Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

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2021-017

Please cite this paper as:
Brunetti, Celso, Jeffrey H. Harris, and Shawn Mankad (2021). "Liquidity Networks, Interconnectedness, and Interbank Information Asymmetry," Finance and Economics Discussion Series 2021-017. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2021.017.

Liquidity Networks, Interconnectedness, and Interbank Information Asymmetry

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Abstract

Network analysis has demonstrated that interconnectedness among market participants results in spillovers, amplifies or absorbs shocks, and creates other nonlinear effects that ultimately affect market health. In this paper, we propose a new directed network construct, the liquidity network, to capture the urgency to trade by connecting the initiating party in a trade to the passive party. Alongside the conventional trading network connecting sellers to buyers, we show both network types complement each other: Liquidity networks reveal valuable information, particularly when information asymmetry in the market is high, and provide a more comprehensive characterization of interconnectivity in the overnight-lending market.

Keywords: banking networks, interconnectedness, liquidity

JEL: G21, C10, G10

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Declarations of interest: none

1 Introduction

Network analysis is a proven and effective tool to assess and understand financial markets. Babus and Hu (2017) provide a theory of trading through intermediaries in over-the-counter (OTC) markets where traders are connected through an informational network and observe others' actions. They show that trading through this informational network is essential to support trade when agents have limited commitment and infrequently meet their counterparties.[1] Empirical evidence in Brunetti and others (2019) supports informational models where information from interbank trading networks forecasts market liquidity problems and is useful to regulators in better monitoring these important markets.

In this paper, we expand on the notion that information is important in forming networks. Rather than simply constructing trading networks between buyers and sellers, we first define liquidity networks as directed networks that map aggressive borrowers (lenders) to passive lenders (borrowers) in the overnight-lending market. The liquidity network uses trade aggressiveness, additional information about interbank trades, to capture the urgency to trade. We argue that this passive/aggressive information serves to help overcome the trading frictions of limited commitment and limited counterparty information in the market.[2]

We then explore differences between trading networks and liquidity networks in the interbank market—trading networks simply map borrowers to lenders while liquidity networks map aggressive traders to passive traders. We demonstrate that the structures

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[1] Castiglionesi and Eboli (2018) model interbank interconnectedness, mapping sellers to buyers and comparing the efficiency of star-shaped, complete, and incomplete networks (where efficiency is the complete transfer of liquidity among banks to prevent costly early liquidation of long-term assets). Babus and Hu (2017) and Castiglionesi and Eboli (2018) show, respectively, that a star network with concentrated intermediation is both constrained efficient and stable with linking costs and less exposed to systemic risk than other complete or incomplete networks.

[2] Supporting the existence of limited commitment in interbank markets, Babus and Hu (2017) note that banks can delay overnight funds delivery until the afternoon in the fed funds market and can both fail to deliver or fail to receive in the repurchase agreement market. See also Bartolini, Hilton, and McAndrews (2010) and Gorton, Laarits, and Muir (2015), respectively.

of the two networks differ. Trading networks can be characterized by a stable core-periphery structure, whereas liquidity networks exhibit multiple core groups of European banks consistently providing aggressive (or passive) liquidity to the market. To the best of our knowledge, the existence of multiple cores of banks is new to the financial networks literature and aligns with the theoretical predictions of particular network topologies made in several recent works (such as star-shaped networks, see Babus and Hu, 2017; Castiglionesi and Eboli, 2018; and Castiglionesi and Navararro, 2020). In this light, we show that the information gleaned from the two networks differs and changes over time, so that these alternative network lenses provide complementary information about the interbank market.

We then explore how information from trading and liquidity networks is useful for forecasting economic conditions where these banks operate. This exercise follows the spirit of comparing various network constructs. Billio and others (2012) show correlation networks (among stock returns) reflect financial interconnectedness and crises, while Brunetti and others (2019) show interbank trading networks forecast market liquidity problems.[3] While Babus and Hu (2017) show intermediaries can alleviate information and commitment frictions between banks, we posit that trade aggressiveness serves both as additional information and as a commitment device (because an aggressive order hits a standing limit order) in a market without intermediaries. Empirically, we find that the passive/aggressive information gleaned from liquidity networks complements the information from trading networks.

We also examine the time-series changes in both trading and liquidity networks and conjecture that the incremental information from liquidity networks is more important during periods when market informational asymmetries are high. For this

[3] Adamic and others (2017) explore how physical trading networks can be used to forecast short-term market conditions as well.

exercise, we utilize the fact that the interbank market in Europe suffered from severe informational asymmetries during the 2007–09 financial crisis.[4]

By comparing trading networks with liquidity networks in the European sphere around the 2007–09 financial crisis, we focus on whether these alternative network characterizations reveal differential information. Importantly, the same set of overnight interbank transactions generates both types of networks.[5] Our work identifies the liquidity network as an alternative dimension for viewing financial markets: The urgency to trade reflected in our liquidity networks is a component of information that differs from, and complements, information gleaned from trading networks.

Tracing both trading and liquidity networks over time and through the 2007–09 financial crisis, we examine many proxies for interconnectedness among European banks, including degree, a clustering coefficient, reciprocity, and the largest strongly connected component (LSCC).[6] We find that these measures of interconnectedness all dropped substantially from the 2006–07 pre-crisis period to the 2009–12 weak recovery period. The LSCC and reciprocity are both consistently lower in the trading network than in the liquidity network. Banks are less likely to be interconnected with other banks for trading purposes but more consistently aggressive (and passive) in utilizing the interbank market to source or provide funds to other banks. In fact, reciprocity is systematically more than three times higher in the liquidity network, indicating that banks that trade with each other are more likely to trade both passively and aggressively when they do so.

These findings show that liquidity networks help provide a more complete characterization of markets and their participants. To the extent that networks aid in

[4] See, for instance, Brunetti, di Filippo, and Harris (2011).
[5] Brunetti and others (2019) use these same data, building on Shin (2009, 2010) and Elliott, Golub, and Jackson (2014).
[6] LSCC is defined as the maximum number of traders that can be reached from any other trader by following directed edges (see Adamic and others, 2017, and Brunetti and others, 2019). Further details are available in section 3.

understanding and diagnosing market activity, our results show that LSCC and reciprocity characteristics computed from liquidity networks capture important dimensions of market quality distinct from those computed from trading networks.

In subperiod analyses, we find that these statistics change over time as the crisis evolved. More specifically, we find that some measures of interconnectedness (degree and LSCC) appear to drop continuously through the 2006–12 period. However, other measures of connectedness (clustering and reciprocity) actually increased at the onset of the crisis before declining as the crisis continued and then abated. These results expose weakening interconnectedness in the European interbank system induced by the crisis.

The decline in interconnectedness occurs in both trading and liquidity networks. However, the decline is more pronounced in the trading network: Banks were less likely to trade with each other but only slightly less aggressive in approaching each other to trade. The changes and trends in interconnectedness reflect structural changes to the topology of each network. At the start of the crisis, both networks feature multiple cores of banks that overlap, but the trading networks evolve to a single core as the crisis abated.

We further explore the differential information from each network by examining whether and how the interbank network forecasts hard and soft macroeconomic information, euro-zone yield spreads, and country-specific yield spreads. Consistent with Babus and Hu (2017) where information asymmetries drive the formation of the network, we find that trade aggressiveness reflected in the liquidity network improves short-term forecasts of soft information and country-specific yield spreads, settings where asymmetric information is likely to be more pronounced.

In the last part of the paper, we compare the information content of trading and liquidity networks with that of traditional volatility and volume measures. We find that in normal market conditions when interconnectedness is high, a further increase in connectivity of either network raises volatility. In the relatively low interconnectedness crisis period, however, an increase in liquidity network connectivity reduces volatility and boosts traded volume. Our results reveal the dual character of interconnectedness—too much interconnectedness may increase systemic risk, but too little may impede market functioning.

Our work contributes to a better understanding of how interbank markets operate and convey information about the real economy. While other papers focus on interbank network structures and contagion (Degryse and Nguyen, 2007, and Mistrulli, 2011), we focus on different network constructs and whether viewing interbank networks under different lenses provides important insights into the macroeconomy.

Examining interbank networks in two dimensions—trading and liquidity networks—adds to the growing literature on the usefulness of network analysis in financial markets.[7] Importantly, we create and study liquidity networks, a new type of physical network that more specifically focuses on liquidity dynamics in financial markets. We find that integrating liquidity characteristics into network analysis marks an important contribution that improves macroeconomic forecasts and links interbank liquidity to the real economy. Given the importance of liquidity and liquidity risk in financial markets, market regulators and participants may benefit from monitoring the dynamics of liquidity networks, whether during financial crises or more stable economic times.

2 Data: e-MID Overnight-Lending Market

In this section, we present a time series of network statistics for trading and liquidity networks constructed from the e-MID platform, the only electronic market for

[7] The vast literature exploring trading networks includes empirical analysis examining how network topology exacerbates or absorbs shocks in different environments (Allen and Gale, 2000; Gai, Haldane, and Kapadia, 2011; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015; Cont, Moussa, and Santos, 2013; Georg, 2013; Glasserman and Young, 2015), tracing the evolution of interbank networks during calm and crises subperiods (van Lelyveld, 2014; Brunetti and others, 2019), and establishing the forecasting power of network statistics (Adamic and others, 2017), among others.

interbank deposits in the euro region.[8] Our detailed trading data span from January 2006 through December 2012 and include 464,772 trades among 212 unique banks. 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.

Given the eventful period covered by our data (and the prospect that the dynamics in this market change over time), we split the data into four subperiods: (1) a pre-crisis period from January 2, 2006, until August 7, 2007 (when the European Central Bank, (ECB) noted worldwide liquidity shortages); (2) the first crisis period (pre-Lehman Brothers) from August 8, 2007, until September 12, 2008; (3) the second crisis period (post-Lehman Brothers) from September 16, 2008, through April 1, 2009 (when the ECB announced the end of the recession); and (4) the period from April 2, 2009, through December 31, 2012, characterized by a weak recovery.

