Discussion Paper

Deutsche Bundesbank
No 07/2024

COVID-19 and the fragmentation of the European interbank market

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Internet http://www.bundesbank.de

ISBN 978–3–95729–976–5
ISSN 2941–7503

Non-technical summary

Research Question

The purpose of this paper is to analyze the differences in the trading patterns of the unsecured and overnight European interbank market and whether COVID-19 is exacerbating these differences. The interbank market, where banks lend and borrow from each other overnight and without securitization, is traditionally considered as the market for banks' short-term liquidity needs. The paper considers the role of banks' liquidity endowments, existing relationships between banks, so-called relationship lending, and monetary policy liquidity provision during the pandemic.

Contribution

COVID-19 changes lending conditions in the interbank market. It can be used as a natural experiment and allows the identification of causal effects. The use of a unique dataset of unsecured overnight interbank loans in the Eurozone at the transaction level between pairs of banks, from the German and European Money Market Statistics (MMSR), allows the use of advanced panel methods. These methods permit the analysis of changes in the supply side of bank lending by fixing the demand side of a loan, such as the borrower's credit risk, which is a key aspect of loan conditions.

Results

The paper provides evidence of a highly fragmented interbank market, i.e. differences in lending and borrowing conditions across Europe, which increased during the pandemic. While the spread of lending rates between Germany and other euro area countries increases, the comparative advantage of institutional loans (loans within the savings or corporate banking sector tend to be more favorable) compared to German private interbank loans decreased during the COVID-19 crisis as conditions in Germany adjusted. The paper also shows the tendency to hoard liquidity during the pandemic. Banks with higher liquidity levels reduced their lending, while banks that were particularly active in borrowing from the interbank market were more likely to participate in the TLTRO III tender. In addition, credit conditions of already existing business relationships tend to be better during the pandemic. However, this phenomenon seems to be specific to the German interbank market.

Nichttechnische Zusammenfassung

Fragestellung

Das vorliegende Papier untersucht die Unterschiede in den Handelsmustern des europäischen Interbankenmarktes für unbesicherte Übernachtkredite, und inwieweit COVID-19 diese Unterschiede noch verschärft. Der Interbankenmarkt, auf dem sich Banken über Nacht und ohne Sicherheiten gegenseitig Geld leihen und verleihen, wird traditionell als Markt für den kurzfristigen Liquiditätsbedarf der Banken angesehen. In dem Papier wird die Rolle der Liquiditätsausstattung der Banken, bestehende Geschäftsbeziehungen zwischen Banken, sogenanntes Relationship Lending, und die geldpolitischen Liquiditätsbereitstellung während der Pandemie untersucht.

Beitrag

COVID-19 verändert die Kreditkonditionen auf dem Interbankenmarkt. Es kann daher als natürliches Experiment verwendet werden und ermöglicht die Identifizierung von kausalen Effekten. Die Verwendung eines spezifischen Datensatzes von unbesicherten Übernacht- Interbankenkrediten im Euroraum auf der Transaktionsebene zwischen Bankenpaaren, aus der deutschen und europäischen Geldmarktstatistik (MMSR), ermöglicht die Anwendung fortgeschrittener Panel-Methoden. Diese Methoden erlauben die Analyse von Veränderungen auf der Angebotsseite der Bankkreditvergabe durch die Fixierung der Nachfrageseite eines Kredits, wie z. B. des Kreditrisikos des Kreditnehmers, das ein Schlüsselaspekt der Kreditbedingungen darstellt.

Ergebnisse

Das Papier zeigt Hinweise auf einen hoch fragmentierten Interbankenmarkt auf, d.h. Unterschiede in der Kreditvergabe und -aufnahme innerhalb Europas. Diese Unterschiede wurden während der COVID-19 Pandemie verstärkt. Während der Unterschied der Kreditraten zwischen Deutschland und der restlichen Eurozone anstieg, so ging der komparative Vorteil von institutionellen Krediten (Kredite innerhalb des Sparkassen- oder Genossenschaftsbankensektor sind tendenziell günstiger) im Vergleich zu privaten Interbankenkrediten innerhalb Deutschlands während der COVID-19 Krise zurück, indem sich die Konditionen in Deutschland anpassten. Des Weiteren zeigt das Papier die Tendenz zu Liquiditätshortung während der Pandemie auf. Banken, mit höherer Liquiditätsausstattung reduzierten ihre Kreditvergabe und Banken, die hingegen besonders aktiv auf dem Interbankenmarkt Kredite aufnahmen, hatten eine höhere Wahrscheinlichkeit in der Teilnahme des TLTRO III Tenders. Zudem tendieren Kreditkonditionen von bereits bestehenden Geschäftsverbindungen während der Pandemie dazu besser auszufallen. Dieses Phänomen scheint jedoch spezifisch für den deutschen Interbankenmarkt zu sein.

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COVID-19 and the Fragmentation of the European Interbank Market*

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Abstract

This paper provides evidence of a highly fragmented European interbank market that is tightened during the COVID-19 pandemic, when the interbank market was under stress. Using a unique dataset of unsecured, overnight interbank loans at the transactional level allows me to apply advanced panel methods. Furthermore, this paper shows liquidity hoarding during the pandemic and relationship lending as a German phenomenon. In addition, there is evidence that borrowers who have to pay higher rates in the market are more likely to participate in tender auctions and that the COVID-19 pandemic had the greatest impact on smaller interbank borrowers.

JEL Codes: G01, G15, G18, G21, D85

Keywords: Interbank Market, Relationship Lending, Liquidity, COVID-19, Monetary Policy

*Thanks to Falko Fecht for supervising me, Ben Craig, Rüdiger Bachmann, Paul Heidhues, Christian Bayer, Amelie Schiprowski and the participants of the Job Market Preparation Seminar at the Verein für Socialpolitik, Emanuel Moench, Jochen Mankart, Björn Imbierowicz, Christian Bittner, Phlipp König, Matthias Hansmann, Kerstin Dornes and the colleagues of the Research Centre and the Money Market Statistics of the Deutsche Bundesbank for helpful comments. The paper represents the author's personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

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1 Introduction

The proper channelling of liquidity via the interbank market, the market for banks' short-term liquidity needs, is important for monetary policy transmission and the intermediation of banks with the real economy. Fragmentation affects the market mechanism, which makes both liquidity provision and monetary policy transmission less effective. Moreover, proper liquidity channelling is needed when it comes to more restrictive monetary policy and economic downturns with high inflation: bank lending should be supported by a well-functioning interbank market. Therefore, it is crucial to understand the mechanism of interbank markets and the interaction with monetary policy, especially during periods of distress such as the COVID-19 pandemic (Acharya and Merrouche, 2013; Cocco, Gomes, and Martins, 2009).

As an external and global shock, the COVID-19 pandemic spread to almost all countries in the world. The paper sticks to the definition of exogeneity used by the International Monetary Fund (2003): According to this, an exogenous shock is an event beyond the control of the authorities that has a significant negative impact on the economy, with three main requirements: the event has to be unexpected, large-scale and come from outside.

In addition to causing human suffering and loss of lives, the pandemic escalated quickly, impacted society and health systems and led to economic downturns. The world's largest economies were particularly hard hit, including those of central Europe and the source of COVID-19 is still unclear (Baldwin and Weder di Mauro, 2020; Elgin, Basbug, and Yalaman, 2020).

Alongside several aid packages by European countries, the ECB announced several monetary policy measures from mid-March onwards such as an easing of longer-term refinancing operations (TLTRO), a €750 billion pandemic emergency purchase programme (PEPP) and new pandemic emergency longer-term refinancing operations (PELTROs) (European Central Bank, 2022b). Nevertheless, shutdowns or restrictions on travel and mobility were accompanied by financial market turmoil and heightened uncertainty (OECD, 2020).

COVID-19 caused changes in lending and borrowing conditions in the interbank market such as rising loan rates and decreasing loan size as well as a lower probability of lending occurring between two banks. Due to the immense liquidity provision via the Eurosystem in the aftermath of the great financial crisis, starting in 2007, COVID-19 emphasises uncertainty rather than a liquidity squeeze in the banking system.

This paper analyses the fragmentation within the European interbank market, the role of liquidity endowment, relationship lending and monetary policy liquidity provision, especially during periods of stress like the COVID-19 pandemic. According to Financial Stability Board (2019), there is no commonly agreed definition of market fragmentation, though it notes that markets can break into fragments either geographically, by product type or by participants. In terms of international banking, the Financial Stability Board (2019) understanding of fragmentation might refer to pools of capital and liquidity being segregated within local markets and unable to move freely across jurisdictions. The interbank market literature also uses the expression *fragmentation*. (Cocco, Gomes, and Martins, 2009, p.25) state that the interbank market is fragmented in nature.

Using a unique dataset of unsecured, overnight interbank loans at the transactional level between bank pairs allows the use of time-varying fixed effects (based on Khwaja and Mian (2008)). Applying time-varying fixed effects fixes the demand side of a loan, for example borrower credit risk, and isolates supply effects. To account for heterogeneity in shocks, the model of Paravisini, Rapport, and Schnabl (2023) is taken into account as a robustness check. They argue that bank lending is specialised (e.g. due to counterparties acting in special sectors, geographical markets or economic activity) and that lender banks have market-specific advantages which might not be substituted by other lenders, because the markets are fragmented. Therefore, participants (lenders and borrowers) might react differently to global shocks.

