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Networks, interconnectedness, and interbank information asymmetry☆

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ABSTRACT

We explore interconnectedness in the interbank overnight lending market and propose the liquidity network and the urgent borrower network which capture the urgency to trade. The liquidity network connects the initiating party in a trade to the passive party, while the urgent borrower network connects passive sellers (lenders) to urgent buyers (borrowers). Along with the buyer/seller trading network, we show these networks complement each other, revealing valuable information that improves short-term forecasts of soft and hard information and country-specific yield spreads. Connectivity increases in these networks during raises volatility and boosts volume, revealing the dual nature of interconnectedness—too much interconnectedness may increase systemic risk, but too little may impede market functioning.

1. Introduction

Network analysis is a proven and effective tool to assess and understand financial markets. In fact, interconnectedness increases contagion and network connections can create channels for contagion among banks, increasing and systemic risk (Glasserman and Young, 2015, 2016). 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. Empirical evidence in Brunetti et al. (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 posit that trade aggressiveness both provides additional information and serves as a commitment device (i.e. aggressive orders de facto commit to trade) in a market without intermediaries.

We expand on the notion that information is important in forming networks and trace the evolution of the e-MID OTC interbank lending market from 2006 through 2012, an important period spanning the 2007–08 financial crisis. Rather than simply constructing trading networks between buyers and sellers, we define two new networks: (i) liquidity networks as directed networks that map aggressive banks (conceptually equivalent to using "market orders") to their passive counter-party in the overnight-lending market and (ii) urgent borrower networks connecting aggressive borrowers to passive lenders.[1] Both liquidity and urgent borrower networks capture the urgency to trade by using trade aggressiveness, helping to overcome limited commitment and limited counterparty information frictions in the OTC market. Importantly for the interbank market, daily regulatory capital requirements create strong incentives for distributing overnight funds among banks, with liquidity and urgent borrower networks reflecting market-wide liquidity conditions among banks.

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[1] While e-MID data does not allow automated execution or "market orders" per se, we classify passive/aggressive trades based on their relation to standing quotes. 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).

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Importantly, though the same set of overnight interbank transactions generates all three types of networks, we expect different network topologies among the three since the urgency to trade adds information beyond trade direction.[2] Our work identifies liquidity and urgent borrower networks as alternative dimensions for viewing financial markets: The urgency to trade reflected in these networks represents information that differs from, and complements, information gleaned from trading networks.

We first explore structural differences among trading, liquidity, and urgent borrower networks. We demonstrate that the structures of the three networks differ—the standard core-periphery model with a single core does *not* fit the interbank market well. In fact, using the Cluster Affiliation Model (a method novel to financial network analysis) we provide rigorous evidence that each network is composed of multiple and overlapping core-periphery structures organized by country. Each network has three overlapping cores before the crisis, but following the 2008 collapse of Lehman Brothers, the number of cores decreases to one for the trading network and two for the liquidity and urgent borrower networks.

To the best of our knowledge, the existence of multiple cores of banks is new to the empirical financial networks literature and aligns with theoretical predictions made in several recent works, including Babus and Hu (2017), Castiglionesi and Eboli (2018), and Castiglionesi and Navarro (2020). Castiglionesi and Navarro (2020), for instance, show that core-periphery networks emerge in equilibrium within the interbank market and optimally balance the trade-off of higher payouts versus bankruptcy risk faced by banks when connecting via interbank trades.[3]

These novel findings of multiple and overlapping core-periphery structures also have important implications for empirical analyses of financial networks. In fact, we show that the information gleaned from the three networks differs and changes over time, highlighting the fact that these alternative network lenses provide complementary information about the interbank market.

Examining the time-series changes in the three networks, we conjecture that the incremental information from liquidity and urgent borrower networks is more important during high market information asymmetry periods and when bank reserves are relatively scarce—-characteristic interbank market conditions during the 2007–09 financial crisis.[4] In particular, we examine the evolution of interconnectedness among European banks around the crisis. We find that various measures of interconnectedness (degree, clustering, reciprocity, and the largest strongly connected component (LSCC))[5] all dropped substantially from 2006 to 2012, with the decline most pronounced in trading and urgent borrower networks: Over time, banks became less likely to trade with each other but only slightly less aggressive in approaching each other to trade. Importantly, the urgent borrower network maintained interconnectivity throughout the crisis, demonstrating a resilience in the interbank market's ability to distribute liquidity from institutions with surplus funds to those in urgent need. In fact, by the end of 2012, urgent borrower degree and reciprocity recover to near pre-crisis levels.

We also find that the LSCC and reciprocity are systematically highest in the liquidity network relative to trading or urgent borrower networks. For example, reciprocity is consistently more than three times higher in the liquidity network than the other networks, indicating that banks trading with each other are more likely to trade both passively and aggressively when they do so.

We subsequently explore whether information from trading, liquidity, and urgent borrower networks is useful for forecasting economic conditions where these banks operate.[6] Consistent with the growing literature on the "sovereign-bank nexus" (where the interbank market transmits important monetary policy with economy-wide repercussions), we find that forecasts of macroeconomic variables and country-specific spreads are more accurate when utilizing all three networks together.[7]

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 network formations and Kroeger et al. (2018), where the interbank market conveys information to the real economy, we find that trade aggressiveness in the liquidity and urgent borrower networks improve short-term forecasts of soft information and country-specific yield spreads.

Our results highlight that connections among interbank networks and the real economy remain even after the 2007–09 crisis when the European Central Bank bolstered the supply of reserves, suggesting that the interbank market continued to inform the real economy. Our results speak to the important conduit between the banking sector and the real economy during a time when the reserve supply is abundant. Moreover, a key policy implication of our findings is that all three networks should be used together to create more accurate forecasts.

Lastly, 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, further increases in connectivity of either network raise volatility. In the relatively low interconnectedness (crisis) period, however, an increase in liquidity network connectivity reduces volatility and boosts trading volume, revealing the dual character of interconnectedness—too much 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 via the sovereign-bank nexus. While other papers focus on interbank network structures and contagion (Degryse and Nguyen, 2007; and Mistrulli, 2011), our focus on different network constructs—trading, liquidity, and urgent borrower networks—shows these different lenses provide important insights into the macroeconomy.[8] Importantly, we create and

[2] Brunetti et al. (2019) use these same data, building on Shin (2009, 2010) and Elliott, Golub, and Jackson (2014).

[3] Babus and Hu (2017) and Castiglionesi and Eboli (2018) show, respectively, that a star network with concentrated intermediation is both constrained efficient and stable and less exposed to systemic risk than other networks. Li and Schuerhoff (2019) document a core-periphery network in the municipal bond market where the same regulatory incentives to trade may not hold. Castiglionesi and Eboli (2018) compare the efficiency of star-shaped, complete, and incomplete interbank trading networks. We document that the overlapping core-periphery e-MID topology matches the interlinked star network of Babus and Hu (2017).

[4] Brunetti, di Filippo, and Harris (2011) demonstrate high asymmetric information while Kroeger, McGowan, and Sarkar (2018) highlight the relative lack of bank reserves in the euro area during the crisis.

[5] LSCC is defined as the maximum number of traders that can be reached from any other trader by following directed edges (see Adamic et al., 2017, and Brunetti et al., 2019). Further details are available in Section 3.2.

[6] This exercise follows the spirit of comparing various network constructs, e.g. Billio et al. (2012) show correlation networks (among stock returns) reflect financial interconnectedness and crises, while Brunetti et al. (2019) show interbank trading networks forecast market liquidity problems.

[7] The growing literature exploring the sovereign-bank nexus and financial stability includes Acharya, Drechsler, and Schnabl (2014); Altavilla, Pagano, and Simonelli (2016); Becker and Ivashina (2018); Bocola (2016); Bolton and Jeanne (2011); Farhi and Tirole (2014); Gennaioli, Martin, and Rossi (2014); and Popov and van Horen (2015).