Figure 1 shows several daily e-MID market statistics. We see that interest rates fell starting with the onset of the 2007–09 financial crisis. Rates started to recover as the crisis abated but fell again to crisis levels in 2012, as Europe experienced a weak recovery. Volatility, defined as the log-price difference, shows a similar pattern, with heightened levels during the 2007–09 and European crisis. Effective spreads remain relatively stable across our sample period, suggesting that interbank market trading costs did not suffer appreciably during the crisis. By contrast, a clear negative trend emerged in the number of active banks trading and in daily volume. Signed volume is also negative throughout our sample period, with a clear increasing trend toward zero.[9] These patterns indicate

[8] E-MID trades represent interbank loans ranging from overnight (one day) to two years in duration, with overnight contracts representing 90 percent of total volume during our sample period (see Brunetti, di Filippo, and Harris, 2011). The e-MID market is open to all banks admitted to operate in the European interbank market, and non-European banks can obtain access to the market through their European branches. As of August 2011, the e-MID market had 192 members from European Union countries and the United States, including 29 central banks acting as market observers (Finger, Fricke, and Lux, 2013). Liquidity in e-MID largely dried up after 2012, when our data end.
[9] Signed volume is constructed as the difference between the amount aggressively bought and the amount aggressively sold.

that banks actively used the e-MID platform for selling funds, though by the end of our sample period, liquidity levels are poor. Trade imbalance (scaled by volume) shows a greater proportion of aggressive lending during the 2007–09 crisis. During the weak recovery in Europe, trade imbalance even became positive for a handful of days, indicating that more banks were aggressively borrowing through e-MID. Last, likely driven by the reduction in banks using the platform, the Herfindahl index rises consistently over our sample period, reflecting greater concentration among banks using e-MID.

3 Measuring Interconnectedness

In sections 3.1 and 3.2, we start with a background discussion on each network and the statistics we use to characterize interconnectedness. In section 3.3, we present the evolution of our network statistics to gain further insights into how the e-MID market evolved from 2006 through 2012.

3.1 Representing Interbank Activity with Trading and Liquidity Networks

Castiglionesi and Eboli (2018) and Babus and Hu (2017) model interconnectedness in the interbank market, mapping sellers to buyers. While Babus and Hu (2017) show that intermediaries can help overcome commitment and information frictions to connect traders (banks) in an OTC market (which exhibits limited commitment and limited information about agents' past actions), we posit that trade aggressiveness may also help overcome these frictions.

In our liquidity networks, aggressive (market) orders execute against standing limit orders posted on e-MID and thus reflect a greater commitment to trade. We surmise that the information impounded in these aggressive orders is complementary to the information about borrowing and lending that emerges from the trading network. Moreover, with the absence of liquidity providers on e-MID, we anticipate that information gleaned from the interbank liquidity network may also serve to forecast economic conditions and other macroeconomic variables in the euro zone.

To illustrate differences between interconnectedness in trading and liquidity networks, consider the hypothetical trading network shown in figure 2A, where banks are labeled A through E. In this trading network, Bank A is the dominant seller. Importantly, these same trades could result in many different liquidity networks. At the extremes, Bank A could actively or passively trade with all other firms by hitting the quotes of other banks or by passively providing quotes that other banks execute against through market orders. Figure 2B presents these extreme cases where Bank A is an active lender (left panel) or passive lender (right panel). Clearly, trades represented in figure 2A might differ dramatically when represented as a liquidity network.

3.2 Network Statistics

It is useful to note that several commonly used network statistics are identical in both trading and liquidity networks. Generally, any network statistic that ignores the directionality of the edges will be invariant between the two types of networks, because they are constructed from the same set of transactions. For example, aggregate statistics like the *overall degree* of the network (total number of connections) remain fixed between the two networks. Note that this invariance includes measures such as *degree* and *clustering coefficient* (the percentage of closed triangles), which analysts have used to measure interconnectivity and liquidity flows (Billio and others, 2012; Adamic and others, 2017; Brunetti and others, 2019).

Network statistics that account for directionality can differ between networks, however. For example, *at the node level,* a bank's in and out degree will generally be different in trading and liquidity networks. More importantly, the interpretation of these statistics also varies. For the trading network, in degree represents borrowing on the interbank market, whereas for the liquidity network, in degree corresponds to trades executed by passively posting quotes. Likewise, out degree corresponds to lending in the trading network but represents aggressive market orders in the liquidity network.

Another important interconnectivity metric based on directionality is the LSCC, defined as the maximum number of banks (subnetwork) that can be reached from any other bank on the network by following directed edges. In addition, *reciprocity* measures the likelihood that pairs of nodes link in both directions. Both measures have been used previously to characterize interconnectedness and systemic risk in interbank networks of Mexico (Martinez-Jaramillo and others, 2014) and Germany (Roukny and others, 2014). These metrics will likely differ when computed through trading or liquidity networks. In the trading network, the LSCC and reciprocity will be closer to their maximum value of one when a large number of banks are buying *and* selling. In the liquidity network, the LSCC and reciprocity are larger when a larger number of banks actively and passively trade.

In this light, these metrics reflect a measure of demand for funds across the interbank trading network: If more banks borrow (while their counterparties lend), the LSCC and reciprocity are high. Conversely, these same metrics reflect more of an urgency to borrow in the liquidity network: If more banks actively seek funds (from passive counterparties), the LSCC and reciprocity in the liquidity network are high.

3.3 Interconnectedness in Trading and Liquidity Networks

Figure 3 depicts our four interconnectedness measures over time, displayed by subperiod, for networks constructed using the transactions from a 30-day rolling window. As discussed earlier, the degree and clustering coefficient for the trading and liquidity networks are identical, as these metrics do not depend on directed edges. The degree of the interbank market falls consistently over each subsequent subperiod, as counterparty problems during the crisis deterred banks from using the OTC e-MID market. However, the onset of the crisis (our Crisis 1 period) reflected a larger clustering coefficient, so that active banks were more likely to be connected among a small set of other banks, even while the average bank was less connected.

Figure 3 also demonstrates differences in connectedness measures that rely on directed edges—the LSCC and reciprocity measures clearly differ in trading and liquidity networks. The LSCC and reciprocity in the trading network are consistently below the LSCC and reciprocity in the liquidity network, respectively. The trading network (connections between borrowers and lenders) appears to reveal less interconnectivity than does the liquidity network (linking aggressive and passive banks). That is, banks in the European interbank market are more likely to be transacting both aggressively and passively than they are to be both borrowing and lending. These differences lend credence to our supposition that examining interconnectivity in both trading and liquidity networks reveals distinct information from the interbank market.

The LSCC and reciprocity measures also evolve differently over time. Similar to degree, the LSCC in both networks falls consistently over time. Figures 3 and 4 display the shrinking LSCC both numerically and visually. Similar to clustering, reciprocity rises during the Crisis 1 period and falls during the next two subperiods. Interestingly, the LSCC and reciprocity fall more than 46 percent in the trading network but only 14 percent and 8 percent, respectively, in the liquidity network. Clearly, the dynamics of these statistics differ over time.

We follow up on these different dynamics by tracing shorter-term (daily) changes in network statistics in figure 4, with some distributional statistics provided for perspective in table 1. As shown in table 1 and figure 4, the degree and clustering coefficient resemble the trend in volume in that both dropped precipitously as the 2007–09 crisis unfolded. The average pre-crisis levels for degree and clustering coefficient were 8,360 and 0.394, respectively, ultimately falling to 3,482 and 0.349 following the failure of Lehman Brothers. As the crisis abated after 2009, the clustering coefficient nearly recovered to pre-crisis levels, although, as Europe suffered a weaker recovery from the crisis, the clustering coefficient fell again in late 2011, indicating lower levels of interconnectivity. Table 1 and figures 3 and 4 also confirm that the time series of degree and clustering coefficient are identical for trading and liquidity networks (because these network statistics are undirected).

The LSCC and reciprocity generally diverge for each network, with the liquidity network reflecting higher average values. Although the LSCC drops for both networks following the failure of Lehman Brothers, the LSCC in the liquidity network recovers slowly to near pre-crisis levels by 2012. In contrast, the LSCC for the trading network continues to fall through 2012. Similarly, reciprocity decreases in both networks following the failure of Lehman Brothers, with reciprocity in the trading network continuing to decline (nearly 50 percent) through 2012. This decrease indicates that banks became less willing to borrow *and* lend funds on the e-MID, instead preferring to trade in one direction only as the crisis unfolded. Like the LSCC, reciprocity in the liquidity network recovers to a level above its pre-crisis starting point following the collapse of Lehman Brothers. In fact, the average reciprocity for the liquidity network from April 2009 onward is higher (0.419) than the average pre-crisis level (0.411). Thus, the remaining banks using the e-MID were increasingly willing to initiate trades through market orders and post quotes on the platform.

Altogether, we see consistent evidence that liquidity decreased significantly in the e-MID market. As the crisis unfolded, banks tended to initiate trades less often or were less willing to post public quotes to borrow. This trend led to a drop in overall activity and a decline in e-MID network interconnectivity. The trading network became less dense and more fragmented between 2006 and 2012.

Despite this overall drop in activity, the liquidity networks show evidence that trust levels recovered following the crisis and remained high between banks that continued to use e-MID. Higher post-crisis reciprocity in the liquidity network indicates that banks continued to be both passive and aggressive in seeking liquidity, whereas lower reciprocity in the trading network denotes that banks were more polarized, either only borrowing or only lending. These results demonstrate how trading and liquidity networks independently reveal differential information about the market, even though the same set of trading data generates both networks.

Note also that the two results are not contradictory: Financially constrained banks in need of funds easily may be willing to borrow either by aggressively trading with other banks posting quotes on e-MID or by posting their own quotes. Likely for the same reason, the LSCC in the liquidity network is larger than in the trading network.

Table 2 shows associations in and between the two network types through correlation analysis for each subperiod. First, we note that the correlation structure in trading network statistics is stable. Each pairwise correlation is positive before the crisis and remains so throughout each subperiod. Correlations among trading network variables increase in crisis periods, reflecting the reduction in traded volume and network connectivity throughout the crisis. In fact, these correlations remain high also in the weak recovery period as trading activity in e-MID never recovers to pre-crisis levels.

