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Interbank network and banks' credit supply

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Abstract

This paper examines how the interbank network structure influences banks' credit supply to the real economy. Using the dynamic UK interbank networks based on the quarterly evolutions of bilateral exposures from 2014 to 2021, we find evidence of both risk-sharing effect through the interbank core-periphery structure and liquidity-insurance effect within interbank lending communities. Core banks with high global centrality and banks in a larger community tend to lend more to non-financial firms. The effect of global centrality is still significant after controlling for the local effects including local centrality and community size. During the Covid-19 pandemic, the effect of risk sharing is mitigated whereas the effect of community lending is strengthened.

Key words: Interbank network, centrality, community, bank loans, Covid-19.

JEL classification: G20, G21, L14.

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1. Introduction

Interbank markets allow liquidity transfer and risk sharing between banks but they are also prone to systemic risk and aggregate uncertainty and can be an important channel of financial contagion (e.g. Bhattacharya and Gale, 1987; Allen and Gale, 2000). The 2008's global financial crisis is an example that efficient risk sharing may not be achieved through interbank relationships due to moral hazard and market frictions in the lending market (e.g. Afonso et al., 2011). Liquidity dry-up and failure of financial intermediaries can further affect corporate borrowers in the credit market without public liquidity support (Acharya and Mora, 2015). Because bank-borrower relationships are sticky, affected borrowers face difficulty in switching to alternative forms of financing during stressed time (Chodorow-Reich, 2014; Chava and Purnanandam, 2011).

In this paper, we examine how the interbank relationships, i.e. the structure of the interbank market affect banks' credit supply to the corporate sector. Using a unique dataset on the exposure-level interbank borrowing and lending in the UK, we build and map out the UK interbank network since 2014. Numerous studies have explored how links between banks are formed and how the network structure affects systemic risks and stability in the financial system (e.g. Allen and Babus, 2009; Acemoglu et al., 2015; Jackson and Pernoud, 2021). Through examining the UK interbank network, we extend the literature by showing that the structure of the interbank market can influence the transmission of the shock from the financial system to the real economy through lending. Using the COVID-19 pandemic as a shock, we also examine how the network structure changes during stressed time and how such change affects banks' liquidity and lending behavior.

We construct the interbank networks using the large exposure (LE) dataset for the UK banking sector, which includes exposures in the banking books that are larger than 10% of a bank's Tier 1 capital or above £300 million. The LE dataset covers not only exposures between credit institutions (banks), but also banks' exposure towards non-financial corporations, non-bank financial institutions as well as governments and central banks. The dataset incorporates UK banks' large exposures vis-à-vis entities (counterparties) located worldwide. Therefore, it captures UK banks' lending relationship both domestically and globally. At the exposure level, the dataset provides a rich set of attributes which allows us to distinguish between debt, equity, derivative and off-balance sheet exposures. Our networks are based on quarterly snapshots (end of quarter), covering the period of the 2^{nd} quarter of 2014 to the 4^{th} quarter of 2021. For this period, the UK interbank network is composed on average by 259 reporting banks, which are lending to 143 UK-based banks, for an average of 767 lending relationships per quarter. Across all reporting quarters, we have 2027 domestic (UK-domiciled) non-financial corporates that are borrowing from at least one reporting bank in the network.

Using the dynamic interbank networks constructed, our aggregate-level evidence shows that, the total outstanding exposure as well as the number of banks and relationships in the interbank network decreases from 2014 to 2021, both the normal periods before 2020 and the Covid crisis period. More banks entered the interbank networks in the beginning of 2020 at the onset of the COVID-19 crisis. However, both total exposure and average exposure per bank dropped in the first three quarters of 2020, suggesting a reduction in liquidity supply in the interbank market responding to the outbreak of the COVID-19 pandemic. The liquidity situation started to improve in the fourth quarter of 2020 with the amount of interbank exposures recovering.

Network theory has developed multiple and distinct measures to capture network structure. We utilize centrality measures to capture the core/peripheral positions and cluster measures to identify the borrowing/lending among communities of banks in the interbank market. A bank is connected to other banks if it is borrowing from or lending to many other counterparties in the interbank market (*degree* centrality). A bank is well-connected if it lies on more "shortest paths" between pairs of other banks in the interbank networks, promoting this bank as a key "broker" of bank relationships (*betweenness* centrality). A bank is in a core position and well-connected throughout the whole network if it is connected to many other well-connected and core banks (*eigenvector* centrality). Therefore, degree centrality captures the direct/local connections whereas betweenness and eigenvector centrality capture the global connections throughout the network. In this paper, we mainly use *eigenvector* centrality to identify *core* banks throughout the interbank network.

While centrality reflects the influence of the individual bank on its interbank peers, community captures a group of banks that have strong borrowing/lending relationships with each other, which is captured by an algorithm of community detection. We then use the size of community that a bank belongs to, which is, the number of the banks in the community scaled by the total number of banks in the interbank market, to capture a bank's community feature.[1]

The summary statistics of the UK interbank market reveal the following facts: there were two significant decreases in the average eigenvector centrality, in early to mid-2016 (when UK voted on Brexit) and in early 2020 (the onset of COVID-19 pandemic), suggesting that core banks are reducing borrowing/lending temporarily, which is evidence of liquidity hoarding when uncertainty is high. Correspondingly, the average cluster size increases significantly in these two periods, indicating that more banks are developing more and stronger local connections and joining larger clusters to obtain liquidity support potentially when risk is high.

We then investigate how these features of the interbank networks affect banks' lending to the UK corporate sector. Our main findings are as follows. First, core banks in the interbank network or banks in a larger community tend to lend more to non-financial firms. One-standard-deviation increase in eigenvector centrality is associated with 10.1 percent increase in corporate loans; and one-standard-deviation increase in cluster size is associated with 8.6 percent increase in corporate loans, all else being equal. Second, the effect of the global centralities (*eigenvector* and *betweenness*) on lending to the

[1] In the paper, we use community and cluster interchangeably.

corporate sector remains positive and significant after controlling for the local centralities (*degree*) and cluster size, suggesting that after taking into consideration the effect of the direct connections in the interbank market, core banks in the interbank market are providing more credit to the corporate sector. These evidence suggests exposures to interbank market improve risk sharing and have positive effects on the lending to the real sector.

Our findings show that the effect of network centrality is more pronounced for larger banks, whereas the effect of community size is stronger for smaller banks. Both effects are more pronounced when bank-borrower relationship is stronger (repeated relationships over time). These results suggest that the risk-sharing effect is stronger when the core bank is a larger bank; however, we also find an insurance effect from the interbank community- a smaller and peripheral bank gets insurance from a connected core bank as well as from other counterparties in the same community, henceforth benefiting more from being in a larger community. The effects of risk sharing and insurance are stronger when the information asymmetry between the bank and the borrower is low.

In March 2020, banks faced the largest increase in liquidity demands from the corporate sector stemming from the advent of the COVID-19 pandemic. In the UK, commercial and industrial (C&I) loans on bank balance sheet increased roughly from £250 billion to £275 billion. The COVID shock hit the UK economy and the banking system also experienced an unprecedented "stress test" on the ability of banks to supply liquidity. We explore how the risk-sharing and insurance effects in the interbank market respond to the COVID-19 crisis and further affect banks' lending decisions to the corporate sector. We find that core banks with high eigenvector centrality reduce their lending, whereas banks in a larger community increase their lending to non-financial firms during the post-COVID period, after controlling for other financial information. This suggests a weaker risk-sharing effect between the core and peripheral banks, but a stronger insurance effect in the community during the crisis.

Our further evidence shows core banks' liquidity situation (cash over total assets) improved during the post-COVID period compared to that before the crisis. Banks in a larger community has better liquidity, especially during the post-COVID period. One possibility is that core banks are still providing liquidity to other banks while reducing their own lending to non-financial firms. Hence we compare the lending behavior between two groups of banks, one in a large community and borrowing from core banks and the other in large community but not borrowing from core banks, and we find the former group of banks are lending significantly more to nonfinancial firms during the COVID period, indicating the liquidity transfer from core banks to other banks to support their lending to non-financial firms.

In order to establish a causal relationship between network structure (centrality and community) and banks' credit supply to the UK corporate sector, we use the COVID-19 crisis as an exogeneous shock to the real economy and henceforth to the interbank networks, and examine how banks respond to the shock afterwards. The COVID-19 pandemic is an unexpected shock to all firms and banks, and affected all industries and regions in the UK. Using the industry-level output and regional COVID case number, we first identify the industries and regions that are highly impacted by the COVID pandemics as well as the banks with at least 33% of total exposures towards these industries and regions (*COVID-impacted banks*). We define the treatment banks as those that are directly lending to the COVID impacted banks with the exposure above £100 million by the last quarter of 2019 but themselves are not highly impacted by the COVID. The control banks are defined as those not highly impacted by the COVID and are not connected to the COVID impacted banks. We also use propensity score matching based on bank size, capital ratio, risk weighted assets, eigenvector as well as lending in the prior quarters to further isolate the difference between the treatment and control bank-groups. Therefore, the only difference between the treatment and control banks should be their linkage to the COVID-impacted banks in the interbank market. We observe a significant increase in eigenvector centrality and community size for the control banks compared to those for the treatment banks during the crisis, suggesting that the COVID crisis is a negative shock to the banks that are lending to COVID-impacted banks in terms of both eigenvector centrality and community size. During the COVID period, the treatment banks have significantly lower lending to nonfinancial firms than the control banks. These results suggest a causal relationship between the network features of the interbank market and credit supply to the domestic corporate sector.

Our paper extends a large literature on the role of banks in providing liquidity to the real economy. For example, Kashyap, Rajan and Stein (2002) show that banks have a natural advantage in providing liquidity because of the synergy between deposit-taking and loan commitments which requires banks to hold balances of liquidity assets to provide liquidity on demand to depositors as well as to credit line borrowers. Recent papers examine banks' liquidity provision during a crisis or stress time. For example, Acharya and Mora (2015) show that during the 2008's financial crisis, banks' liquidity provision was only possible due to the explicit and large support from the government and government related entities. Santos and Viswanathan (2020) find that during recessions, credit lines offer significant support to large borrowers even when credit ratings are downgraded. Iyer et al. (2014) find that banks relying more on interbank borrowing before the crisis cut their credit supply more than other banks did during the crisis.

A growing literature has explored banks' lending during the COVID-19 crisis (Li, Strahan and Zhang, 2020; Acharya et al., 2021; Li and Strahan, 2021; Hasan, Politsidis and Sharma, 2021; Colak and Oztekin, 2021). For example, Li et al. (2020) document that the increase in liquidity demands at the onset of the COVID-19 was concentrated at the largest banks who served the largest firms in the US. However, Li and Strahan (2021) further show that after the Paycheck Protection Program (PPP) which targeted small businesses as part of the government support was launched in the US, large banks experienced contractions in lending. Using a sample of banks from 125 countries, Colak and Oztekin (2021) find that bank lending is weaker in countries that are more affected by the COVID crisis. While a large number of papers rely on data on syndicate loans and examine how bank lending is affected by the COVID crisis, we use a different source, the UK's large exposure data, which covers not only syndicate loans but all the large loan exposures to the corporate sector above £300 millions or 10% of a bank's Tier 1 capital. We are the first paper to capture the interconnectedness in the UK interbank market before and during the COVID crisis and examine how the structural features, i.e. core-periphery structure and community relationship, of the interbank network affects banks' liquidity conditions as well as their credit supply to the real economy.