This paper provides evidence of a highly fragmented interbank market which tightened during the pandemic, within the Eurozone and also within Germany. The three pillar banking system in Germany, consisting of private, public and cooperative banks, has different lending and borrowing conditions in each of its pillars and these also differ to the conditions in the rest of the Eurozone.[1]

While the spread of loan rates between Germany and other Eurozone countries increased, the comparative advantage of institutional loans versus regular loans within Germany diminished during the COVID-19 pandemic. [2]

Relationship lending was a harming factor during the crisis, but there is evidence that relationship lending is a German phenomenon. While there is no relationship lending effect for Eurozone countries other than Germany on loan level, the effect for Germany is economically large. In addition, aggregated relationship effects at the borrower level show that being a major borrower compensates for the shock, but having a relationship with a major lender has the opposite effect. Therefore, there is evidence that the direction of relationship lending plays an important role.

In addition, liquidity hoarding took place during the COVID-19 pandemic and central bank liquidity did not enter the market. The effect is larger for Germany than for the Eurozone as a whole. Furthermore, smaller borrowers are affected more than large ones by COVID-19. And finally, borrower banks that have to pay higher borrowing rates the week before a tender is announced are those with a higher probability of participating.

The results are robust to placebo tests and different COVID-19 measures.

The paper is related to several recent strands of literature covering interbank markets and financial networks, the interaction between monetary policy, liquidity provision and endowment, the behaviour of the banking system and the recent literature on

[1] Figure A.1 shows Germany's three pillar banking systems in more detail.

[2] An institutional loan is classified as a loan within the German savings or corporate banking sector while a regular loan is a loan either between private banks or private banks and savings or cooperative banks.

the pandemic and COVID-19.

To my knowledge, this is the first paper to combine the European and German money markets and provide evidence of the fragmentation of the European interbank market by analysing unsecured overnight interbank loans subject to a global exogenous shock outside the system. As well as contributing to several recent strands of literature, this paper is relevant for financial stability and monetary policy decision making.

The paper is organised as follows: After describing the contribution to the literature in Section 2, Section 3 describes the underlying data and variables and shows descriptive statistics. Section 4 motivates the empirical strategy and describes the hypothesis tested. Sections, Sections 5 and 6 show the results and their robustness and Section 7 concludes.

2 Literature

In theory, interbank markets are defined as the private market for banks' short-term liquidity needs in trading liquidity, both overnight and unsecured. The intermediation of banks with the real economy could be stressed if liquidity is not channelled through the banking system as, where it is most efficient. Additionally, the monetary policy transmission mechanism is less effective. Therefore, the major central banks around the world (the Federal Reserve, the Bank of England and the ECB, to name but a few) provide liquidity by means of emergency lending operations or asset purchase programmes in times of financial distress such as the great financial crisis which started in 2007 (Acharya and Merrouche, 2013).

While unconventional monetary policy measures have remained in place since 2007, the interbank market is often seen as irrelevant (Deutsche Bundesbank, 2019). Comparing descriptive statistics from Bräuning and Fecht (2017) with the underlying data of Figure 1b shows the activity of the market: while in the period from March

1, 2006 to August 8, 2007 and after the outbreak of the financial crisis on 9 August 2007, the German interbank market had a total volume of granted loans of €5 billion and €8 billion (Bräuning and Fecht, 2017, p.42) the interbank market in the first half of 2020 had an average volume of €21 billion per day prior to the COVID-19 pandemic and €15 billion per day afterwards. Bednarek, Dinger, and von Westernhagen (2016); Afonso, Kovner, and Schoar (2011); Affinito (2012); Cocco, Gomes, and Martins (2009) also find, that interbank markets did not dry up in Germany, Italy, Portugal or the US in periods of distress.

Analysing the structure of interbank market networks, Bräuning and Fecht (2017) show that relationship lending prevails. Using transactional data of unsecured German interbank loans from the RTGSplus system[3] and analysing it via an algorithm similar to Furfine (1999), they provide empirical evidence that relationship lending reduces asymmetric information problems (counterparty risk) and matters for the pricing and availability of interbank loans. In detail, they show that relationship lending has a positive effect on access to liquidity and a negative effect on bilateral interest rates during market distress. Afonso, Kovner, and Schoar (2013) support these findings, using data on the federal funds market in the US.

Han, Nikolaou, and Tase (2022) document strong and stable relationships within the secured money market, by analysing triparty repos within the US short-term funding market. They find evidence that relationships affects the probability of trading, the volume and the price of a trade and that those relationships support stability during periods of stress.

Cocco, Gomes, and Martins (2009) study the Portuguese interbank market and argue that interbank markets are fragmented in nature. While direct loans, negotiated between lender and borrower, are agreed on one-to-one basis other – smaller – banks do not have similar access to the same terms. They describe bank relationships as an important determinant of the availability of liquidity and the ability to access

[3] The precursor of TARGET 2.

the market. Furthermore, they find that banks with larger imbalances in reserve deposits are more likely to borrow from relationship lenders to receive a lower rate. In addition, they find that smaller banks with a higher share of non-performing loans have limited access to the market and rely more on relationship lenders. They also find that banks with more volatile changes in daily liquidity rely more on relationship lending with counterparts that have less volatile liquidity balances, and construct relationships with banks with which they have a lower correlation of liquidity shocks. Instead, Ashcraft and Duffie (2007) argue that relationships are due to search frictions and repeated interbank lending. They analyse the federal funds market before the 2007-09 crisis and document a significant impact of relationships on lending and a smaller one for borrowing. They argue that larger institutions are more likely to be counterparties and that more active banks are in a better position, by taking profits.

Interbank markets are strongly connected to monetary policy implementation due to its primary objective of channelling liquidity. As stated before, if interbank markets do not work properly, the monetary policy transmission mechanism is less effective. Therefore, many papers analyse the interaction between central bank liquidity, liquidity endowment and interbank networks.

In a recent paper, Duncan, Horvath, Iercosan, Loudis, Maddrey, Martinez, Mooney, Ranish, Wang, and Warusawitharana (2022) evaluate the bank regulatory framework in the US during COVID-19 as a stress test. They find a COVID-19 related increase in liquidity, mainly driven by central bank reserves. Furthermore, they find that banks choose to retain their liquidity holdings and use Federal Reserve liquidity facilities. They argue that banks prefer larger liquidity buffers in times of economic uncertainty. This is in line with a theoretical model by Acharya and Rajan (2022), who argues that flooding banks with central bank reserves does not necessarily expand liquidity in the market. Instead, previous research by Ashcraft and Duffie (2007) finds that there is a strong link between the counterparty liquidity balance and the probability of trading a loan in the Federal Funds market. Higher balances come along with an increasing probability of being a lender while lower ones increase the probability of being a borrower. Furthermore, they show that increasing balances result in reducing loan rates during the last hours of the trading day. Again, more active banks negotiate a higher loan rate if they are lenders and a lower rate if they are borrowers.

From a theoretical perspective, Afonso and Lagos (2015) develop a model of the federal funds market that accounts for the search for counterparties and bilateral negotiations. Unsecured money markets are decentralised over-the-counter (OTC) markets without central clearing and without a clearing price. The authors describe bilateral bargaining as being driven by the private value of liquidity, i.e. the balance of reserves over the trading day. They observe that most frequent trading takes place in the last two hours of a trading day, when traders have information on the transactions of the day and when the probability of uncertain shocks decreases. Furthermore, they state that idiosyncratic liquidity shocks affect the private value of liquidity, bilateral bargaining and thus the lending probability, as well as the volume and spread of a loan.

Since the global financial crises that began in 2007, a huge range of economic crisis research has been done. The outbreak of COVID-19 has affected the global economy and is not only challenging from a healthcare and medical viewpoint but also from an economic perspective. Therefore, the Centre for Economic Policy Research (CEPR) launched a dedicated series of papers entitled COVID-19 Economics Papers at the End of March 2020. This is open to all areas of economics which acknowledge the importance of the research area (Centre for Economic Policy Research, 2022).

Highlighting banking research on COVID-19, Sedunov (2021) analyse the relationship between Federal Reserve emergency actions and systemic risk in the US during the global financial crisis and the COVID-19 pandemic. The paper finds that liquidity provision and open market operations were linked to a reduction in systemic risk during the global financial crisis but that no such effects are identified for the COVID-19 pandemic.

Levine, Lin, Tai, and Xie (2021) investigate the massive liquidity inflow through deposits during the pandemic. They find a higher decline in deposit interest rates for bank branches in high COVID-19 incidence counties than in countries with lower infection rates. They provide evidence that higher local COVID-19 infection rates are related to households' greater anxiety about income losses and future employment, which results in reduced spending and increased saving via deposits.

Bräuning, Fillat, and Wang (2022) provide evidence that small and mid-sized firms in the US with higher leverage had tighter constraints in accessing bank credit after the outbreak of COVID-19. Those firms with higher pre-COVID-19 leverage received smaller loan amounts and had to pay higher rates. The effect is driven by loans, granted by banks with below median capital buffers. The firms most strongly affected were not able to substitute the debt, therefore they faced a higher reduction in total debt, a decline in investment and employment. The public support measures, especially the Paycheck Protection Program (PPP) in the US mitigated the effects.

Duncan, Horvath, Iercosan, Loudis, Maddrey, Martinez, Mooney, Ranish, Wang, and Warusawitharana (2022) use COVID-19 as a stress test on the bank regulatory framework in the US. Despite the findings about liquidity requirements, mentioned before, they find overall robust capital and liquidity levels, which resulted in a resilient banking system and that lending and market making were maintained through the early stage of the pandemic.

Further research on COVID-19, e.g. the interaction with central bank liquidity (Anderson, Chang, and Copeland, 2020) or financial markets (Ali, Alam, and Rizvi, 2020) has been done.

There is little research on the effects of COVID-19 and the interbank market or financial network. Bodnár (2021) examines the structure of the Hungarian unsecured interbank network descriptively. He finds an increase in turnover of roughly 30 % post COVID-19, accompanied by higher and more volatile interest rates. Furthermore, he finds a higher borrower concentration and more banks acting as lenders than as borrowers.