Similar results apply to correlations among liquidity network variables except that the LSCC often negatively correlates with other liquidity network metrics. As shown in Figure 3, although network connectivity at the single node (average degree), two node (reciprocity), and three node (clustering) returns to the pre-crisis level, overall network connectivity measured by the LSCC never recovers. For associations between trading and liquidity network measures, during the post–Lehman Brothers subperiod, all pairwise correlations become positive as banks that remain in the e-MID become tightly interconnected, relying on each other for short-term funding.

Figure 5 depicts the generalized Impulse Response (IR) functions for one standard deviation innovation to each network variable for the full sample.[10] IRs indicate that network variables react to each other's innovations. In particular, trading network LSCC and reciprocity exhibit the largest responses to each other's innovations. Moreover, the LSCC and reciprocity from both trading and liquidity networks are highly connected (with the exception that liquidity network reciprocity and trading network LSCC are unrelated). These results corroborate our hypothesis that the two networks, though related, convey different information.

4 Characterizing Interbank Market Structure

Having demonstrated that trading and liquidity networks reflect different dimensions of interconnectedness, we compare higher-order community structure within each network. Specifically, we evaluate evidence for core-periphery topology in the trading and liquidity networks in light of the large literature establishing its prevalence in financial markets.[11] Fricke and Lux (2015) examine e-MID trading networks from 1999 to 2010 and find strong evidence for core-periphery structure in the trading network composed only of Italian banks. We extend this approach and derive new insights by analyzing subgraphs of each network by country in addition to confirming that the core-periphery structure extends to the entire network of all active e-MID banks.

With a core-periphery network, nodes can be classically grouped into either core or periphery. The banks composing the core are densely connected to each other compared with connections to peripheral banks. Further, peripheral banks are minimally connected

[10] For brevity, we report results for the full sample. Results for the four sub-samples are largely consistent with the results in table 2.

[11] Soramaki and others (2007) and Bech and Atalay (2008) document that the interbank network of U.S. commercial banks is sparse, with a core-periphery structure. Similar structures are found for interbank networks in Austria, Canada, Germany, Japan, and the United Kingdom. See also Boss and others (2004), Inaoka and others (2004), Embree and Roberts (2009), Craig and von Peter (2014), and Langfield, Liu, and Ota (2014), respectively. Core-periphery structure has also been found in credit default swaps markets of the United States (Markose, Giansante, and Shaghaghi, 2012) and the United Kingdom (Abel and Silvestri, 2017).

to each other. Different mathematical models capture these key characteristics (Borgatti and Everett, 2000). For example, discrete models explicitly assign banks to one of the groups, leading to a partitioning of the adjacency matrix (Craig and von Peter, 2014; Fricke and Lux, 2015). Here, we estimate the asymmetric continuous model of Boyd and others (2010), which allows for banks to have varying degrees of importance to the directed and weighted network.

Let A_{ij} be the weighted adjacency denoting the volume-weighted edge from bank i to bank j. Then, the asymmetric continuous model estimates an incoming coreness for each bank, $u_i \geq 0$, and an outgoing coreness for each bank, $v_i \geq 0$, with the following optimization problem:

$$\min_{u,v} \sum_i \sum_{j \neq i} \left(A_{ij} - u_i v_j\right)^2, \tag{1}$$

which can be solved using Singular Value Decomposition (SVD).[12] Define the percentage of reduced error (PRE) as

$$\text{PRE} = 1 - \frac{\sum_i \sum_{j \neq i} \left(A_{ij} - u_i v_j\right)^2}{\sum_i \sum_{j \neq i} \left(A_{ij} - \bar{A}\right)^2}, \tag{2}$$

where $\bar{A}$ is the average of all elements of A excluding the diagonal. To evaluate goodness of fit, we use the criteria from Boyd and others (2010), which states that the PRE should exceed 0.5 for evidence in favor of the core-periphery model.

Figure 6 shows the PRE obtained from estimating the model for the liquidity and trading networks. Several notable patterns emerge. First, the core-periphery model fits the trading network better than the liquidity network. The PRE is consistently about 10 percent higher for the trading network. Further, the liquidity network is never above

[12] See Boyd and others (2010) and Fricke and Lux (2015) for details. Because equation (1) searches for a rank 1 approximation of a non-negative matrix, two theorems from linear algebra establish that the optimal solution for the coreness vectors are the left and right singular vectors from SVD. The first is the Perron–Frobenius theorem, which guarantees that the principle singular vectors are non-negative when the matrix being decomposed is non-negative. Then the Eckart–Young theorem establishes that the SVD solution is optimal for the norm used in equation (1).

the 0.5 threshold, indicating that the core-periphery model does not fit the liquidity network well, as there appears to be no core of aggressive (or passive) liquidity providers. Interestingly, even for the trading network (for which a sizable literature shows a core-periphery structure), the model provides a good fit only in the weak recovery period—the PRE crosses the 0.5 threshold in late 2009.

Figure 7 shows evidence that the core-periphery structure is more prevalent within subgraphs composed of banks domiciled in the same country. Specifically, banks from Germany, Greece, France, and Italy traded with other banks of the same country such that a core of high centrality banks emerged.[13] The within-country core-periphery structure is consistently present in both liquidity and trading networks before the weak recovery period, which explains why, when analyzed as a whole, a model that assumes a single core does not fit these networks well. These novel findings have important implications for empirical analysis given the prominence of emergent core-periphery structures in the theoretical financial networks literature.

To rigorously test for multiple and overlapping core-periphery structures, we estimate the Cluster Affiliation Model of Yang and Leskovec (2014), a model that essentially expands the coreness score into a multidimensional vector (one score for each community) that determines connection probabilities. The model can be fit using a form of non-negative matrix factorization (Yang and Leskovec, 2013), which allows for principled selection of the number of communities via cross-validation (Owen and Perry, 2009; Mankad and Michailidis, 2013). Figure 8 shows the optimal number of communities according to cross-validation is three in the pre-crisis era for both networks. The number of communities decreases midway through the first crisis subperiod before stabilizing at a single core-periphery structure for the trading network and two for the liquidity

[13] The core-periphery model is applied at the country level only when a sufficient number of within-country transactions (at least 10 transactions) form a meaningful subgraph. The four countries presented have the highest number of days with such subgraphs.

network. Thus, the structure in the e-MID trading networks before 2010 and the liquidity networks over the entire data span resembles the stylized representation in figure 9 of overlapping core-periphery subgraphs. The results also provide empirical evidence aligned with the theoretical predictions of star-shaped networks made in Babus and Hu (2017), Castiglionesi and Eboli (2018), and Castiglionesi and Navararro (2020).

5 Forecasting Macrovariables

Having established that trading and liquidity networks reflect distinct dimensions of interconnectedness and structure, we further assess whether and how these differences might be useful in forecasting short-term macroeconomic conditions. Importantly, our data cover interbank trades in the euro zone surrounding the 2007–09 financial crisis so we explore whether a multidimensional analysis of interbank trading behavior during this turbulent period might prove useful for extracting information relevant to policymakers and others.

As we previously show, interconnectedness computed from both trading and liquidity networks generally falls from 2006 through 2012, but the levels and dynamics of the interconnectedness metrics differ between the two network types over time. These forecasting exercises are intended to examine whether the liquidity networks incorporating the aggressiveness of trades reflect incrementally more information than the trading networks. To test this conjecture, we use connectedness metrics from both networks to forecast various macroeconomic variables.[14]

These forecast exercises address the question concerning which dimension of liquidity more closely ties to the real economy. Along the lines of Babus and Hu (2017), who note that informational frictions affect how networks develop, we examine three general types

[14] Several works provide a theoretical basis for networks to align with economic conditions. Elliott, Georg, and Hazell (2018) show that interconnectedness among German banks allowed economic shocks to propagate during the recent financial crisis. Likewise, Safonova (2017) links shocks to bank networks with the real sector. Kopytov (2018) develops a dynamic general equilibrium model wherein financial interconnectedness endogenously changes over the business cycle.

of macroeconomic variables, differing by informational type: (1) hard information, such as industrial production and retail sales; (2) soft information, such as the purchasing managers index (PMI); and (3) regional and country-specific yield spreads. For the regional spread, we examine the spread between the euro-area interbank offered rate and the overnight index swap (the EURIBOR-OIS spread), a measure of health of the banking system. Our country-specific spreads include the spread between the 10-year Greek, Italian, Portuguese, and Spanish government bond yields and the German government bond yield.[15]

In Babus and Hu (2017), soft information between counterparties plays a role in how networks develop.[16] In this framework, we conjecture that soft macroeconomic information will be more likely reflected in banks' trading aggressiveness and, therefore, incrementally more important in the liquidity network. Similarly, given the likelihood of information asymmetries across borders, we expect that trading aggressiveness (and the liquidity network, more generally) will better forecast country-specific yield spreads in the euro zone.

With hard information that is more publicly verifiable to all banks, the liquidity network may add no incremental explanatory forecasting power. Likewise, given that all e-MID banks operate within the same euro zone, we conjecture that information asymmetries (among banks) about the EURIBOR-OIS spread are minimal except potentially during crisis subperiods when information asymmetries are higher. Therefore, we expect improvement in forecasts of the EURIBOR-OIS spreads during the crisis subperiods and no incremental improvement during the weak recovery subperiod when we include trade aggressiveness via the liquidity network.

[15] When levels of these macrovariables are not stationary, we consider the first difference.
[16] Bańbura and Rünstler (2011) also show that soft information may be important in forecasting.

With these conjectures in mind, we produce one-step-ahead forecasts for macrovariables using the following model:

$$z_{i,t} = \gamma_0 + \gamma_1 Degree_{g,t-1} + \gamma_2 CC_{g,t-1} + \gamma_3 Reciprocity_{g,t-1} + \gamma_4 LSCC_{g,t-1} + \beta z_{i,t-1} + u_{i,t} \ , \quad (3)$$

where $z_{i,t}$ represents each macrovariable described earlier (we consider one variable at a time) and the subscript g denotes the network type. Table 3 reports the out-of-sample root mean square forecasting error from equation (3) for each subperiod, where the model is estimated using an extending window from January 2006 until the end of the previous subperiod.