Our paper contributes to the literature on interbank networks (e.g. Allen and Gale, 2000; Craig and von Peter, 2014; Beltran et al., 2021) as well as interbank liquidity during crises (e.g. Freixas and Jorge, 2008; Allen et al., 2009; Bruche and Suarez, 2010; Acharya and Merrouche, 2013). For example, using a network for all commercial banks in the US during the Great Depression, Mitchener and Richardson (2018) find that the interbank lending networks amplified the contraction in lending during the Great Depression. Using a hyperstructure approach, Accominotti et al. (2022) construct the networks of the sterling money market during 1880 to 1913 and find that failure of individual money market actor could only cause limited impact on the network as intermediaries were highly substitutable. Our paper is closely related to Kiernan et al. (2021), who investigate the interconnectedness of the syndicate loan market and show that the fronting commitments provide a significant amount of liquidity insurance to the corporate sector. In this paper, we examine the dynamic structure of the UK interbank market since 2014 and explores both the core-periphery structure and community features. To examine the core-periphery structure, we concentrate on the global centrality which captures the global importance of individual banks beyond the local/direct borrowing and lending relationships in the interbank market.

The remainder of the paper is organized as follows. Section 2 describes the data source, sample construction and variables. Section 3 provides the stylized facts of the aggregate-level evidence and summary statistics of the UK interbank networks. Section 4 discusses the empirical methodology and results. Section 5 discusses the identification strategy by using the COVID-19 pandemic as a shock. Section 6 concludes.

2. Sample and data description

2.1 Data source

In order to study how the interbank network structure affects lending relationships with non-financial corporates, we rely on the large exposures (LE) dataset for the UK banking sector[2]. This dataset includes exposures in both the banking and trading book and it is limited to those exposures that are larger than 10% of a bank's Tier 1 capital or are above £300 million[3]. The LE dataset is constructed with an entity to entity relationship. Each counterparty is identified with the legal name or group name and where possible with a Legal Entity Identifier (LEI code). Additional counterparty information is provided such as the SECTOR, COUNTRY (of incorporation) and NACE classification of the entity. The LE dataset also provides a rich set of exposure attributes, which allow us to distinguish between debt, equity, derivate and off-balance sheet exposures. The LE dataset is quite comprehensive covering banks' exposures towards non-financial corporations (NFC), non-bank financial corporations (FC), credit institutions (CI), governments (GG) and central banks (CB). The dataset is a global dataset, capturing UK banks' large exposures vis-à-vis entities located worldwide. The dataset is UK-centric, meaning that on the reporting side, only UK banks, subsidiaries of international banking groups domiciled in the UK or UK consolidation groups are present.

For our scope, we focus on those exposures on the banking book, and specifically on gross original direct debt exposure amounts which captures UK banks' lending relationships. Although the LE dataset is very rich, constructing a consistent network of bilateral relationships is not immediate. Consistent identification of counterparty entities across reporting banks is challenging since Legal Entity Identifiers are not always available and counterparty names are spelled often differently, and counterparty attributes might not be reported. In this respect, we rely on the cleaning and mapping procedure developed by Covi et al. (2022) to improve the mapping of counterparties' attributes such as LEI, SECTOR, COUNTRY and NACE codes[4].

2.2 Sample construction

Thank to this, we comfortably subset the dataset according to counterparties classified as NFCs and located within the UK in order to create the network of lending relationships towards UK NFC. Moreover, we subset the dataset to those counterparties that are classified as credit institutions (CI) located within the UK in order to derive the UK interbank network of lending relationships. The dataset has a quarterly frequency starting from Q2-2014 till Q4-2021, for a total of 30 quarterly snapshots.

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[2] Supervisory framework for measuring and controlling large exposures.

[3] Since 1st January 2022, this threshold was set at £260 million.

[4] This clean version of the LE dataset is available internally at the bank of England. The mapping accuracy of counterparty information for the LE dataset improves up to 91% for LEI codes (from 55%), up to 93% for COUNTRY codes (from 35%), up to 100% for SECTOR codes (from 35%), and up to 85% for NACE codes (from 22%)

UK interbank networks

In the period of 2014 to 2021, the UK interbank network is composed on average by 259 reporting banks, which are lending towards 143 UK-based credit institutions, for an average of 767 lending relationships per quarter as reported in Panel A of Table 1. The total amount of exposures captured by the network is on average £87 billion, with an average exposure amount of £113 million. Moreover, the UK interbank network is a sparse network with a density of less than 2% of total possible linkages[5]. In total, the UK interbank network dataset covers 24,540 observations across all quarters. Covi et al. (2022) give a detailed description how the UK interbank market is constructed.

Table 1: Sample construction

Panel A: Yearly Average of Quarterly Interbank Network Statistics

YEAR	2014	2015	2016	2017	2018	2019	2020	2021	AVG
Banks	286	278	269	257	243	232	255	250	259
UK CI	184	158	146	131	136	127	133	131	143
Edges	900	869	816	777	710	674	704	686	767
Billion £	117	96	87	84	78	80	72	82	87

Panel B: Yearly Average of Quarterly NFC network statistics

YEAR	2014	2015	2016	2017	2018	2019	2020	2021	AVG
Banks	104	97	104	109	104	112	109	108	106
UK NFC	315	341	332	338	335	349	384	399	349
Edges	443	523	495	530	495	535	576	595	524
Billion £	101	126	107	121	101	93	102	110	108
Banks*	201	217	212	213	226	232	234	226	220
UK NFC*	664	699	698	697	706	724	728	724	705
Edges*	2327	2593	2536	2546	2778	2920	2956	2839	2687

Note: Variables flagged with (*) refers to the final re-constructed NFC network made of zero and non-zero relationships.

Banks' lending to corporate sector

Overall, across all reporting quarters, we have 259 unique reporting banks and 2027 unique non-financial corporates located within the UK. Nevertheless, banks may enter and exit the NFC network on a quarterly basis for multiple reasons. Banks may not roll-over the loan exposure, so stop reporting vis-a-vis a specific counterparty, or the exposure amount may fall below the reporting threshold, or a bank may have merged with another bank, or because the counterparty has stopped the funding relationship or has changed its lender. Stated that, by looking at Panel B of Table 1, which reports the yearly average of the main quarterly NFC network statistics, we can see that the number of reporting credit institutions is quite stable over time, floating between 97 and 112, with an average of

[5] We want to emphasize that the LE dataset captures quite comprehensively interbank exposures as already described in Covi et al. (2022) for the UK and Montagna et al. (2021) for the euro area, since interbank exposures tend to be sizable enough to overcome the LE reporting threshold.

106 active banks per quarter[6]. Similarly the number of UK NFC counterparties is quite stable, floating between 315 and 399, with average of 349, whereas the number of quarterly edges average around 524 per quarter. On average, UK banks are exposed on a quarterly basis towards UK NFC with roughly £108 billion of outstanding loan exposures.

These descriptive network statistics only capture active relationships on a quarterly basis, that is, when an exposure ceases to exist, it is not reported with 0 for that specific quarter bank-NFC pair relationship. We have roughly 17,000 non-zero observations. In this respect, to obtain a balance panel of constant relationships across quarters, we impute all zero relationships between each bank-NFC pair that has at least one non-zero relationship across the whole time coverage. We so increase the size of the dataset to 344.000 zero and non-zero observations[7].

In the end, we remove those NFCs which exhibit less than 5 lending relationships across all banks in all quarters to avoid stale data. Therefore we are left with roughly 114,000 observations. The size of the dataset is so reduced by 2/3.[8]

Finally, we link a complete set of time-variant control variables for each reporting bank such as balance-sheet information like total assets, risk weighted assets, capital ratio using supervisory data sources as well as bank-specific network measures as eigenvector centrality, pagerank, cluster coefficient. By doing this, we reduce further the number of non-missing observations in our dataset, ending with 80,299 data points. Statistics flagged in Table 1 with a star, refer to the number of banks, NFCs and edges that are representative of the final version of the dataset.

2.3 Variables

2.3.1 Centrality and clusters

We apply network methodology to construct the UK interbank network and investigate its network features. In graph theory, a network is generally described by a square "adjacency" matrix, reflecting the strength of connection among each node in the networks. In our setting, the interbank network captures how each bank in the interbank market is connected to other banks through borrowing and lending. Therefore, the networks are directed and weighted; and the matrix representing the network is asymmetric. Each node in the network represents a bank. The direction indicates the borrowing or lending between a pair of banks and the weights indicate the amount of borrowing or lending between two banks, and hence, reflects the influence of the bank in the interbank market.

[6] Number of banks having lending relationships with UK NFCs is smaller compared to the number of reporting banks in the interbank network given that exposures to UK NFC are more constrained by the LE reporting threshold. Exposures to other credit institutions tend to be more sizable compared to exposures to UK NFCs, thereby entering into the LE dataset.

[7] Statistics in Table 1 flagged with (*) refer to this newly constructed NFC network.

[8] As a robustness check, we also try dropping the NFCs with less than 3 lending relationships across all banks in all quarters and the results we document in the paper all hold.

Two central features of network structure are centrality and cluster (community). Centrality has been widely used in the prior literature (e.g. e.g. Ahern and Harford, 2014; Larcher, So, and Wang, 2013). Following the literature, we construct two types of centrality measures, i.e. local and global centralities, based on the UK interbank network. The former includes in-weighted-degree, out-weighted-degree and total-weighted degree centrality, which capture how banks are connected to each other through borrowing and lending directly (locally); the latter includes eigenvector and betweenness centrality, which capture how important each bank is in the entire set of networks (globally) (Jackson, 2008).

We describe each measure of centrality conceptually as following: suppose there are N banks in the network, denoted $[N] = \{1,2 \ldots N\}$. Denote $C = \{c_{ij}, (i,j) \in V \times V\}$ as the set of edges, with c_{ij} being interpreted as the amount of borrowing/lending between bank *i* on *j*. We also define $x_i = (x_{i1}, \ldots, x_{ip})$ as a p dimensional bank i's characteristics. For example, those characteristics could be bank size, capital ratio, risk weighted asset ratio, location, etc. The whole network can be fully formalized as

$$G = \left\{[N], C, (x_i)_{i\in[N]}\right\}$$

Weighted degree centrality measures the strength of first-degree links to each bank. In-weighted-degree is defined as $Indegree_i = \sum_{j\in V} c_{ij}$, and out-weighted-degree is defined as $Outdegree_i = \sum_{j\in V} c_{ji}$, both weighted by the amount of exposures between banks. *Total Degree* or *Degree* is the sum of *In-degree* and *Out-degree*. *Betweenness* reflects the well-connectedness of a node in terms of the shortest paths that it lies on (Bonacich, 1972; Freeman, 1977). Therefore, a bank might be well-connected if it lies on more shortest paths between other pairs of banks defined by betweenness centrality, making such a bank as a key broker in the interbank network. In our setting, bank j and k are connected through bank *i* if there exists a shortest link denoted as $(jl \ldots piq \ldots mk)$ such that

$$c_{jl} .. c_{pi} c_{iq} \ldots c_{mk} > 0$$

$$P_i = \{(j,k) \in V \times V, \exists (jl \ldots piq \ldots mk)\ s.t.\ c_{jl} .. c_{pi} c_{iq} \ldots c_{mk} > 0\}$$

Hence, betweenness is defined as $Betweenness_i = \frac{\sum_{(j,k)} I\{(j,k)\in P_i\}}{\sum_i \sum_{j,k} I\{(j,k)\in P_i\}}$.

Globally in the network, the importance of a bank can be affected by the importance of its direct links, i.e. the neighbours in the network. Eigenvector centrality can be used to capture such notions of global influence of a bank in the interbank market. Formally, eigenvector is defined recursively as $\lambda x_i^* = \sum_{j\in[N]} C_{ij} x_j^*$, where $x^* = (x_1^*, x_2^*, \ldots, x_N^*)'$ is the centrality of the bank given the interbank connection matrix C (Bonacich, 1987; Bonacich and Lloyd, 2001; Bonacich, 2007). Finally, we take the natural logarithm of the original centralities for the regression analysis.

