period (see bottom right panel of **Fig. 1**), reflecting greater concentration among banks using e-MID. Signed volume is negative throughout our sample period, indicating that banks actively use e-MID for selling funds.

## 5. Network interconnectedness

We compute various measures of interconnectedness by utilizing the correlation networks (from bank stock returns) and physical networks (from e-MID trading data). Our correlation networks infer edges between banks through Granger-causality tests between stock returns (as in Billio et al., 2012). Our physical networks are formed by direct trades in the e-MID interbank market. Since interbank trades are directly observed, our physical network

**Table 2**  
Summary statistics of e-MID daily financial variables.

	Pre-crisis: 2-Jan-06 - 8-Aug-07		
	Mean	Median	St. Dev.
Δ(Price)	-0.0232	-0.0150	0.0871
Effective spread	1.3782	1.3888	0.0988
Volume	22,834	22,337	4902
Trade imbalance	0.0049	0.0046	0.0018
Herfindahl index	0.0159	0.0157	0.0014
Signed volume	-13,154	-12,715	5,6309
Crisis 1: 9-Aug-07 - 12-Sep-08			
Δ(Price)	-0.1236***	-0.0600	0.2224
Effective spread	1.3685	1.3804	0.1015
Volume	14,512***	14,132	3537
Trade imbalance	0.0067***	0.0064	0.0024
Herfindahl index	0.0173**	0.0169	0.0022
Signed volume	-8.7772***	-8.5914	3.4672
Crisis 2: 16-Sep-08 - 1-Apr-09			
Δ(Price)	-0.2832***	-0.2500	0.2566
Effective spread	1.3629	1.3754	0.0939
Volume	7796***	7763	2568
Trade imbalance	0.0078***	0.0072	0.0027
Herfindahl index	0.0202***	0.0199	0.0026
Signed volume	-4.3513***	-4.0138	2.1801
Crisis 3: 2-Apr-09 - 31-Dec-12			
Δ(Price)	-0.0070**	0.0000	0.1945
Effective spread	1.3329	1.3465	0.1234
Volume	4002***	3997	1522
Trade imbalance	0.0199***	-0.0190	0.0101
Herfindahl index	0.0521***	0.0484	0.0062
Signed volume	-1.8971***	-1.8283	1.4590

Trade imbalance is computed as the difference between number of buys and number of sells, normalized by volume. Signed volume is computed as the difference between aggressive buy volume and aggressive sell volume.

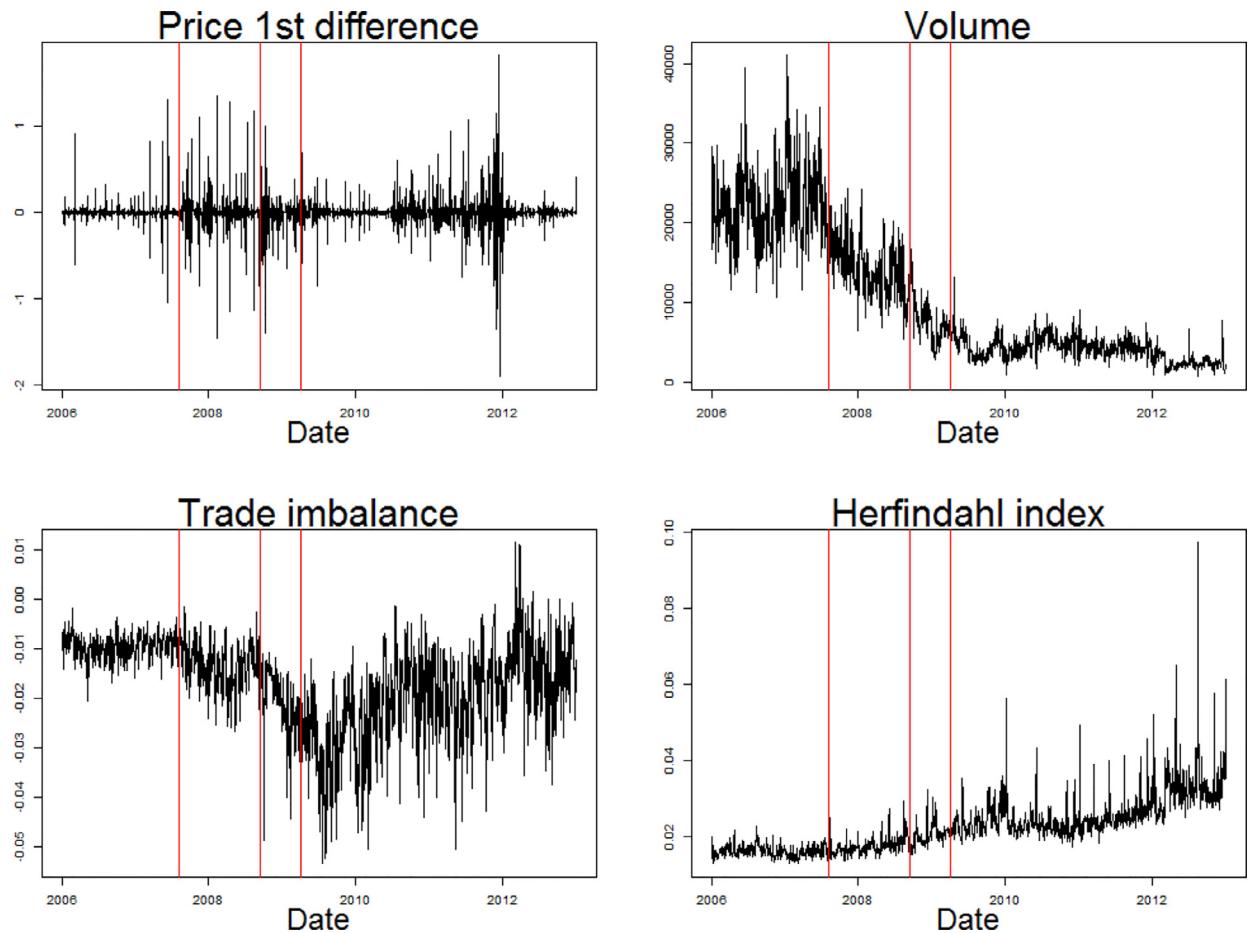
\*, \*\* and, \*\*\* refer to significance levels of 10%, 5%, and 1% for testing the mean difference between each sub-period and the pre-crisis period. Standard errors are computed using bootstrapping.

is more similar to social networks, where a relationship exists between nodes (see Newman, 2010; and Jackson, 2008). We emphasize the fact that the 54 banks composing the correlation network are also part of the physical network, but their connections in one network do not necessarily imply the same connections in the other.

For the correlation network, we utilize returns for individual banks to establish Granger-causality links between banks. In particular, if the return of bank A Granger-causes the return of bank B, then we draw a directed edge from A to B. Granger-causality tests are run using both monthly data with 36-month rolling windows, and daily data with 44-day rolling windows.

The physical network maps lenders to borrowers over each month. Specifically, if bank B borrows from bank A within the time interval of interest, then an edge is drawn from A to B. In this manner, interbank lending networks capture funding liquidity by distinguishing banks providing funds from banks receiving funds.<sup>18</sup> Similar to the correlation network, we construct daily and monthly physical

<sup>18</sup> Weighting the edge in the physical network by volume does not change our main findings.



**Fig. 1.** e-MID daily financial variables among 212 European banks from August 8, 2007, through December 31, 2012. Volume is in number of contracts. Trade imbalance is computed as the difference between number of buys and number of sells, normalized by volume. The vertical lines indicate the four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and the third crisis period April 2, 2009 – December 31, 2012.

networks that account for all e-MID transactions during a day or a month.

We extract various network interconnectedness metrics and display these results in Table 3, taking care to normalize these statistics by the number of banks in the network so that appropriate comparisons can be made between each network on these metrics. First, we estimate the degree of each network, defined as the number of connections as a proportion of all possible connections. We follow the notation in Billio et al. (2012) and introduce the indicator function  $A \rightarrow B$  denoting whether an edge exists from bank  $A$  to bank  $B$ . Degree is then defined as

$$\text{Degree} = \frac{1}{N(N-1)} \sum_{A=1}^N \sum_{B \neq A} A \rightarrow B, \quad (9)$$

where  $N$  is the total number of banks (nodes) in the network. Degree is a network-wide measure used by Billio et al. (2012) to estimate the risk of a systemic event. Within the physical network, lower average degree may indicate a lower level of liquidity on e-MID.