[8] 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 et al., 2019), and establishing the forecasting power of network statistics (Adamic et al., 2017), modeling the structure of banks (Flood et al., 2021), among others.

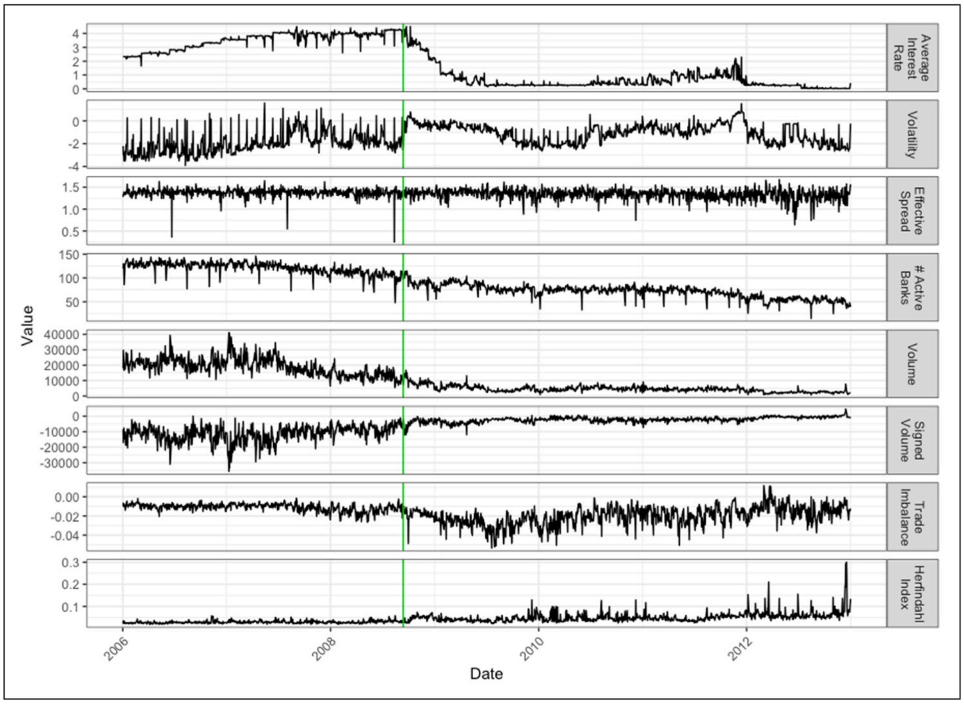

Fig. 1. Financial statistics at the daily resolution from the e-MID interbank market. The vertical line marks the collapse of Lehman Brothers on September 12, 2008.

study liquidity and urgent borrower networks, new types of physical networks that more specifically focus on liquidity dynamics in financial markets. We find that networks integrating these dynamics link interbank liquidity to the real economy and improve macroeconomic forecasts. Given the importance of liquidity and liquidity risk in financial markets, market regulators and participants may benefit from monitoring the dynamics of liquidity and urgent borrower networks, whether during financial crises or in more stable economic times.

2. Data: e-MID overnight-lending market

In this section, we present background information on the e-MID market and examine its activity using financial statistics. Established in 1990 as a Bank of Italy initiative, the e-MID managed the only interbank unsecured deposit market on an electronic platform for the euro system. The e-MID held an estimated 17%– 22% market share in all euro interbank transactions prior to 2007 (with this share decreasing thereafter). More than 200 commercial banks in 29 countries utilized e-MID during our study, posting public quotes (i.e., bids, offers, or both) and executing trades primarily for overnight interbank deposits, helping banks to meet regulatory capital, liquidity, and daily reserve requirements.[9]

In the e-MID market banks can observe each other's quotes, including top of book (highest bid and lowest offer) and others displayed by descending price terms. The trading mechanism stems from the quote-driven display, like a limit order book in a stock market (without consolidation). When a bank hits a displayed quote, the system allows both banks to negotiate quantity and interest rate terms. When an aggressor bank actively chooses a quoted order, consummated trades are processed and automatically settled through the TARGET2 system. The platform also allows credit line checking and mandates trade confirmation by both counterparties.[10]

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 two subperiods: (1) a pre-crisis period from January 2, 2006, until September 12, 2008; (2) a post-crisis (post-Lehman Brothers) period from September 16, 2008, through December 31, 2012, characterized by a weak recovery.

Fig. 1 shows several daily e-MID market statistics. We see that interest rates fell starting with the collapse of Lehman Brothers.[11] Rates started to recover as the crisis abated but fell again to crisis levels in 2012, as Europe experienced a weak recovery. Volatility shows a similar pattern, with heightened levels following the collapse of Lehman Brothers. Effective spreads remain relatively stable across our sample

[9] e-MID trades represent 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, 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). Volume on e-MID largely dried up after 2012, when our data end. In Fig. A1 in the Appendix, we show countries grew their reserves while decreasing their activity and connectedness in the e-MID, particularly in the post-Lehman period, consistent with liquidity hoarding (see Heider, Hoerova, and Holthausen, 2015).

[10] Further details on the e-MID market can be found in Brunetti et al. (2011).

[11] Average interest rate is the mean interest rate over all trades. Volatility is defined as the high-low log-price difference. Effective Spread is defined as twice the square root of the first-order autocovariance of interest rate log-returns. Number of active banks is the count of banks that participated in at least one trade. Volume is defined as the total number of contracts bought or sold. Signed volume is constructed as the difference between the number of contracts aggressively bought and the number of contracts aggressively sold. Trade Imbalance is the count of aggressive buys minus the count of aggressive sells divided by the volume. The Herfindahl index is the sum of the square of the market share (based on volume) of each active bank in the market.

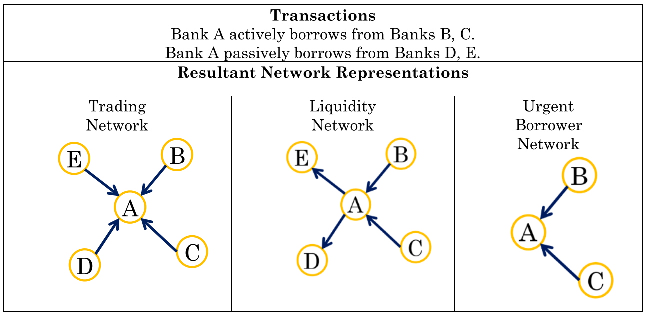

Fig. 2. Hypothetical trading, liquidity, and urgent borrower networks to represent a sequence of trades where Bank A borrowers from other banks.

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.

These patterns indicate 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. Defining trading, liquidity, and urgent borrower 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 and urgent borrower 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 trading, liquidity, and urgent borrower networks, consider the hypothetical trading network shown in Fig. 2, where banks are labeled A through E. In this trading network, Bank A is the dominant buyer, with active trades with Banks B and C, and passive buys with Banks D and E. The trading network represents buy/sell relationships, the liquidity network represents passive/aggressive relationships, and the urgent borrower network combines both together to focus exclusively on aggressive buys, a particularly important dimension for bank funds.

3.2. Network Statistics

We use four network statistics to characterize connectivity in each network. The first network statistic is the *Average Weighted Degree,* defined as.

$$\text{Average Weighted Degree } = \frac{1}{n}\sum_{i,j} W_{ij},$$

where W_{ij} denotes the volume-weighted edge on the network from bank i to bank j. This is a standard network statistic in financial network analysis (Billio et al., 2012; Adamic et al., 2017; Brunetti et al., 2019) because of its straightforward interpretation as the average volume traded per bank. Note that average weighted degree is identical between the liquidity and trading networks because the statistic aggregates over all banks and both networks are composed from the same set of transactions.[12] On the urgent borrower network, passive borrowing is excluded, so the average weighted degree represents the average volume traded (passively lent or urgently borrowed) per bank.