While centrality captures the importance of each individual bank in the interbank network, a community/cluster reflects a group of nodes that have strong ties to each other. Usually, communities are relatively stable over time. We analyze communities of interbank networks because it can capture relationship lending in the interbank market. To detect communities, we use two types of cluster detection algorithm based on Modularity optimization, which reflects whether the connection is dense or not. Suppose there are *N* banks, *M* communities with the *h-th* community comprising n_h banks. Then throughout the network $N_h = \sum_{h=1}^{H} n_h$ banks belong to communities and $N - N_h$ do not. Let c_h denote community *h* and $\delta_{ij}(c_h)$ be an indicator equal to one when bank *i* and *j* belong to the same community h.

Community detection chooses the number of groups *H*, the size of each group n_h , and the set of indicators $\delta_{ij}(c_h)$, to maximize *Modularity*, Q:

$$\mathrm{Q} = \frac{1}{2m}\sum_{h}\sum_{i,j}\left[a_{ij} - \frac{d_i - d_j}{2m}\right]\delta_{ij}(c_h)$$

where 2m is the total number of edges in the network; a_{ij} is the observed number of links between bank *i* and *j*; $\frac{d_i - d_j}{2m}$ is the number of links between *i* and *j* that would be expected by chance. Modularity is therefore the difference between actual incidence of in-community links minus its expected value across all communities. When the modularity is high, the number of actual ties between the banks in communities exceeds that if the edges were distributed at random, while the low modularity indicates the opposite. Through optimizing the modularity in the equation above, we identify banks into different communities/clusters. We use two measures of community-detection algorithm, respectively the Cluster-Leiden algorithm (Traag et al., 2019) and Cluster-Fast-Greedy (Clauset et al. 2004).

2.3.2 Bank lending and other characteristics

Given the nature of the dataset, to capture banks' lending decision to non-financial firms, we use the outstanding loan exposure at the end of each quarter between each pair of bank and borrower (UK non-financial firm) covered in the data. *Log of loan amount* is defined as the natural logarithm of the amount of outstanding loan exposure by each quarter between banks and borrowers. For bank characteristics that might affect lending decisions, we consider the ratio of risk weighted assets over total assets (*Risk weighted assets*), and the ratio of own funds capital over total assets (*Capital ratio*) as banks' risk profiles are likely to be correlated with the loan amounts. *Bank size* is defined as natural logarithm of bank total assets.

2.3.3 Borrower characteristics

For other borrower characteristics that might affect the amount of loans, we control for the size of borrowers' total assets (*Borrower size*). We also consider banks' relationship with borrowing firms as repeated relationship can help reduce information asymmetry and affect lending decisions. *Freq ratio* defines a frequent borrower when the firm has a ratio of non-zero borrowing relationships over its total zero and non-zero borrowing relationships across time in the top 75th percentile, that is, above 34%. Banks might share information with each other if a firm borrows frequently from different banks. *BB freq ratio* is defined similarly as *Freq ratio* but calculated between each borrower-bank peer, that is, those borrower-bank relationships that have at least 50% of non-zero values across time (top-75th percentile). Therefore, it captures the specific relationship between the borrowing firm and a lender (bank).

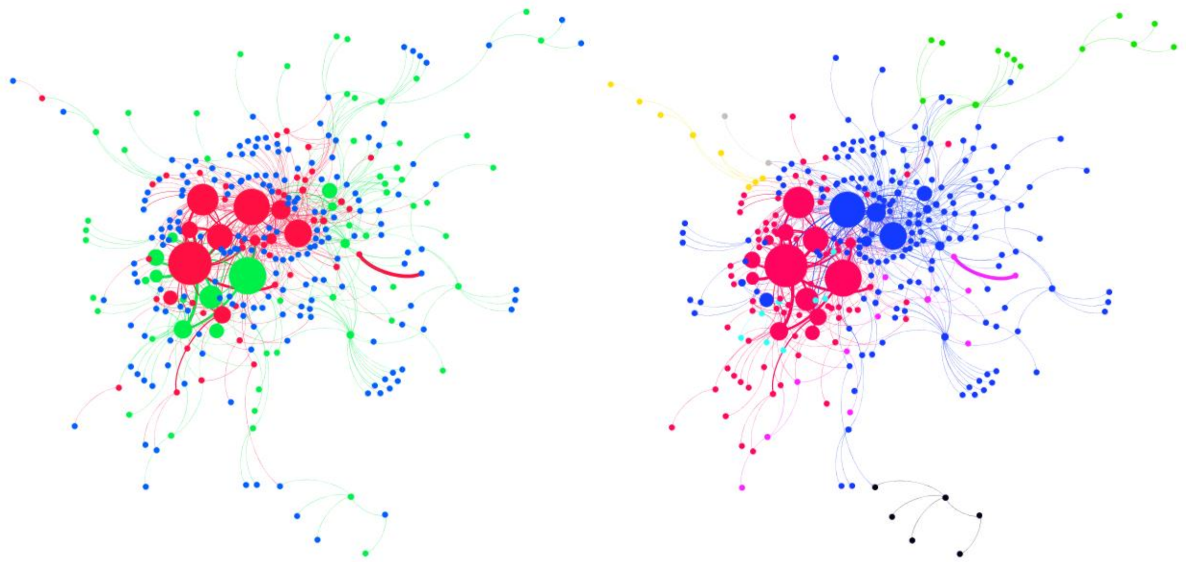
3. Aggregate-level evidence and summary statistics

3.1 Stylized facts: UK Interbank and Economic Network

Panel (a) of Figure 1 plots the lending and borrowing relationships in the UK interbank network for the fourth quarter of 2021. The nodes represent banks and the edges represent the exposures, i.e. borrowing or lending between banks. The size of the nodes equals to each bank's eigenvector centrality, and the size of the edges denotes the relative exposure amount. The color of the nodes is attributed as follows: 1) red for those banks that both lenders and borrowers in the interbank market; 2) blue if a bank is only a lender in the interbank market; and 3) green if a bank is only a borrower in the interbank market. The color of the edges is attributed according to the target node's color.

Figure 1: UK Interbank Network in Q4-2021

Panel (a) – Lenders and Borrowers *Panel (b) - Communities*

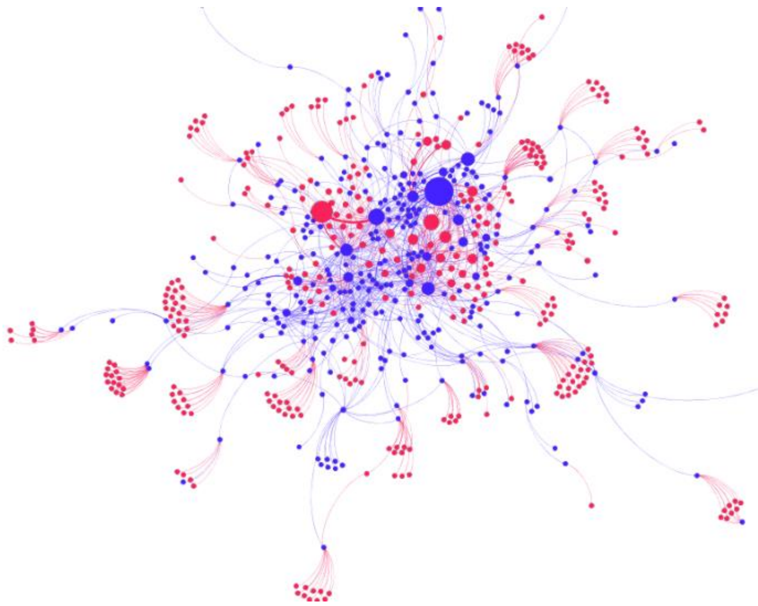


Note: The size of the nodes is equal to each bank's eigenvector centrality measure, and the size of the edges to the relative exposure amount. The colour of the nodes has been attributed as follows: 1) red for those banks that are both lenders and borrowers in the interbank market; 2) blue if a bank is only a lender in the interbank market; and 3) green if a bank is only a borrower in the interbank market. In the end, the colour of the edges is attributed according to the target node's colour.

In this respect, we have 15% of banks that are both borrower and lender in red; 62% of banks are blue and 23% of banks are green. By the end of 2021, banks as both borrowers and lenders (in red) tend to have higher eigenvector centrality; banks only as lenders (in blue) tend to have smaller eigenvector centrality and are periphery nodes in the networks. Whereas, panel (b) reports the same network graph but assigns a different colour to each banking community. Overall, the chart highlights that the UK interbank network shows a core-periphery structure and interbank communities may define a specific set of borrowing-lending relationships which characterizes a sub-network structure, which differs from the attribute of the nodes, whether lender or borrower.

Next, Figure 2 depicts UK banks' lending relationships to domestic (UK-domiciled) non-financial corporations (NFC), that is, the UK economic network, and interbank network relationships. The network is characterized by banks as blue nodes, and by UK NFC as red nodes. The size of the nodes captures the absolute amount each NFC or Bank is borrowing. The economic network displays a core-periphery structure too. The core of the network consists of those NFCs which receive funding from more than one bank (degree of interconnectedness and overlapping portfolios), whereas the periphery captures those exclusive funding relationships between one bank or few banks and multiple NFC counterparties. The thickness of the edges represents the size of the exposure, thereby highlighting the degree of risk concentration.

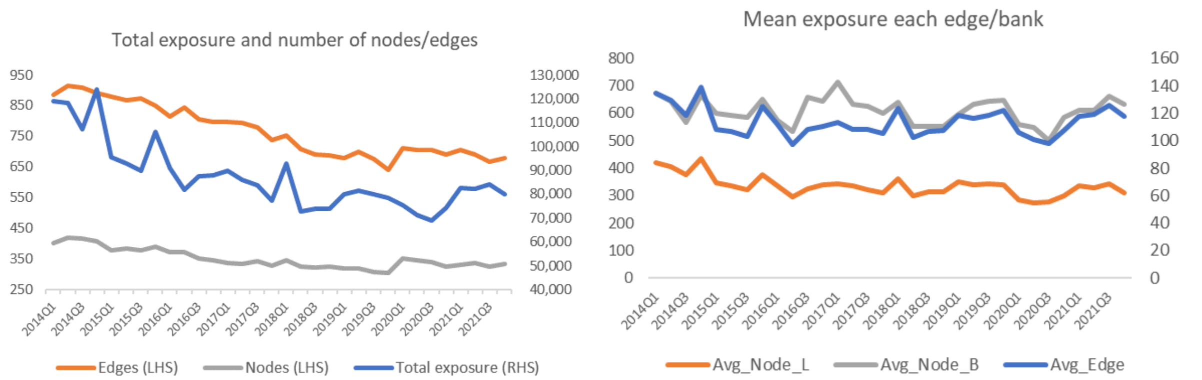
Figure 2: UK Banks' Economic Network in Q4-2021



Note: The size of the nodes is equal to in-weighted degree, and the size of the edges to the relative exposure amount. Blue nodes are banks, whereas red nodes are UK non-financial corporates. In the end, the colour of the edges is attributed according to the target node's colour, that is, blue for interbank exposures, and red for exposures towards NFCs.