The second measure of interconnectivity we utilize is closeness, which measures how many steps are between banks on average. To construct this measure, let  $C_{AB}$  be the length of the shortest path from bank  $A$  to bank  $B$ , where  $C_{AB} = N - 1$  if there is no path from bank  $A$  to bank  $B$ . Then closeness is defined as

$$\text{closeness} = \frac{1}{N(N-1)} \sum_{A=1}^N \sum_{B \neq A} C_{AB}. \quad (10)$$

Closeness is normalized to be between zero and one, where larger values indicate larger relative distance between banks on the network.

Our third metric of connectivity is the clustering coefficient, which measures how often triangular connections occur or the probability that neighbors of a bank are themselves connected. The clustering coefficient (CC) is defined as

$$CC = \frac{3 \times \text{number of connected triples}}{\text{number of possible connected triples}}, \quad (11)$$

**Table 3**  
Summary statistics of monthly correlation and physical networks.

	Correlation network			Physical network			
	Pre-crisis			Pre-crisis			
	2-Jan-06 - 8-Aug-07	Mean	Median	St. Dev.	2-Jan-06 - 8-Aug-07	Mean	Median
Degree	0.0419	0.0412	0.0048	0.0638	0.0632	0.0036	
Closeness	0.0303	0.0303	0.0060	0.0053	0.0051	0.0004	
CC	0.1459	0.1429	0.0247	0.3434	0.3405	0.0258	
EVCentrality	0.0104	0.0095	0.0035	0.0170	0.0131	0.0090	
LSCC	0.3411	0.3846	0.1666	0.4839	0.4858	0.0276	
	Crisis 1			Crisis 1			
	9-Aug-07 - 12-Sep-08			9-Aug-07 - 12-Sep-08			
Degree	0.0540***	0.0532	0.0180	0.0556***	0.0561	0.0050	
Closeness	0.0386***	0.0388	0.0127	0.0051***	0.0051	0.0003	
CC	0.1587	0.1527	0.0610	0.3512	0.3590	0.0263	
EVCentrality	0.0147***	0.0133	0.0073	0.0113***	0.0091	0.0062	
LSCC	0.4393***	0.5000	0.2345	0.4140***	0.4340	0.0378	
	Crisis 2			Crisis 2			
	16-Sep-08 - 1-Apr-09			16-Sep-08 - 1-Apr-09			
Degree	0.1061***	0.1081	0.0165	0.0415***	0.0393	0.0061	
Closeness	0.0637***	0.0591	0.0087	0.0049***	0.0050	0.0004	
CC	0.2761***	0.2780	0.0502	0.2881***	0.2795	0.0349	
EVCentrality	0.0456***	0.0485	0.0119	0.0899***	0.0501	0.0781	
LSCC	0.7088***	0.6923	0.0537	0.2358***	0.2170	0.0587	
	Crisis 3			Crisis 3			
	2-Apr-09 - 31-Dec-12			2-Apr-09 - 31-Dec-12			
Degree	0.1256***	0.1338	0.0261	0.0405***	0.0407	0.0049	
Closeness	0.1029***	0.0894	0.0386	0.0051***	0.0051	0.0001	
CC	0.3295***	0.3395	0.0693	0.3018***	0.3039	0.0330	
EVCentrality	0.0583***	0.0641	0.0177	0.0238***	0.0143	0.0232	
LSCC	0.7653***	0.7308	0.0824	0.1758***	0.1745	0.0457	

Degree refers to the average degree in each network. Closeness measures the average distance, in terms of edges, between banks in the network. CC indicates the clustering coefficient. EVCentrality refers to the eigenvalue from eigenvector centrality, and LSCC refers to the proportion of nodes in the largest strongly connected component.

\*, \*\*, and \*\*\* refer to significance levels of 10%, 5%, and 1% for testing the mean difference between each sub-period and the pre-crisis period. Standard errors are computed using bootstrapping.

where a connected triple means any three banks  $A$ ,  $B$ , and  $C$  such that  $A \rightarrow B$ ,  $A \rightarrow C$ , and  $B \rightarrow C$ . Clustering coefficients approaching the maximum value of 1 would indicate higher levels of connectedness.

The fourth measure of interconnectivity is eigenvector centrality, which is calculated by taking the first eigenvector of the adjacency matrix of network relations  $[X]_{AB} = A \rightarrow B$ . In addition to being closely related to the best rank-1 approximation of  $X$ , the scores for each bank can also be interpreted as being proportional to the sum of the centralities of those banks to whom it is connected, so that banks with high eigenvector centralities are those that are connected to many other banks that are, in turn, connected to many others (and so on). The scores are between zero and one, where larger values indicate banks that are more important to interconnectivity.

The fifth and last measure of network connectivity, the largest strongly connected component (or LSCC), is the proportion of banks that are connected to other banks by following directed edges on the network scaled by the total number of banks in the network. Hence, the LSCC also measures the level of interconnectedness in the network with an LSCC of one indicating that any bank can reach

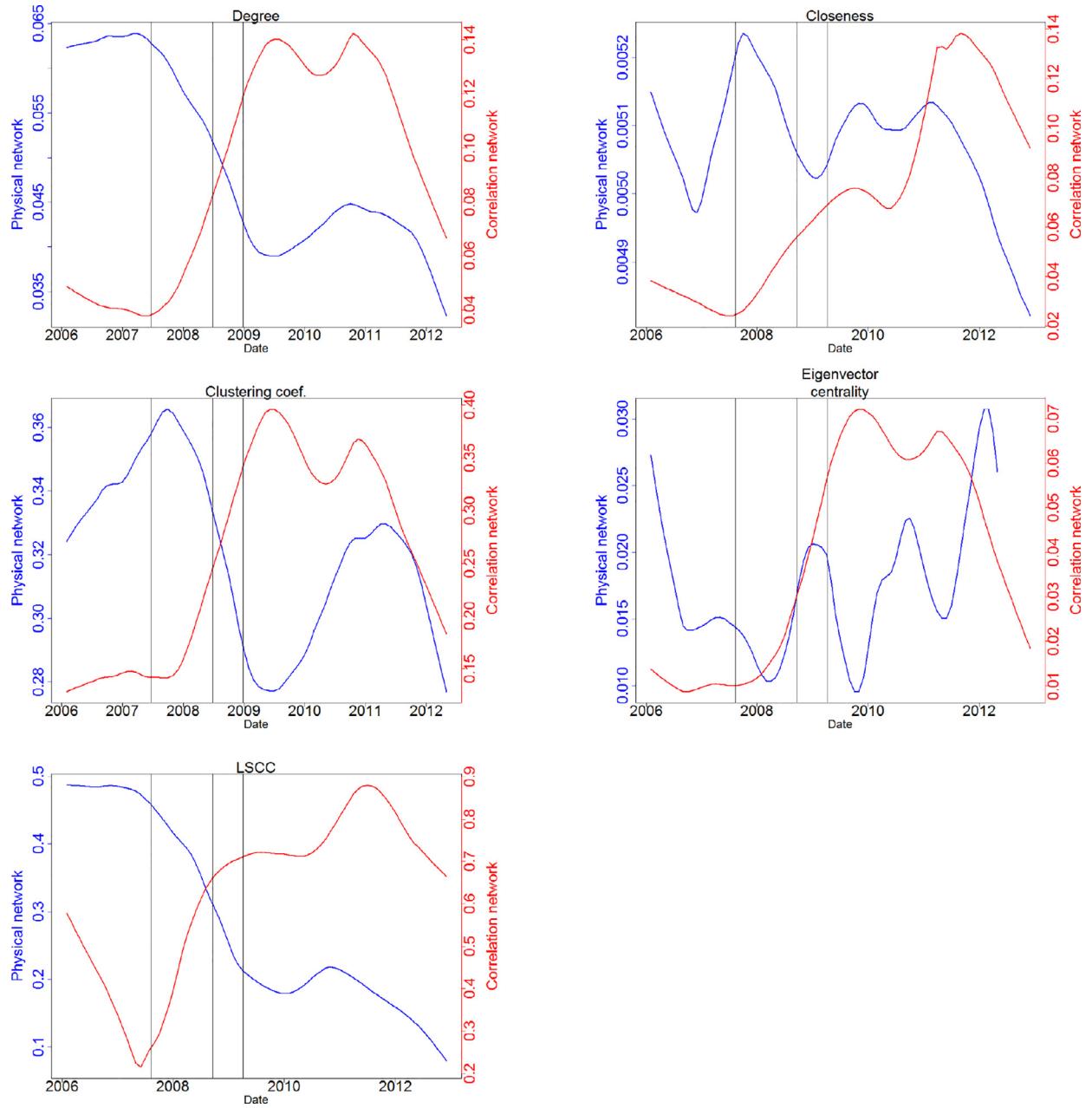
every other bank, while an LSCC closer to zero indicates a highly fragmented network.