Our second network statistic, the *clustering coefficient*, has been used to measure interconnectivity and liquidity flows in the interbank and stock markets (Billio et al., 2012; Adamic et al., 2017; Brunetti et al., 2019). Additionally, higher clustering levels are also linked to higher levels of information in Duffie et al. (2014). The clustering coefficient is a measure of transitivity in the network, i.e., if bank i trades with bank j, and bank j trades with bank k, clustering measures whether bank i also trades directly with bank k. We quantify clustering using the global clustering coefficient (Newman, 2002),

$$\text{Clustering Coefficient } = \frac{T_{\text{Closed}}}{T},$$

where T represents the total number of connected triples of three banks (i, j and k) and T_{Closed} represents the number of closed triples where bank i trades with bank j, bank j trades with bank k, and bank i also trades directly with bank k.[13] Economically, the clustering coefficient captures liquidity in the market. Connected triples represent the presence of at least one liquidity provider so that larger clustering coefficients are associated with greater liquidity. In the extreme case where a single trader is responsible for all trades as in Fig. 2, no closed triples exist, and the clustering coefficient is zero. At the other extreme, the clustering coefficient is one when all triples involve three traders connected as a 'closed triple.' As with degree, this statistic is identical between the trading and liquidity networks. We also expect the clustering coefficient to be lower on the urgent borrower network because higher levels require that banks to buy *and* sell aggressively at the same time.

Dispersion of information or liquidity in the market may also be measured using connected components (Adamic et al., 2017; Brunetti et al., 2019). The *largest strongly connected component (LSCC)* is the maximum number of banks that can be reached from any other bank by following directed edges on the network. We compute the largest strongly connected component as

$$\text{LSCC} = \frac{\text{LSCC}_{\text{Max}}}{n},$$

where LSCC_{Max} is the count of banks in the largest strongly connected component and n is the total number of banks in the network. This ratio ranges between zero (e.g., one bank connects all other banks as in Fig. 2) and one (all banks are reachable from any other bank). Like clustering, a larger LSCC indicates greater connectivity, which is linked to higher levels of information in Duffie et al. (2014) and indicates higher demand for funds.

[12] Network statistics (and their interpretations) at the node-level will usually differ between the two networks, however. For example, in the trading network, in degree simply represents borrowing, whereas for the liquidity network, in degree corresponds to passive borrowing or lending. Similar interpretations differentiate out degree in the two networks.

[13] Following Adamic et al. (2017) and Brunetti et al. (2019), we treat the edges as undirected when computing the clustering coefficient.

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

	Trading Network			Liquidity Network			Urgent Borrower Network		
Pre-Lehman (2-Jan-06–12-Sep-08)									
	Mean	Median	St. Dev.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
LSCC	0.666	0.671	0.044	0.818	0.816	0.021	0.386	0.403	0.087
Reciprocity	0.127	0.125	0.022	0.431	0.426	0.025	0.039	0.038	0.014
Degree	7498	7716	1618	7498	7716	1618	1798	1874	477
Clustering Coef.	0.408	0.406	0.023	0.408	0.406	0.023	0.269	0.265	0.032
Post-Lehman (16-Sep-08–31-Dec-12)									
LSCC	0.450	0.454	0.061	0.734	0.727	0.043	0.139	0.128	0.092
Reciprocity	0.078	0.076	0.019	0.418	0.419	0.038	0.022	0.021	0.011
Degree	2544	2503	647	2544	2503	647	826	756	283
Clustering Coef.	0.355	0.353	0.029	0.355	0.353	0.029	0.193	0.188	0.030

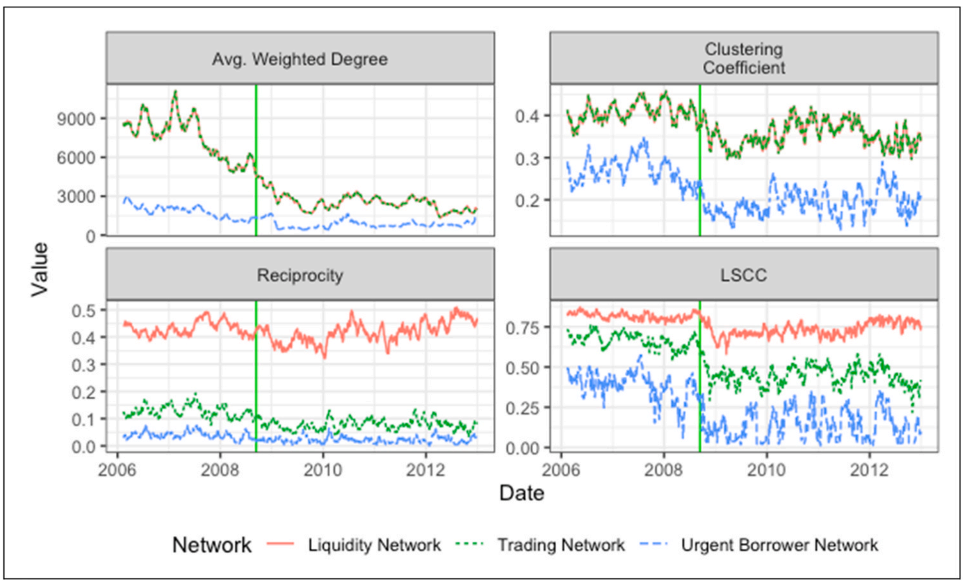

Fig. 3. Network statistics corresponding to 30-day rolling liquidity (solid red), trading dotted green), and urgent borrower (dashed blue) networks from the e-MID interbank market. The vertical line marks the collapse of Lehman Brothers on September 12, 2008.

The last network statistic that we compute is *reciprocity*, which measures how often pairs of banks are linked to each other in both directions and is defined as the count of reciprocally connected bank pairs divided by the count of non-reciprocally and reciprocally connected bank pairs:

$$\text{Reciprocity} = \frac{\sum_{i,j} I\{W_{ij}>0\} I\{W_{ji}>0\}}{\sum_{i,j} I\{W_{ij}>0\} + I\{W_{ji}>0\} - I\{W_{ij}>0\} I\{W_{ji}>0\}},$$

where $I\{\cdot\}$ is the indicator function. Higher reciprocity on the trading network means that Bank A borrowed money from Bank B and at another time Bank B borrowed from Bank A. In the liquidity network, reciprocal edges mean that Bank A traded with Bank B through a market order while at another time Bank B did so from Bank A using a market order. On the urgent borrower network, reciprocity increases when pairs of banks urgently borrow from each other at different times. As shown in previous works (i.e. Cocco, Gomes, Martins, 2009, and Di Maggio, Kermani, Song, 2017), relationships play a key role in how counterparties are selected. Reciprocity can therefore represent trust (i.e., lower expected counterparty risk), particularly for urgent borrowers.

Both LSCC and reciprocity have been used previously to characterize interconnectedness and systemic risk in Mexico and Germany[14] and these metrics should differ for each network. In the trading network, the LSCC and reciprocity will be closer to their maximum value of one when many 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 the urgent borrower network, banks must both urgently buy and passively lend.

3.3. Interconnectedness in Trading, Liquidity, and Urgent Borrower Networks

Table 1 presents summary statistics and Fig. 3 depicts our four interconnectedness measures over time for each network constructed using the transactions from a 30-day rolling window.[15] As discussed earlier, the degree and clustering coefficient for the trading and liquidity networks are identical, as these metrics aggregate over all banks using the same set of transactions. The degree of the interbank market falls consistently over time, as counterparty problems during the 2007–2009 crisis deterred banks from using the OTC e-MID market. As shown in Table 1, the average daily degree decreased by more than 60% after the collapse of Lehman Brothers. The clustering coefficient also fell post-Lehman, though not as dramatically. The average daily clustering

[14] See Martinez-Jaramillo et al. (2014), and Roukny et al. (2014), respectively.