Figure 3 plots the interbank market size and banks' participation in the interbank market across quarters from 2014 to 2021. The top left panel shows the total outstanding exposure (in million GBP) as well as the number of nodes/edges in the interbank network by the end of each quarter. It shows that overall, the total outstanding exposure and the number of nodes/edges decrease over time. However, while the outstanding exposure continues to decrease in the first to the third quarters of 2020, it started to pick up since Q4-2020. In Q1-2020, the beginning of the COVID-19 pandemic, there is also an increase in the number of nodes and edges, suggesting that more banks are joining the interbank market. Specifically, we find both numbers of borrowers and lenders are increasing. Number of borrowing banks increase from 230 in Q4-2019 to 264 in Q1-2020, by 15 percent; number of lending banks increase from 121 in Q4-2019 to 135 in Q1-2020, by 12 percent. As a result, the mean exposure per edge reduces from 122.2 million GBP in Q4-2019 to 106 million GBP in Q1-2020, shown in the top right panel. For each lender, the average lending reduces from 340.7 million GBP in Q4-2019 to 285.5 million GBP in Q1-2020; for each borrower, the average borrowing reduces from 647.6 million GBP in Q4-2019 to 558.3 million GBP in Q1-2020. Overall, summary statistics show that although more banks participated in the interbank market in the outbreak of the COVID-19 pandemic, the average exposure is lower, suggesting evidence of liquidity hoarding in beginning of COVID period. However, the liquidity situation is improved since the last quarter of 2020, with both total outstanding exposure and mean exposure per bank going up.

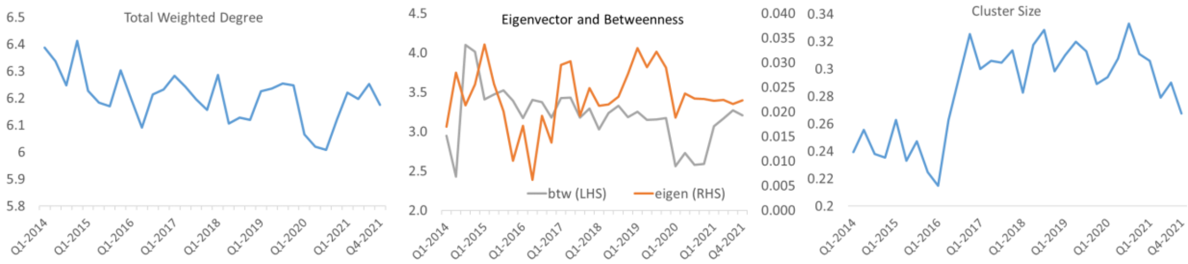
Figure 3: Interbank market size



Note: This figure plots the interbank market size and participation by quarter from 2014 to 2021. The left panel plots the number of nodes/edges (LHS) by the end of each quarter, and the total outstanding interbank exposure (in million GBP, RHS). The right panel plots the mean exposure per bank (LHS), and per edge (RHS).

We then explore how the network features, i.e. centrality and cluster (community) change over time for the UK interbank market over the period of 2014 to 2021. We calculate network centralities including local centrality, i.e. total (weighted) degree, and global centrality, i.e. eigenvector and betweenness, and detect clusters/communities using the Leiden algorithm. Figure 4 plots the change of centralities (all in natural logarithm) and the size of clusters (the ratio of the number of banks in the cluster where the bank identified over the total number of banks in the network). Both local and global centralities have shown a significant drop in the first year of COVID in 2020. The average weighted degree and betweenness centralities have recovered to a certain amount whereas the average of eigenvector centrality has remained low. This might be driven by the fact that more periphery banks have joined the interbank networks for short-term funding. The average size of clusters experiences significant growth both in 2016 and 2020, increasing from 0.21 in Q1-2016 to 0.32 in Q4-2016 and then from 0.29 in Q4-2019 to 0.33 in Q3-2020. This suggests that when the pandemic hit the economy, more banks are switching to bigger communities on average.

Figure 4: Interbank network characteristics: Centrality and cluster size



Note: This figure plots the change of network features, including the average local centrality (total degree) and the average global centrality (eigenvector and betweenness) as well as the average size of the clusters in the UK interbank market from 2014 to 2021. The size of the cluster is defined as the ratio of the number of banks in the community where the bank belongs to (identified by community detection using Leiden Algorithm).

3.2 Descriptive statistics

3.2.1 Summary statistics of network centralities and cluster

Table 2 provides the summary statistics of the exposure-based dataset as well as banks' balance sheet and network characteristics. Specifically, *Risk weighted assets* (as a share of total assets) ranges from 0.000 to 0.999, with the sample mean of 0.263 and a standard deviation of 0.241, suggesting that on average the risk weighted assets account for 26.3 percent of the bank total assets. Next, *Capital ratio*, which is approximated by CET1 capital over RWA, shows an average of 24.8 percent. *Bank size* ranges from 15.470 to 28.687, with a sample mean of 23.180 and a standard deviation of 2.213, suggesting that on average the bank total assets are £11.66 billion.

In degree centrality (in Log) ranges from 0.000 to 9.888, with a sample mean of 1.562 and a standard deviation of 2.941, suggesting that on average each bank is borrowing £3.77 million from other banks in the interbank network. *Out degree* centrality ranges from 0.000 to 9.435, with a sample mean of 3.214 and a standard deviation of 2.643, suggesting that on average each bank is lending £23.88 million to other banks in the interbank market. *Total degree* centrality ranges from 0.000 to 10.318, with a sample mean of 3.655 and a standard deviation of 2.877, suggesting that on average each bank's total exposure is £37.67 million in the interbank market. The mean value and standard deviation of *Betweenness* centrality is 0.994 and 2.118, respectively. *Eigenvector* centrality ranges from 0.000 to 8.273, with a sample mean of 0.040 and standard deviation of 0.121.

Cluster leiden ranges from 0.000 to 0.574, with a sample mean of 0.283 and a standard deviation of 0.263, suggesting that defined by laiden algorithm, an average cluster has 73 banks (=0.283*259) and the largest cluster has 148 banks (=0.574*259). *Cluster fast greedy* ranges from 0.000 to 0.520, with a sample mean of 0.140 and a standard deviation of 0.126, suggesting that defined by fast greedy algorithm, an average cluster has 35 banks (=0.140*259) and the largest cluster has 134 banks (=0.520*259).

Table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log of loan amount	80,299	2.462	6.160	0.000	23.920
Risk weighted assets	80,299	0.263	0.241	0.000	0.999
Capital ratio	80,299	0.248	0.140	0.006	1.000
Bank size	80,299	23.180	2.213	15.470	28.687
In weighted degree	80,299	1.562	2.941	0.000	9.888
Out weighted degree	80,299	3.214	2.643	0.000	9.435
Total weighted degree	80,299	3.655	2.877	0.000	10.318
Eigenvector	80,299	0.040	0.121	0.000	0.693
Betweenness	80,299	0.994	2.118	0.000	8.273
Cluster leiden	80,299	0.283	0.263	0.000	0.574
Cluster fast greedy	80,299	0.140	0.126	0.000	0.520
Liquidity	41,936	0.146	0.125	0.000	0.97

Note: *Risk weighted assets* are provided as share of total assets; *Capital ratio* is defined by own funds over risk weighted assets; *Bank size* is defined as log of total assets; *In/Out/Total degree* is the log of the sum of incoming, outgoing and total interbank loan exposures; Cluster leiden and cluster fast greedy is defined as the ratio of the number of banks in a cluster over total banks in the network; liquidity is measured as cash available over total assets.

4. Empirical results

4.1 Empirical methodology

We start by examining the effects of banks' network position in the interbank market on banks' lending decision to UK non-financial firms using the model below:

$$Log\ of\ loan\ amount_{i,j,t} = \alpha_{ij} + \delta_t + \beta_0 + \beta_1 \cdot Centrality_{i,t-1} + \beta_2 \cdot Cluster_{i,t-1} + \beta_3 \cdot (Bank\ \ characteristics)_{i,t-1} + \beta_4 \cdot (Firm\ \ characteristics)_{j,t-1} + \varepsilon_{i,j,t} \quad (1)$$

where *Log of loan amount* is the dependent variable and α_{ij}, δ_t are bank-firm pair fixed effects and quarter fixed effects respectively. The key explanatory variables are centrality and cluster measures of the interbank network. We also incorporate an assortment of banks' financial information as well as borrower characteristics as control variables. Bank characteristics include *Risk weighted assets*, *Capital ratio* and *Bank size*. Firm characteristics include *Borrower size*, and the frequency of bank loans. However, since we have limited information for borrowers, and including borrower size would reduce our sample by about 70 percent, in the baseline results, we control for bank-firm fixed effects but do not control for borrower characteristics in the regressions. Standard errors are clustered at the bank level. In addition to bank-firm pair fixed effects, we also incorporate quarter fixed effects to account for both bank-firm and time heterogeneities.

4.2 Baseline results

Does a bank's network position in the interbank market affect its lending behavior to non-financial firms? The baseline results, reported in Table 3, suggest that it does. In the specifications, we include one centrality or cluster measure at a time, and we control for bank characteristics as well as bank-firm pair and quarter fixed effects in each specification. Column (1) to (5) show that the coefficients of the centrality measures are all positive and significant at the 1% level, meaning that centralities in the interbank network are positively associated with banks' lending to non-financial firms. When banks have higher degree, eigenvector and betweenness centralities, they tend to lend more non-financial firms on average. This suggests that, when banks have more direct exposures in the interbank network, or banks are in core or broker position throughout the interbank network, then they tend to have higher exposure to non-financial firms. Column (6) to (7) show that the coefficients of cluster measures all also both positive and significant at the 1% level, meaning that cluster size is positively associated with bank loan to non-financial firms. If a bank belongs to a larger cluster with more banks, then it tends to lend more to non-financial firms.

Table 3: Baseline results: interbank network features and bank lending

Dep Var	*Log of loan amount*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
In degree	0.0893**						
	(0.0417)						
Out degree		0.469***					
		(0.0373)					
Degree			0.164***				
			(0.0250)				
Eigenvector				6.228***			
				(0.710)			
Betweenness					0.833***		
					(0.0632)		
Cluster leiden						0.744***	
						(0.168)	
Cluster fast-greedy							0.782***
							(0.264)
Risk weighted	0.459	0.307	0.444	0.430	0.245	0.478	0.488
	(0.424)	(0.425)	(0.424)	(0.423)	(0.420)	(0.424)	(0.423)
Capital ratio	-2.543***	-1.704***	-2.286***	-2.470***	-2.389***	-2.377***	-2.466***
	(0.394)	(0.400)	(0.396)	(0.396)	(0.396)	(0.396)	(0.396)
Bank size	-0.199**	-0.202***	-0.206***	-0.210***	-0.119	-0.211***	-0.204***
	(0.0785)	(0.0779)	(0.0779)	(0.0779)	(0.0778)	(0.0782)	(0.0780)
Cons	7.279***	5.698***	6.887***	7.421***	4.737**	7.459***	7.410***
	(1.917)	(1.889)	(1.887)	(1.888)	(1.894)	(1.889)	(1.889)
Bank-firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	80299	80299	80299	80299	80299	80299	80299
R-sq	0.0000221	0.0669	0.0150	0.0455	0.123	0.0114	0.0220

Note: This table reports the baseline results of the regressions examining the effects of interbank network features on the amount of bank loans to non-financial firms. The dependent variable, *Log of loan amount* is defined as the natural logarithm of the amount of bank loans to non-financial firms. The key explanatory variables are the features of interbank networks including network centrality and cluster. *Cluster leiden* and *Cluster fast-greedy*, capturing the size of the cluster where the bank is located in the interbank networks, are defined as the ratio of the numbers of banks in the cluster detected by the algorithms of leiden and fast-greedy over total number of banks in our sample. All other variables are defined in the Appendix A. Robust standard errors are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

The impact of network positions is also economically significant. Taking column (3) and (5) as examples, one-standard-deviation increase in *Degree* is associated with 24.3 percent (=3.655*0.164/2.462) increase in *Log of loan amount* to firms, and one-standard-deviation increase in *Eigenvector* is associated with 10.1 percent (=6.228*0.040/2.462) increase in *Log of loan amount* to firms, all else being equal. Taking column (6) as an example, one-standard-deviation increase in cluster size (*Cluster leiden*) is associated with 8.6 percent (0.744*0.283/2.462 increase in *Log of loan amount* to firms, all else being equal. Therefore, on average, a bank tends to lend more to the real sector when it has more exposure or it is a core/broker bank in the interbank network.