As shown in Table 3, the variation of monthly network statistics in the correlation network is larger than that in the physical network.<sup>19</sup> Within correlation networks, the change in connectedness from pre-crisis to the first, second, and third crisis periods is statistically significant. Clustering, eigenvalue centrality, degree and LSCC all remain elevated for European banks from 2009 into 2011 before falling off in the second half of 2011 through 2012.

However, through the lens of the physical market, connectedness appears to have been significantly diminished. Connectivity in the physical network drops significantly at the outset of the crisis and remains below pre-crisis levels through the third crisis period.

These disparate results show that the correlation and physical networks capture different notions of connectedness. The crisis permanently diminished interconnectedness between banks in the physical interbank trading network, while interconnectedness increases when measured via stock return correlation networks. While the physical

<sup>19</sup> Similar results are obtained from the daily sampling frequency.



**Fig. 2.** Measures of interconnectedness (with statistics smoothed using local polynomial regression) for monthly physical networks for interbank lending among 212 European banks and correlation network statistics from 54 publicly traded European banks from August 8, 2007, through December 31, 2012. The two networks show generally opposite connectivity patterns, with the physical network losing connectivity versus the correlation network gaining connectivity. The vertical lines indicate the four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and (4) the third crisis period April 2, 2009 – December 31, 2012.

connections between banks in the interbank market are diminished, these same banks are connected to a common factor that does not affect interbank trading. Indeed, [Cont and Wagalath \(2012, 2013\)](#) use a structural equation model to link the behavior of large institutional investors to equity correlations, the basis of our correlation networks.

[Fig. 2](#) displays the monthly time series of the network measures from the two types of networks and clearly shows that connectivity increases in the correlation network at the onset of the first crisis sub-period and keeps rising in the subsequent sub-periods. Overall, we find that interconnectedness increases after the failure of Lehman Brothers in the correlation network but decreases in the

physical network. [Lagunoff and Schreft \(1999\)](#), 2) claim that “A financial crisis is a breakdown of the economy's financial linkages, a collapse of all or part of the financial structure.” The physical network clearly captures this phenomenon.

The two networks also behave differently in other respects. As [Fig. 3](#) shows, correlation networks are sparser than the physical networks in the pre-crisis period, perhaps expected with only 54 banks in the correlation network. However, despite the lower number of banks, the correlation network becomes more interconnected throughout our sample period. Conversely, the physical network in the third crisis period is characterized by a “core” of banks highly interconnected and several banks that have a low degree of interconnectedness.<sup>20</sup>

To further study the evolution of the two network structures during the crisis, we identify individual banks that contribute most to market connectivity using a matrix factorization-based technique.<sup>21</sup> These results (omitted here for brevity) show that a small subset of banks contributed most to the physical network connectivity during the crisis and beyond. Interestingly, some banks became more connected in the physical network, even though the overall market became less connected. However, in the correlation network, the onset of the crisis brought a spike in connectivity among all bank returns.

While our interbank trading data do not allow us to specifically identify individual banks, we are able to classify banks by region. We use these classifications and the matrix factorization-based technique described above to explore which regions contribute most to directional interconnectedness during our sample period.

[Fig. 4](#) displays the centrality measures by region over time, based on both correlation (incoming and outgoing) and physical networks (borrowing and lending). As shown, banks from peripheral countries contribute most to correlation networks throughout the sample period, followed by banks from core countries and then banks from other countries.

Results from the physical networks are much more volatile. While banks from other countries are largely least influential in terms of borrowing and lending, banks from peripheral and core European countries are most important at different times. Generally, banks from core countries fall off in importance over time but reach their lowest levels of both borrowing and lending immediately following the failure of Lehman Brothers (during Crisis 2). While importance measured here is somewhat subjective, [Fig. 4](#) clearly shows that physical and correlation networks have markedly different dynamics.

<sup>20</sup> While the number of banks in the physical (up to 212) and correlation ( $N=54$ ) networks differ in robustness tests, we generate similar patterns across time in the physical network when we randomly sample 54 of the most active 78 banks (those above the 75th percentile) from our trading data. Eigenvector centrality, however, spikes more often and often at different times when using the “partial network” of just 54 banks. These results are available upon request.

<sup>21</sup> See [Mankad and Michailidis \(2013\)](#) and [Mankad et al. \(2014\)](#). We briefly review this technique in the [appendix](#).

## 6. Economic shocks and network connectedness

We explore these differing dynamics further by analyzing how these network structures reflect economic shocks. Given that markets react to announcements (e.g., [Faust et al., 2007](#)), we aim to compare and contrast how announcements are reflected in the stock market and interbank market. We are particularly interested in two types of shocks. The first type refers to ECB announcements and interventions. During our sample period, the ECB adopted both conventional and unconventional monetary interventions. In particular, for the ECB interventions,<sup>22</sup> we distinguish among long term refinancing operations (LTRO), main refinancing operations (MRO) and other types (OT) of ECB operations. For the announcements, we follow [Rogers et al. \(2014\)](#) and consider conventional and unconventional ECB operations.

The second type of shocks we consider refer to more general changes in macroeconomic conditions. We first capture these shocks using the real activity (surprise and uncertainty) indices developed in [Scotti \(2016\)](#). The surprise index summarizes economic data surprises and captures optimism/pessimism about the state of the economy. The uncertainty index measures uncertainty related to the state of the economy.<sup>23</sup> We also consider the evolution of the European stock market (the Dow Jones index for Europe) and the spread between the Euro Interbank Offered Rate (EURIBOR) and the overnight indexed swap (OIS), a measure of health of the banking system.

To fully capture the ECB shocks, we use daily data. Hence, for this exercise we adopt daily networks. Following [Kilian and Vega \(2011\)](#), we estimate the following models for each sub-period and for each network type:

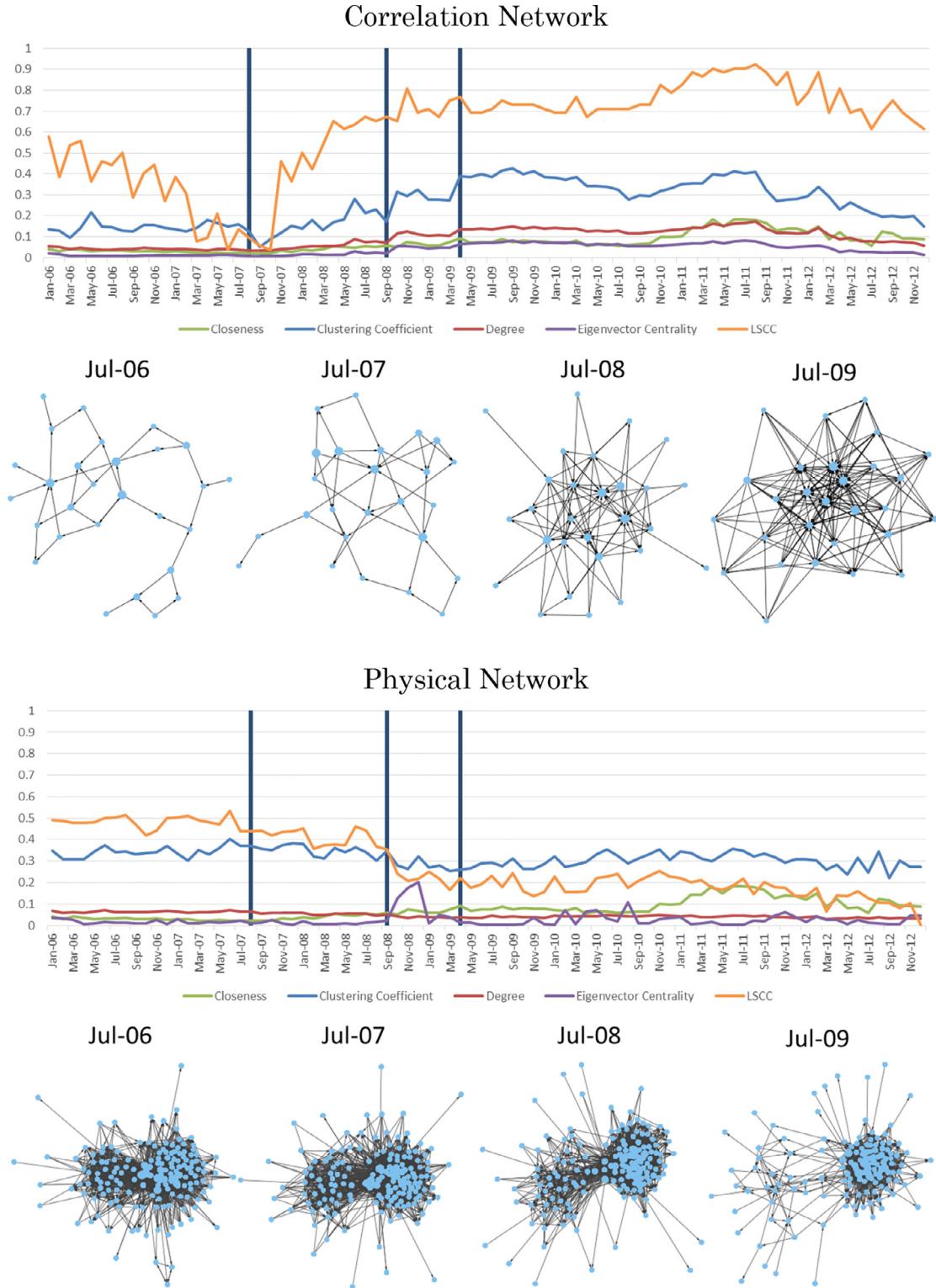
$$y_{t+k} = \alpha + \beta_1 U_t + \beta_2 S_t + \beta_3 DJST_t + \beta_4 EONIA_t + \beta_5 EURIBOR\_OIS_t + \beta_6 LTRO_t + \beta_7 MRO_t + \beta_8 OT_t + \gamma y_{t-1} + \varepsilon_t, \quad (12)$$

$$y_{t+k} = \alpha + \beta_1 U_t + \beta_2 S_t + \beta_3 DJST_t + \beta_4 EONIA_t + \beta_5 EURIBOR\_OIS_t + \beta_6 Annoucements_t + \gamma y_{t-1} + \varepsilon_t, \quad (13)$$

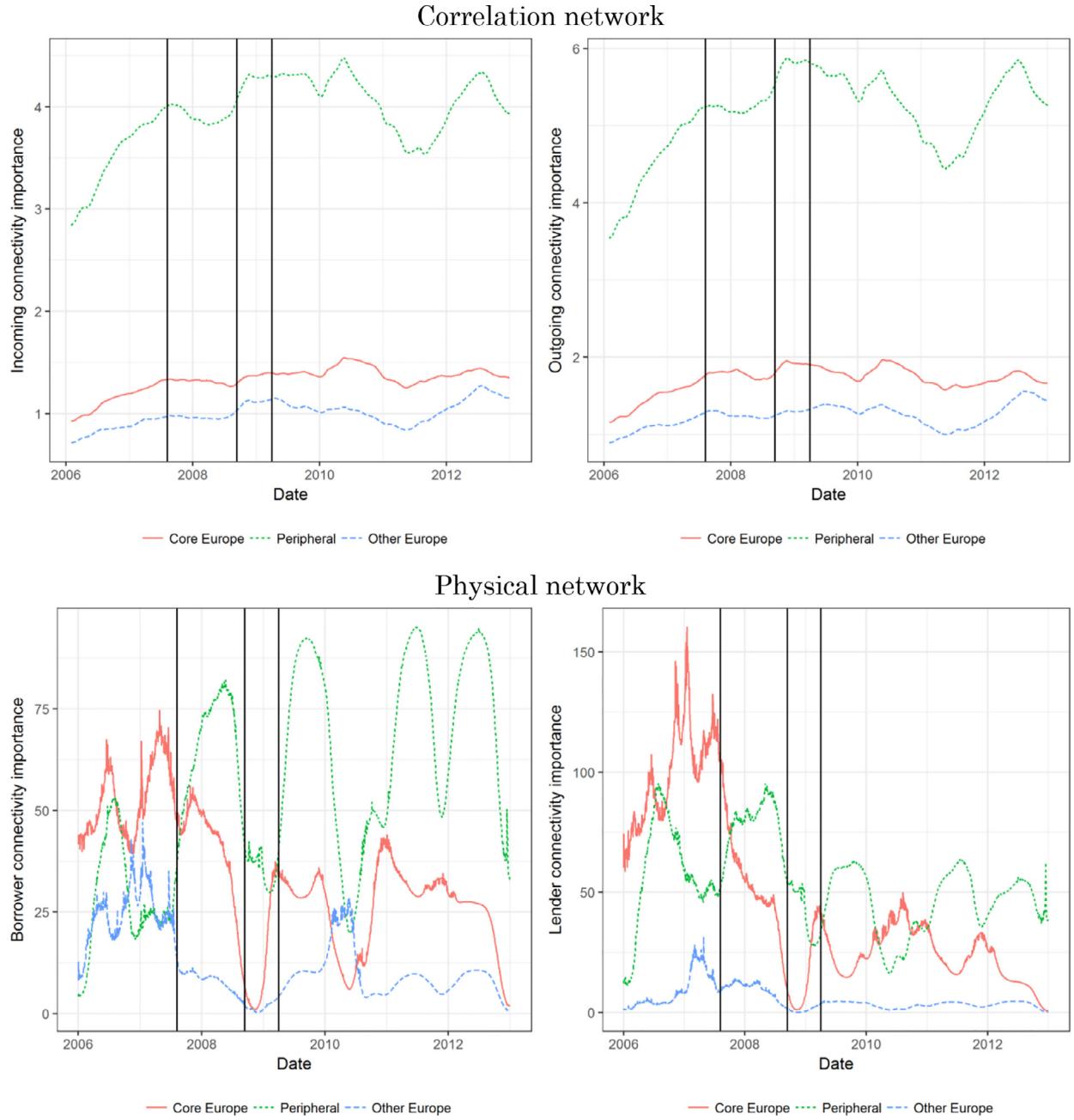
where  $y_{t+k}$  represents network statistics (degree, closeness, clustering coefficient, eigenvector centrality, and LSCC) on day  $t$ ,  $U_t$  is the economic uncertainty index, and  $S_t$  the economic surprise index from [Scotti \(2016\)](#);  $DJST_t$  is the DJ Europe stock index;  $EONIA_t$  is the Euro Overnight Index Average;  $EURIBOR\_OIS_t$  is the spread between the EURIBOR and OIS rate,  $LTRO_t$  is a dummy for ECB long term refinancing operations;  $MRO_t$  is a dummy for ECB main refinancing operations;  $OT_t$  is a dummy for other types of ECB operations; and  $Annoucements_t$  is a dummy variable that captures both conventional and unconventional ECB

<sup>22</sup> These data are available from the ECB website.

<sup>23</sup> The indices, on a given day, are weighted averages of the surprises or squared surprises from a set of macro releases, where the weights depend on the contribution of the associated real activity indicator to a business condition index.



**Fig. 3.** Time series of network statistics and corresponding graphs showing increasing connectivity in correlation networks and decreasing connectivity in physical networks. The vertical lines indicate the four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; (4) the third crisis period April 2, 2009 – December 31, 2012.