3 Data

The main data source covers all unsecured overnight interbank loans reported under the Money Market Statistical Reporting (MMSR) scheme, banks' current accounts and minimum reserve requirements as well as data from the Eurosystem's TLTRO-III tender operation.

The MMSR is a transaction-by-transaction dataset which covers the European money market, with the main objective of calculating the Euro Short-Term rate (€STR). Under the MMSR Regulation, the 47 largest European banks have to report their money market transactions in Euro on a daily base. Due to the heterogeneous structure of the banking sector in Germany, the Bundesbank decided to create a German subset, which contains 115 reporting agents[4] from Germany. 14 out of the 115 agents are based upon the ECB criterion, which results in 148 reporting agents in total. The banks are obligated to report each single money market transaction in the following segments: secured, unsecured, foreign exchange swaps and overnight index swaps. The data contains several items of identifier, counterparty, trading time, pricing and interest rate information, volumes and terms of the transactions. Furthermore, the banks have to report whether they are the lending or borrowing party. If there are reporting agents, trading with each other, there are double transactions in the dataset, which have to be cleaned by an algorithm

[4]Reporting agents have to report all money market transactions conducted with financial corporations (i.e. banks), general government or non-financial corporations, either acting as a borrower or a lender bank. Given the large number of counterparties, the number of reporting agents differ from the number of lender and borrower banks.

(Hirsch and Yalcin-Rode, 2022; European Central Bank, 2022a).

The underlying data are restricted to the unsecured segment and covers overnight loans between banks where both counterparties are available: 118 banks act as lender and 739 banks act as borrower and in total, the network contains 1,091 bank-pairs. The data covers a period from January 1, 2020 to June 9, 2020, which marks the end of the third maintenance period in 2020.

3.1 Variables and Descriptive Statistics

Restricting the data to the unsecured, overnight interbank market, the main variable of interest are *Loan Amount*$_{ijt}$, the corresponding logarithm *Log(Loan Amount)*$_{ijt}$, *Loan Rate*$_{ijt}$ and *Loan Dummy*$_{ijt}$ which equals one for a loan and zero otherwise, for lender i, borrower j and day t. In addition the network measures of loan preference and borrower preference index (LPI_{ijt} and BPI_{ijt}) as well as *Excess Reserves*$_{it}$ of lender banks are used. According to Bräuning and Fecht (2017) interbank relationship measures are calculated in equations 1 and 2:

$$\mathrm{LPI}_{ijt} = \frac{\sum_{t' \in T} y_{i,j,t'}}{\sum_i \sum_{t' \in T} y_{i,j,t'}} \tag{1}$$

The Lender Preference Index (LPI_{ijt}) is a ratio of loans between two banks, lender bank i and borrower bank j, over total lending of bank i. LPI_{ijt} is calculated within a rolling window of the last 30 days. LPI_{ijt} shows the concentration of a lender bank to a specific borrower bank.

$$\mathrm{BPI}_{ijt} = \frac{\sum_{t' \in T} y_{i,j,t'}}{\sum_j \sum_{t' \in T} y_{i,j,t'}} \tag{2}$$

The Borrower Preference Index (BPI_{ijt}) is similar to LPI_{ijt}. The numerator and the rolling window stay the same while the denominator captures the borrowing of bank j instead of bank i's lending. So BPI_{ijt} shows the concentration of a borrower bank to a specific lender bank.

$$\text{Excess Reserves}_{it} = \frac{(\text{Reserve Holdings}_{it} - \text{Minimum Reserve Requirment}_{it})}{\text{Days left within the Maintenance Period}} \quad (3)$$

The liquidity measure $\textit{Excess Reserves}_{it}$ describes the excess reserves of a lender i at day t, normalised by the days left within the maintenance minimum reserve period.[5] Table 1 shows descriptive statistics of the different datasets. Panel A represents summary statistics at the transaction level, of all loans at the unsecured overnight interbank market. In total, 60,576 unsecured interbank loans are traded overnight during the period January 1, 2020 to June 9, 2020. The average $\textit{Loan Amount}_{ijt}$ equals €45.1 million with a $\textit{Loan Rate}_{ijt}$ of -0.381%. Lender banks hold on average €1.204 million $\textit{Excess Reserves}_{it}$, borrower's average $\textit{Excess Reserves}_{jt}$ are €338.4 million. The ratio of borrower concentration by lender, measured by LPI_{ijt}, equals 0.154 on average while borrower banks have a much higher concentration to their lender, measured by BPI_{ijt}, of on average 0.745.

86.5 % of all transactions are Eurozone loans, 79.7% are German loans, 71.1% institutional loans and 8.6% German, private, non-institutionals. A Eurozone or German loan is characterised if both counterparts are located within the Eurozone or Germany, respectively. An institutional loan is characterised by lender and borrower from the same bank subsector: savings/federal state or corporate banks[6], trading within their own banking subsector while non-institutional German loans are the remaining, private, loans within Germany. In total 82.6% loans are domestic loans, within the national interbank market and 17.4% loans are traded cross-border. Focusing on the lender side, 88.7% of all loans have an Eurozone lender, 80% a German and 11.3% a non-Eurozone lender bank. The COVID-19 pandemic marks 52.4% of all observations, starting after March 12, 2020, the day after the WHO declared COVID-19 as a pandemic (WHO, 2020).

[5] The analysis includes just the lender side; for the sake of completeness the liquidity endowment for borrowers is shown in the descriptive statistics.

[6] The German subsector of 'Sparkassen', 'Landesbanken' or 'Genossenschaftsbanken'.

Due to the heterogeneity of the European banking sector, I identify five subgroups within the European interbank market: Eurozone (Panel B), Germany (Panel C), German non-institutionals (Panel D), German institutionals (Panel E) and Eurozone w.o. Germany (Panel F).
In Panel B, both counterparts are within the Eurozone. The *Loan Amount* $_{ijt}$ is smaller and the *Loan Rate*$_{ijt}$ higher compared to the dataset where worldwide trading in Euro is included. Relationship measures deviate slightly. The German interbank market represent 92.2% of the Eurozone loans, 95.5% of the loans are domestic and just 4.5% cross-border trades within the Eurozone. 92.4% loans have a German lender.
Not surprisingly, the German descriptive statistics in Panel C are similar to those of the Eurozone except of the excess reserves. While the *Excess Reserves*$_{it}$ of lender banks are quite similar (€1.1 million in Germany and the Eurozone), those of borrower banks differ substantially (€28.27 million in Germany vs. €137.8 million in the Eurozone). Within Germany, 89.2% loans are institutional and 10.8% are private loans. Due to the high share, the German descriptive statistics seem to be driven by institutional loans and again quite similar. Differences are found in comparing descriptive statistics of German non-institutional, private, loans to those of institutional loans. Especially the *Loan Rate*$_{ijt}$ and the relationship measures differ most. While both groups lend on average roughly the same amounts (average *Loan Amount*$_{ijt}$ €43.94 million for non-institutionals vs. €41.42 million for institutionals) the non-institutionals are those who are paying more volatile and higher *Loan Rates*$_{ijt}$ of on average 1 basis points. Institutional loans seems to be much more concentrated on lenders than on borrowers (average LPI_{ijt} 0.028 and BPI_{ijt} 0.889) than non-institutionals (average 0.276 LPI_{ijt} and 0.528 BPI_{ijt}).
Descriptive statistics of the European non-German interbank market are noticeably different to those for Germany. Loan size and rates are much smaller and Eurozone banks seem to be highly concentrated on borrowers rather than lenders (average

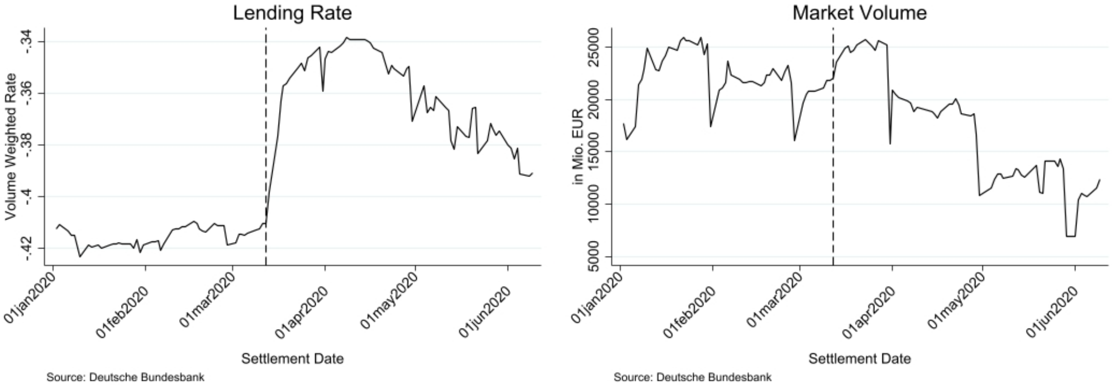
LPI_{ijt}: 0.74, BPI_{ijt}: 0.291). The excess reserves are much higher for borrowers in the Eurozone excluding Germany (€1,497 million) and almost the same for lender as in Germany. While in Germany domestic lending marks more than 95%, 50.5% of Eurozone others than Germany trading is cross-border but within the Eurozone. To analyse aggregated effects a panel at the borrower level is used. While the average volume-weighted $Borrowing\ Rate_{jt}$ is similar to the rate at the transaction level, $Total\ Borrowing_{jt}$ reflects the total borrowing amount per day. On average, a borrower bank borrows €58.83 million and receives 1.29 loans per day. The relationship measures are volume-weighted and similar to the transaction level. The German share of borrower banks' borrowing is 0.92%. 5.5% of the borrower banks are ECB and 1.8% large German reporting agents[7] while roughly 85% of the borrower banks are institutional borrowers.
At the tender level, the probability of receiving a loan, the week before the TLTRO-III is announced (March 9 to 13, 2020) is on average up to 90%. The average volume-weighted borrowing rate during that week is -0.392 and on average 83% of banks participating in the tender operation are active in the market the week before. Conversely, 114 (20.2%) of the trading banks were participating in the TLTRO-III. The amount settled is €1.008 billion.