4.3 Heterogeneous effects

4.3.1 Heterogeneity of banks

We then investigate the heterogenous effects of network positions on lending to the real sector across different banks or borrowers, and we first focus on the heterogeneity of banks, i.e. how bank size influences the impact of network centrality and cluster size. Larger banks are more likely to be in the core positions while smaller banks are more likely to be in the periphery positions in the interbank network. Altinoglu and Stiglitz (2020) argue that risk sharing between the systemically important financial institutions (SIFIs) and non-SIFIs are generates a core-periphery structure The interbank market channels funds to investment opportunities with higher risks and as a result, SIFIs are relatively risky compared to smaller banks. In the mean time, the implicit insurance provided by a SIFI's liabilities, finally implicit guaranteed by the government, enables smaller and peripheral banks to take excessive risks. Therefore, we would expect that the effect of risk sharing should be stronger for larger banks. For smaller banks, the insurance comes not only from the connected core banks, but also from the connected counterparties in the same cluster. Therefore, we would expect the effect of the cluster size should be stronger for smaller banks.

Table 4 reports the results on this. We use similar specifications as the baseline results, and also include the interactions of *Bank size* and network centralities or cluster size. The results in column (1) to (5) show that the coefficients of the interaction terms of *Bank size* and centrality are positive and significant at the 1% level. This suggests that the effect of centrality on loans to non-financial firms relies on the size of the bank and are more pronounced for larger banks. For example in column (3), the coefficients show that on average, one-standard-deviation increase in *Degree* is associated with 30.3 percent (=(0.110*3.655*23.180-2.346*3.655)/2.462) increase in log amount of loan exposure. However, one-standard-deviation decrease in *Bank size* can reduce the effect by 9.9 percent (=2.213*0.110/2.462). Similarly, in column (5), one-standard-deviation decrease in *Bank size* can reduce the effect by 0.43 percent (=0.267*0.040/2.462). However, the coefficients of *Cluster* and *Bank size* in column (6) and (7) are both negative and significant at the 1% level, suggesting that the effect of cluster size on loans to non-financial firms also relies on the size of the bank but are more pronounced for smaller banks. Taking column (6) as an example, on average, one standard-deviation increase in *Cluster leiden* is associated with 4.6 percent (=(9.727*0.263-0.263*0.401*23.180)/2.462); and one-standard-deviation increase in *Bank size* can mitigate the effect by 36.0 percent (=2.213*0.401/2.462). Overall, the results suggest that although both centrality and cluster size have positive effects on banks' lending to the real sector, the effect of centrality is more pronounced for larger banks, whereas the effect of cluster size is more pronounced for smaller banks.

Table 4: Heterogeneity of banks: Large vs. small banks

Dep Var	*Log of loan amount*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	In degree	Out degree	Degree	Eigenvector	Betweenness	Cluster leiden	Cluster fast greedy
Centrality	-4.301***	-3.594***	-2.346***	-46.06***	-6.086***		
	(0.828)	(0.321)	(0.466)	(8.621)	(0.482)		
Centrality × Bank size	0.186***	0.167***	0.110***	1.920***	0.267***		
	(0.0354)	(0.0138)	(0.0204)	(0.329)	(0.0197)		
Cluster						9.728***	15.28***
						(2.848)	(2.948)
Cluster × Bank size						-0.401***	-0.638***
						(0.125)	(0.130)
Risk weighted	0.590	0.436	0.589	0.515	0.205	0.309	0.542
	(0.423)	(0.425)	(0.428)	(0.423)	(0.419)	(0.420)	(0.423)
Capital ratio	-2.428***	-2.037***	-2.212***	-2.434***	-2.306***	-2.424***	-2.376***
	(0.397)	(0.395)	(0.395)	(0.396)	(0.395)	(0.397)	(0.395)
Bank size	-0.230***	-0.514***	-0.437***	-0.212***	-0.172**	-0.169**	-0.0765
	(0.0790)	(0.0818)	(0.0897)	(0.0779)	(0.0780)	(0.0780)	(0.0785)
Cons	0.590	0.436	0.589	0.515	0.205	0.309	0.542
	(0.423)	(0.425)	(0.428)	(0.423)	(0.419)	(0.420)	(0.423)
Bank-firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	80299	80299	80299	80299	80299	80299	80299
R-sq	0.136	0.139	0.154	0.0481	0.134	0.0501	0.0165

Note: This table reports the regressions examining the heterogenous effects of bank size on the relationship between interbank networks and loans to non-financial firms. The dependent variable, *Log of loan amount* is defined as the natural logarithm of the amount of bank loans to non-financial firms. The key explanatory variables are the features of interbank networks including network centrality and cluster. In column (1) to (5) we use *In degree*, *Out degree*, *Degree*, *Eigenvector*, *Betweenness* for Centrality respectively; in column (6) to (7) we use *Cluster leiden* and *Cluster fast-greedy* for Cluster respectively. *Bank size* is the natural logarithm of bank total assets. All other variables are defined in the Appendix A. Robust standard errors are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

4.3.2 Heterogeneity of borrowers

We then examine how the effect of banks' position in the interbank network relies on heterogeneity of borrowing firms, in terms of borrowing frequency. For a specific borrower, we define borrowing frequency in two ways: *Freq. Ratio*, which equals to the ratio of total non-zero borrowing relationships from all the banks in our sample period, over total zero and non-zero borrowing relationships; and *BB Freq. Ratio*, which equals to the ratio of non-zero borrowing relationships from a specific bank in our sample period, over total zero and non-zero borrowing relationships vis-à-vis that lender. It is less risky to lend to a frequent borrower in the loan market because the information asymmetry is lower for repeated relationships.

Table 5 reports the results on heterogeneity of borrowers. In Panel A, we use the frequency measure, *Freq ratio*. In all the specifications, we include *Freq ratio* as well as its interaction with centrality or cluster measure. The coefficients on the interaction terms in column (1)-(5) are all positive and statistically significant at the 1% level, except in column (1), suggesting that banks at more central positions in the interbank market tend to lend more to frequent borrowers in the loan market. The coefficients on the interaction terms in column (6)-(7) are both positive and statistically significant at the 1% level, suggesting that banks in larger clusters also tend to lend more to frequent borrowers in the loan market. In Panel B, we use the second frequency measure, *BB freq ratio*. Consistently, in all the specifications, we include *BB freq ratio* as well as its interactions with centrality or cluster measure. The coefficients on the interactions in column (2)-(5) are all positive and significant, suggesting that core banks in the interbank market tend to lend more to their repeated borrowers with less information asymmetry. The coefficients on the interaction terms in column (6)-(7) are also positive significantly, suggesting that banks in larger clusters tend to lend more to repeated borrowers. Overall, the results in Table 5 suggest that when core banks or banks in larger clusters take on more risks by increasing lending to the real sector, they tend to lend more to borrowers with less information asymmetry.

Table 5: Heterogeneity of borrowers

Panel A: frequent vs. non-frequent borrowers

Dep Var	*Log of loan amount*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	In degree	Out degree	Degree	Eigenvector	Betweennes	Cluster leiden	Cluster fast greedy
Centrality	0.0952**	0.172***	0.0541*	2.762***	0.463***		
	(0.0437)	(0.0355)	(0.0304)	(1.058)	(0.0689)		
Centrality × Freq ratio	-0.0400	1.898***	0.846***	16.24***	1.970***		
	(0.374)	(0.279)	(0.316)	(4.711)	(0.387)		
Cluster						-0.00619	-0.119
						(0.171)	(0.255)
Cluster × Freq ratio						5.886***	6.819***
						(1.708)	(2.204)
Freq ratio							
Risk weighted	0.460	0.325	0.452	0.448	0.188	0.533	0.515
	(0.422)	(0.431)	(0.427)	(0.423)	(0.420)	(0.423)	(0.421)
Capital ratio	-2.544***	-1.726***	-2.266***	-2.477***	-2.366***	-2.345***	-2.460***
	(0.395)	(0.397)	(0.396)	(0.396)	(0.395)	(0.397)	(0.396)
Bank size	-0.199**	-0.178**	-0.198**	-0.210***	-0.127	-0.201**	-0.204***
	(0.0783)	(0.0777)	(0.0778)	(0.0778)	(0.0777)	(0.0781)	(0.0780)
Cons	7.277***	5.084***	6.579***	7.417***	4.885***	7.160***	7.379***
	(1.915)	(1.890)	(1.889)	(1.887)	(1.891)	(1.888)	(1.888)
Bank-firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	80299	80299	80299	80299	80299	80299	80299
R-sq	0.000562	0.353	0.316	0.0799	0.184	0.0804	0.00289

Panel B: Frequent vs non-frequent bank-borrower relationship

Dep Var	*Log of loan amount*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	In degree	Out degree	Degree	Eigenvector	Betweenness	Cluster leiden	Cluster fast
Centrality	0.0393	0.0300*	0.0338**	2.320***	0.0631**		
	(0.0258)	(0.0158)	(0.0162)	(0.673)	(0.0298)		
Centrality × BB freq ratio	0.404	2.482***	1.393***	11.46***	2.783***		
	(0.256)	(0.147)	(0.292)	(1.950)	(0.159)		
Cluster						-0.0221	0.354**
						(0.0950)	(0.177)
Cluster× BB freq ratio						7.460***	3.375**
						(1.497)	(1.458)
BB freq ratio							
Risk weighted assets	0.434	0.179	0.368	0.454	0.0919	0.510	0.497
	(0.423)	(0.432)	(0.429)	(0.423)	(0.421)	(0.424)	(0.422)
Capital ratio	-2.541***	-1.970***	-2.302***	-2.474***	-2.351***	-2.391***	-2.488***
	(0.394)	(0.389)	(0.393)	(0.396)	(0.395)	(0.394)	(0.396)
Bank size	-0.204***	-0.144*	-0.197**	-0.211***	-0.140*	-0.201**	-0.204***
	(0.0783)	(0.0773)	(0.0777)	(0.0778)	(0.0776)	(0.0781)	(0.0780)
Cons	7.299***	4.307**	6.134***	7.445***	5.134***	7.091***	7.406***
	(1.915)	(1.881)	(1.890)	(1.887)	(1.886)	(1.888)	(1.889)
Bank-firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	80299	80299	80299	80299	80299	80299	80299
R-sq	0.284	0.791	0.810	0.193	0.428	0.598	0.0112

Note: This table reports the regressions examining the heterogenous effects of borrower on the relationship between interbank networks and loans to non-financial firms. The dependent variable, *Log of loan amount* is defined as the natural logarithm of the amount of bank loans to non-financial firms. The key explanatory variables are the features of interbank networks including network centrality and cluster. In column (1) to (5) we use *In degree*, *Out degree*, *Degree*, *Eigenvector*, *Betweenness* for Centrality, respectively; in column (6) to (7) we use *Cluster leiden* and *Cluster fast-greedy* for Cluster, respectively. *Freq ratio* and *BB freq ratio* captures respectively whether a NFC is a frequent borrower in the network and for a specific bank. All other variables are defined in the Appendix A. Robust standard errors are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

4.4 Global vs local effects

We then examine the global versus local effects of the interbank networks. To identify the global effects, in each regression we control for local effects, i.e. both *in-degree* and *out-degree* centrality, or cluster size, and then further incorporate global centralities (either *Eigenvector* or *Betweenness*). By isolating the effects of the local (direct) connections, global centralities can better capture the core/peripheral positions throughout the entire interbank network, and hence, the global effects can better reflect the risk sharing via the bilateral exposures throughout the network.

Table 6 reports the results. In columns (1) and (2) we control for local centralities, in column (3) and (4) we control for *Cluster leiden*, and in columns (5) and (6) we control for *Cluster fast-greedy*.