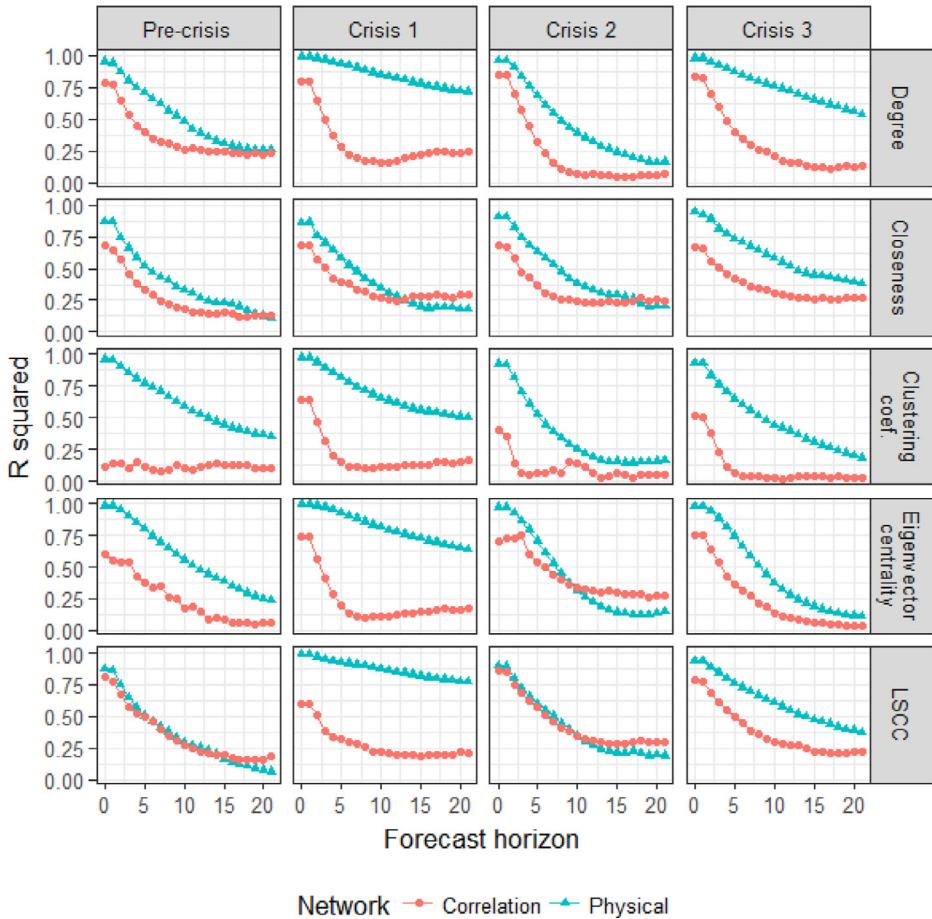
**Fig. 4.** Directed bank (node) centrality measures (see Appendix) aggregated by geographic region. Banks from peripheral countries contribute most to correlation networks throughout the sample period, followed by banks from core countries and then banks from other countries. Results from the physical networks are much more volatile. The vertical lines indicate the four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and (4) the third crisis period April 2, 2009 – December 31, 2012.

intervention announcements.<sup>24</sup>  $U_t$ ,  $S_t$ ,  $DJST_t$ ,  $EONIA_t$ , and  $EURIBOR\_OIS_t$  are proxies for fundamental shocks in the economy, while  $LTO_t$ ,  $MRO_t$ ,  $OT_t$ , and  $Announcements_t$  capture monetary policy shocks.

<sup>24</sup> The announcements variable is constructed from Rogers et al. (2014) Table 3 data.

**Fig. 5** shows the  $R^2$  for each network type, over all dependent variables and forecasting horizons,  $k$ , for Eq. (12).<sup>25</sup> With the exception of the clustering coefficient and eigenvector centrality, it seems that both networks

<sup>25</sup> Results for Eq. (13) are very similar.



**Fig. 5.**  $R^2$  for the regressions in Eq. (12) showing that the physical network reacts more to ECB interventions and macroeconomic shocks during the crisis and following. The physical network statistics for interbank lending are computed from 212 European banks and correlation network statistics from 54 publicly-traded European banks. The results are stratified by four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and (4) the third crisis period April 2, 2009 – December 31, 2012.

capture the same information before the crisis. However, there is a clear pattern showing that the physical network reacts more to ECB interventions and macroeconomic shocks during the crisis and following.

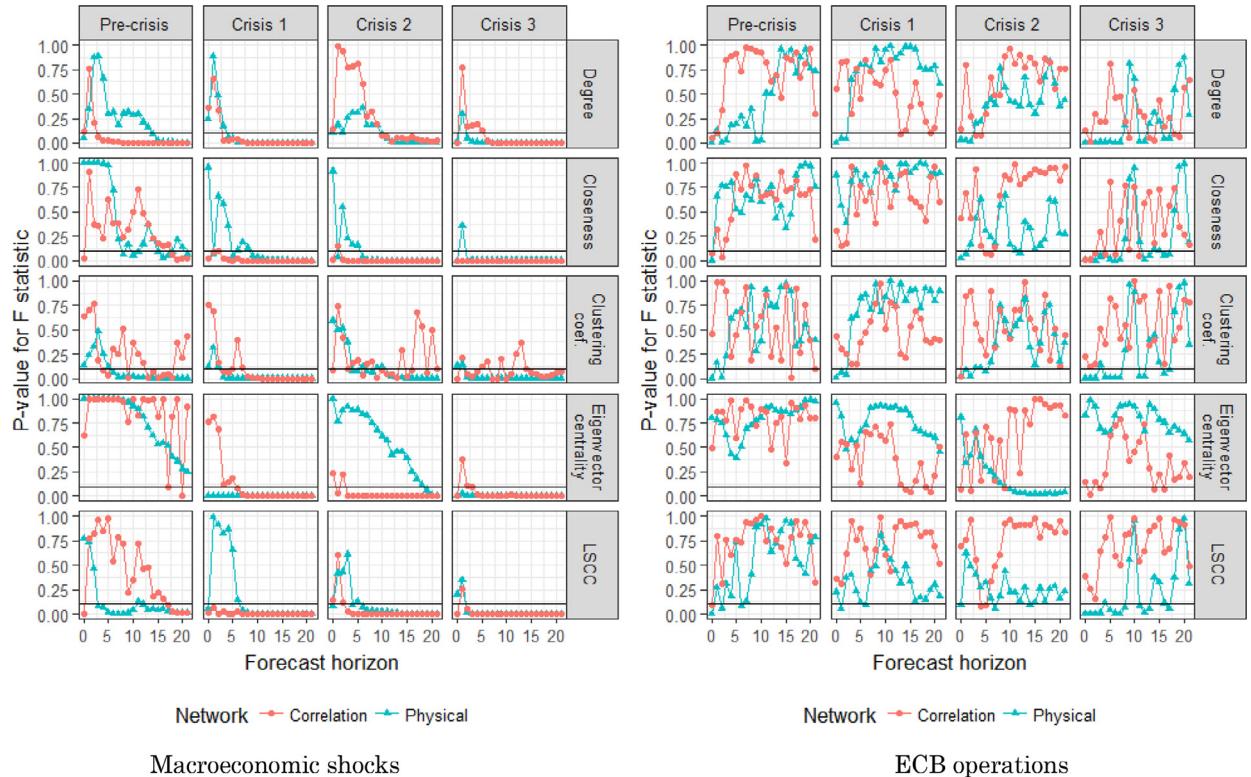
Analysis of the estimated coefficients (not reported here) reveals that the correlation network reacts to shocks captured by the  $EONIA_t$ , which plays an important role in explaining the structure of the correlation network in all sub-periods. The EURIBOR-OIS spread,  $EONIA$ , and the uncertainty index are the most important factors in the physical network and seem so dominant that they overshadow the other variable effects. This evidence is consistent with the vast literature showing that uncertainty has important effects on the real economy.<sup>26</sup> Our evidence shows that the network structures we study react to uncertainty shocks as well.