4 Empirical Strategy and Hypothesis

4.1 COVID-19

Figure 1a and 1b show the market reaction after the start of the COVID-19 pandemic in Europe.[8] While the market volume decreases over time, the average loan rate immediately jumped by roughly 5 basis points. It took about three months to stabilise the rates to almost the level, before the outbreak, despite the intervention

[7]ECB reporting agents are the 47 largest European banks while large German reporting agents are the largest 14 banks which report based on ECB criteria.
[8]Horizontal line: March 12, 2020.



(a) Lending Rate Europe **(b)** Market Volume Europe

Figure 1: COVID-19 Effects

of the Eurosystem.

Referring to Figures 1a and 1b, the first regression equations and hypotheses uses the COVID-19 pandemic as a natural experiment. This brings us to the first Research Question:

Research Question 1 *How does the European interbank market, especially the lending and borrowing conditions, react to the global COVID-19 pandemic shock?*

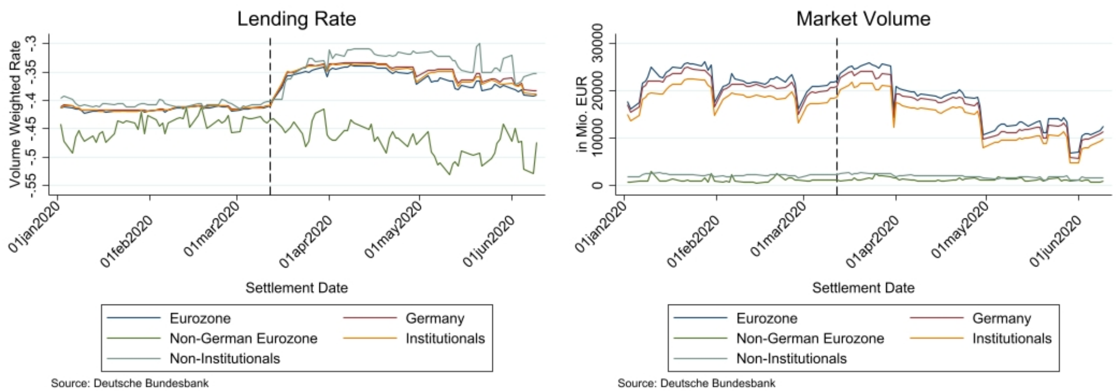
To answer Research Question 1 , I set up a baseline model, described in equation 4.

$$\text{y}_{ijt} = \beta_0 + \beta_1 \text{Post Covid}_t + \alpha_i + \gamma_j + \epsilon_{ijt} \tag{4}$$

y_{ijt} is either the *Loan Rate*$_{ijt}$, *Log(Total Amount)*$_{ijt}$ or *Loan Dummy*$_{ijt}$. *Post Covid*$_t$ is a dummy variable which equals one for the post-COVID-19 period (from March 12, 2020 to June 9, 2020) and zero otherwise. α_i and γ_j captures lender and borrower fixed effects and ϵ_{it} the error term. Standard errors are clustered at the bank-pair and date level. Based on previous research, hypotheses 1 summarises the possible channels.

Hypothesis 1 *The pandemic, as an exogenous shock, results in higher loan rates, lower loan amounts and a decreasing probability of trading interbank loans.*

4.2 Fragmentation of the European Interbank Market



(a) Lending Rate per Subgroup **(b)** Market Volume per Subgroup

Figure 2: Fragmentation

The European banking system in general and the German banking system in particular are considered to be highly heterogeneous (Hirsch and Yalcin-Rode, 2022). Figures 2a and 2b give first indications. While the average loan rate shows an immense increase, the Eurozone excluding Germany react differently. While German loans (and the subgroups where those loans are included) show the same jump in loan rates, loans of the Eurozone excluding Germany tend to be unaffected or even decline over time. As regards market volume, it seems that institutional loans (and the subgroups where those loans have higher shares), decline over time while German non-institutionals and loans from the Eurozone excluding Germany are much less volatile in market volume. Therefore, the second Research Question is:

Research Question 2 *Is the European interbank market fragmented in lending and borrowing conditions, especially during COVID-19?*

To answer Research Question 2, equation 5 estimates differences between subnetworks:

$$\mathrm{y}_{ijt} = \beta_0 + \beta_1 \mathrm{x}_{i(j)t} + \beta_2 \mathrm{x}_{i(j)t} \times \text{Post Covid}_t + \alpha_i + \varphi_{jt} + \epsilon_{ijt} \tag{5}$$

y_{ijt} is again either the *Loan Rate*$_{ijt}$, *Log(Total Amount)*$_{ijt}$ or *Loan Dummy*$_{ijt}$. *Post Covid*$_t$ is a dummy variable which equals one for the post COVID-19 period (from March 12, 2020 to June 9, 2020) and zero otherwise. $x_{i(j)t}$ is either one of the following dummy variables, which marks different subnetworks within the interbank market: *German Loan*$_{ijt}$, *Institutional Loan*$_{ijt}$, *Cross-Border Loan*$_{ijt}$ or *Non-Eurozone Lender*$_{it}$. α_i captures lender fixed effects while φ_{jt} captures time-varying borrowing-day fixed effects and ϵ_{it} the error term. Standard errors are clustered at the bank-pair and date level.

Hypothesis 2 summarises the possible channels.

Hypothesis 2 *The European interbank market is highly fragmented. There are differences in loan conditions between subgroups and COVID-19 has a negative impact on fragmentation.*

4.3 Liquidity Endowment

Given the interaction between liquidity endowment, monetary policy implementation and the interbank market for unsecured overnight liquidity, there is an endogeneity problem between liquidity endowment and trading measures. Having an exogenous shock like the COVID-19 pandemic allows me to identify causal effects by using interaction terms. This leads us to the third Research Question:

Research Question 3 *What is the effect of liquidity endowment during the COVID-19 pandemic? Does central bank liquidity via central bank reserves get channelled properly?*

To answer Research Question 3, I set up the following regression equation:

$$\mathrm{y}_{ijt} = \beta_0 + \beta_1 \mathrm{Reserves}_{it-1} + \beta_2 \mathrm{Reserves}_{it-1} \times \mathrm{Post\ Covid}_t + \alpha_i + \varphi_{jt} + \epsilon_{ijt} \quad (6)$$

y_{ijt} is either the *Loan Rate*$_{ijt}$, *Log(Total Amount)*$_{ijt}$ or *Loan Dummy*$_{ijt}$. *Post Covid*$_t$ is a dummy variable which equals one for the post COVID-19 period (from March 12, 2020 to June 9, 2020) and zero otherwise. *Reserves*$_{it-1}$ is the first lag of excess reserves of the lender bank, defined in equation 3. φ_{jt} are time-varying borrowing day fixed effects and ϵ_{ijt} the error term. Standard errors are clustered at the bank-pair and date level. Hypotheses 3a and 3b summarise the possible channels.

Hypothesis 3a *Liquidity does not enter the market. Higher lender liquidity endowment leads on average to an increase in loan prices and a reduction in loan size, associated with a lower probability of trading a loan.*

Hypothesis 3b *Higher liquidity endowment results in higher market activity. Higher loan supply results in lower rates, a higher probability of trading a loan and higher loan amounts. The market is used to channel central bank liquidity.*

4.4 Relationship Lending

Several papers analyse the role of relationships in financial networks. Most of them find a positive effect of relationship lending, especially during times of distress. This part focuses on the lender side of the analysis. Most common network measures (i.e. centrality) measure the location or the role within the network but do not account for relationships, market power and/or the importance of the counterparties. However preference indices according to Bräuning and Fecht (2017) measure the importance of specific counterparties in relation to the overall activity, as well as the role of the bank (lender or borrower). This part focuses on lending activities, so the appropriate measure is LPI_{ijt}, which measures the importance of a specific borrower for a lender bank. One reason to focus on LPI_{ijt} instead of BPI_{ijt} in this section is market power.

If lenders have more market power (e.g. head institutions of cooperative or saving banks), they do not care about a high BPI_{ijt} of the corresponding counterpart if their own LPI_{ijt} for a specific borrower bank is low, i.e. not important. Therefore, Research Question 4 is:

Research Question 4 *What is the role of relationship lending during COVID-19? Do relationships harm the effect of distressed markets and do they differ between subgroups?*

To analyse question 4, the relationship measure is included, shown in equation 7:

$$\mathrm{y}_{ijt} = \beta_0 + \beta_1 \mathrm{Relationship}_{ijt} + \beta_2 \mathrm{Relationship}_{ijt} \times \mathrm{Post\ Covid}_t + \alpha_i + \varphi_{jt} + \epsilon_{ijt} \tag{7}$$

y_{ijt} is again either the *Loan Rate*$_{ijt}$, *Log(Total Amount)*$_{ijt}$ or *Loan Dummy*$_{ijt}$. *Post Covid*$_t$ is a dummy variable which equals one for the post COVID-19 period (from March 12, 2020 to June 9, 2020) and zero otherwise. *Relationship*$_{ijt}$ is the network measure LPI_{ijt}, defined in equation 1. α_i captures lender fixed effects while φ_{jt} captures time-varying borrowing day fixed effects and ϵ_{it} the error term. Standard errors are clustered at the bank-pair and date level.