The coefficients of *Eigenvector* and *Betweenness* are positive and significant at the 1% level in all the specifications, indicating that after controlling for the local effects, including both the direct borrowing and lending exposures or the cluster size, the global effects are still strongly positive. The economic impact is also not trivial. Taking column (1) and (3) as examples, one-standard deviation increase in *Eigenvector* is associated with 18.1 percent (=0.121*3.690/2.462) increase in log amount of loan when controlling for in-degree and out-degree centralities. The economic impact is larger when controlling for cluster size. In the meanwhile, the coefficient of *Cluster leiden* decrease from 0.744 (in Table 3) to 0.684. The economic influence is still significant: one-standard-deviation increase in *Cluster leiden* is associated with 7.9 percent (=0.684*0.283/2.462) increase in log amount of loan. This set of tests confirms our main findings that core banks and banks in bigger cluster in the interbank network tend to lend more to the corporate sector.

Table 6: Interbank network and bank lending: global vs local centrality

Dep Var	*Log of loan amount*					
	(1)	(2)	(3)	(4)	(5)	(6)
Eigenvector	3.690***		6.180***		6.363***	
	(0.590)		(0.711)		(0.711)	
Betweenness		0.709***		0.830***		0.831***
		(0.0625)		(0.0633)		(0.0633)
Cluster leiden			0.684***	0.639***		
			(0.168)	(0.169)		
Cluster fast-greedy					1.097***	0.574**
					(0.262)	(0.266)
In degree	0.0504	-0.197***				
	(0.0424)	(0.0492)				
Out degree	0.430***	0.248***				
	(0.0344)	(0.0259)				
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	80299	80299	80299	80299	80299	80299
R-sq	0.119	0.111	0.0703	0.128	0.0612	0.125

Note: This table reports the results of the regressions examining the effects of global centrality (*Eigenvector* or *Betweenness*) on bank loans to non-financial firms after controlling for the local centrality (*In degree* and *Out degree*) as well as the size of the cluster. The dependent variable, *Log of loan amount* is defined as the natural logarithm of the amount of bank loans to non-financial firms. The key explanatory variables are the features of interbank networks including network centrality and cluster. All other variables are defined in the Appendix A. Robust standard errors are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

The network effects of the interbank markets might be different during a crisis. Bolton et al. (2016) show that relationship banks gather information on their borrowers so that they can offer continuous lending at more favourable terms than transaction banks during a crisis. COVID-19 is an aggregate shock to the real economy when banks faced a dramatic increase in liquidity demands ever observed. Li, Strahan and Zhang (2020) provide a first evidence using US data for banks' liquidity provision during the COVID crisis and they find that banks' increase in liquidity demands was concentrated at the largest banks, who serve the largest firms. We also investigate how the network effects differ during pre- and post-COVID periods. COVID started hitting the UK economy in the beginning of March 2020 and the banking system also experienced an unprecedented stress on the ability of banks to supply liquidity. It is an 'ideal' shock for us to examine how the interbank network structure affects banks' lending behaviour to the real economy.

Table 7: Interbank network and bank lending: post-COVID vs pre-COVID

Dep Var	*Log of loan amount*					
	(1)	(2)	(3)	(4)	(5)	(6)
Eigenvector	4.128***		6.454***		6.528***	
	(0.607)		(0.729)		(0.728)	
Eigenvector×Covid	-3.580**		-2.690**		-1.867*	
	(1.558)		(1.156)		(1.114)	
Betweenness		0.726***		0.844***		0.843***
		(0.0648)		(0.0658)		(0.0657)
Betweenness×Covid		-0.112		-0.0888		-0.0683
		(0.0991)		(0.0670)		(0.0632)
Cluster leiden			0.371**	0.420**		
			(0.176)	(0.176)		
Cluster leiden×Covid			1.185***	0.848***		
			(0.306)	(0.312)		
Cluster fast-greedy					0.623**	0.109
					(0.282)	(0.289)
Cluster fast-greedy×Covid					1.648***	1.690***
					(0.589)	(0.591)
In degree	0.0207	-0.202***				
	(0.0470)	(0.0507)				
In degree×Covid	0.0996	0.0376				
	(0.0626)	(0.0614)				
Out degree	0.428***	0.246***				
	(0.0347)	(0.0269)				
Out degree×Covid	-0.0183	0.0164				
	(0.0372)	(0.0401)				
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	80299	80299	80299	80299	80299	80299
R-sq	0.116	0.113	0.0620	0.130	0.0659	0.127

Note: This table reports the regressions examining the differences for the post-covid and pre-covid periods in the effects of global centrality on bank loans to non-financial firms after controlling for the local centrality (in degree and out degree) or cluster size. *Covid* is defined as one for the first quarter of 2020 to the fourth quarter of 2021; and zero otherwise. The dependent variable, *Log of loan amount* is defined as the natural logarithm of the amount of bank loans to non-financial firms. The key explanatory variables are the features of interbank networks including network centrality and cluster. All other variables are defined in the Appendix A. Robust standard errors are in parentheses.

Table 7 reports the results. We incorporate the interactions of centrality and *Covid* as well as the interactions of cluster size and *Covid*, and in all the specifications, we have both global centrality and local network structure. The results show that, on one hand, our main findings still hold, that both global centralities and cluster size are positively associated with amount of bank loans. On the other hand, the interactions of *Eigenvector* and *Covid* are negative and significant, while those of cluster size and *Covid* are positive and significant. These suggest that core banks that have higher eigenvector in the interbank networks tend to lend less during the COVID crisis, whereas banks in larger cluster tend to lend more during the COVID crisis. This indicates the diverging effects of core-periphery position and community size during a crisis: the effect of risk sharing through core-periphery structure tends to be mitigated and core banks might be hoarding liquidity during a crisis, whereas the effect of liquidity support and lending within a community tends to be strengthened and banks in a larger cluster might get liquidity support from more potential counterparties during a crisis.

How does the liquidity situation change before and after the COVID crisis to support the lending to the real sector? We then examine how liquidity situation relies on the interbank network structure by interacting centrality and cluster measures with the COVID dummy. We use cash assets scaled by total assets to measure bank liquidity. Table 8 reports the results. The coefficient of *Eigenvector* is significantly negative, suggesting that on average, core banks with high eigenvector tend to have less liquidity. The coefficient of *In degree* is positive and significant, suggesting that on average, a bank borrowing more from the interbank market tends to have better liquidity. The coefficient of *Cluster size* is positive and significant (although less significant when we use *Cluster leiden*), showing that on average, a bank in a larger cluster tends to have better liquidity. The interactions of *Eigenvector* and *Covid* and those of *Cluster* and *Covid* are both significantly positive, except that the coefficient of the interaction in column (1) positive but insignificant, suggesting that during COVID, both core banks with high eigenvector and banks in a larger cluster tend to have better liquidity. The interactions of *In degree* (or *Out degree*) and *Covid* both show opposite signs with *In degree* (or *Out degree*) alone, suggesting that during COVID the effect of local degree centralities tends to be mitigated: the marginal effect of *In degree* on liquidity is reduced to close to zero (slightly positive); the marginal effect of *Out degree* on liquidity is positive and significant. Overall, five out of seven interactions with *Covid* are positive and significant in columns (1) to (3).

Therefore, the results in Table 7 and Table 8 so far, altogether show that during the crisis, core banks have better liquidity while lend less to the real sector; banks in larger communities have better liquidity and lend more to the real sector; high in-degree banks have less improved (but still better) liquidity and high out-degree banks have better liquidity but both of them do not tend to change significantly their lending to the real sector. These suggest that core banks with higher centrality might be hoarding liquidity during the COVID crisis. However, one possibility is that core banks are still providing liquidity to other banks while reducing their own lending to non-financial firms. Hence we compare the lending behavior between two groups of banks, one in a large community and borrowing from core banks, and the other in a large community but not borrowing from core banks. The results are shown in column (4) of Table 8. The dummy *Treated Cluster* is defined as one if a bank belongs to a large cluster (above mean value of cluster size using leiden algorithm) and at the same time is borrowing from a high-eigenvector bank; and zero otherwise if a belongs to a large cluster but is not borrowing from a high-eigenvector bank. The coefficient of *Treated Cluster* is not significant, showing that both groups of banks do not seem to differ significantly in lending to the real economy during normal times. However, the coefficient of *Treated Cluster* and *Covid* is positive and significant at the 1% level, suggesting that the bank being in a large community with the connection to high-eigenvector banks tend to lend more during the COVID. This further indicates the liquidity transfer from core banks to other banks to support their lending to non-financial firms.

Table 8: Interbank network, liquidity and lending to non-financial firms

Dep Var	Liquidity			Log of loan amount
	(1)	(2)	(3)	(4)
Eigenvector	-0.00947***	-0.00907***	-0.00426**	
	(0.00352)	(0.00202)	(0.00192)	
Eigenvector×Covid	0.0111	0.0103*	0.0253***	
	(0.0101)	(0.00565)	(0.00590)	
Cluster leiden		0.00674		
		(0.00414)		
Cluster leiden×Covid		0.0167***		
		(0.00634)		
Cluster fast-greedy			0.0181***	
			(0.00605)	
Cluster fast-greedy×Covid			0.0733***	
			(0.0119)	
In degree	0.00153**			
	(0.000627)			
In degree×Covid	-0.00134***			
	(0.000485)			
Out degree	-0.000459			
	(0.000340)			
Out degree×Covid	0.00334***			
	(0.000664)			
Treated Cluster				-1.546
				(3.267)
Treated Cluster * Covid				1.349***
				(0.406)
Other controls	Yes	Yes	Yes	Yes
Bank-firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
# of obs	41936	41936	41936	21693
R-sq	0.150	0.149	0.156	0.281

Note: This table reports the results of the regressions examining the effect of the interbank network structure on banks' liquidity as well as loans to the corporate sector. *Treated Cluster* is defined as one if the bank belongs to a large cluster (above mean value of cluster size using leiden algorithm) and at the same time is borrowing from a high-eigenvector bank; and zero if the bank belongs to a large cluster but is not borrowing from a high-eigenvector bank.

5. Identification: the shock of the COVID-19 pandemic

There might be unobservable factors that are correlated to both banks' centrality/cluster feature in the interbank network and banks' lending decisions. In order to further address the endogeneity concern and identify the causal effect of interbank network structure on banks' loan to non-financial firms, we utilize the COVID-19 pandemic as an exogenous shock to the interbank networks and explore how the shock is transmitted throughout the networks and affects banks' lending behavior. The COVID-19 outbreak was unexpected health crisis to the globe and therefore an exogenous shock to the UK economy and the interbank market. So far, existing literature shows mixed evidence about bank lending during the pandemic. Using the evidence from the US banks, Li et al. (2021) show that the onset of the global COVID-19 pandemic initiated a market panic that led to a dramatic increase in firm drawdowns on existing credit lines, and the increase in liquidity demand was concentrated at the largest banks, who served the largest firms too. Colak and Oztekin (2021) use the evidence from 125 countries and find that bank lending is weaker in countries more affected by the COVID-19 pandemic.

The COVID crisis affects banks through their exposure to borrowers. Therefore, it is a shock to the banks that are largely exposed to the industries negatively impacted by the COVID (e.g. industries such as recreation, wholesale and retail trade, etc) or to the regions that are highly impacted by the COVID. The shock might further transmit through the interbank network, and affect banks that are directly connected to the banks in Covid-impacted industries/regions in the interbank network via lending and borrowing relationships. Specifically, negative spillover in the interbank market may take place via lending relationships given a deterioration of counterparty risk, which requires a bank to set aside more capital, and via borrowing relationships given a deterioration in a bank's liquidity positon. We use industry output or COVID case number (scaled by population) to define COVID-impacted industries or COVID-impacted regions. Using NACE classification and the industrial GVA output data from Eurostat from 2019Q4 to 2020Q4, the industries that experienced the largest contraction in output in the UK are Arts, entertainment and recreation and other services; Professional, scientific and technical activities; Manufacturing; Wholesale and retail trade, transport, accommodation; Real estate activities. Alternatively, to be more precise, we also use the industry classification (sub-industries of SIC07) provided by the UK Office for National Statistics (ONS) and identify an industry as *COVID-impacted industry* if its output shrank at least 10% in 2020 compared to that in 2019.[9] *COVID-impacted regions* are those with top 25% case number (scaled by population) among all the counties in the UK.