Consistent with the conjecture that interbank liquidity can affect the real economy, we find strong evidence that the statistics derived from liquidity networks generally produce forecasts that are statistically preferred over forecasts produced from trading network statistics. Focusing first on the crisis subperiods, we find that liquidity network forecasts are statistically preferred over those generated by the trading network for the country-specific yield spreads and the EURIBOR-OIS spread, as assessed by Diebold–Mariano tests. In contrast, the liquidity network forecast does not consistently add incremental explanatory power over the trading network forecast for hard information (industrial production and retail sales).

For the weak recovery subperiod, the liquidity network forecast adds incremental explanatory power over the trading network forecast for soft macroeconomic information (PMI), the Portuguese yield spread, and a form of hard information (industrial production). The trading network forecasts are statistically preferred for the EURIBOR-OIS spread and the remaining country-specific yield spreads.

As we conjecture, and consistent with liquidity networks capturing greater information asymmetries between banks, we find that the incremental information reflected in liquidity networks largely improves short-term forecasting only when macroeconomic information is soft or may be more susceptible to asymmetric information (here, country-specific credit information).

For policymakers, these results show that the interbank market provides valuable information about the future state of the economy, consistent with trading network results in Brunetti and others (2019). Importantly, however, we show that liquidity networks provide incrementally more valuable information in forecasting soft macroeconomic variables and country-specific yield spreads. In this regard, our results suggest that monitoring both types of interbank networks provides a more comprehensive view and better forecasts of the banking sector and the real economy, particularly when information asymmetries in the market may be large. Trading networks capture important borrowing/lending activity, whereas liquidity networks more specifically capture the urgency to borrow/lend (the dynamics of liquidity demand/supply).

6 Networks, Volume, and Volatility

How information percolates through financial markets has long been a central theme in the finance literature. Historically, the discussion anchored around the relation between price volatility and trading volume as the key variables capturing information.[17] The Kyle (1985) and Glosten and Milgrom (1985) models show how private information is embedded into prices. Our evidence presented earlier shows that trading and liquidity networks convey different information, despite that both are generated by the same trading process. Therefore, in this section, we empirically examine the linkages among volume, volatility and network variables.

For each subperiod using daily data, we estimate a vector autoregression (VAR) with liquidity network LSCC and reciprocity, trading network LSCC and reciprocity,

[17] More precisely, price changes follow a mixture of distributions, and volume is the mixing variable.

trading volume, and price volatility.[18] We are interested in the impulse response functions and, for the time being, we are agnostic about the identification strategy, so we use the generalized impulse responses of Pesaran and Shin (1998).

Figure 10 depicts the IRs of volatility and volume to one standard deviation innovations to network variables and *vice versa*, for the pre-crisis period. Volatility and volume generally increase with interconnectedness. In these normal market conditions, when interconnectedness is already elevated (see figure 3), a further rise in market connectivity increases volatility. This result is to be expected if too much interconnectedness increases contagion and systemic risk in the market. In fact, interconnectedness is one of the five criteria used by regulators for designating global systemically important banks.[19]

During the pre-crisis period, the LSCC of both liquidity and trading networks does not significantly respond to innovations in volume and volatility. Only reciprocity increases in response to innovations in volatility.

In figure 11, we report the same analyses for the Crisis 2 period (September 16, 2008, to April 1, 2009), unarguably the most critical period for Europe because it coincides with the beginning of the so-called sovereign debt crisis involving many peripheral economies. This subperiod is characterized by low interconnectedness (see figure 3), low trading volume, and high volatility (see figure 1). During this crisis period, innovations to liquidity network LSCC reduce volatility and increase volume, highlighting that in stressful times, interconnectedness is beneficial to the market. These results also underscore the dual nature of interconnectedness: Too much interconnectedness may increase systemic risk, but too little may impede market functioning. Interestingly, liquidity networks seem to capture well this characteristic of network connections.

[18] For volatility, we use the daily log-price range. In each subperiod, we ensure that all variables are stationary and select optimal lag length using the Akaike information criterion.
[19] See Bank for International Settlements, Basel Committee on Banking Supervision (2014).

Two more results are worth mentioning: (1) Innovations to trading network variables do not have any statistically significant effect on volume and volatility, and (2) innovations to volatility and volume do not generate any significant response from trading and liquidity network interconnectedness measures.

While these results stem from the generalized VAR identification structure, evidence (Adamic and others, 2017) suggests that network variables are primitive to volatility and volume because the price process is measured with error (for example, bid-ask bounce), whereas network variables are quantified more precisely. Based on this insight, we run the VAR analysis using a Cholesky decomposition where innovations to network variables affect volume and volatility but not vice versa. The results are very similar to those reported in figures 10 and 11.[20]

7 Conclusions

During the past decade, network analysis has grown as a major research thrust in financial economics. Researchers have aimed to better understand how interconnectedness between market participants results in spillovers, amplifies or absorbs shocks, and creates other nonlinearities that ultimately affect key markers of market health. In this paper, we benchmark to Babus and Hu (2017) and Castiglionesi and Eboli (2018) to explore the incremental informational content of different networks composed from the same set of interbank trades. More specifically, we propose a new network construct, the liquidity network (based on the aggressiveness of supplying and demanding liquidity), and use it to examine connectedness in the physical overnight-lending market in Europe.

We show how trading and liquidity networks complement each other to characterize interconnectivity in the interbank market. Generating liquidity and trading

[20] Moreover, we flip the Cholesky factorization and assume that shocks to volume and volatility feed into network variables but not vice versa and obtain similar results. Results for the Crisis 1 and weak recovery periods are in line with what we presented in figures 10 and 11.

networks from the same set of overnight interbank transactions, we demonstrate that the directed edges that differ between these networks produce meaningful differences in network interconnectedness measures. We also establish that the interbank networks of Europe reflect core-periphery structures within countries but not across the continent. Across the euro zone, there are multiple, overlapping cores of aggressive (or passive) liquidity-providing banks, whereas post-crisis trading networks exhibit a classical single core-periphery structure.

The fact that the liquidity network includes incremental information about trade aggressiveness in the market allows us to test whether and how this dimension of trade affects short-term market forecasts. Consistent with network models that reflect information asymmetries, we find that the liquidity network better forecasts soft macroeconomic information and country-specific yield spreads in Europe.

These differences are important for policymakers in that statistics generated through the liquidity network outperform similar statistics from the trading network when employed in forecasting these macrovariables. In this light, liquidity networks more closely capture financial market liquidity dynamics that tie to the real economy, particularly in settings where information asymmetries are higher. These findings motivate future work in developing unified financial network methods that jointly model different network types.

In this spirit, we also study how these two network constructs relate to volume and volatility. We find that in normal market conditions, a further increase in connectivity of either network increases volatility. In crisis periods, an increase in liquidity network connectivity reduces volatility and increases traded volume. Altogether, our findings contribute to a better understanding of how interbank markets operate, convey information about the real economy, and demonstrate that viewing financial networks under different lenses provides important insights into market structure and the macroeconomy.

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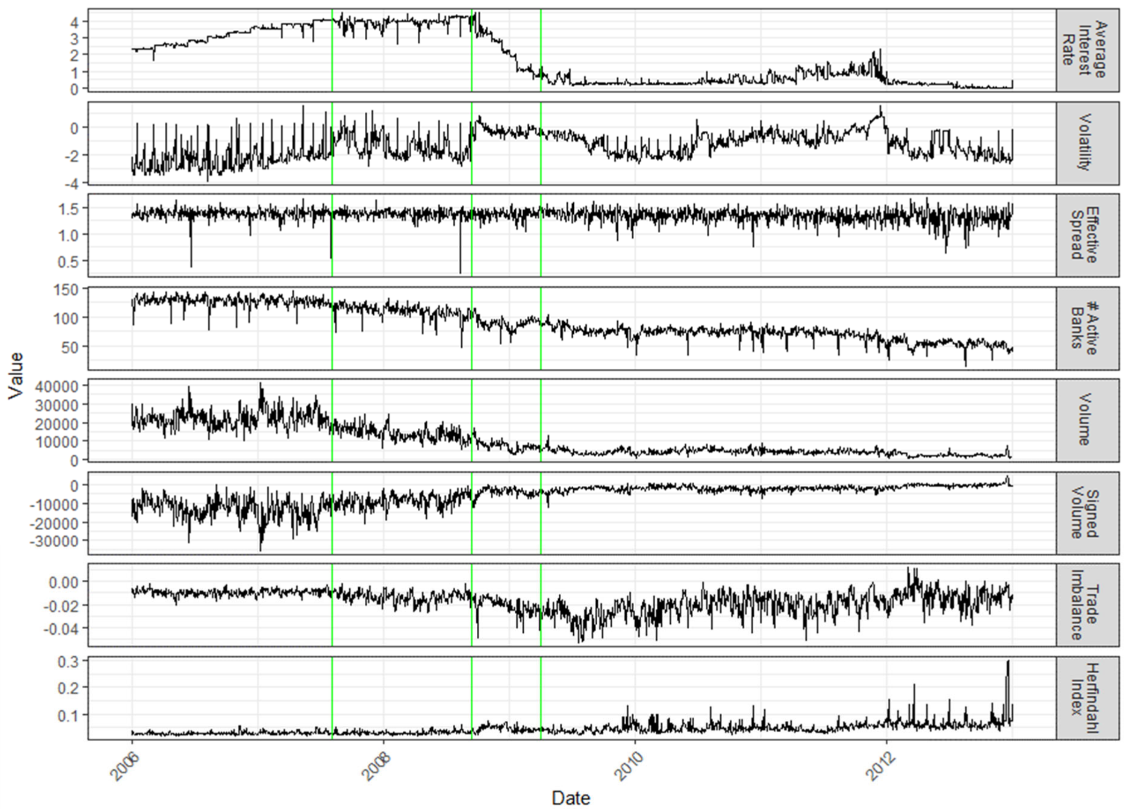


Figure 1: Financial statistics at the daily resolution from the e-MID interbank market. Vertical lines mark subperiods: Pre-crisis, January 2, 2006, to August 7, 2007 (when the European Central Bank (ECB) noted worldwide liquidity shortages); Crisis Period 1 (pre-Lehman Brothers), August 8, 2007, to September 12, 2008; Crisis Period 2 (post-Lehman), September 16, 2008, to April 1, 2009 (when the ECB announced the end of the recession); weak recovery period, April 2, 2009, to December 31, 2012.