In addition, to further analyse questions 4, regression equation 8 is used:

$$\begin{aligned}
\mathrm{y}_{ijt} = {} & \beta_0 + \beta_1 \mathrm{x}_{i(j)t} + \beta_2 \mathrm{LPI}_{ijt} + \beta_3 \mathrm{Post\ Covid}_t + \beta_4 \mathrm{x}_{i(j)t} \times \mathrm{Post\ Covid}_t \\
& + \beta_5 \mathrm{x}_{i(j)t} \times \mathrm{LPI}_{ijt} + \beta_6 \mathrm{LPI}_{ijt} \times \mathrm{Post\ Covid}_t \\
& + \beta_7 \mathrm{x}_{i(j)t} \times \mathrm{LPI}_{ijt} \times \mathrm{Post\ Covid}_t + \alpha_i + \varphi_{jt} + \epsilon_{ijt}
\end{aligned} \tag{8}$$

y_{ijt} is again either the *Loan Rate*$_{ijt}$, *Log(Total Amount)*$_{ijt}$ or *Loan Dummy*$_{ijt}$. $x_{i(j)t}$ is either one of the following dummy variables which mark different subgroups within the interbank market: *German Loan*$_{ijt}$, *Institutional Loan*$_{ijt}$, *Non-Eurozone Lender*$_{it}$ or *Cross-Border*$_{ijt}$. LPI_{ijt} is the lending preference index, shown in equation 1.

Hypothesis 4 *The network structure, in particular a strong and stable relationship within the interbank market, mitigates shocks and spillovers. The fragmentation results in different effects for different subgroups.*

4.5 The Eurosystem's Tender Auction

This Section analyses the interaction between the European interbank market and the liquidity provision of the Eurosystem. To do so, I have created a cross-sectional data set of 474 banks. It includes all active banks on the interbank market the week before the tender announcement, on March 16, 2020 (individual bid limits and borrowing allowance) and overall conditions on March 17, 2020. Therefore, interbank borrowing is taken into account from March 9 to 13, 2020, the week before the pandemic hit the market. The sharp increase in loan rates seen in Figure 1a is part of the aggregates.

Research Question 5 *How do interbank conditions the week before the TLTRO-III tender influence the decision in participating?*

To answer the question in a first step the probability of trading is estimated in a balanced panel during the week before the tender auction.

$$\text{Loan}_{jt} = \beta_0 + \beta_1 \text{x}_{jt} + \gamma_j + \epsilon_{jt} \tag{9}$$

Loan_{jt} is a dummy variable which is one for borrowing and zero otherwise. x_{jt} is either BPI_{jt} or LPI_{jt} while γ_j capture borrower fixed effects. The regression estimation estimates the average probability of borrowing per bank as a function of the underlying relationship measures. The fitted value of regression equation 9 is used as a regressor in regression equation 10.[9]

$$\text{Tender}_b = \beta_0 + \beta_1 \text{Log(Total Borrowing)}_b + \beta_2 \text{Borrowing Rate}_b + \beta_2 \hat{\text{Loan}}_b + \epsilon_b \tag{10}$$

Tender$_b$ is a dummy variable which is one for tender participation and zero otherwise. *Log(Total Borrowing)*$_b$ capture the logarithm of total borrowing, *Borrowing Rate*$_b$ the volume-weighted borrowing rate and $\hat{Loan}_b$ the fit of regression 9. Hypotheses 5a and 5b summarise the possible channels. Hypothesis 5a refers to the market mechanism and evaluate tender auctions as substitutes for the market and 5b refers to the liquidity hoarding argument.

Hypothesis 5a *Banks with a higher probability of receiving loans via the market due to relationship measures are those who have a lower probability in participating in tender auctions. Paying higher rates and receiving less liquidity increases the probability of tender participation.*

Hypothesis 5b *Liquidity hoarding is happening via tender auctions. Those banks who are very active in borrowing higher amounts have also a higher probability of participating in the market.*

4.6 The Aggregated Borrowing Side

In earlier Sections of this paper, I run analyses at the transactional level, which has advantages such as time-varying fixed effects. However, the models do not allow me to control for aggregated effects at the bank level. Having knowledge about changes

[9]Following (Wooldridge, 2010, p.116f.), replacing an unobserved variable q_i by a generated regressor $\hat{q}_i$ does not cause consistency problems. Consider the first-stage coefficient of the unobserved regressor q_i as δ and the coefficient of $\hat{q}_i$ in the second stage to be γ. Standard errors and test statistic of the second stage are invalid because they ignore the sample variation in $\hat{\delta}$ (usually the first stage regression uses the same sample of data than the second stage). Nevertheless, there is one important exception where the sampling variation of $\hat{\delta}$ can be ignored, which I apply here: the null hypothesis $H_0 : \gamma = 0$ in stage two, which is the case in standard OLS regressions by definition. The t-statistic on $\hat{q}_i$ has a limited standard normal distribution under H_0 and can thus be used to test under normal OLS assumptions.

in loan conditions due to COVID-19, fragmentation and relationship lending, it is crucial to know about aggregated effects and which part of the interbank borrowing is hit most. Therefore Research Question 6 is summarised as follows:

Research Question 6 *Which borrower banks face higher costs associated with COVID-19?*

I construct an aggregated sample at the borrower level. Descriptive statistics can be found in Section 3 and table 1. Regression equation 11 describes the model.

$$\mathrm{y}_{jt} = \beta_0 + \beta_1 \mathrm{x}_{jt} + \beta_2 \mathrm{x}_{jt} \times \text{Post Covid}_t + \gamma_j + \delta_t + \epsilon_{jt} \tag{11}$$

y_{it} is either the aggregated and volume-weighted *Borrowing Rate*$_{jt}$ or *Log(Total Borrowing)*$_{jt}$ per day. *Post Covid*$_t$ is a dummy variable which equals one for the post-COVID-19 period (from March 12, 2020 to June 9, 2020) and zero otherwise. x_{jt} is either one of the following variables: the dummy variables *ECB Borrower*$_j$ and *Large BBK Borrower*$_j$, which both are one for the ECB sample (47 largest banks) or the German banks based on the ECB criterion (14 banks) and zero otherwise. Both dummies are proxies for the largest Eurozone or German banks. *German Lender*$_{jt}$ and *Institutional Loans*$_{jt}$ both control for the share of German or institutional lending per borrower. Furthermore, x_{jt} can be one of the following network measures: *LPI*$_{jt}$, capturing the volume-weighted and aggregated relationship measure of borrower's lenders and *BPI*$_{jt}$, which controls for the aggregated and volume-weighted borrower relationship. γ_j captures borrower fixed effects while δ_t captures date fixed effects and ϵ_{it} is the error term. Standard errors are clustered at the borrower and date level. Hypothesis 6 summarises the possible channels.

Hypothesis 6 *Based on earlier analyses, COVID-19 results overall in higher borrowing costs and lower total borrowing. Larger borrowers are less affected than smaller ones. Borrower with stable networks are better able to compensate for the shock, but only if they represent a relevant role in the relationship.*

5 Main Results

5.1 COVID-19

Figure 1a and 1b provide graphical evidence of the reaction of loan rates and the interbank market volume. While Figure 1a shows an sharp increase in loan rates by roughly 5 basis points, 1b shows a decline of the market volume of 50% over time. To substantiate this finding, table 3 shows the results from estimating equation 4 and reports the results at the transactional levels of panel A. Y_{ijt} is the *Loan Rate*$_{ijt}$ in column 1, *Log(Total Amount)*$_{ijt}$ in 2 as well as *Loan Dummy*$_{ijt}$ in 3. *Post Covid*$_t$ is a dummy variable which equals one during the pandemic (after March, 12, 2020) and zero otherwise. All regressions use the Ordinary-Least-Square (OLS) method. Standard errors are clustered at the bank-pair and date level.

Controlling for single borrower and lender fixed effects, the coefficient of β_1, is statistically highly significant in all regressions of table 3 at the 1% significance level. An interbank loan has on average during the COVID-19 pandemic a 5.94 basis points higher loan rate than before. Compared to the average loan rate of -0.381 this increase is economically large. Moreover, COVID-19 results in an, on average, 8.9% lower loan size (at the disaggregated transactional level), which is again an economically large result given the continuous decreasing of total market volume over time, seen in Figure 1a. The probability of trading a loan decreases slightly by on average 0.03 percentage point.

Table 4 shows the variation in fixed effects for the *Loan Rate*$_{ijt}$. All combinations of fixed effects result in highly significant coefficients, even the most restrictive combinations of lender-borrower pair fixed effects.

This findings support hypothesis 1, more precisely, the COVID-19 pandemic seems to be an exogenous shock to the market. Even though the market is not short of liquidity, the increasing uncertainty of the pandemic is associated with significantly higher loan rates, lower loan amounts and a lower probability of trading a loan.

5.2 Fragmentation of the European Interbank Market

To document the fragmentation within the European interbank market, tables 5 and 6 show the results of equation 5. Y_{ijt} is the *Loan Rate*$_{ijt}$ in columns 1 and 2, *Log(Total Amount)*$_{ijt}$ in 3 and 4 as well as *Loan Dummy*$_{ijt}$ in 5 and 6. Lender and time-varying borrower-day fixed effects as well as clustered standard errors at the bank-pair and day level are used in all regressions.

Table 5 shows the heterogeneity within the European interbank market. Columns 1, 3 and 5 use the Eurozone panel B and check whether loans from Germany have different loan conditions than those of the Eurozone excluding Germany. *German Loan*$_{ijt}$ is a dummy variable, equals one for a German loan and zero otherwise. The interaction term *Post Covid*$_t \times$ *German Loan*$_{it}$ shows the additional effect of having a German loan during the pandemic.