[15] Finger et al. (2003) find that meaningful and non-random structures appear for month-long construction periods with e-MID data. We also find our results stabilize when using at least a 30-day estimation window. Jurgilas and Zikes (2014) document an economically significant intraday interest rate that reflects the opportunity cost of pledging collateral during the trading day, highlighting how networks can evolve over different time scales.

coefficient decreased by less than 30% for all three networks before partially recovering as the crisis resolved. The collapse of degree with a more resilient clustering coefficient shows that active banks remain connected among a small set of other banks, even while volume fell.[16] As expected, the urgent borrower network evolves similarly, at lower levels.

Fig. 3 and Table 1 also show that the LSCC and reciprocity are consistently lowest for the urgent borrower network and highest for the liquidity network. For all three networks, LSCC dropped precipitously with the collapse of Lehman Brothers though the decrease was least severe in the liquidity network. Reciprocity also decreased concurrently in all three networks, with reciprocity in the trading and urgent borrower networks continuing to decline (nearly 50%) through 2012. In fact, the decrease in interconnectivity was least severe in the urgent borrower network. This decrease indicates that banks became less willing to borrow *and* lend funds on the e-MID, instead preferring to trade in only one direction as the crisis unfolded. Reciprocity in the liquidity network recovers to above pre-crisis levels following the Lehman Brothers collapse. The remaining e-MID banks were increasingly willing to initiate trades through market orders *and* post quotes on the platform post-Lehman.

Altogether, we see consistent evidence that participation decreased significantly in the e-MID market. As the crisis unfolded, banks initiated trades less often or were less willing to post public quotes to borrow. This trend led to a decrease in overall activity and a decline in e-MID network interconnectivity. For example, lower reciprocity in the trading network reveals that banks were more polarized, either only borrowing or only lending. The trading and urgent borrower networks became less dense and more fragmented between 2006 and 2012.

Despite this overall decline in activity, interconnectivity did not dissolve in the urgent borrower network and the interbank market continued to serve its primary function by channeling liquidity to institutions in urgent need from those with surplus. Further, 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 combined with lower levels in the urgent borrower network indicate that financially constrained banks in need of funds continued to borrow either via aggressive market orders or by passively posting quotes on e-MID. Similarly, the LSCC in the liquidity network is larger than in the trading and urgent borrower networks. These results demonstrate that the three networks, generated by the same data, independently reveal differential information about the market.

Fig. 4 shows associations in and between the three network types through correlation analysis for each subperiod. First, we note that the correlation structure in the trading and urgent borrower network statistics is stable. Each pairwise correlation is positive throughout each subperiod. Similar results apply to correlations among liquidity network variables except that the LSCC often negatively correlates with other liquidity network metrics. As shown in Fig. 3, although liquidity 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, pairwise correlations tend to become positive as banks that remain in the e-MID become tightly interconnected, relying on each other for short-term funding. The urgent borrower network is less correlated with the other networks following the collapse of Lehman Brothers, indicating that passive borrowing was more prevalent and thus composing more of the trading and liquidity networks.[17]

3.4. Characterizing Interbank Market Network 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 three networks in light of the large literature establishing its prevalence in financial markets.[18]

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 to each other. In the e-MID interbank market a core-periphery structure would arise when safer banks tend to trade with each other and consistently lend to the broader market. In fact, Castiglionesi and Navarro (2020) note that such a topology is optimal in balancing the trade-off of higher payouts with bankruptcy risk faced by banks when connecting via the interbank market. Given this theoretical mechanism that leads to core-periphery topology and the broader literature detecting core-periphery in other interbank trading networks, we expect both the trading and urgent borrower networks to be core-periphery.

Different mathematical models capture the key characteristics of core-periphery networks (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 et al. (2010), which allows for banks to have varying degrees of importance to the directed and weighted network.

Let W_{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:

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

which can be solved using Singular Value Decomposition (SVD).[19] Define the percentage of reduced error (PRE) as

$$\mathrm{PRE} = 1 - \frac{\sum_i \sum_{j \neq i} \left(W_{ij} - u_i v_j\right)^2}{\sum_i \sum_{j \neq i} \left(W_{ij} - \overline{W}\right)^2}, \tag{2}$$

[16] On whether banks engage in traditional or "agency" dealing, we find no banks with net (in minus out) degree equal to zero on most days.

[17] Generalized Impulse Response functions (not reported) corroborate that the three networks, though related, convey different information. Network variables react to each others' innovations.

[18] Soramaki et al. (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 et al. (2004), Inaoka et al. (2004), Embree and Roberts (2009), Craig and von Peter (2014), and Langfield, Liu, and Ota (2014), respectively. Fricke and Lux (2015) detect core-periphery structure of Italian banks in the e-MID from 1999 to 2010. A 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).

[19] See Boyd et al. (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).

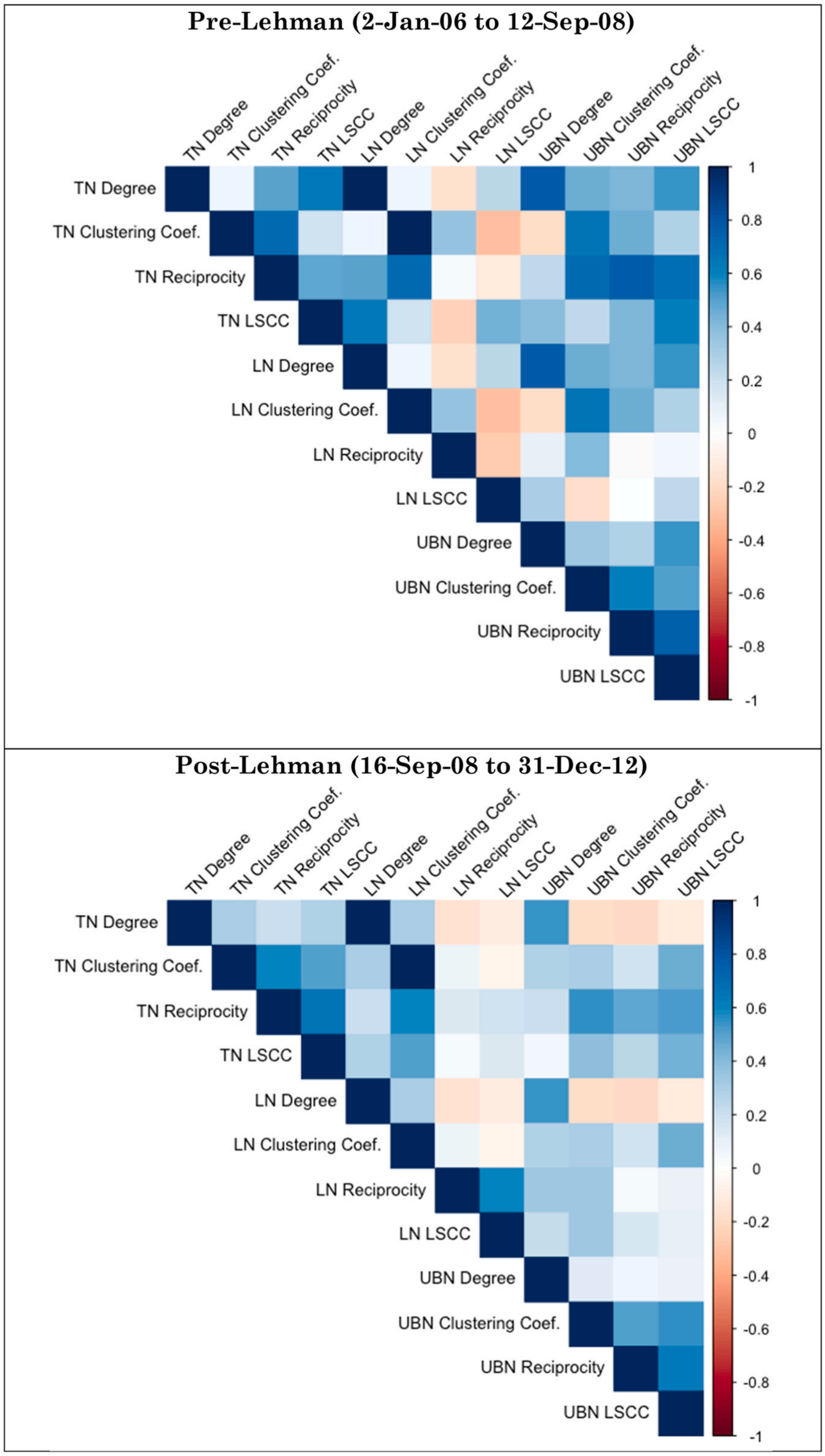

Fig. 4. Correlation matrix by subperiod between network statistics computed at the daily level using a 30-day rolling window. TN denotes trading network, LN denotes liquidity network, and UBN denotes the urgent borrower network.