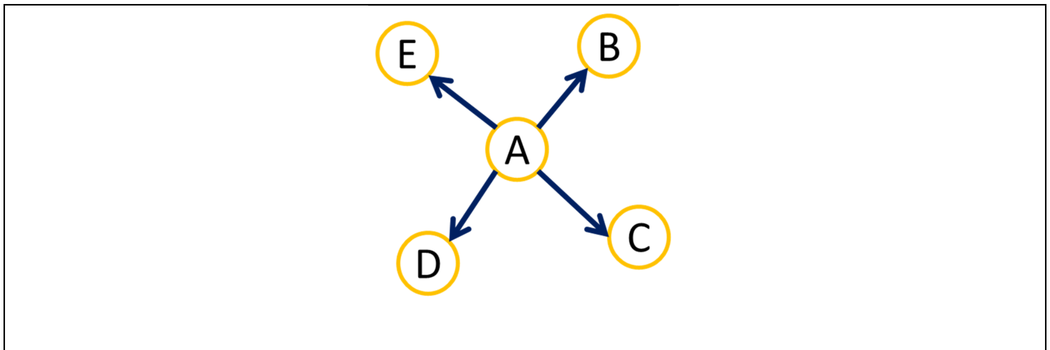


Figure 2A: A hypothetical *trading network*, where the banks (nodes) are labeled A through E. Directed edges represent loans from Bank A to other banks.

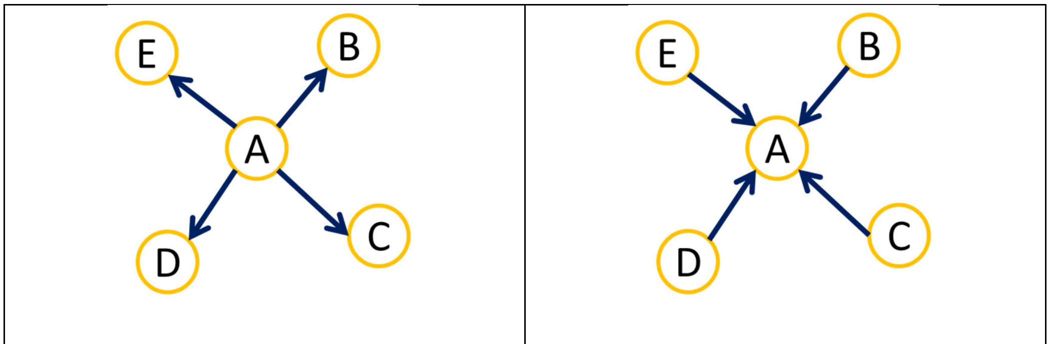


Figure 2B: Two hypothetical *liquidity networks*, where the banks (nodes) are labeled A through E. Directed edges represent active loans from Bank A to other passive banks (left panel) or where Banks B, C, D, and E actively borrow from Bank A by hitting posted quotes (right panel).

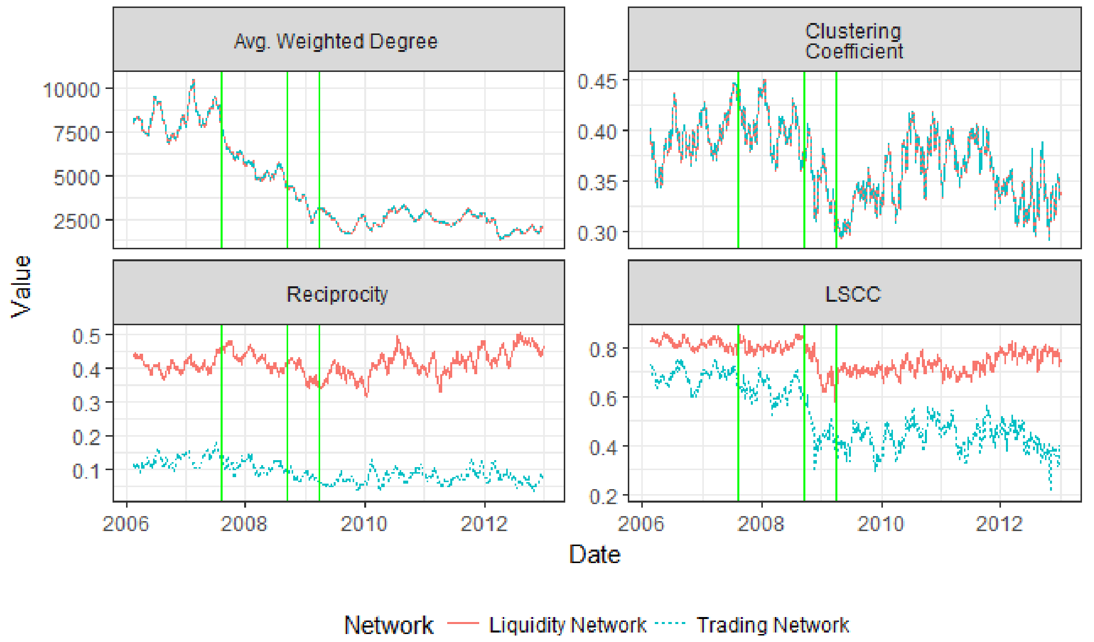


Figure 3: Network statistics corresponding to 30-day rolling liquidity (solid red) and trading (dashed blue) networks from the e-MID interbank market. Vertical lines mark subperiods: Pre-crisis, January 2, 2006, to August 7, 2007 (when the European Central Bank (ECB) noted worldwide liquidity shortages); Crisis Period 1 (pre-Lehman Brothers), August 8, 2007, to September 12, 2008; Crisis Period 2 (post-Lehman), September 16, 2008, to April 1, 2009 (when the ECB announced the end of the recession); weak recovery period, April 2, 2009, to December 31, 2012.

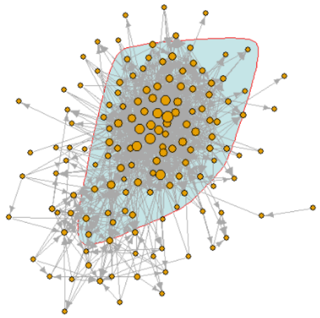
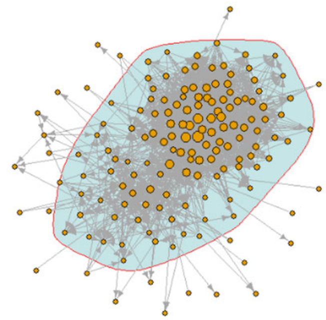
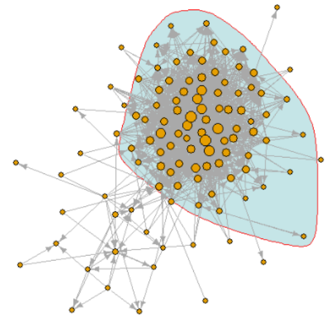
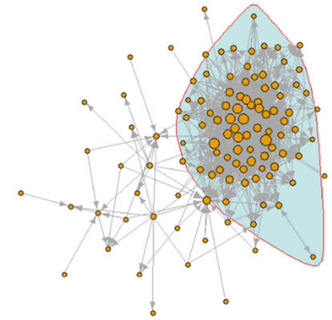
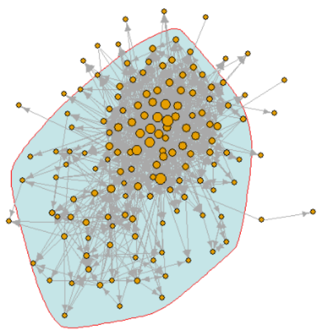
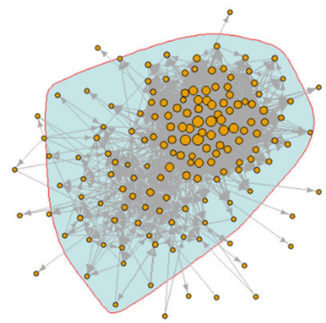
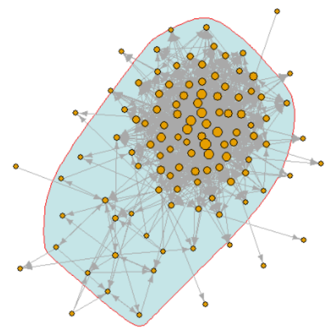
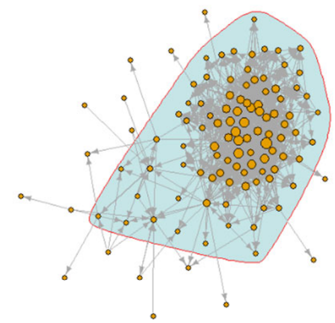
	Pre-Crisis	**Crisis 1**	**Crisis 2**	**Weak Recovery**
Trading Network				
Liquidity Network				
Network Statistics for Each Exemplar Network				
Degree	8,119	5,652	2,468	2,325
Clustering Coef.	0.393	0.438	0.406	0.353
Trading LSCC	0.726	0.683	0.522	0.389
Liquidity LSCC	0.817	0.789	0.752	0.699
Trading Reciprocity	0.113	0.123	0.095	0.061
Liquidity Reciprocity	0.434	0.442	0.394	0.399

Figure 4: Exemplar Networks and Statistics constructed using a 30-day rolling window from each subperiod. Nodes (banks) in the blue area compose the largest strongly connected component. *Degree*, *clustering,* the *largest strongly connected component* (*LSCC*), and *reciprocity* are computed as defined in section 3.