In normal times, German loans have on average a 1.96 basis points higher loan rate, a 183% higher loan size and a 1.93 percentage point higher probability of trading than loans from the Eurozone excluding Germany. While the loan rate is significant at the 5 % level, the loan size and the loan dummy are highly significant at the 1% level. COVID-19 increases the fragmentation of loan rates on average by 0.91 basis point and lowers the gap in lending probability by 0.12 percentage point. Again, the pandemic interaction term of the loan rate is significant at the 5% level and the interaction term of the loan dummy at the 1% level. There is no additional effect on loan size due to COVID-19. A 2.9 basis points difference in loan rates is economically large, in particular taking into account, the fact that 95.5% of the Eurozone market is domestic and highly standardized. Moreover, a loan size difference of almost twice as high in Germany compared to the rest of the Eurozone is economically very large, even if there is no additional COVID-19 effect.

Columns 2, 4 and 6 use panel C, the domestic German interbank market and show the effect of having an institutional loan compared to a private, non-institutional German loan. *German Institutional Loan*$_{ijt}$ is a dummy variable which equals one in case of an institutional loan within Germany and zero otherwise. The interaction term $Post\ Covid_t \times German\ Institutional\ Loan_{ijt}$ shows the additional effect of having an institutional loan during the pandemic.

Institutional loans have on average a 4.6 basis points lower loan rate, a 60.7% higher size and a 2.94 percentage point higher probability of trading compared to private, non-institutional loans in Germany. All coefficients are highly significant at the 1% level. Within Germany, COVID-19 diminishes the fragmentation in loan rates by 3.2 basis points and the probability of trading by 0.3 percentage point. Again, there is no additional effect of loan size due to COVID-19. While the differences in all three loan characteristics are economically large COVID-19 appears to diminish the comparative advantage of being part of the institutional lending network.

While table 5 shows evidence of fragmentation between having a domestic German loan vs. loans in the Eurozone excluding Germany, table 6 analyses foreign vs. domestic borrowing of German banks.[10] Columns 1, 3 and 5 shows the effect of domestic vs. foreign borrowing in Germany; the interaction term $Post\ Covid_t \times Cross\text{-}Border_{ijt}$ shows the effect of having German cross-border borrowing during the pandemic. German cross-border borrowing has on average a 6.35 basis points higher loan rate and a 0.13 higher probability of trading during COVID-19; both coefficients are statistically highly significant at the 1% level. There is no effect on loan size.

Columns 2, 4 and 5 of table 6 compare the effect of having a lender outside or inside the Eurozone for German borrowers, therefore the interaction term $Post\ Covid_t \times Non\text{-}Eurozone\ Lender_{it}$ shows the effect of a German borrower having a non-Eurozone lender during the pandemic. German borrowing from a non-Eurozone lender has on average 3.26 basis points higher loan rates and a 0.07 percentage points higher probability of trading during COVID-19 compared to lender inside the Eurozone. The coefficient of the loan rate is significant at the 5% and for the loan dummy

[10] Cross-border borrowing is just 4.5% of German borrowing. Having time-varying borrower-day fixed effects enables me to perform a reduced-form regression of an interaction term of COVID-19.

at the 1% level. There is no effect on loan size. Again, the effects for domestic vs. foreign borrowing are economically large.

Both results support hypothesis 2: the European interbank market seems to be highly fragmented. Between the subgroups in the European interbank markets loan rates, loan size and the probability of trading differ significantly. COVID-19 increases the fragmentation in loan pricing at the European level, while loan size does not show any effect. Within Germany, the advantage of having an institutional loan decreases by lowering the gap in loan rates and trading probabilities. Instead of having a convergence of both groups, just the institutional loans surrender their advantages. Furthermore, there are differences in loan conditions for domestic vs. foreign borrowing in Germany.

5.3 Liquidity Endowment

Table 7 shows the results of equation 6 and analysis the effect on loan conditions of liquidity endowment. Y_{ijt} is the *Loan Rate*$_{ijt}$ in columns 1 and 2, *Log(Total Amount)*$_{ijt}$ in 3 and 4 as well as *Loan Dummy*$_{ijt}$ in 5 and 6. *Excess Reserves*$_{it\text{-}1}$ is the first lag of liquidity in excess of a lender's minimum reserve requirement, divided by the number of days left in the maintenance period, defined in equation 3. The interaction term *Post Covid*$_t \times$*Excess Reserves*$_{it\text{-}1}$ reflects the additional effect of liquidity endowment during COVID-19. Columns 1, 3 and 5 show the results of the entire sample in panel A while columns 2, 4 and 6 shows the results for the German panel C. Lender and time-varying borrower-day fixed effects as well as clustered standard errors at the bank-pair and day level are used in all regressions.

A one standard deviation increase in the first lag of the lenders' excess reserves (2.96) during COVID-19 increases the loan rate on average by 1.2 basis points, loan size decreases by 13.7% and the probability of trading decreases by 0.03 percentage point. The coefficient of the loan rate is highly significant at the 1% level while loan size and loan trading probability are significant at the 10% level.

The effects are similar in Germany: one standard deviation increase on lenders' excess reserves within Germany (1.89) during COVID-19 increases loan rates on average by 0.79 basis point, while the loan size decreases by 10% and the probability of trading decreases by 0.2 percentage point. The effect within Germany has larger absolute coefficients but is slightly smaller in the interpretation, due to a smaller standard deviation.

The results support hypothesis 3a: Liquidity does not enter the market. Higher lender liquidity endowment leads on average to an increase in loan prices and a reduction in loan size, which go along with a lower probability of trading a loan. The coefficients are higher in Germany than in the entire Eurozone.

5.4 Relationship Lending

Tables 8 to 10 show the results of equations 7 and 8 and analyses the effect of relationship lending. In all tables, Y_{ijt} is the *Loan Rate*$_{ijt}$ in columns 1 and 2, *Log(Total Amount)*$_{ijt}$ in 3 and 4 as well as *Loan Dummy*$_{ijt}$ in 5 and 6. Lender and time-varying borrower-day fixed effects as well as clustered standard errors at the bank-pair and day levels are used in all regressions.

Table 8 shows the effect of having a close relationship to a borrower as a lender bank. Columns 1, 3 and 5 use panel A and check whether there is an effect in the entire sample. LPI_{ijt} is the lender preference index, shown in equation 1. The interaction term *Post Covid*$_t \times$*German Loan*$_{ijt}$ shows the additional effect of having an important borrower during the pandemic. Surprisingly there is no relationship effect during periods of distress in the Eurozone. Columns 2, 4 and 6 shows the results for Germany. A one standard deviation increase in LPI (0.18) during COVID-19 decreases loan rates on average by 0.96 basis point and loan size increases by 15.75% within Germany. The loan rate is highly significant at the 1% level, the loan size at the 5% level and there is no effect for the probability of trading. The German effects are economically very large.

Table 9 shows the results of interacting the LPI_{ijt} with German and institutional loans and the $Post\ Covid_t$ dummy. Columns 1, 3 and 5 use the Eurozone panel B and the interaction term $German\ Loan_{ijt} \times LPI_{ijt} \times Post\ Covid_t$ compares the relationship effects between Germany and the Eurozone excluding Germany during the pandemic. For German loans an increase of one standard deviation (0.261) results in on average 1.4 basis points lower loan rates and 27.72% higher loan size during COVID-19, compared to loans from the Eurozone excluding Germany. While both interactions terms are statistically highly significant at the 1% level, the probability of trading does not result in an additional effect due to COVID-19. Within Germany there is no difference in relationship lending during distressed times between the subgroups.

Table 10 shows the results of interacting the LPI_{ijt} with cross-border lender and non-Eurozone lender and the $Post\ Covid_t$ dummy for German borrowing. All columns use a subset of German borrowing. Columns 1, 3 and 5 uses the interaction term $Non\text{-}Eurozone\ Lender_{it} \times LPI_{ijt} \times Post\ Covid_t$ and compares the relationship effects between Eurozone and the non-Eurozone Lender for German borrowing during the pandemic. Having a non-Eurozone lender in columns 1, 3 and 5, an increase by one standard deviation in LPI_{ijt} (0.21)[11] during COVID-19 result on average in a 1 basis point higher loan rate and 13.8% lower loan size for borrowing from a non-Eurozone lender compared to domestic German borrowing. The coefficient of the loan rate is significant at the 1% level, that of loan size at 10% while there is no difference in the probability of trading.

For cross-border borrowing in general, in columns 2, 4 and 6, a one standard deviation increase (0.21) in LPI_{ijt} results on average in 1.2 basis point higher loan rates and 15.9% lower loan size compared to domestic German borrowing during COVID-19. Again, the coefficient of the loan rate is significant at the 1% level, of

[11] The German sample contains domestic loans, while this sample contains all loans of German borrowers (domestic *and* foreign borrowing). Descriptive statistics of LPI: mean 0.073, sd 0.21, p25 0, p75 1

loan size at the 10% while there is no difference in the probability of trading.

The results support hypothesis 4 partially: The network structure, in particular strong and stable relationships within the interbank market mitigates shocks and spillovers but the effect seems to be a German phenomenon.

5.5 The Eurosystem's Tender Auction

Table 11 shows the results of regression equations 9 and 10. Columns 1 and 3 show the first stage while columns 2 and 4 show the results of the second stage. The first stage is a panel OLS regression on a balanced panel, using borrower fixed effects. The time frame is the week before the tender was announced (March 9 to 13, 2020). The second stage is a cross-sectional OLS regression of 474 banks, with one aggregated observation per bank. Standard errors are clustered at the bank and date levels.