In Fig. 6, we distinguish between macroeconomic shocks and monetary policy shocks (of course, the two

might be correlated) and formally test whether the network structure of the correlation and of the physical networks react to these two types of shocks. Our null hypotheses are that all macro shocks have no effect on the network structure (i.e., the coefficient of  $U_t$ ,  $S_t$ ,  $DJST_t$ ,  $EONIA_t$ , and  $EURIBOR\_OIS_t$  in Eqs. (12) and (13) are jointly equal to zero), and, similarly, all ECB shocks have no impact on the network structure (i.e., the coefficients of  $LTO_t$ ,  $MRO_t$ , and  $OT_t$  in Eq. (12) are jointly equal to zero in Eq. (12), and the coefficient for  $Announcements_t$  in Eq. (13) is equal to zero). A  $p$ -value close to zero indicates rejection of the null—e.g., macro and/or ECB shocks are statistically relevant. In the pre-crisis period, macroeconomic shocks are important for the correlation network metrics (except in eigenvector centrality) at most all forecasting horizons, while the physical network reacts to macroeconomic shocks largely at horizons beyond the three days. Moreover, the right panel in Fig. 6 generally shows that the physical network responds more than the correlation network to ECB operations as well.

We explore the partial  $R^2$  from Eq. (12) related to the macroeconomic shocks in Fig. 7. Conditional on ECB

<sup>26</sup> Bloom (2009) and Leduc and Liu (2012), e.g., provide evidence that uncertainty in the recent crisis has reduced economic activity (firm investment) and incrementally increased US unemployment.



**Fig. 6.** *p*-Values from *F*-tests for the regressions in Eq. (12). The left panel shows the *p*-value for the test statistic corresponding to the null hypothesis  $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$  – macro shocks do not affect the network structure. The right panel shows the *p*-value for the test statistic corresponding to  $H_0: \beta_6 = \beta_7 = \beta_8 = 0$  – ECB interventions do not affect the network structure. The physical network statistics for interbank lending are computed from 212 European banks and correlation network statistics from 54 publicly-traded European banks. The results are stratified by four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and (4) the third crisis period April 2, 2009 – December 31, 2012.

operations, macroeconomic shocks impact both networks on a more permanent basis, especially at longer time horizons. Fig. 8 displays the partial  $R^2$  from Eq. (13) related to the announcements alone (during the pre-crisis period, no announcement were made). Importantly, the incremental information impounded by the announcements, conditional on the general impact of macroeconomic factors, is only mildly reflected in both the correlation and the physical network at short horizons and dissipates at horizons greater than ten.

In all three crisis periods, the correlation network is more responsive to macroeconomic shocks than the physical network, consistent with Puliga et al. (2014) who show that during the crisis, increased correlations in credit default swap premiums depend on macroeconomic factors.

The *F*-tests for the ECB interventions in Eq. (12) show that these types of shocks are mainly important to physical networks. In particular, the physical network reacts to ECB interventions mainly at short horizons.<sup>27</sup> To further isolate the effect of ECB shocks, we also examine the hypotheses above within a partial regression analysis setting.

<sup>27</sup> We obtain similar results when analyzing *F*-tests for the macro and ECB shocks in Eq. (13) where ECB shocks refer to ECB conventional and unconventional monetary policy announcements.

Specifically, let  $\hat{y}_{t+k|1:4}$  denote the fitted values resulting from estimating the following regression model

$$y_{t+k} = \alpha + \beta_1 U_t + \beta_2 S_t + \beta_3 DJST_t + \beta_4 EONIA_t + \beta_5 EURIBOR_OIS_t + \gamma y_{t-1} + \varepsilon_t. \quad (14)$$

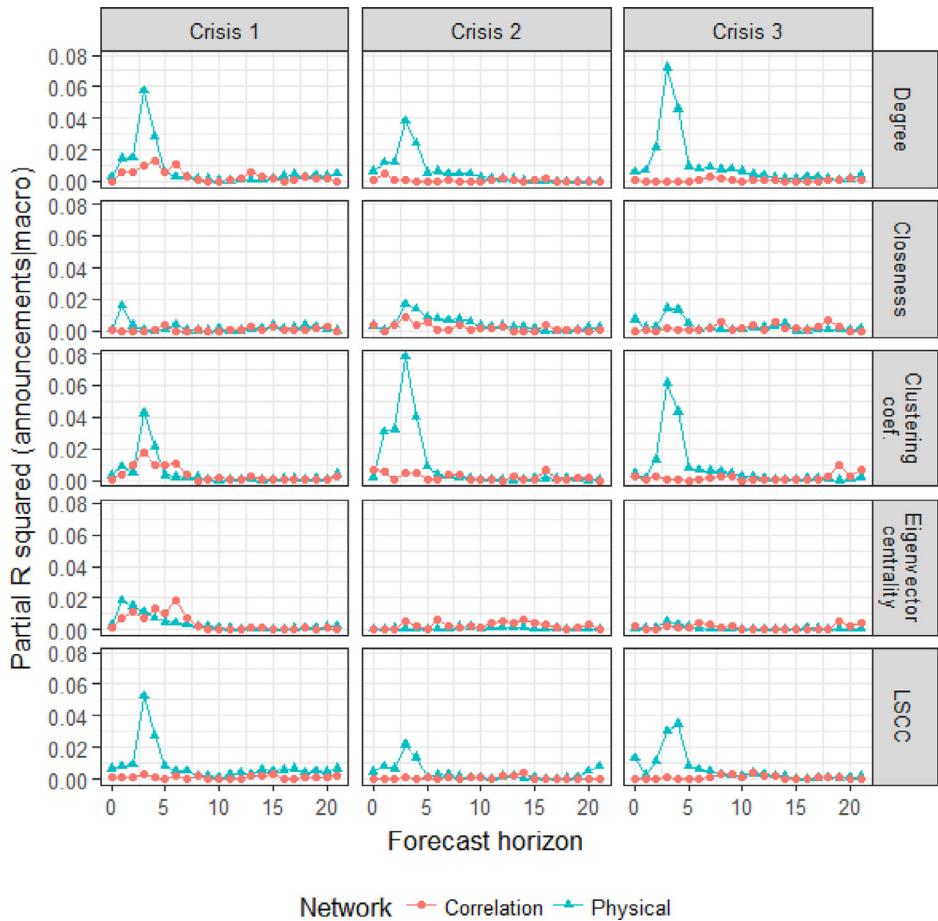
We test the significance of variables in the following regression models

$$y_{t+k} - \hat{y}_{t+k|1:4} = \beta_0 + \beta_6 LTR_O_t + \beta_7 MRO_t + \beta_8 OT_t + e_t \quad (15)$$

$$y_{t+k} - \hat{y}_{t+k|1:4} = \beta_0 + \beta_6 Announcements_t + \nu_t. \quad (16)$$

Fig. 9 depicts the *F*-test for the null  $H_0: \beta_6 = \beta_7 = \beta_8 = 0 \mid \beta_1, \beta_2, \beta_3, \beta_4, \beta_5 \neq 0$  for Eq. (15). In all sub-periods, the correlation network responds to ECB interventions only contemporaneously (i.e.,  $k=0$ ). This is also true for the physical network. However, physical network interconnectedness reacts to ECB interventions contemporaneously and across subsequent days in all crisis sub-periods.<sup>28</sup>

<sup>28</sup> Similar results are obtained for test statistic corresponding to the partial regression null hypothesis  $H_0: \beta_6 = 0 \mid \beta_1, \beta_2, \beta_3, \beta_4, \beta_5 \neq 0$  in Eq. (16).



**Fig. 7.** Partial  $R^2$  values of announcements conditional on macro shocks for the regressions in Eq. (13). The physical network statistics for interbank lending are computed from 212 European banks and correlation network statistics from 54 publicly-traded European banks. The results are stratified by three subsamples: (1) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (2) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and (3) the third crisis period April 2, 2009 – December 31, 2012.

Overall, Figs. 5–9 show that the physical and correlation networks respond differently to shocks and therefore reflect different information sets. To the extent that correlation networks based on stock prices are more forward looking, we conjecture that the relatively muted response is related to anticipated macroeconomic changes. Conversely, since our physical networks respond more strongly to shocks, we surmise that the physical network more closely reflects connectedness between and among banks, a connectedness that is more sensitive to economic shocks.