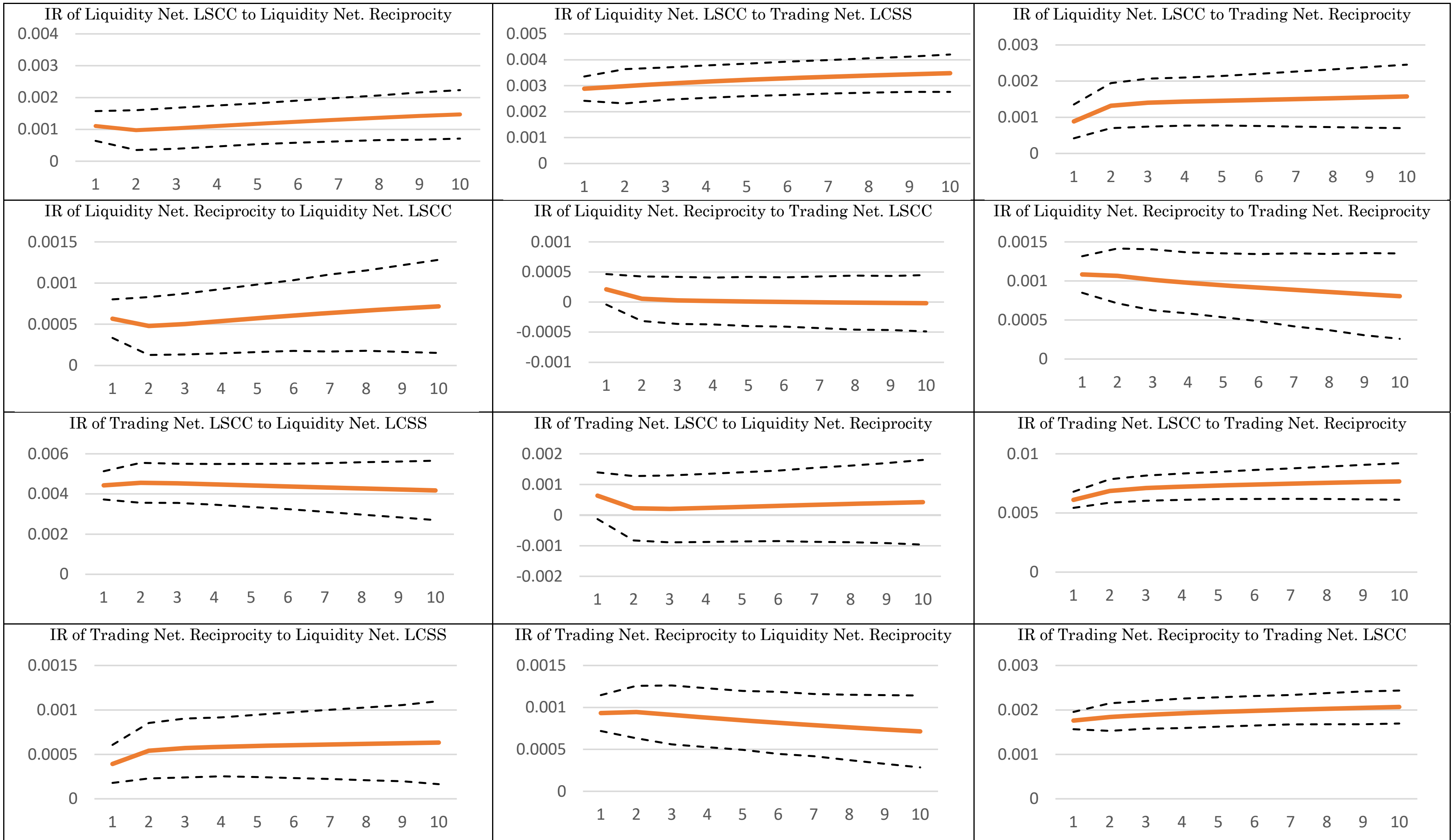


Figure 5: 10-Day Generalized Impulse Responses (IR) of network variables to one standard deviation innovations. Optimal lag length is 2 and is selected with Akaike information criterion. Standard errors: Monte Carlo (1,000 repetitions). Full sample.

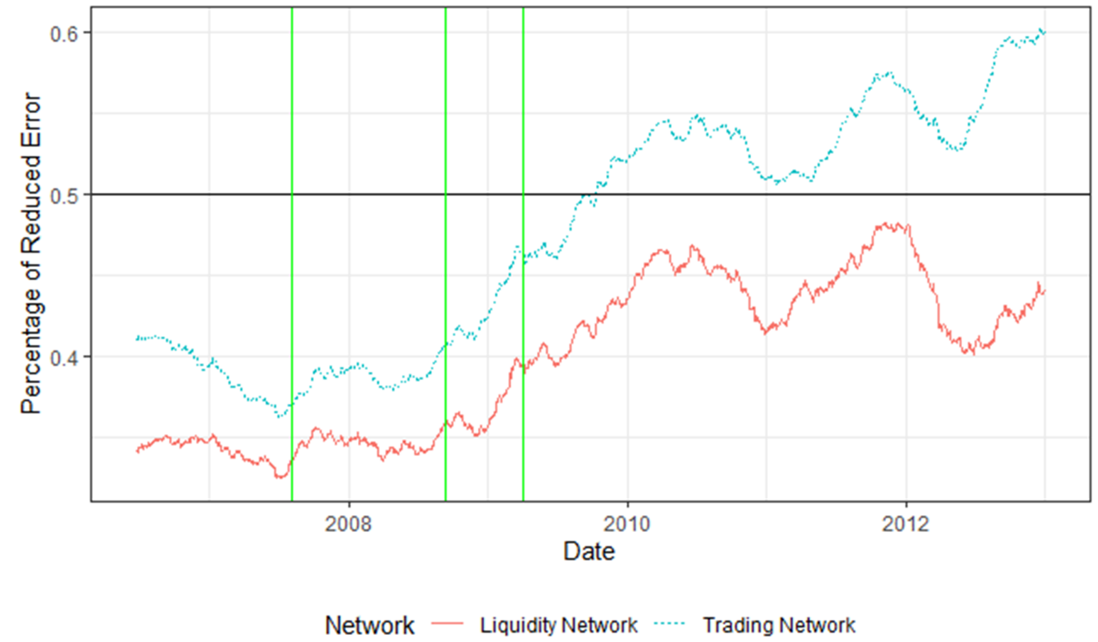


Figure 6: The percentage of reduced error from estimating the asymmetric continuous core-periphery model for the liquidity (solid red) and trading (dashed blue) networks from the e-MID interbank market. Values above 0.5 provide evidence for the core-periphery model. Vertical lines mark subperiods: Pre-crisis, January 2, 2006, to August 7, 2007 (when the European Central Bank (ECB) noted worldwide liquidity shortages); Crisis Period 1 (pre-Lehman Brothers), August 8, 2007, to September 12, 2008; Crisis Period 2 (post-Lehman), September 16, 2008, to April 1, 2009 (when the ECB announced the end of the recession); weak recovery period, April 2, 2009, to December 31, 2012.

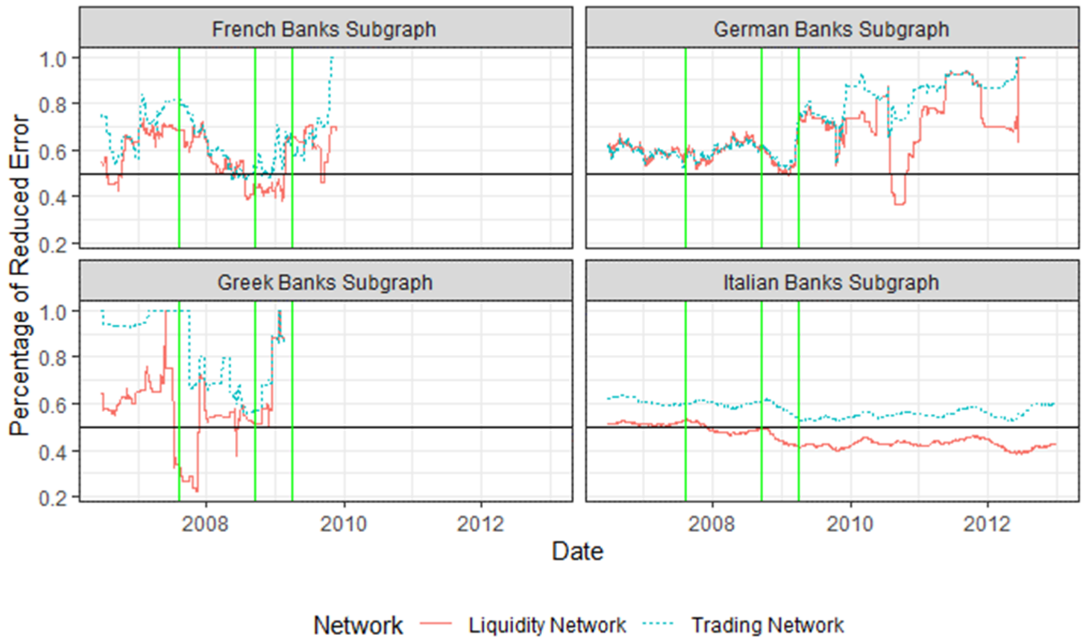


Figure 7: The percentage of reduced error from estimating the asymmetric continuous core-periphery model for country subgraphs on the liquidity (solid red) and trading (dashed blue) networks from the e-MID interbank market. Values above 0.5 provide evidence for the core-periphery model. Vertical lines mark subperiods: Pre-crisis, January 2, 2006, to August 7, 2007 (when the European Central Bank (ECB) noted worldwide liquidity shortages); Crisis Period 1 (pre-Lehman Brothers), August 8, 2007, to September 12, 2008; Crisis Period 2 (post-Lehman), September 16, 2008, to April 1, 2009 (when the ECB announced the end of the recession); weak recovery period, April 2, 2009, to December 31, 2012.