Increasing $\mathit{Log(Total\ Borrowing)}_b$ by 10% increases on average the probability of participation in the tender auction by on average 0.16 to 0.19 percentage point, ceteris paribus.[12] An increase of $\mathit{Borrowing\ Rate}_b$ by one standard deviation (0.071), increases the probability of participating by on average 3.3 percentage points, ceteris paribus. The probability of borrowing via the interbank market does not influence the tender participation, neither for the BPI_b nor for LPI_b.

These findings partially support both hypotheses: higher borrowing costs are associated with a higher loan rate participation (hypothesis 5b). Bank who borrow more in the markets have a higher probability of participating in the tender action. This finding supports the liquidity hoarding argument in hypothesis 5a and already seen in Section 5.3.

[12] Dependent on the relationship measure in the first stage.

5.6 The Aggregated Borrowing Side

The tables 12 to 15 show results of regression equation 11. Except for tables 12 and 13 column 1, all regressions use borrower and day fixed effects. All regressions use OLS while standard errors are clustered at the bank and date levels.

Tables 12 and 13 column 1 show single regressions of *Post Covid*$_t$ on *Borrowing Rate*$_{jt}$ and *Log(Total Borrowing)*$_{jt}$. The pandemic is associated with on average 6.9 basis points higher borrowing costs and on average 15.08% lower total borrowing, both of which are statistically highly significant at the 1% level. Compared with an average volume-weighted borrowing rate per day of -0.361 and total borrowing of €58.83 million those single effects are economically large.

Comparing the borrowing costs between groups in table 12 shows reduced-form regressions. During COVID-19 the largest 47 Eurozone banks pay on average 7.87 basis points lower rates than smaller borrower while for the top 14 German banks the average effect is 5.85 basis points, compared to smaller German borrowers. Both effects are statistically highly significant (1%) and economically large. Having a high share of German lenders during COVID-19 results in higher borrowing costs at the 1% level: an increase by one standard deviation (0.267) increases the borrowing costs by on average 1.79 basis points. Banks with a maximum of German borrowing have on average 6.72 basis points higher borrowing costs during the pandemic than banks with no German borrowing. High shares of institutional loans increase the borrowing costs significantly during COVID-19 (1% level). A rise of one standard deviation (0.349) in institutional loans increases borrowing costs by 0.85 basis point. The average borrower has 85% institutional loans and 92.2% German lenders, which means that the results are economically important.

The COVID-19 effects on total borrowing for different groups are less strong, shown in table 13. While overall borrowing decreases during the pandemic, just the top 47 Eurozone banks have differences in total borrowing: their total borrowing is on average 21.57% higher than that of smaller banks. However, the effect is slightly significant at the 10% level.

Table 14 shows the results of aggregated relationship on borrowing costs. Being important for the borrower's lender reduces borrowing costs during COVID-19 significantly: A one standard deviation increase in the aggregated and volume-weighted LPI_{jt} (0.216) reduces borrowing rates by an average of 2.3 basis points during COVID-19. Dependence on a single lender instead increases the borrowing costs: an increase in BPI_{jt} by one standard deviation (0.23) results in an average increase in borrowing costs of 0.18 basis points. Taking into account the high mean of BPI_{jt} of 0.896 infers high average borrowing costs. German borrowers have similar, but a bit smaller effects in absolute terms.[13]

Being important for borrower's lender increases total borrowing, shown in table 15: an increase in LPI_{jt} by one standard deviation (0.216) increases total borrowing by on average 6.2% during COVID-19. The coefficient is highly significant at the 1% level.

An increase in BPI_{jt} by one standard deviation (0.207) for German borrower results in lower borrowing amounts of on average 7.3% during normal times (1% level) while COVID-19 reduces the gap by increasing on average by 6%.

The results support hypothesis 6: Based on the preceding analysis, COVID-19 results overall in higher borrowing costs and lower total borrowing. Larger banks are less affected than smaller ones. Borrower with stable networks are better in compensating the shock, but only if they represent the relevant role in the relationship. Being, on average, an important borrower compensates but having just an important lender result in opposite effects.

[13]While the disaggregated, transactional level does not show relationship effects for the entire sample, the sample used here creates an average relationship measure per borrower per day. Given the fact that the German lender share is 92.2% it is hardly surprising that both samples show similar results for relationship.

6 Robustness

To further assess the robustness and validity of the results for COVID-19 effects, I performed different robustness checks, shown in tables 16, 17 and 18.

The main concern in estimating natural experiment models using time dummies is to measure effects outside the scope of the analysis. Especially during distressed times, confounding factors might drive results. Therefore I use three alternative measures of $Post\ Covid_t$ for the German subsample in table 16 and run a placebo test in table 17, re-estimating equation 6, which allows me to include time-varying borrower-day fixed effects.

The Robert Koch Institut (2022) provides data on German COVID-19 cases, a 14-day rolling window incidence of cases per 100,000 of the population and number of deaths caused by COVID-19. On average 1142.85 infections takes place and 54 people died of or with COVID-19. The average incidence is 18.6. Holding $Excess\ Reserves_{it\text{-}1}$ constant, an increase by one standard deviation of $COVID\ Cases_t$ (1712.71) results in on average 0.7 basis point higher loan rates. Using the $Incidence_t$ the effect is quite similar. An increase of one standard deviation (26.26) increases the loan rate on average by 0.6 basis point. For the number of $Deaths_t$, a one standard deviation increase (82.46) increases the loan rate on average by 0.3 basis point. All measures are highly significant at the 1% level.

Regressions on $Loan\ Amounts_{ijt}$ show a negative, at the 10% significant level, coefficient for $Incidence_t$ and $Deaths_t$: Holding $Excess\ Reserves_{it\text{-}1}$ constant, an increase by one standard deviation of $Incidence_t$ (26.26) result in a decrease of on average 4.5% in loan size and for $Deaths_t$ (82.46) on average 2.08%. The extensive margin shows a significant effect for $Deaths_t$: an increase of one standard deviation result in a 0.049 percentage point lower probability of trading.

All three measures confirm the results shown above. Nevertheless, continuous COVID-19 measures have the weakness of being lender- and borrower-specific if both counterparties are located in different countries. It would not be possible to measure the effect properly, as borrower time-varying fixed effects would absorb the effects for borrowers. Furthermore, calculating different effects for different countries in the Eurozone was not feasible due to insufficient cross-country variation. Therefore, the exercise is done for the German subsample.

Table 16 runs a placebo test, using the period January 1 to June 9 in 2017, 2018 and 2019.[14] $Placebo_t$ is a dummy variable which equals one after March 12 (the same post period as COVID-19) and zero otherwise. All three interaction terms turns out to be insignificant. So $Post\ Covid_t$ does not measure time trends during that time of the year.

The last robustness check follows the approach of Khwaja and Mian (2008). According to Paravisini, Rapport, and Schnabl (2023), there are limits of Khwaja and Mian (2008) when it comes to specialisation of banks in lending. The authors analyse bank specialisation in export markets in Peru and argue that firms take the pattern of bank specialisation into account when selecting their lending banks and that credit supply shocks disproportionally affect firms' exports to markets where the lender is specialised. Furthermore, they argue that the approach of Khwaja and Mian (2008) i.e. the use of time-varying borrower fixed effects, assumes that credit demand shocks cannot induce firms to systematically shift their borrowing to another bank. The assumption holds under the proviso that the source of the credit supply shock is uncorrelated with anything affecting the specialisation of demand, in other words if a change in credit demand is, in expectation, equally distributed across all banks lending to the firm. This is the case in non-specialised lending.

Paravisini, Rapport, and Schnabl (2023) add a term that captures the heterogeneity in lending. The authors identify a bank lender specific credit-supply shock and create a dummy which captures specialisation in three steps. First, they compute the lending share per bank to a specific economic activity c over total lending of the bank. Second, they compute the relative debt concentration in spirit of a re-

[14] Table 16 column 3 is an exception. Due to computing power limitations, the balanced panel and the huge size of the sample, the regression uses the period January 1, 2019 to June 9, 2019.

vealed comparative advantage measure by dividing the bank lender specific measure of step 1 over the total share of aggregated bank lending to economic activity c. While data of a specific economic activity c is not observable, the authors proxy the final measure by the use of debt contracts between firms and banks and the exports of those firms to specific countries, which they define as specific activity c. And in a final step, they rank the specialisation measure in quantiles and create a dummy variable which equals 1 if the specialisation measure of a specific bank is ranked in one of the four quantiles.

While Paravisini, Rapport, and Schnabl (2023) have to proxy the overall unobservable lending to activity c, the underlying data have the advantage of having a large number of active banks and an almost closed interbank network. Transferring the idea of specialisation to the interbank market, the major groups where lenders can be specialised are private and institutional interbank loans, cross-border lending and non-Eurozone lenders, i.e. those contracts which offer the deposit facility rate to banks outside the Eurozone. Taking the idea of a special economic activity, $Specialisation_{ijt}$is defined as a dummy variable which equals 1 if a borrower j bank actively borrows within at least one subnetwork in which the lender bank is active within a rolling window of 30 days and the lending amount within the subnetwork of the corresponding lender i is within either the second (Q2), third (Q3) or fourth (Q4) quantile, and zero otherwise.