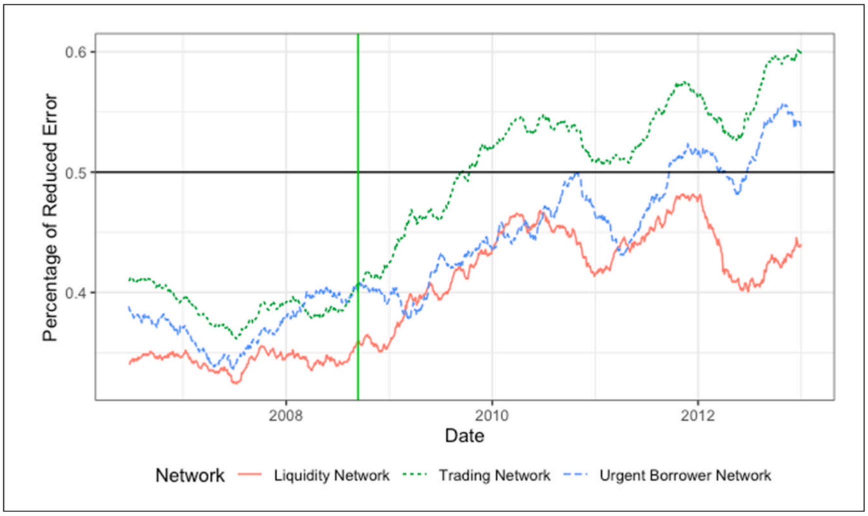

Fig. 5. The percentage of reduced error from estimating the asymmetric continuous core-periphery model for the liquidity (solid red), trading (dotted green), and urgent borrower (dashed blue) networks from the e-MID interbank market. Values above 0.5 provide evidence for the core-periphery model. The vertical line marks the collapse of Lehman Brothers on September 12, 2008.

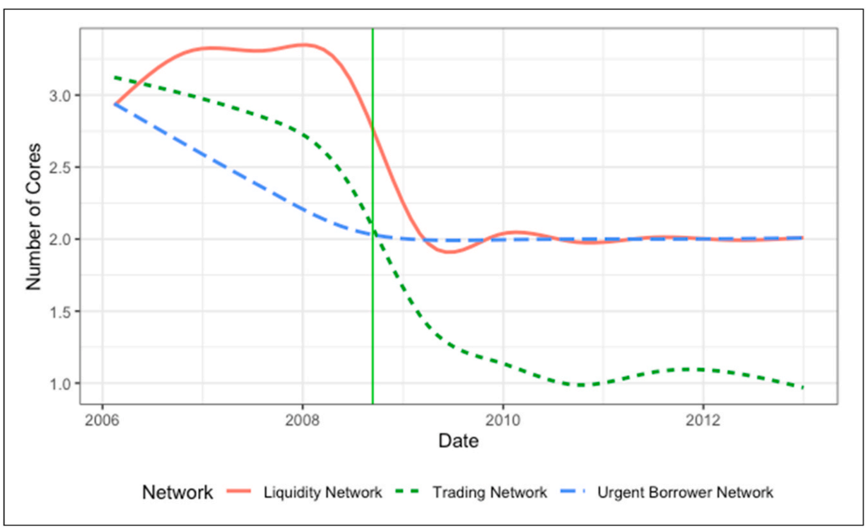

Fig. 6. The optimal daily number of cores using the Cluster Affiliation Model on the liquidity (solid red), trading (dotted green), and urgent borrower (dashed blue) networks from the e-MID interbank market. A smoothed version by local polynomial regression is shown for readability. The vertical line marks the collapse of Lehman Brothers on September 12, 2008.

where $\overline{W}$ is the average of all elements of W excluding the diagonal. To evaluate goodness of fit, we use the criterion from Boyd et al. (2010), which states that the PRE should exceed 0.5 for evidence in favor of the core-periphery model, i.e., that a majority of the variance in the data is explained by the model.

Fig. 5 shows the PRE obtained from estimating the model for each network. Several notable patterns emerge. First, the core-periphery model fits the trading network best, followed by the urgent borrower network. Post-Lehman, the trading network PRE is about 10% higher compared to the liquidity network and 5% higher than the urgent borrower network. Further, the liquidity network never rises above the 0.5 threshold–the core-periphery model does not fit the liquidity network well as there is no core of aggressive (or passive) liquidity providers. The PRE is above 0.5 only in 2012 for the urgent borrower network. Interestingly, even for the trading network (for which a sizable literature shows a core-periphery structure), the model provides a good fit only after the 2007–09 crisis resolved—the PRE crosses the 0.5 threshold in late 2009.

Note that the PRE would be relatively low if a given network has multiple cores, because a model assuming a single core (i.e., a rank 1 matrix factorization) cannot fit the data well. Therefore, 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.[20] Fig. 6 shows the optimal number of communities according to cross-validation is three in the pre-crisis era for all three networks. The

[20] 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).

Table 2
Forecasting performance of hard information for each network, where root mean square forecasting error is computed for 1-step ahead forecasts using the model in Eqs. (3) and (4) trained on data from January 2006 to September 12, 2008. Industrial production (IP) and retail sales (RS) are at the monthly level. Boldface indicates the minimum error and shaded cell indicates the forecast is more accurate than that of the Trading Network. Asterisks * and * * denote significance at the 5% and 1% levels, respectively, from the Diebold–Mariano test for whether the network forecast is more accurate than that of the Trading Network.

	Trading Network	Liquidity Network	Urgent Borrower Network	Trading + Liquidity	Trading + Urgent Borrower	Liquidity + Urgent Borrower	Trading + Liquidity + Urgent Borrower
Euro-Area Δ(RS)	1.351	1.653	1.284	**1.058** *	1.116	1.284	1.211
France Δ(IP)	1.371	2.347	2.188	**1.367**	1.424	1.621	1.508
Germany Δ(IP)	2.138	2.369	1.771 * *	1.958 *	1.820 * *	**1.767** * *	1.807 * *
Greece Δ(IP)	**4.476**	7.618	5.467	5.969	6.720	7.769	7.105
Ireland Δ(IP)	4.266	4.564	5.071	**3.936**	4.389	5.127	4.509
Italy Δ(IP)	2.360	2.499	2.234	2.221	2.210 * *	**2.144** * *	2.177 * *
Spain Δ(IP)	**2.067**	2.110	2.226	2.182	2.384	2.457	2.458
United Kingdom Δ(IP)	**1.127**	1.226	1.525	1.335	1.287	1.248	1.309

number of communities decreases just prior to the Lehman Brothers default before stabilizing at a single core-periphery structure for the trading network and two for the liquidity and urgent borrower networks. [21]

4. Forecasting Macrovariables

Having established that trading, liquidity, and urgent borrower 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 for each network generally falls from 2006 through 2012, but the levels and dynamics of the interconnectedness metrics differ between the three network types over time. These forecasting exercises are intended to examine whether liquidity and urgent borrower networks, which incorporate the aggressiveness of trades, reflect incrementally more information than trading networks. To test this conjecture, we use connectedness metrics from all three networks to forecast various macroeconomic variables.[22]

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 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 Aruoba, Diebold and Scotti (ADS) business condition index[23]; 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.[24]

In Babus and Hu (2017), soft information between counterparties plays a role in how networks develop.[25] 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 and urgent borrower networks. Similarly, given the likelihood of information asymmetries across borders, we expect that trading aggressiveness (and the liquidity and urgent borrower networks, 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 and urgent borrower networks 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. Therefore, we expect no incremental improvement when we include trade aggressiveness via the liquidity or urgent borrower network.