[9] The sub-industry of SIC07 from UK ONS provides 77 sub-industries under the main industry categories. For example, under manufacturing, some sub-industries including manufacturing of beverages, tobacco products, textiles, leather products, non-metallic mineral products, basic metals, fabricated metal products etc have larger output loss while the others do not. The detailed sub-industries allow us to identify COVID-impacted banks through industry more precisely. We also construct the connections through either only lending or both lending and borrowing. We find less significant results when only using borrowing exposure to trace interbank connections from the Covid-impacted banks. The robustness results are reported in the Online Appendix Table A.1.

Accordingly, *COVID-impacted bank* is defined as one if a bank has at least 33% of total exposures exposed to the COVID-impacted industries or regions, and zero otherwise. Then we trace the banks that are directly lending to the COVID-impacted banks but themselves are not exposed to the COVID-impacted industries or regions.[10] Therefore, the COVID crisis can affect these banks only through the channel of interbank networks but not the channel of the lending to the real economy directly.

Specifically, we define *Treated* as one if a bank, 1) is not exposed to COVID-19 impacted industries (or regions) and, 2) is directly lending to Covid impacted banks in the interbank network with the exposure of at least £100 million in Q4-2019, and zero for control firms.[11] In the main paper, we define COVID-impacted banks using the NACE industry classification and report the results based on that. Alternatively, we also trace the connections from Covid-impacted banks using either only lending exposure or both lending and borrowing exposure. The results using sub-industry classification from the UK ONS and COVID case number and using different exposures for interbank connections are reported in Table A.1 in the Appendix. We end up with 63 banks as COVID-impacted banks and 16 banks in the treatment group, and the rest 218 banks in the control group. In order to further isolate the difference between the treatment and control banks in other dimensions, we use one-to-one propensity score matching with caliper of 0.002 and select the control firms that have the closest features with treatment firms based on the risk-weighted assets, bank size and capital ratio as well as the loan amount in the prior year.

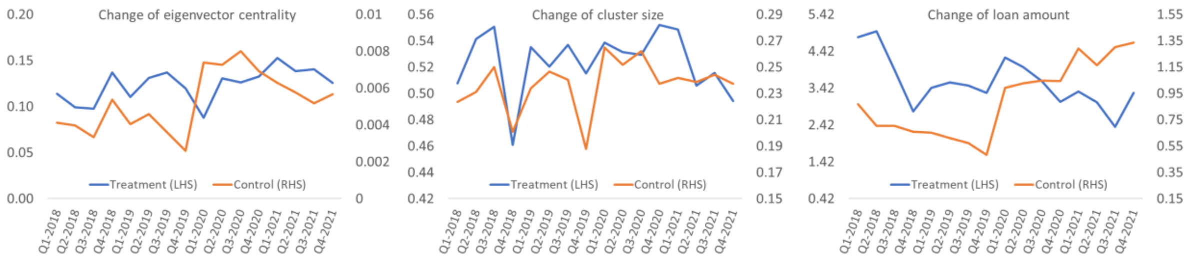
Figure 5 plots the change of eigenvector centrality and of cluster size before and after the COVID crisis for the treatment and control banks. Both eigenvector centrality and cluster size show similar pattern for the treatment and control banks in the two years before the COVID crisis. In the first year of the COVID crisis (in Q4-2020 compared to Q4-2019), the eigenvector of the control banks increases significantly more than that of the treatment banks: the mean value of eigenvector increases by 164.9 percent for the control banks and by 10.7 percent for the treatment banks; in the meanwhile, cluster size of the control banks increases slightly more than that of the treatment banks: the mean value of cluster size increases by 26.3 percent for the control banks, and increases by 7.2 percent for the treatment banks. In the second year of the COVID crisis (in Q4-2021 compared to Q4-2020), eigenvector of both treatment and control banks reduces, for a similar percentage: the mean value of eigenvector reduces by about 5.5 percent for the treatment banks and by 17.9 percent for the control banks; in the meanwhile, cluster size of the control banks increases slightly, whereas that of the treatment banks reduces by 10.5 percent. Overall, we observe the following network structure change

[10] We also consider banks that are either lending to or borrowing from COVID-impacted banks in the interbank market and the reports are reported Table A.1 in the Online Appendix.
[11] We set-up this threshold in order to capture economic-relevant exposures among Covid-impacted banks and banks that are directly connected to Covid-impacted banks, and avoid stale data. In fact, we want to avoid weak links between Group B banks and Group A banks. By doing this, we remove roughly 3% of total amounts of interbank exposures. Variations of the thresholds do not change qualitatively the results. The higher is the threshold, the larger is the associated regression coefficient.

in the two years since the pandemic: in the first year (especially the first three quarters from Q1-2020 to Q3-2020), eigenvector is playing a dominating role and it reduces largely for the treatment relative to that for the control banks; whereas in the second year, cluster size is the main changing factor in the network structure and it reduces for the treatment relative to that for the control banks. Therefore, the COVID pandemic appears to be a negative shock to the treatment banks compared to the control banks in the interbank network.

The right panel of Figure 5 plots the gap of loan amount between two groups of banks before and after the COVID shock. In the two years before the COVID crisis, loan amount shows a similar pattern between the treatment and control banks, which indicates a parallel trend before the shock. In Q1-2020, the first quarter of the COVID crisis, loan amount for the control banks rises immediately compared to that for the treatment banks, and continues to grow in the two years afterwards; whereas the loan amount for the treatment banks start to cut back in the following two years.

Figure 5: Change of network structure and bank loans by groups: pre- and post-COVID



Note: This figure plots the change of eigenvector centrality and cluster size in the two years before and after the COVID crisis for the treatment and control banks. The treatment banks are defined as those that are directly lending to COVID-impacted banks in the interbank network, with exposures above GBP 100 million by Q4-2019, but themselves are not highly exposed to the COVID-impacted industries. Control banks includes the rest of banks (excluding COVID-impacted banks and treatment banks). We have 63 banks as COVID-impacted banks, 16 banks as treatment banks, and 218 banks as control banks.

In Panel A of Table 9, we report the results of the difference-in-difference regression analysis. *Covid* is defined as one for the period from Q1-2020 to Q4-2021, and zero otherwise. In column (1) and (2), we include the *Treated (industry)* dummy and its interaction with *Covid* and use the full sample of the treatment and control banks. The results show that the coefficient of the treatment dummy is significantly positive and the coefficient of the interaction is significantly negative, suggesting that the treatment banks have on average higher amount of lending to non-financial firms; however, during the COVID crisis, the difference between the treatment and control banks is lower. In column (3) and (4), we use the one-to-one propensity-score-matched sample of the treatment and control banks, and our observation number reduces from 26,279 to 2,587. The results show that the coefficient of treated dummy becomes negative and the coefficient of the interaction is still negative and significant. This suggests that after matching by bank characteristics, we find consistent results, that the treatment banks cut more loans to non-financial firms compared to the control banks after the COVID shock.

Table 9: Identification: the shock of the COVID-19 pandemic

Panel A: Difference-in-difference

Dep Var	*Log of loan amount*					
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		PSM sample			
Treated (industry)	1.771***	2.163***	-1.468*	-0.635		
	(0.588)	(0.608)	(0.755)	(0.742)		
Treated (industry)×Covid		-0.840*		-1.500**		
		(0.463)		(0.695)		
Covid-impacted banks (industry)					2.943***	3.116***
					(0.203)	(0.222)
Covid-impacted banks (industry)×Covid						-0.349*
						(0.198)
Risk weighted assets	1.230***	1.208***	2.707**	2.835**	1.290***	1.257***
	(0.311)	(0.310)	(1.374)	(1.370)	(0.324)	(0.326)
Capital ratio	-0.788***	-0.806***	1.667	1.915	-1.813***	-1.790***
	(0.196)	(0.198)	(2.143)	(2.142)	(0.349)	(0.347)
Bank size	0.226***	0.230***	1.336***	1.313***	0.310***	0.314***
	(0.0510)	(0.0513)	(0.185)	(0.180)	(0.0426)	(0.0426)
Cons.	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	26279	26279	2587	2587	44077	44077
R-sq	0.0651	0.0652	0.138	0.152	0.128	0.128

We are also curious to see how the crisis affects the lending for the Covid-impacted banks. In column (5) and (6), we further include the Covid-impacted banks (identified by industry) back into the sample and rerun the regressions with similar specifications. Accordingly, the observation number increases to 44,077. The results show that the coefficient of the dummy variable, *Covid-impacted banks (industry)*, is significant and positive, and that of its interaction with *Covid*, is negative and significant. This suggests that on average, Covid-impacted banks have higher amount of loan to non-financial firms; however, since the COVID shock, they have cut more loans, compared to the rest of the banks in the UK financial system. This finding is consistent with Colak and Oztekin (2021) that bank lending is weaker in regions that are more affected by the COVID crisis.

To examine whether the parallel trends assumption is satisfied and the dynamic effects during COVID, we apply the dynamic difference-in-difference method. We report the results in Panel B of Table 9. In column (1) we use the full sample of the treatment and control banks; and in column (2) we use the one-to-one propensity-score-matched sample of the two groups. *Quarter (0)* is defined one for Q1-2020, and zero otherwise. Similarly, *quarter(1)* to *quarter(7)* are defined as one for the quarters afterwards, and zero otherwise; and *quarter (-8)* to *quarter(-1)* are defined as one for Q1-2018 to Q4-2019, the quarters before the Covid shock, and zero otherwise. The results show that the coefficients of the interactions are insignificant for the period before the COVID, and turn significant and negative since the fourth quarter of 2020. This suggests a parallel trend before the COVID shock and a significant negative impact on the lending to the corporate sector during the pandemic. The negative effect on lending to the real economy was not significant for the first three quarters of 2020 and tended to be strongest in the first two quarters of 2021. Overall, the results confirm the causal relationship that a negative shock to the network structure (both eigenvector and cluster size) for the treatment banks leads to lower loan amount to the corporate sector.