Given that correlation and physical networks capture different phenomena, we assess whether and how the network topology might help to serve policy makers in forecasting relevant macroeconomic variables. In this regard, we utilize monthly networks and consider several of the macro variables including:

- Hard information, such as Industrial production (IP) and Retail sales (RS);
- Soft information, such as the Purchasing manager index (PMI) – [Bańbura and Rünstler \(2011\)](#) show that soft information may be important in forecasting;

- The spread between the EURIBOR and the OIS, which is considered a measure of health of the banking system;
- The spread between the ten-year Greek, Italian, Portuguese, and Spanish government bond yields and the German government bonds yield, denoted by GRSP, ITSP, PTSP, and SPSP, respectively.<sup>29</sup>

We estimate the following model from January 2006 until December 2008 (36 months) and then produce one-step-ahead forecasts for the macro variable from January 2009 until March 2010.

$$z_{i,t} = \gamma_0 + \gamma_1 \text{Degree}_{j,t-1} + \gamma_2 \text{CC}_{j,t-1} + \gamma_3 \text{Closeness}_{j,t-1} + \gamma_4 \text{LSCC}_{j,t-1} + \gamma_5 z_{i,t-1} + u_{j,t} \quad (17)$$

where  $z_{i,t}$  represents the macro variable described above (we consider one variable per time), and  $j$  denotes the correlation and the physical network, respectively.

[Table 4](#) reports the  $R^2$  of the regressions (from January 2006 until December 2008) and root mean squared error (RMSE) for the forecasting exercise.

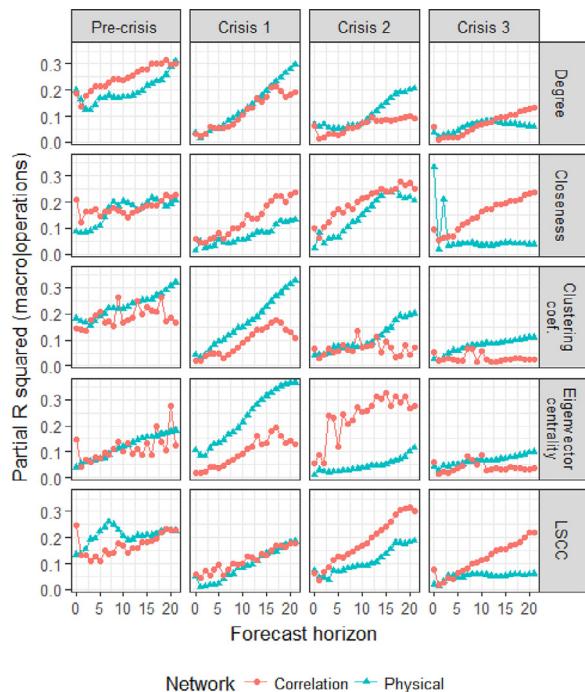
<sup>29</sup> Some of the macro variables are not stationary; in these cases, we consider the first difference.

**Table 4**

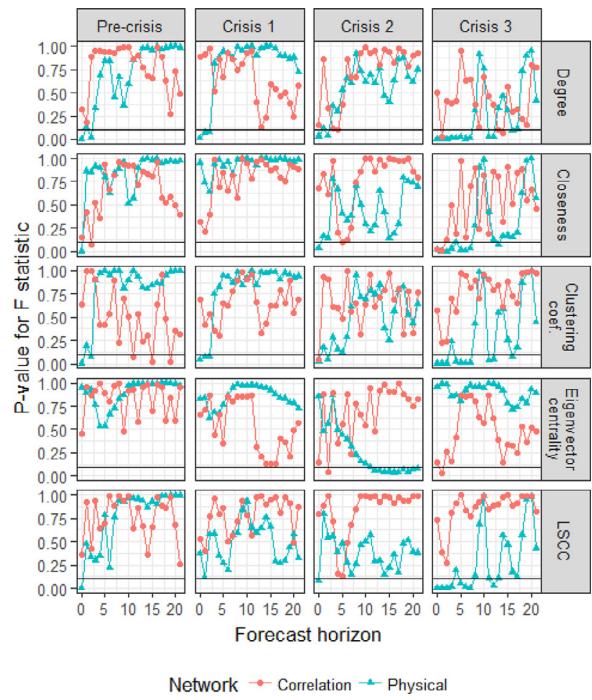
Linear regression results of the network variables on the macro variables.

	R <sup>2</sup>			RMSE		
	Correlation network	Physical network	Difference	Correlation network	Physical network	Difference
Hard information						
Δ(IP)	0.3143	0.2763	0.0380	3.1867	2.9624	0.2243
Δ(RS)	0.2146	0.1944	0.0202	1.9719	1.3710	0.6009*
Soft information						
Δ(PMI)	0.3806	0.4730	-0.0924**	6.9828	4.3975	2.5853**
Banking system health						
EURIBOR-OIS Spread	0.6773	0.6739	0.0033	0.2255	0.7928	-0.5673*
Country-specific spreads						
ITSP	0.0949	0.1795	-0.0846**	0.9620	0.8750	0.0870
PTSP	0.0190	0.1764	-0.1574**	1.1201	0.5976	0.5225*
GRSP	0.1156	0.1922	-0.0766**	1.6393	1.4050	0.2343*
SPSP	0.2777	0.1499	0.1279**	1.2028	0.5798	0.6229*

R<sup>2</sup> refers to the regression of the network variables (Degree, CC, Closeness, Eigenvector centrality, and LSCC) on the macro variables in the first column over the period January 2006 – December 2008. RMSE refers to one-step-ahead forecasts from January 2009 until March 2010. Monthly observations. \* and \*\* refer to significance levels of 10% and 5%. IP is industrial production, RS is retail sales, PMI is purchasing manager index, EURIBOR-OIS spread is the spread between the Euro Interbank Offered Rate and the Overnight Indexed Swap Rate, and ITSP, PTSP, GRSP, and SPSP represent spreads between the ten year Italian, Portuguese, Greek, and Spanish government bond yields and the ten year German government bond yields, respectively.



**Fig. 8.** Partial R<sup>2</sup> values of macro shocks conditional on ECB interventions (operations) from the regressions in Eq. (12). The physical network statistics for interbank lending are computed from 212 European banks and correlation network statistics from 54 publicly-traded European banks. The results are stratified by four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and (4) the third crisis period April 2, 2009 – December 31, 2012.



**Fig. 9.** p-Values for the regressions in Eq. (15) corresponding to the null hypothesis that ECB interventions do not affect the network structure conditional on the macroeconomic variables ( $H_0 : \beta_6 = \beta_7 = \beta_8 = 0 \mid \beta_1, \beta_2, \beta_3, \beta_4, \beta_5 \neq 0$ ). The physical network statistics for interbank lending are computed from 212 European banks and correlation network statistics from 54 publicly-traded European banks. The results are stratified by four subsamples: (1) pre-crisis period January 2, 2006 – August 7, 2007; (2) the first crisis period (pre-Lehman), August 8, 2007 – September 12, 2008; (3) the second crisis period (post-Lehman) September 16, 2008 – April 1, 2009; and (4) the third crisis period April 2, 2009 – December 31, 2012.

The results show that both the correlation and the physical networks exhibit statistically similar  $R^2$  for the regression of the network variables (Degree, CC, Closeness, Eigenvector centrality and LSCC) on hard information—i.e., IP, RS. This is also the case for the spread between the EU-RIBOR and the overnight indexed swap spread.

The physical network is able to better explain, in terms of  $R^2$ , soft information and the Italian, Portuguese, and Greek spreads. Notably, the correlation network has better forecasting performance for the Spanish spread. However, the physical network is better suited for forecasting all the other macro variables. For policy makers, the interbank market appears to provide valuable information about the future state of the economy. In this regard, we suggest that monitoring interbank markets provides a valuable gage for assessing the state of the bank sector and the effectiveness of interventions.