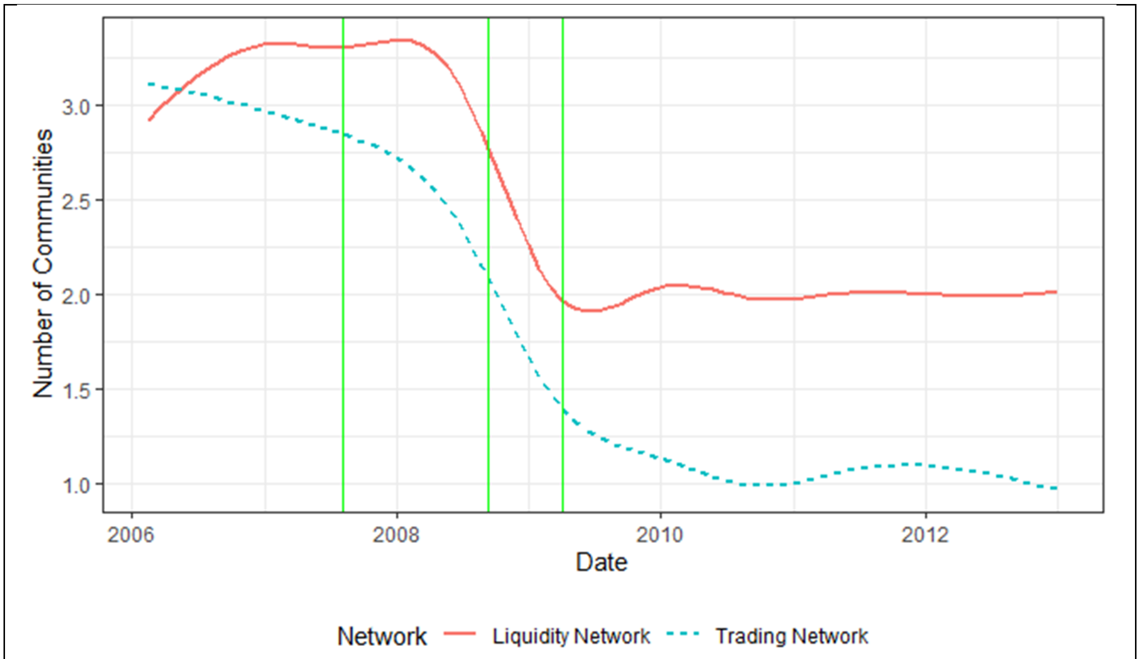


Figure 8: The optimal daily number of communities using the Cluster Affiliation Model on the liquidity (solid red) and trading (dashed blue) networks from the e-MID interbank market. A smoothed version by local polynomial regression is shown for readability. Vertical lines mark subperiods: Pre-crisis, January 2, 2006, to August 7, 2007 (when the European Central Bank (ECB) noted worldwide liquidity shortages); Crisis Period 1 (pre-Lehman Brothers), August 8, 2007, to September 12, 2008; Crisis Period 2 (post-Lehman), September 16, 2008, to April 1, 2009 (when the ECB announced the end of the recession); weak recovery period, April 2, 2009, to December 31, 2012.

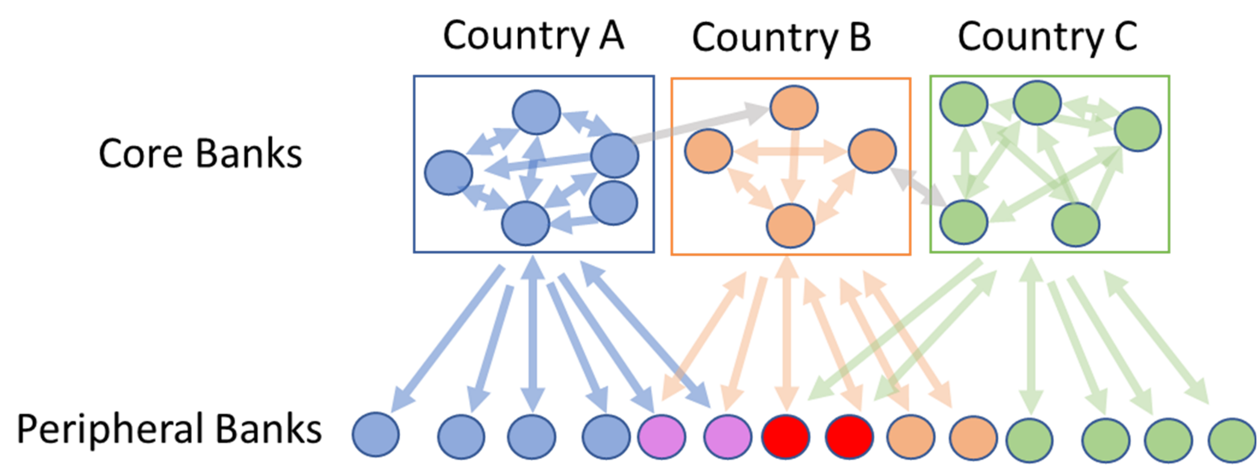


Figure 9: Stylized representation of the e-MID liquidity and trading networks, where there exist multiple and overlapping core-periphery structures organized by country. Colors represent different communities that result from the overlapping subgraphs.

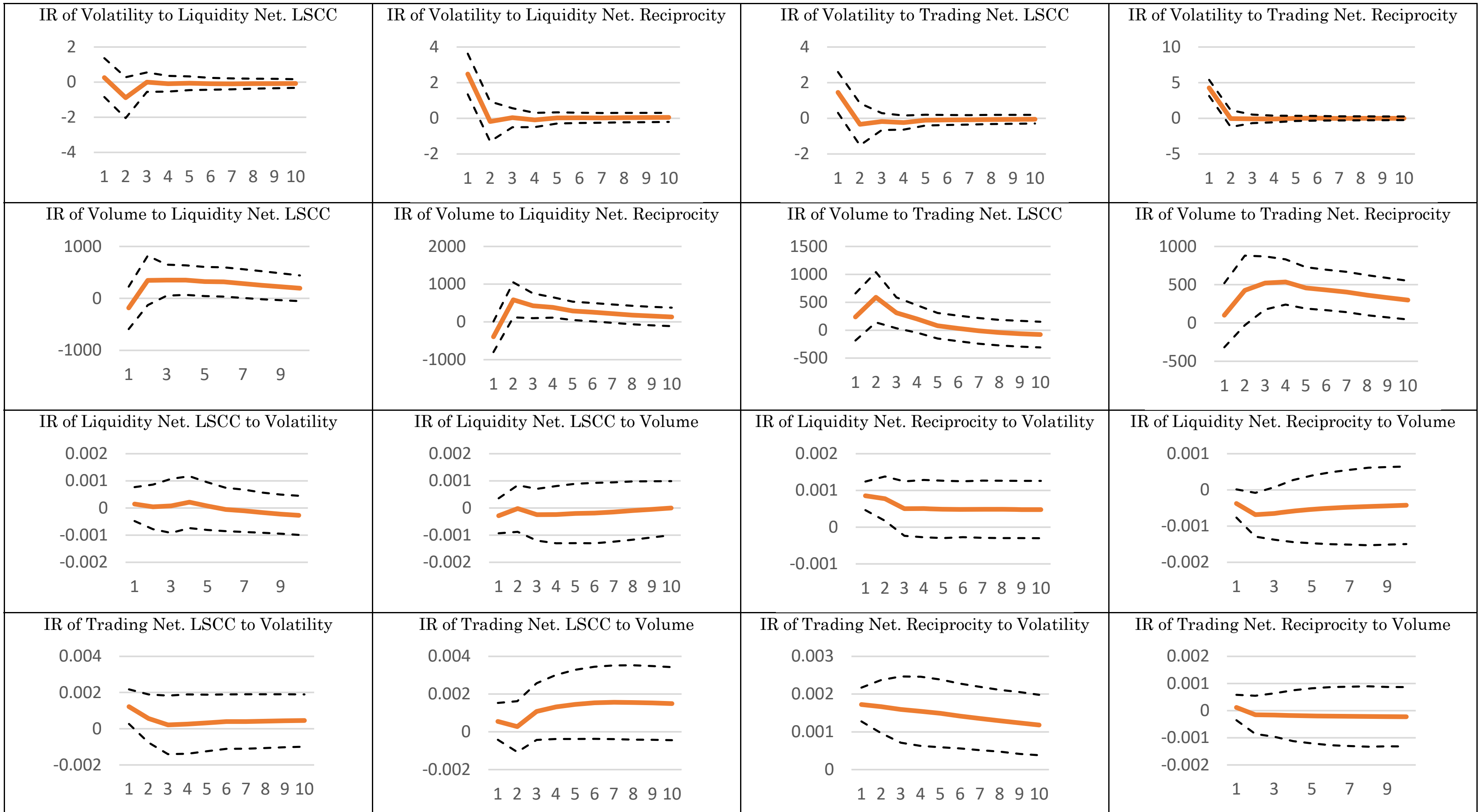


Figure 10: **10-Day Generalized Impulse Responses** (IR) of volume, volatility, and network variables to one standard deviation innovations. Optimal lag length is 2 and is selected with AIC. Standard errors: Monte Carlo (1,000 repetitions). Pre-crisis period January 2, 2006, to August 7, 2007 (when the European Central Bank noted worldwide liquidity shortages).