With these conjectures in mind, we forecast macrovariables using each network separately and combined. To produce one-step-ahead with each network separately, we use the following model:

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

where $z_{i,t}$ represents each macrovariable described earlier (we consider one variable at a time) and the subscript g denotes the network type. To combine information from multiple networks together, we take a weighted average at each time of all network statistics by projecting them onto their first principal component. Then, we use the projected time-series to produce one-step-ahead forecasts with information from the three networks:

$$z_{i,t} = \gamma_0 + \gamma_1 PC_{t-1} + u_{i,t}, \tag{4}$$

where PC_{t-1} is the first principal component of the network statistics from multiple networks. Tables 2, 3, and 4 reports the out-of-sample root mean square forecasting error from Eqs. (3) and (4) 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

[21] In unreported results, we find evidence that the cores are organized by 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.
[22] Several works provide a theoretical basis for networks to align with economic conditions. Elliott, Georg, and Hazell (2021) show that interconnectedness among German banks allowed economic shocks to propagate during the last 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.
[23] See Aruoba, Diebold and Scotti (2009). Erik, Lombardi, Mihaljek and Shin (2019) show that PMI is a powerful indicator of real economic activity and link PMI to financial variables.
[24] When levels of these macrovariables are not stationary, we consider the first difference.
[25] Bańbura and Rünstler (2011) also show that soft information may be important in forecasting.

Table 3
Forecasting performance of soft information for each network, where root mean square forecasting error is computed for 1-step ahead forecasts using the model in Eqs. (3) and (4) trained on data from January 2006 to September 12, 2008. The purchasing managers index (PMI) and ADS series are at the monthly level. Boldface indicates the minimum error and shaded cell indicates the forecast is more accurate than that of the Trading Network. Asterisks * and * * denote significance at the 5% and 1% levels, respectively, from the Diebold–Mariano test for whether the network forecast is more accurate than that of the Trading Network.

	Trading Network	Liquidity Network	Urgent Borrower Network	Trading + Liquidity	Trading + Urgent Borrower	Liquidity + Urgent Borrower	Trading + Liquidity + Urgent Borrower
Euro-Area Δ(ADS)	**0.370**	0.598	0.600	0.400	0.411	0.456	0.433
France Δ(PMI)	3.435	3.627	2.985 * *	3.426	**2.790** * *	2.959 * *	3.040 * *
Germany Δ(PMI)	3.016	2.484 * *	2.414 * *	2.480 * *	2.227 * *	**2.139** * *	2.227 * *
Ireland Δ(PMI)	3.465	3.821	3.618	3.550	**3.374**	3.772	3.564
Italy Δ(PMI)	2.010	**1.957**	2.558	2.230	2.229	2.249	2.267
Spain Δ(PMI)	4.320	4.152	4.245	3.927 *	**3.925** *	4.113	4.194
United Kingdom Δ(PMI)	2.732	**2.213** * *	2.365 * *	2.943	3.101	2.873	3.061

Table 4
Forecasting performance of euro-zone yield spread and country-specific yield spreads for each network by subperiod, where root mean square forecasting error is computed for 1-step ahead forecasts using the model in Eqs. (3) and (4) trained on data from January 2006 to September 12, 2008. All series are at the daily level. Boldface indicates the minimum error and shaded cell indicates the forecast is more accurate than that of the Trading Network. Asterisks * and * * denote significance at the 5% and 1% levels, respectively, from the Diebold–Mariano test for whether the network forecast is more accurate than that of the Trading Network.

	Trading Network	Liquidity Network	Urgent Borrower Network	Trading + Liquidity	Trading + Urgent Borrower	Liquidity + Urgent Borrower	Trading + Liquidity + Urgent Borrower
Banking System Health							
EURIBOR-OIS Spread	0.063	0.060 * *	0.055 * *	0.097	**0.049** * *	0.049 * *	0.050 * *
Country-Specific Spreads							
SPSP	0.0027	0.0027	0.0025 * *	0.0022 * *	**0.0022** * *	0.0022 * *	0.0022 * *
GRSP	0.0761	0.0749 * *	0.0738 * *	0.0684 * *	**0.0678** * *	0.0681 * *	0.0680 * *
ITSP	0.0023	0.0023	0.0023	**0.0018** * *	0.0018 * *	0.0019 * *	0.0018 * *
PTSP	0.0115	0.0115	0.0117	**0.0079** * *	0.0083 * *	0.0085 * *	0.0082 * *

real economy, we find strong evidence that combining the statistics derived from liquidity, trading urgency, and trading networks generally produce forecasts that are statistically preferred over forecasts produced from either network separately. Focusing first on Table 2, we find that the forecasts of hard information from combining the trading and liquidity networks together are more accurate in over half of the cases than those generated by any network separately.

Table 3 shows that, when forecasting soft information, forecasts from utilizing the urgent borrower network (either alone or with the trading network) improves forecasts for over half of the cases. As we conjecture, and consistent with liquidity and urgent borrower networks being more informative when information asymmetry in the market is high, we find that the incremental information reflected in these networks improves short-term forecasting of soft macroeconomic information. The results in Table 3 indicate that information captured in all three networks is valuable in forecasting PMIs and, therefore, links the interbank market to economic activity and financial conditions.

Table 4 shows that forecasts from the combined models dominate when forecasting the country-specific yield spreads and the EURIBOR-OIS spread. These links between yield spreads and interbank networks highlight the strong "sovereign-bank nexus" in the euro region during our sample period.[26]

The sovereign-bank nexus links sovereigns to the interbank market through three main channels: i) the sovereign exposure channel, because of banks holding large amounts of sovereign debt; ii) the safety net channel, which links central banks to sovereigns when providing backstops to distressed banks; iii) the macroeconomic channel, where slow economic activity generates sovereign crises and negatively impact the banking sector. Using the same e-MID data Brunetti a, b) et al. (2022) find that market Sidedness and the ratio of active to passive trades for overnight funds (Granger-cause) sovereign CDS spreads across several countries.[27] In this spirit, combining information from all three interbank networks proves useful in forecasting real and financial variables as predicted by the sovereign-bank nexus.[28]

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 et al. (2019). Importantly, however, we show that liquidity and urgent borrower networks provide incrementally more valuable information in forecasting soft macroeconomic variables and country-specific yield spreads. In this regard, our results suggest that monitoring the three types of interbank networks offers 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 and urgent borrower networks more specifically capture the urgency to borrow/lend, the dynamics of liquidity demand/supply.

[26] Results in Table 4 also demonstrate that the relative sparsity (the lack of French and German banks) in e-MID networks does not diminish the usefulness of network information gleaned from these interbank markets. We interpret these consistent results to show that sample selection bias does not appear to be an issue for our analyses. An important future work will be to investigate policy effects through more formal causal inference tests.

[27] Our tests for Granger non-causality between network variables and 10-year CDS spreads for sovereign debt reveal significant relations in both directions–sovereign risk leads urgent interbank borrowing and urgent interbank borrowing presages changes in sovereign risk.

[28] Granger causality results (in Appendix, Table A1) confirms our findings that the networks can aide in forecasting economic variables, particularly country-specific spreads and soft information.