In unreported results, we estimate Granger-causality tests between the connectedness variables in correlation and physical networks using a bivariate VAR-X with the addition of explanatory variables as in Eq. (13). These tests indicate significant lead-lag connectedness relations between the two network types, but neither network consistently leads the other across measures or across time. The fact that each network feeds back into the other is in line with our other results that correlation and physical networks reflect different kinds of information, and thus both should be considered for policy analysis and academic research.<sup>30</sup>

## 7. Transmission between the US and Europe

Our tests above show that macroeconomic shocks impact both networks on a relatively permanent basis, and the Lehman Brothers failure (marking our Crisis 1 and Crisis 2 periods) also appears to have altered the dynamics of how physical and correlation networks react to shocks in Europe. Interconnectedness among European banks increases after the Lehman failure in the correlation network but falls in the physical network. While we are (unfortunately) not privy to interbank transactions among US banks, we construct a US bank correlation network using publicly traded banks in the US over the same 2006–2012 period. Given the evidence that macroeconomic shocks during the crisis are not isolated to individual continents, we explore the lead-lag relations between U.S. and European correlation networks.<sup>31</sup>

More specifically, following Billio et al. (2012), we first extract the principal components from daily returns for individual banks (using a 36-day window for estimation). Both Europe and the US show increases in the fraction of the total variance explained by the first principal component after the advent of the crisis. We then estimate both

<sup>30</sup> We also estimate two alternatives: (i) a simple bivariate VAR between correlation and physical network variables; and (ii) a bivariate VAR-X with the addition of explanatory variables as for Eq. (12) and find similar results. Complete results are available upon request.

<sup>31</sup> Given the fact that 54 publicly traded banks from multiple countries are in the data, there are most certainly significant overlapping business relationships within this set of European banks.

**Table 5**

Granger causality results to measure the US – EU transmissions in network statistics.

	Degree		
	US → EU	EU → US	Lags
Pre-crisis	0.0006***	0.6340	3
Crisis 1	0.0321***	0.1669	2
Crisis 2	0.7613	0.0539***	1
Crisis 3	0.5375	0.3265	4
	Closeness		
Pre-crisis	0.5834	0.9045	2
Crisis 1	0.5568	0.9577	2
Crisis 2	0.5873	0.4738	2
Crisis 3	0.0073***	0.0441***	4
	Clustering coefficient		
Pre-crisis	0.0062***	0.4466	2
Crisis 1	0.0783**	0.7521	2
Crisis 2	0.4872	0.0202***	2
Crisis 3	0.7709	0.7507	4
	Eigenvector centrality		
Pre-crisis	0.0618**	0.1841	4
Crisis 1	0.0105***	0.3144	3
Crisis 2	0.7127	0.0455***	1
Crisis 3	0.5778	0.6320	5
	LSCC		
Pre-crisis	0.6127	0.6071	2
Crisis 1	0.0949**	0.7924	2
Crisis 2	0.9612	0.0822**	2
Crisis 3	0.1480	0.0703**	4

US → EU indicates that the US network Granger-causes the European network; EU → US indicates that the European network Granger-causes the US network; \*, \*\*, and \*\*\* refer rejection of the null of Granger-noncausality at significance levels of 10%, 5%, and 1%. The four subsamples are (1) pre-crisis period Jan 2, 2006 – Aug 7, 2007; (2) the first crisis period (pre-Lehman), Aug 8, 2007 – Sep 12, 2008; (3) the second crisis period (post-Lehman) Sep 16, 2008 – April 1, 2009; and (4) the third crisis period Apr 2, 2009 – Dec 31, 2012. The last column reports the optimal lag-length selected by the Akaike information criterion (AIC).

US and European correlation networks after removing the first principal component from the return series and run Granger-causality tests between the US and European networks. The results are presented in Table 5.

The main finding is that during the Pre-crisis and Crisis 1 periods, the US network variables significantly Granger-cause the European network variables (in seven of ten pairwise tests). During these first two sub-periods, European network variables never Granger-cause US network variables. However, after the failure of Lehman Brothers, the reverse is true. During Crisis 2 and Crisis 3 periods, European network variables tend to significantly Granger-cause U.S. network variables (in six of ten pairwise tests) while Granger-causation from the U.S. to Europe is significant in only one of ten pairwise tests during these post-Lehman periods. These findings largely mirror the volatility connectedness documented between the US and Europe in Yilmaz (2014).

## 8. Concluding remarks

During the recent financial crisis, market dynamics changed dramatically, with some markets seizing up as

market uncertainty and asymmetric information between banks created unprecedented problems in the world economy. In this paper, we analyze the detailed trading data from the European (e-MID) interbank market to better understand how interbank trading reflected these economic problems. We construct and examine physical networks of trade that allow us to examine bank connectedness over time. Further, we compare and contrast correlation networks (constructed based on Granger-causality between stock returns) with physical networks (constructed from interbank trades) to better interpret results from each.

We demonstrate that correlation and physical networks reflect important, but different, economic conditions in the European banking sector. During the crisis, physical bank networks reveal a breakdown in connectivity in the interbank market. Interestingly, correlation networks show increased co-movements in market returns during the crisis that have been interpreted as an increase in connectivity.

We further explore the source of these interconnected changes by region of Europe. Within correlation networks, banks from peripheral European countries (Greece, Ireland, Italy, Portugal, and Spain) contribute most to changes in interconnectedness. However, banks from both core European countries (Austria, Belgium, France, Germany, Luxembourg, and the Netherlands) and peripheral countries consistently contribute to interconnectedness changes within the physical networks.

Moreover, correlation and physical networks respond differently to monetary and macroeconomic shocks. Interconnectedness in physical networks adjusts strongly and quickly to central bank operations and to announcements of new information, revealing important markers of liquidity at short (daily) horizons. Conversely, while interconnectedness in correlation networks marks the onset of the crisis, this metric changes little in response to central announcements and interventions.

We also show that the Lehman Brothers failure not only altered the dynamics of how physical and correlation networks react to shocks in Europe, but also altered the lead-lag relations between interconnectedness in the correlation networks of European and US banks. US network variables significantly lead the European network variables prior to the Lehman failure, but European network variables significantly lead US network variables after Lehman failed.

Our results demonstrate that correlation and physical networks can identify (and forecast) hard information like industrial production and retail sales. Complementarily, physical interbank trading networks serve to identify weakening interconnectedness in the interbank system that may lead to liquidity problems. Moreover, physical networks can identify systemically important and problem banks on an ongoing basis. From a policy perspective, monitoring both types of networks would be useful.

## Appendix

Let  $A_t$  be the network adjacency matrix at time  $t$ . Then, the given network sequence can be approximated with

$$A_t \approx U_t V_t^T,$$

where  $U_t$  and  $V_t$  are both vectors that are constrained to be nonnegative, i.e., each element of  $U_t$  and  $V_t$  is greater than or equal to zero. Interpretations of  $U_t$  and  $V_t$  are straightforward. The  $j$ th element of  $U_t$  measures the importance of bank  $j$  to average outgoing connectivity at time  $t$ . Likewise, the  $j$ th element of  $V_t$  measures the importance of bank  $j$  to the average incoming connectivity at time  $t$ . Together,  $U_t$  and  $V_t$  are useful for highlighting banks by their importance to interconnectivity.

Constraints that force evolving factors  $U_t$  and  $V_t$  to exhibit temporal smoothness are imposed on the factorizations to enhance their visualization and interpretability. This ensures that bank trajectories are visually smooth when drawn, and as a consequence, time plots of each bank become informative. Thus, centrality measures over time are found by minimizing an objective function that consists of a goodness of fit component and a smoothness penalty

$$\min_{\{U_t, V_t\}} \sum_{t=1}^T \left| \left| A_t - U_t V_t^T \right| \right|_F^2 + \lambda_1 \sum_{t=2}^T \left| \left| U_t - U_{t-1} \right| \right|_F^2 \\ + \lambda_2 \sum_{t=2}^T \left| \left| V_t - V_{t-1} \right| \right|_F^2,$$

where the parameters  $\lambda_1$  and  $\lambda_2$  are set by the user to control the amount of memory or smoothness in the factors over time, and  $U_t$  and  $V_t$  are both vectors that are constrained to be nonnegative. The interpretation is again intuitive. For the physical network,  $U_t$  measures importance to selling (outgoing edges) and  $V_t$  to buying (incoming edges). For the correlation network,  $U_t$  measures importance of banks whose returns are predictive of other bank returns (outgoing edges) and  $V_t$  to banks whose stock returns are predicted by other banks' stock returns (incoming edges).

To minimize the objective function and obtain the centrality measures, gradient descent algorithms standard for matrix factorization can be utilized. Extensive discussion, including estimation and other implementation details, can be found in [Mankad and Michailidis \(2013\)](#) and [Mankad et al. \(2014\)](#).

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