Table 9: Identification: the shock of the COVID-19 pandemic

Panel B: Dynamic effects of the Covid Shock

Dep Var	*Log of loan amount*	
	(1)	(2)
	Full sample	PSM sample
Treated (industry)	2.818***	1.311
	(0.439)	(1.247)
Quarter (-8) * Treated (industry)	-	-
	-	-
Quarter (-7) * Treated (industry)	0.697	2.141
	(0.597)	(1.824)
Quarter (-6) * Treated (industry)	-0.183	2.367
	(0.597)	(1.691)
Quarter (-5) * Treated (industry)	-1.339**	-1.964
	(0.598)	(1.708)
Quarter (-4) * Treated (industry)	-0.804	-0.716
	(0.597)	(1.641)
Quarter (-3) * Treated (industry)	-0.400	-1.477
	(0.597)	(1.697)
Quarter (-2) * Treated (industry)	-0.469	-1.370
	(0.598)	(1.651)
Quarter (-1) * Treated (industry)	-0.618	-2.209
	(0.597)	(1.855)
Quarter (0) * Treated (industry)	-0.275	-0.287
	(0.602)	(1.753)
Quarter (1) * Treated (industry)	-0.445	0.782
	(0.602)	(1.658)
Quarter (2) * Treated (industry)	-0.851	-2.336
	(0.602)	(1.678)
Quarter (3) * Treated (industry)	-1.562***	-3.756**
	(0.602)	(1.635)
Quarter (4) * Treated (industry)	-1.383**	-6.317***
	(0.602)	(1.670)
Quarter (5) * Treated (industry)	-1.602***	-6.230***
	(0.602)	(1.603)
Quarter (6) * Treated (industry)	-2.492***	-5.290***
	(0.602)	(1.678)
Quarter (7) * Treated (industry)	-1.513**	-4.785***
	(0.602)	(1.651)
Other controls	Yes	Yes
Quarter FE	Yes	Yes
# of obs	26279	2587
R-sq	0.0550	0.179

Note: Panel A of this table reports the results of the regressions using COVID as an exogenous shock to the interbank network. We first define *Covid-impacted banks* using the exposures of bank loans to the highly impacted industries. Therefore, *Covid-impacted banks (industry)* equals to one if a bank's loan exposure to these industries is at least 33% of its total exposure, or zero otherwise. Then, we trace the banks that are 1) directly lending to Covid impacted banks in Q4-2019 with the exposure larger than £100 million and, 2) not highly exposed to Covid-impacted industries by Q4-2019, and define these banks as the treatment group. Therefore, *Treated* equals to one if a bank belongs to the treated group, or zero otherwise. In column (1)-(2), we run the regressions using the full sample including the treatment and control banks. In column (3)-(4), we run the regressions using the propensity-score-matched sample, based on bank features including eigenvector, cluster, risk-weighted assets, capital ratio and bank size. Panel B of this table reports the results of dynamic different-in-different regressions.

6. Conclusion

In this paper, we examine how the interbank lending relationships, i.e. the structure of the interbank networks affect banks' credit supply to the real economy. Using the dynamic UK interbank networks based on the bilateral exposures in the period of 2014 to 2021, we find evidence of both an effect of risk sharing through the core-periphery structure and an effect of liquidity insurance within lending communities in the interbank market. Specifically, core banks with high global centrality and banks in a larger community tend to lend more to non-financial firms, and the effect of global centrality remains significant after controlling for the local effects including the local centrality or the size of the community. However, during the COVID-19 pandemic, core banks reduce their lending to non-financial firms when the liquidity improves; whereas banks in a larger community increase their lending to non-financial firms, suggesting a weaker risk-sharing effect through the interbank core-periphery structure but a stronger insurance effect within the interbank community. For identification, we use the COVID-19 pandemic as an exogenous shock to the UK interbank market and examine the bank lending behaviors of the banks (treatment banks) that are directly lending to the COVID-impacted banks (by industry or region) and not exposed to COVID crisis themselves compared to that of the banks (control banks) that are not directly lending to the COVID-impacted banks. We find that the COVID crisis as a negative shock to the treatment banks leads to a decrease in corporate lending.

Reference

Accominotti, O., D. Lucena-Piquero and S. Ugolini, 2022. Intermediaries' Substitutability and Financial Network Resilience: A Hyperstructure Approach. CEPR Working Paper.

Acemoglu, D., A. Ozdaglar and A. Tahbaz-Salehi, 2015. Systemic Risk and Stability in Financial Networks, *American Economic Review,* 105(2): 564-608.

Acharya, V., and O. Merrouche, 2013. Precautionary Hoarding of Liquidity and Interbank Market: Evidence from the Subprime Crisis, *Review of Finance* 17: 107-160.

Acharya, V. and N. Mora, 2015. A Crisis of Banks as Liquidity Providers, Journal of Finance, 70, 1-43.

Acharya, V., H. Almeida, F. Ippolito and A. Perez-Orive, 2021. Credit Lines and the Liquidity Insurance Channel. *Journal of Money, Credit and Banking*, 53: 901-938.

Allen, F., and D. Gale, 2000. Financial Contagion. *Journal of Political Economy*, 108(1): 1-33.

Allen, Franklin, and Babus, Ana (2009), Networks in Finance, in Kleindorfer, Paul R., Wind, Yoram R., and Gunther, Robert E. (eds), *The Network Challenge: Strategy, Profit, and Risk in an Interlinked World*, Prentice Hall, 367-381.

Afonso, G., A. Kovner, and A. Schoar, 2011. Stressed, not Frozen, The Federal Funds Market in the Financial Crisis, *Journal of Finance* 66(4): 1109-1139.

Bhattacharya, S., and D. Gale, 1987. Preference Shocks, Liquidity and Central Bank Policy, in W. Barnett and K. Singleton (eds.), *New Approaches to Monetary Economics,* Cambridge University Press, 69-88.

Bolton, P., X. Freixas, L. Gambacorta and P. Mistrulli, 2016. Relationship and Transaction Lending in a Crisis. *Review of Financial Studies*, 29(10): 2643-2676.

Bruche, M., and J. Suarez, 2010. Deposit insurance and money market freezes. *Journal of Monetary Economics* 57(1): 45-61.

Chava, S. and A. Purnanandam, 2011. The Effect of Banking Crisis on Bank-dependent Borrowers, *Journal of Financial Economics,* 99(1): 116-135.

Chodorow-Reich, G., The Employment of Effects of Credit Market Disruptions: Firm-level Evidence from the 2008's financial crisis, *Quarterly Journal of Economics,* 129, 1-59.

Clauset A., M.E.J. Newman and C. Moore, 2004. Finding Community Structure in Very large Networks. *Physical Review E* 70(6)

Colak, Gonul, and Ozde Oztekin, 2021. The Impact of COVID-19 Pandemic on Bank Lending Around the World, *Journal of Banking and Finance*, 133, 106207.

Craig, B., and G. von Peter, 2014. Interbank Tiering and Money Center Banks, *Journal of Financial Intermediation*, 23(3): 322-347.

Hasan, I., P. Politsidis and Z. Sharma, Global Syndicated Lending During the COVID-19 Pandemic. *Journal of Banking and Finance*, 133, 106121.

Iyer, R., Peydro, J.L., da-Rocha-Lopes, S., and A. Schoar, 2014. Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007-2009 Crisis, *Review of Financial Studies* 27(1):347-372.

Jackson, M. and A. Pernoud, 2021. Systemic Risk in Financial Networks: A Survey, *Annual Review of Economics*, 13: 171-202.

Kashyap, A., R. Rajan, and J. Stein, 2002. Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit Taking, *Journal of Finance*, 57(1): 33-73.

Kiernan, K., V. Yankov, and F. Zikes, 2021. Liquidity Provision and Co-insurance in Bank Syndicates. FEDS Working Paper, Federal Reserve Board, 2021-060.

Li, L., P. Strahan, and S. Zhang. 2020. Banks as Lenders of First Resort: Evidence from the COVID-19 Crisis. *Review of Corporate Finance Studies*, 9, 472-500.

Li, L., and P. Strahan, 2021. Who Supplies PPP Loans (and Does It Matter)? Banks, Relationships, and the COVID Crisis. *Journal of Financial and Quantitative Analysis*, 56(7): 2411-2438.

Mitchener, K., and G. Richardson, 2019. Network contagion and interbank amplification during the Great Depression, *Journal of Political Economy* 127(2): 465-507.

Santos, J. and S. Viswanathan, 2020. Bank Syndicates and Liquidity Provision, NBER Working Paper No. 27701.

Traag, V.A., L. Waltman, and N.J. van Eck, 2019. From Louvain to Leiden: guaranteeing well-connected communities, Scientific Reports 9:5233

Appendix

Table A1: Identification: the shock of the Covid-19 pandemic

Dep Var	*Log of loan amount*									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated L (sub-industry)	3.874***	4.835***								
	(0.543)	(0.599)								
Treated L (sub-industry)×Covid		-1.946***								
		(0.429)								
Treated LB(sub-industry)			7.449***	8.846***						
			(0.887)	(0.996)						
Treated LB (sub-industry)×Covid				-2.746***						
				(0.793)						
Treated L (region)					2.811***	3.454***				
					(0.493)	(0.534)				
Treated L (region) ×Covid						-1.284***				
						(0.398)				
Treated LB (region)							4.266***	4.850***		
							(0.685)	(0.765)		
Treated LB (region) ×Covid								-1.196*		
								(0.619)		
Treated L (sub-industry, region)									2.685***	3.718***
									(0.608)	(0.689)
Treated L (sub-industry, region) ×Covid										-2.037***
										(0.527)
Cons.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	36529	36529	33323	33323	44077	44077	40741	40741	40319	40319
R-sq	0.0589	0.0614	0.0921	0.0949	0.0565	0.0574	0.0624	0.0629	0.0495	0.0512

Note: This table reports the results of the robustness tests for identification. We define the exposure to the COVID shock either by industry or by region using COVID cases. In column (1) to (2), we define COVID-impacted banks as one if a bank's loan exposure to highly impacted industries is at least 33% of its exposures, or zero otherwise. Alternatively to Table 9 in the main paper, here we use the subsectors (sub-industries of SIC07) according to the industry classification of Office for National Statistics of the UK and identify an industry as COVID-impacted industry if its output shrank at least 10% in 2020 compared to that in 2019. In column (3) to (4), we use the COVID case number and define COVID-impacted regions as those with top 25% case number among all the counties in the UK. Accordingly, COVID-impacted banks are defined as those with at least 33% of the exposures towards the COVID-impacted regions. Similarly, then we trace the banks that are 1) directly lending to (or both lending to and borrowing from) COVID-impacted banks in 2019Q4 with the exposure at least £100 million and, 2) not highly exposed to COVID-impacted industries itself by 2019Q4 and define these banks as the treatment group. Therefore, Treated L (or Treated LB) equals to one if a bank belongs to the treated group and is connected to COVID-impacted banks through lending (or both lending and borrowing), or zero otherwise.

Table A2: Interbank network structure and bank lending: global networks including foreign banks

Dep Var	*Log of loan amount*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
In degree	0.0898**						
	(0.0429)						
Out degree		0.713***					
		(0.0490)					
Degree			0.683***				
			(0.0793)				
Eigenvector				16.95***			
				(1.628)			
Betweenness					0.568***		
					(0.0445)		
Cluster leiden						0.675***	
						(0.237)	
Cluster fast-							1.453***
							(0.344)
Risk weighted	0.508	-0.328	-0.0336	0.566	0.395	0.443	0.497
	(0.414)	(0.502)	(0.499)	(0.413)	(0.411)	(0.414)	(0.414)
Capital ratio	-2.524***	-1.965***	-2.374***	-2.297***	-2.383***	-2.445***	-2.482***
	(0.394)	(0.529)	(0.520)	(0.395)	(0.392)	(0.395)	(0.394)
Bank size	-0.244***	-0.413***	-0.401***	-0.300***	-0.180**	-0.271***	-0.256***
	(0.0779)	(0.0886)	(0.0904)	(0.0777)	(0.0773)	(0.0785)	(0.0776)
Cons	8.279***	8.785***	8.534***	9.128***	6.093***	8.929***	8.534***
	(1.907)	(2.157)	(2.146)	(1.885)	(1.886)	(1.897)	(1.881)
Bank-firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	81397	71674	71674	81397	81397	81397	81397
R-sq	0.0308	0.000662	0.0298	0.0385	0.0598	0.0866	0.0135

Note: This table reports the results of the robustness check examining the effects of interbank network features on the amount of bank loans to non-financial firms, using the interbank networks including both UK banks as well as the foreign banks that UK banks are borrowing from or lending to. The dependent variable, *Log of loan amount* is defined as the natural logarithm of the amount of bank loans to non-financial firms. The key explanatory variables are the features of interbank networks including network centrality and cluster. *Cluster leiden* and *Cluster fast-greedy*, capturing the size of the cluster where the bank is located in the interbank networks, are defined as the ratio of the numbers of banks in the cluster detected by the algorithms of leiden and fast-greedy over total number of banks in our sample. All other variables are defined in the Appendix A. Robust standard errors are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.