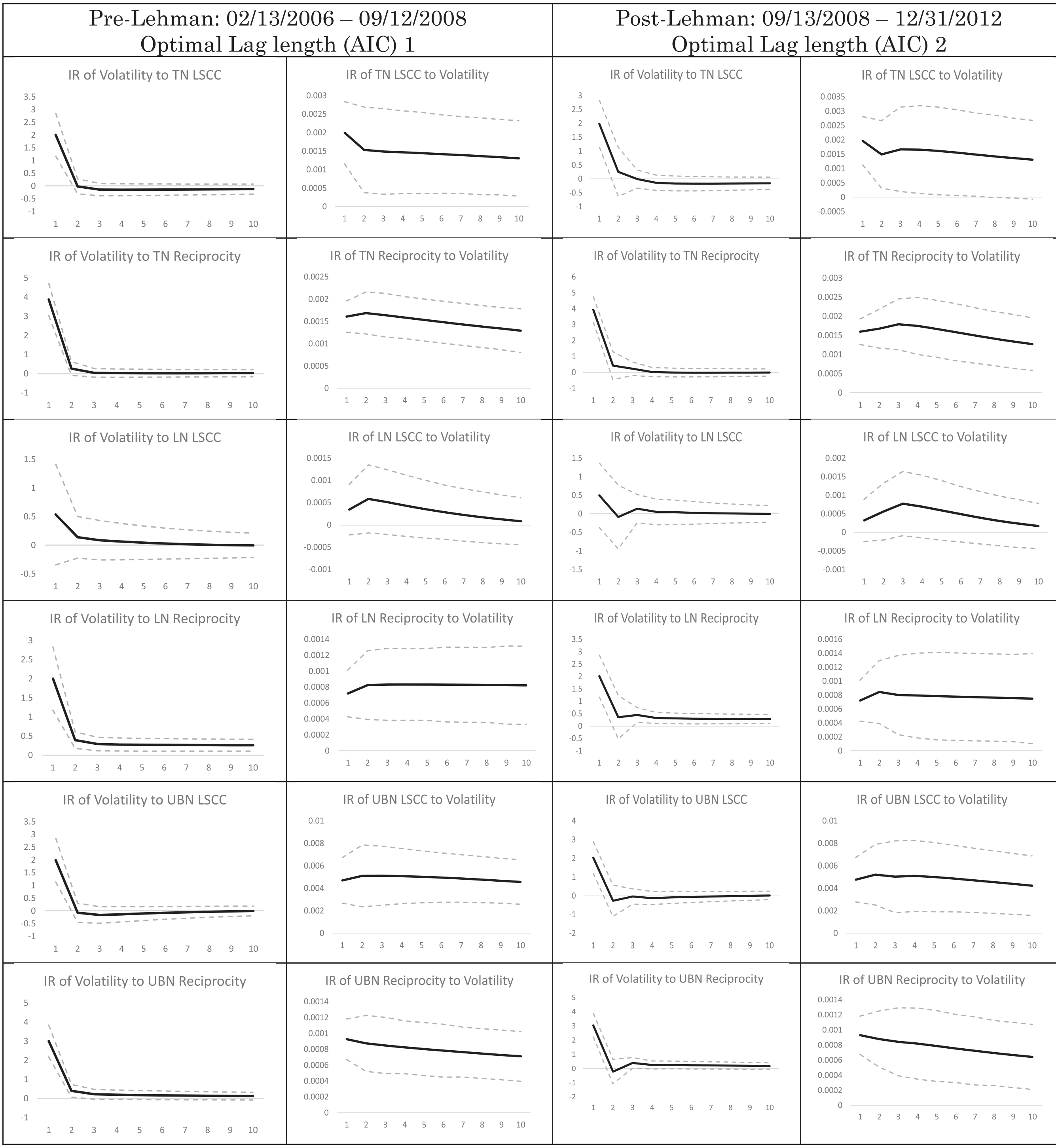

Fig. 7. 10-Day Generalized Impulse Responses (IR) of volatility, and network variables to one standard deviation innovations. Standard errors are calculated using 1000 Monte Carlo repetitions.

Fig. 8. 10-Day Generalized Impulse Responses (IR) of volume, and network variables to one standard deviation innovations. Standard errors are calculated using 1000 Monte Carlo repetitions.

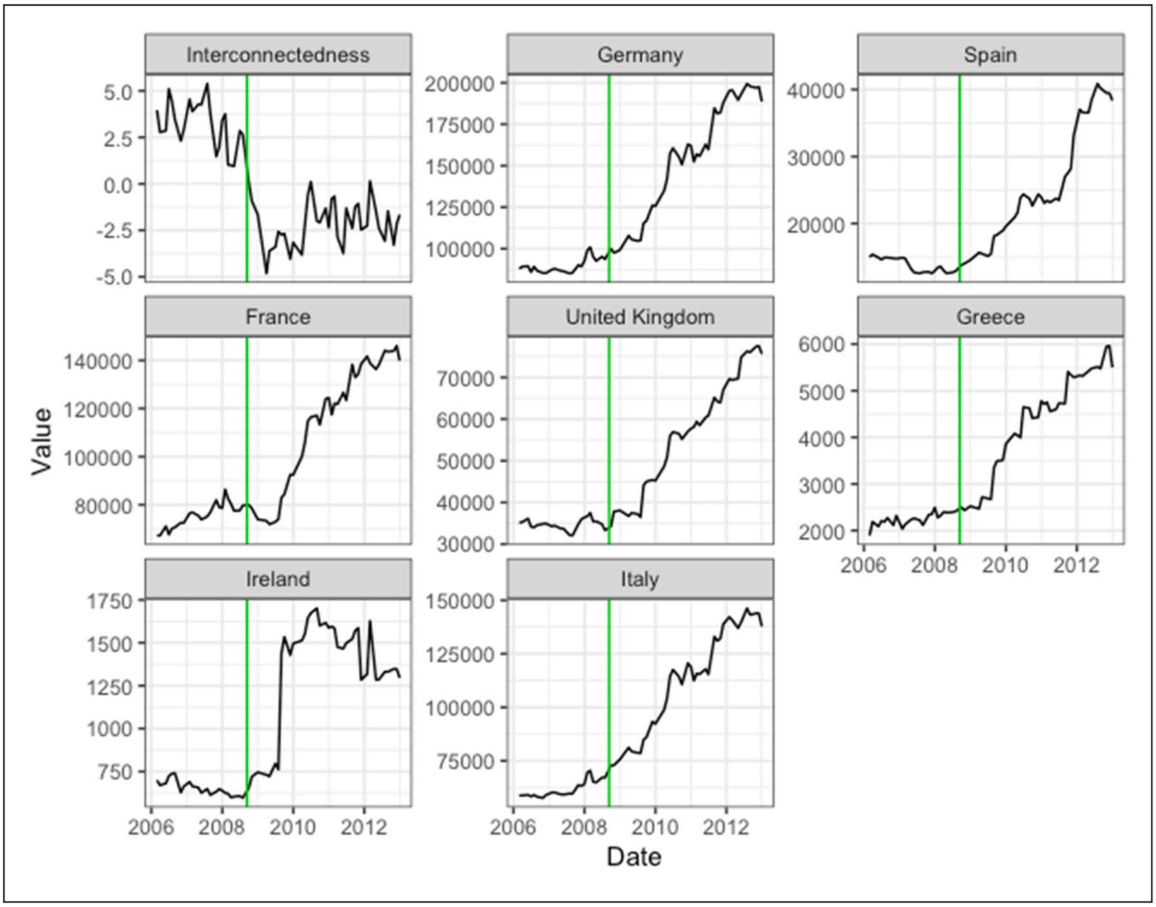

Fig. A1. Interconnectedness in the e-MID (first principal component of statistics from all three networks) and monthly aggregate reserves (in millions of Euros) by country.

5. 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.[29] Our evidence above shows that trading, liquidity, and urgent borrower networks convey different information, despite being generated by the same trading process. We therefore empirically examine the linkages among volume, volatility and network variables using Vector AutoRegression (VAR) and generalized impulse response functions.