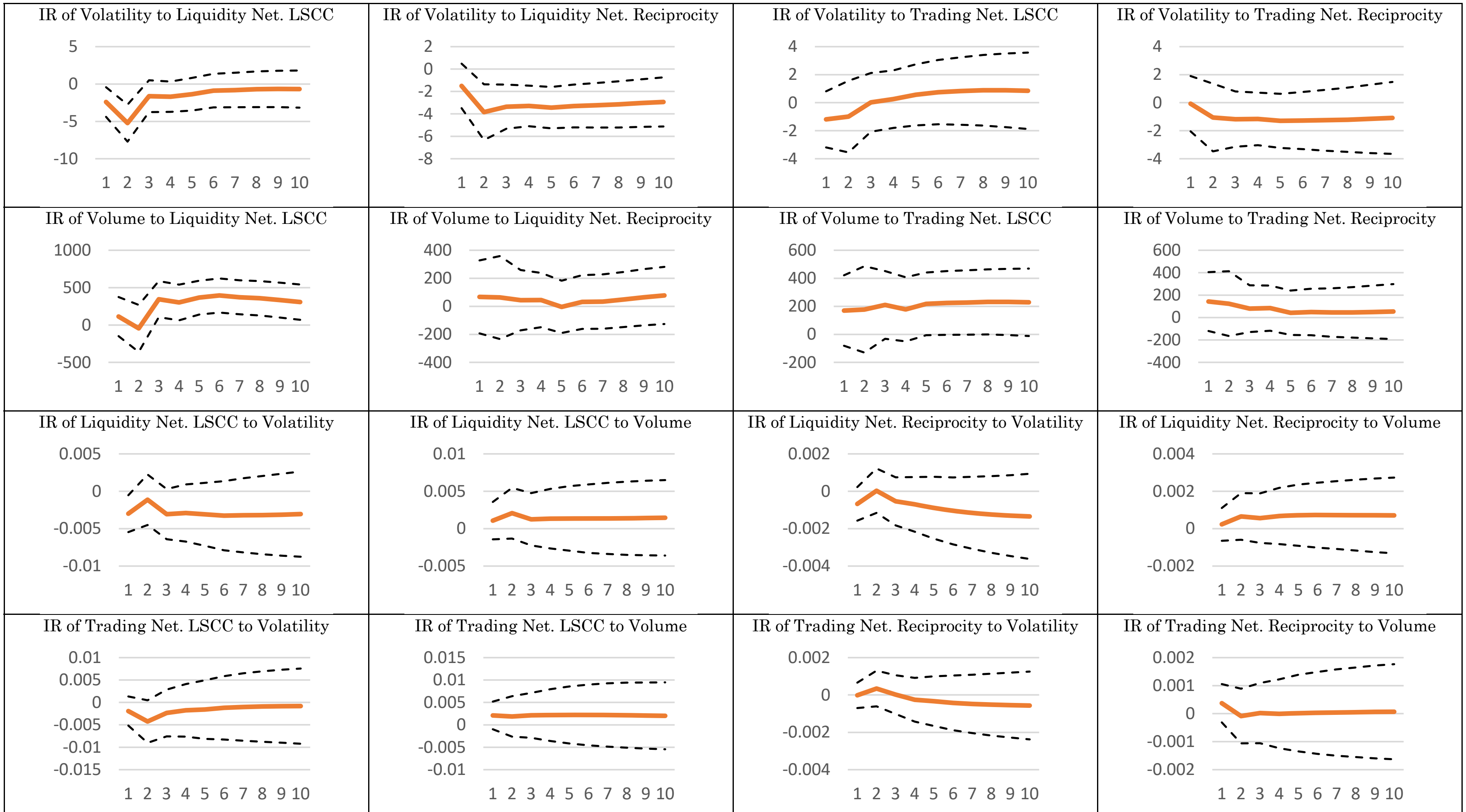


Figure 11: **10-Day Generalized Impulse Responses** (IR) of volume, volatility, and network variables to one standard deviation innovations. Optimal lag length is 2 and is selected with AIC. Standard errors: Monte Carlo (1,000 repetitions). Crisis 2 period (post-Lehman Brothers), September 16, 2008, to April 1, 2009 (when the European Central Bank announced the end of the recession).

	Trading network			Liquidity network		
	Pre-crisis			**Pre-crisis**		
	2-Jan-06 to 8-Aug-07			**2-Jan-06 to 8-Aug-07**		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
LSCC	0.683	0.687	0.035	0.817	0.817	0.019
Reciprocity	0.126	0.125	0.020	0.411	0.408	0.020
Degree	8361	8254	815.8	8361	8254	815.8
Clustering Coef.	0.394	0.391	0.023	0.394	0.391	0.023
	Crisis 1			**Crisis 1**		
	9-Aug-07 to 12-Sep-08			**9-Aug-07 to 12-Sep-08**		
LSCC	0.630	0.630	0.039	0.808	0.806	0.022
Reciprocity	0.110	0.108	0.017	0.432	0.431	0.027
Degree	5637	5605	744.3	5637	5605	744.3
Clustering Coef.	0.404	0.403	0.022	0.404	0.403	0.022
	Crisis 2			**Crisis 2**		
	16-Sep-08 to 1-Apr-09			**16-Sep-08 to 1-Apr-09**		
LSCC	0.461	0.449	0.066	0.713	0.700	0.064
Reciprocity	0.078	0.077	0.015	0.390	0.390	0.028
Degree	3482	3572	625.2	3482	3572	625.2
Clustering Coef.	0.349	0.351	0.028	0.349	0.351	0.028
	Weak Recovery			**Weak Recovery**		
	2-Apr-09 to 31-Dec-12			**2-Apr-09 to 31-Dec-12**		
LSCC	0.434	0.438	0.058	0.732	0.723	0.038
Reciprocity	0.074	0.073	0.020	0.419	0.418	0.039
Degree	2351.	2382	474	2351	2382	474
Clustering Coef.	0.353	0.351	0.030	0.353	0.351	0.030

Table 1: Summary statistics of the network metrics within each subperiod by network type.

Note. LSCC = largest strongly connected component.

Panel A: Pre-crisis Correlations, January 2, 2006, to August 7, 2007

		Trading Network				Liquidity Network			
		LSCC	Reciprocity	Degree	Clustering Coefficient	LSCC	Reciprocity	Degree	Clustering Coefficient
Trading Network	LSCC	1.000	0.155	0.345	0.238	0.262	0.019	0.345	0.238
	Reciprocity		1.000	0.355	0.846	-0.472	0.198	0.355	0.846
	Degree			1.000	0.431	-0.151	0.226	1.000	0.431
	Clustering Coefficient				1.000	-0.446	0.291	0.431	1.000
Liquidity Network	LSCC					1.000	-0.163	-0.151	-0.446
	Reciprocity						1.000	0.226	0.291
	Degree							1.000	0.431
	Clustering Coefficient								1.000

Panel B: Crisis 1 Correlations, August 8, 2007, to September 12, 2008

		Trading Network				Liquidity Network			
		LSCC	Reciprocity	Degree	Clustering Coefficient	LSCC	Reciprocity	Degree	Clustering Coefficient
Trading Network	LSCC	1.000	0.736	0.350	0.681	0.327	0.025	0.350	0.681
	Reciprocity		1.000	0.359	0.792	0.138	0.252	0.359	0.792
	Degree			1.000	0.506	-0.037	0.616	1.000	0.506
	Clustering Coefficient				1.000	-0.054	0.331	0.506	1.000
Liquidity Network	LSCC					1.000	-0.296	-0.037	-0.054
	Reciprocity						1.000	0.616	0.331
	Degree							1.000	0.506
	Clustering Coefficient								1.000

Panel C: Crisis 2 Correlations, September 16, 2008, to April 1, 2009

		Trading Network				Liquidity Network			
		LSCC	Reciprocity	Degree	Clustering Coefficient	LSCC	Reciprocity	Degree	Clustering Coefficient
Trading Network	LSCC	1.000	0.658	0.461	0.696	0.560	0.399	0.461	0.696
	Reciprocity		1.000	0.455	0.826	0.348	0.338	0.455	0.826
	Degree			1.000	0.692	0.681	0.796	1.000	0.692
	Clustering Coefficient				1.000	0.419	0.475	0.692	1.000
Liquidity Network	LSCC					1.000	0.893	0.681	0.419
	Reciprocity						1.000	0.796	0.475
	Degree							1.000	0.692
	Clustering Coefficient								1.000

Panel D: Weak Recovery Correlations, April 2, 2009, to December 31, 2012

		Trading Network				Liquidity Network			
		LSCC	Reciprocity	Degree	Clustering Coefficient	LSCC	Reciprocity	Degree	Clustering Coefficient
Trading Network	LSCC	1.000	0.682	0.234	0.531	0.085	0.051	0.234	0.531
	Reciprocity		1.000	0.147	0.542	0.232	0.168	0.147	0.542
	Degree			1.000	0.347	-0.170	-0.156	1.000	0.347
	Clustering Coefficient				1.000	-0.144	0.057	0.347	1.000
Liquidity Network	LSCC					1.000	0.563	-0.170	-0.144
	Reciprocity						1.000	-0.156	0.057
	Degree							1.000	0.347
	Clustering Coefficient								1.000

Table 2: Correlation matrix by subperiod between network statistics computed at the daily level using a 30-day rolling window.

Note. LSCC = largest strongly connected component.

	Crisis 1			Crisis 2			Weak Recovery		
	Liquidity Network	**Trading Network**	**Difference**	**Liquidity Network**	**Trading Network**	**Difference**	**Liquidity Network**	**Trading Network**	**Difference**
Hard information									
Δ(IP)	3.853	3.914	-0.060	12.526	12.053	0.473	3.809	4.132	-0.323**
Δ(RS)	1.941	2.055	-0.114	1.099	1.268	0.169*	2.323	2.286	0.037**
Soft information									
Δ(PMI)	2.728	1.827	0.901	6.906	6.433	0.473	6.167	7.309	-1.142**
Banking system health									
EURIBOR-OIS Spread	0.072	0.073	-0.001**	0.080	0.082	-0.002*	0.044	0.042	0.002**
Country-specific spreads									
ITSP	1.377	1.923	-0.546**	7.923	7.660	0.263**	1.364	1.131	0.233**
PTSP	3.012	2.279	0.733**	1.035	1.064	-0.029**	5.848	5.939	-0.091**
GRSP	2.279	2.540	-0.261**	5.045	5.126	-0.081**	4.931	3.623	1.308**
SPSP	5.358	6.669	-1.311**	6.317	6.653	-0.336**	1.916	1.310	0.606**

Table 3: Forecasting performance of each network by subperiod, where root mean square forecasting error is computed for 1-step ahead forecasts using the model in equation (3) trained on data from January 2006 to the end of the previous subperiod. At the monthly level is industrial production (IP), retail sales (RS), and the purchasing managers index (PMI). At the daily level is the spread between the euro-area interbank offered rate and the overnight index swap Rate (EURIBOR-OIS spread) and spreads between the 10-year Italian, Portuguese, Greek, and Spanish government bond yields and the 10-year German government bond yields (ITSP, PTSP, GRSP, and SPSP, respectively). Asterisks denote significance at the 5 percent and 1 percent levels from the Diebold–Mariano test.