For each subperiod using daily data, we estimate a VAR with price volatility, trading volume and LSCC and reciprocity of each network structure (trading, liquidity and urgent borrower).[30] Fig. 7 depicts the IRs of volatility and volume to one standard deviation innovations to network variables and vice versa, for the two sub-periods. In both subperiods a rise in market connectivity increases volatility (see columns 1 and 3). This result is to be expected if too much interconnectedness increases contagion and systemic risk and network connections create channels for contagion (Glasserman and Young, 2015, 2016).[31] In fact, interconnectedness is one of the five criteria used by regulators for designating global systemically important banks.[32]

All networks (with the only exception of liquidity network LSCC) strongly respond to innovations in volatility. A shock to the volatility process increases interconnectedness in all three networks indicating that high volatility incentivizes market participants to be more connected in an attempt to diversify risk.

In Fig. 8, we report the same analyses for volume. In the Pre-Lehman period, a shock to trading network reciprocity and urgent borrower LSCC increase traded volume in the long run (after 3 and 5 days, respectively). Similar feedback effects are present when looking at how network interconnectedness responds to innovations in volume.

During both periods, innovations to network interconnectedness increase volume, highlighting that in stressful times, interconnectedness benefits the market. These results also underscore the dual nature of interconnectedness: Too much interconnectedness may increase systemic risk (higher volatility), but too little may impede market

[29] More precisely, price changes follow a mixture of distributions, and volume is the mixing variable. The Kyle (1985) and Glosten and Milgrom (1985) models show how private information is embedded into prices.

[30] For volatility, we use the daily log-price range. We are interested in the impulse response functions and are agnostic about the identification strategy, so we use the generalized impulse responses of Pesaran and Shin (1998). In each subperiod, we ensure that all variables are stationary and select optimal lag length using the Akaike information criterion.

[31] Gai et al. (2011) also illustrates how greater complexity and concentration in financial networks may amplify fragilities in interbank lending markets.

[32] See Bank for International Settlements, Basel Committee on Banking Supervision (2014).

Table A1
Granger causality relations between economic variables and the first principal component of network statistics from the trading, liquidity, and urgent borrower network. The number of lags is chosen according to the AIC criterion.

Variable 1	Granger Causal Relation	Variable 2
Hard Information		
Euro-Area Δ(RS)		Trading + Liquidity + Urgent Borrower
France Δ(IP)		Trading + Liquidity + Urgent Borrower
Germany Δ(IP)	→	Trading + Liquidity + Urgent Borrower
Greece Δ(IP)		Trading + Liquidity + Urgent Borrower
Ireland Δ(IP)		Trading + Liquidity + Urgent Borrower
Italy Δ(IP)		Trading + Liquidity + Urgent Borrower
Spain Δ(IP)	→	Trading + Liquidity + Urgent Borrower
United Kingdom Δ(IP)	→	Trading + Liquidity + Urgent Borrower
Soft Information		
Euro-Area Δ(ADS)	→	Trading + Liquidity + Urgent Borrower
France Δ(PMI)		Trading + Liquidity + Urgent Borrower
Germany Δ(PMI)		Trading + Liquidity + Urgent Borrower
Ireland Δ(PMI)	←	Trading + Liquidity + Urgent Borrower
Italy Δ(PMI)		Trading + Liquidity + Urgent Borrower
Spain Δ(PMI)	←	Trading + Liquidity + Urgent Borrower
United Kingdom Δ(PMI)	←	Trading + Liquidity + Urgent Borrower
Banking System Health		
EURIBOR-OIS Spread	→	Trading + Liquidity + Urgent Borrower
Country-Specific Spreads		
SPSP		Trading + Liquidity + Urgent Borrower
GRSP	→	Trading + Liquidity + Urgent Borrower
ITSP	←	Trading + Liquidity + Urgent Borrower
PTSP		Trading + Liquidity + Urgent Borrower

functioning. Interestingly, trading, liquidity, and urgent borrower networks seem to capture well this characteristic of network connections.[33]

6. Conclusions

During the past decade, network analysis has grown as a major research thrust in financial economics (Flood et al., 2020). 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 (Bisias et al., 2012). In this paper, we benchmark to Castiglionesi and Navarro (2020), 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 new network constructs, the liquidity network and urgent borrower network (based on the aggressiveness of supplying and demanding liquidity) and use them to examine connectedness in the physical overnight-lending market in Europe. Since daily regulatory capital requirements create strong incentives for distributing overnight funds among banks, our liquidity and urgent borrower networks constructed with interbank trades aim to characterize market-wide liquidity conditions among banks.

We show that trade aggressiveness both provides additional information and serves as a commitment device (i.e. aggressive orders de facto commit to trade) in the e-MID OTC interbank lending market from 2006 through 2012, an important period spanning the 2007–08 financial crisis. We identify liquidity and urgent borrower networks as complementary dimensions for viewing financial markets and the structures of the three networks differ—each network has three overlapping cores before the crisis, but following the 2008 collapse of Lehman Brothers, the number of cores decreases to one for the trading network and two for the liquidity and urgent borrower networks. The incremental information from liquidity and urgent borrower networks is more important during high market information asymmetry periods and when bank reserves are relatively scarce—characteristic interbank market conditions during the 2007–09 financial crisis. Various measures of interconnectedness (degree, clustering, reciprocity, and the largest strongly connected component (LSCC)) all dropped substantially from 2006 to 2012, Over time, banks became less likely to trade with each other but only slightly less aggressive in approaching each other to trade–the urgent borrower network maintained interconnectivity throughout the crisis, demonstrating resilience in distributing interbank liquidity.

We also explore whether information from trading, liquidity, and urgent borrower networks is useful for forecasting economic conditions where these banks operate. Consistent with the growing literature on the "sovereign-bank nexus" we find that forecasts of macroeconomic variables and country-specific spreads are more accurate when utilizing all three networks together. Indeed, trade aggressiveness in the liquidity and urgent borrower networks improve short-term forecasts of soft information and country-specific yield spreads. These results highlight that connections among interbank networks and the real economy remain even after the 2007–09 crisis when the European Central Bank bolstered the supply of reserves–the interbank market continued to inform the real economy.

Lastly, we compare the information content of trading and liquidity networks with that of traditional volatility and volume measures and find that in normal market conditions when interconnectedness is high, further increases in connectivity in these networks raise volatility. In the relatively low interconnectedness (crisis) period, however, an increase in liquidity network connectivity reduces volatility and boosts trading volume, revealing the dual character of interconnectedness—too much 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 via the sovereign-bank nexus. Liquidity and urgent borrower networks that specifically focus on liquidity dynamics serve to link interbank liquidity to the real economy and improve macroeconomic forecasts. Given the importance of liquidity and liquidity risk in financial markets, market regulators and participants may benefit from monitoring these

[33] While these results stem from the generalized VAR identification structure, evidence in Adamic et al. (2017) suggests that network variables are primitive to volatility and volume. Based on this insight, we run the VAR 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 9 and 10. Moreover, we flip the Cholesky factorization and assume that shocks to volume and volatility feed into network variables but not vice versa and also obtain similar results.

networks, whether during financial crises or in more stable economic times.

We recognize that various other interbank market features (e.g. the importance of counterparty relationships) might also be useful in the forecasting sense, but the scope of examining these questions lies beyond this current paper so we leave these dimensions to future work. Given that our results are driven by the dynamic composition of banks that remained in the e-MID, representing less than a quarter of all euro interbank transactions, and several potential sovereign-bank nexus channels that link the interbank market and the broader economy, other future work might combine other auxiliary data with e-MID to provide a more complete view of the overnight interbank lending market.

Declaration of Competing Interest

None.

Data Availability

The authors do not have permission to share data.

Appendix A

See Appendix Fig. A1 and Table A1 here.

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