Table 18 shows the results of the exercise. The regression includes lender i and borrower×day jt fixed effects. Column 1 includes single effects of $Specialisation_{ijt}$. According to Paravisini, Rapport, and Schnabl (2023) the dummy variables of $Specialisation_{ijt}$ within the different percentiles measure the change in the loan rate of borrower j that borrows from a subnetwork in which the lender i has some specialisation, relative to borrowers that do not (lowest bottom quantile). While the second and fourth quantiles do not result in significant effects, borrowers who borrow from lenders located in the third quantile within the last 30 days seem to pay rates that are on average 0.6 basis point higher (significant at the 5% level) compared to borrower-lender relationships where no specialisation takes place. Contrary to the study of Paravisini, Rapport, and Schnabl (2023), the single effect of the shock event cannot be taken into account because it is not just lender bank specific but a global shock and therefore absorbed by borrower×day fixed effects. Therefore, column 2 includes the interaction of $Specialisation_{ijt}$ with $Post\ Covid_t$. This specification does not result in significant effects. Overall, the application of Paravisini, Rapport, and Schnabl (2023) is very helpful in discussing the heterogeneity of shocks. Although the application is difficult and requires a high data quality and granularity, it gives first indication of shock heterogeneity by measuring single effects which do not seem to play a role in the interaction regression.

7 Conclusion

In this paper, I provide evidence that the European interbank market is highly fragmented, especially during distressed times. Using transactional data of the European interbank market provides evidence that there are significant differences in loan conditions between the Eurozone and Germany as well as within Germany.

COVID-19 put the market under stress by increasing interest rates, decreasing loan size and the probability of trading and thus strengthened the fragmentation. The shock goes back to uncertainty rather than liquidity shortage. Therefore, COVID-19 is used as an external and exogenous shock to provide a period of market distress.

Between the subgroups within the Eurozone (Eurozone excluding Germany, Germany, German institutional and German private, non-institutional loans) loan rates, loan size and the probability of trading differ significantly. There are loan rate differences up to 5 basis points, loan size differences up to 180% and the probability of trading differs up to 2 percentage points between subgroups. COVID-19 increases, in particular, the fragmentation in loan pricing within the Eurozone, while loan size shows no effects at all. Within Germany, the advantage of having an institutional loan decreases due to a reduction in the spread in loan rates and trading probabilities during the pandemic. There are differences in loan conditions between domestic and foreign borrowing. Cross-border borrowing is on average more than 6 percentage points more expensive during COVID-19 than domestic borrowing. Having a non-Eurozone lender is on average more than 3 basis points more expensive than borrowing from inside the Eurozone during the pandemic.

Liquidity does not enter the market and there is evidence of liquidity hoarding. Lenders with higher liquidity endowment increase on average loan prices and reduce both the loan size and the probability of trading. The effects are larger in Germany than in the Eurozone excluding Germany.

Relationship lending mitigates shocks and spillovers but the effect seems to be a German phenomenon. While the German results are economically very large, there are no effects or for the Eurozone excluding Germany. Within Germany, there is no difference in relationship effects. Borrower with stable networks are better able to compensate the shock, but only if they represent the relevant role in the relationship. Being on average, an important borrower compensates but having only an important lender result in opposite effects.

The liquidity hoarding hypothesis is confirmed via Eurosystem's liquidity provision. Bank who borrow more at the markets are those who have a higher probability of participating in the tender auction. Furthermore, those borrowers who pay higher rates have a higher probability of participating in the tender auction.

Finally, there is evidence that COVID-19 results overall in higher borrowing costs and lower total borrowing. Larger banks are less affected than smaller ones.

The results are robust to different COVID-19 measures, sample splits and interaction estimation. Placebo tests do not show trends in estimation.

The normalisation of monetary policy, with the objective of cementing the path of inflation at the target rate, reduces excess liquidity. Money markets, in particular interbank markets and the main objective of channelling liquidity properly, become more important. From a policy perspective, the fragmentation should be reduced or at least taken into account to ensure the effectiveness of monetary policy. More restrictive monetary policy is in conflict with taking over liquidity provision on a large scale. Therefore, in economic downturns with high inflation the interaction with the real economy, especially bank lending should be supported by a well functioning interbank market and proper liquidity channelling rather than impaired by market frictions like fragmentation.

Furthermore, network effects like relationship lending should be monitored carefully to ensure that the promotive effects of having relationship prevail and dependencies, especially for small banks with less market power, do not result in the opposite effect.

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Appendix

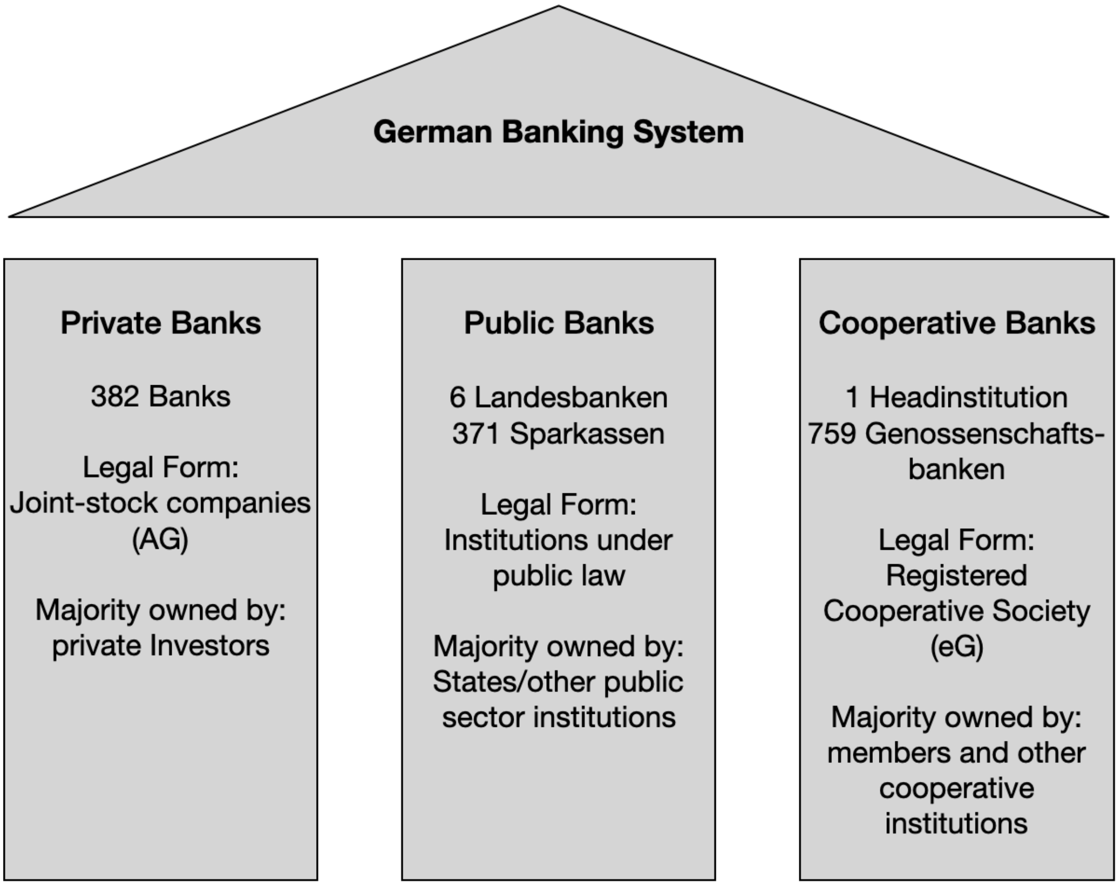

Figure A.1: German Banking System

Source: Own representation, based on Garrido and Damyanova (2019)

Table 1: Descriptive Statistics: Panel A represents descriptive statistics of all € overnight interbank loans, worldwide, reported by the 47 largest European (includes 14 German) and 101 smaller German banks, so in total 148 banks. Panel B reports the transactions for banks within the Eurozone.

Panel A: All	N	Mean	SD	p25	p75
Loan Amount$_{\mathrm{ijt}}$ [in €mn]	60,576	45.10	64.64	7	55
Log(Loan Amount)$_{\mathrm{ijt}}$	60,576	3.080	1.325	2.079	4.025
Loan Rate$_{\mathrm{ijt}}$	60,576	-0.381	0.117	-0.430	-0.350
LPI$_{\mathrm{ijt}}$	60,576	0.154	0.309	0.003	0.063
BPI$_{\mathrm{ijt}}$	60,576	0.745	0.371	0.429	1
Excess Reserves$_{\mathrm{it}}$ (Lender) [in €mn]	53,708	1.204	2.960	0.213	1.258
Excess Reserves$_{\mathrm{jt}}$ (Borrower) [in €mn]	57,038	338.4	2,169	0.590	25.77
Dummy Eurozone Loan$_{\mathrm{ijt}}$	60,576	0.865	0.342	1	1
Dummy German Loan$_{\mathrm{ijt}}$	60,576	0.797	0.402	1	1
Dummy Institutional Loan$_{\mathrm{ijt}}$	60,576	0.711	0.453	0	1
Dummy Non-Institutional German Loan$_{\mathrm{ijt}}$	60,576	0.086	0.280	0	0
Dummy Domestic Loan$_{\mathrm{ijt}}$	60,576	0.826	0.380	1	1
Dummy Cross-Border Loan$_{\mathrm{ijt}}$	60,576	0.174	0.379	0	0
Dummy German Lender$_{\mathrm{it}}$	60,576	0.800	0.400	1	1
Dummy Eurozone Lender$_{\mathrm{it}}$	60,576	0.887	0.316	1	1
Dummy Non-Eurozone Lender$_{\mathrm{it}}$	60,576	0.113	0.316	0	0
Post Covid$_{\mathrm{t}}$	60,576	0.524	0.500	0	1
Panel B: Eurozone	N	Mean	SD	p25	p75
Loan Amount$_{\mathrm{ijt}}$ [in €mn]	52,375	41.03	54.50	6.890	50
Log(Loan Amount)$_{\mathrm{ijt}}$	52,375	3.019	1.308	2.066	3.932
Loan Rate$_{\mathrm{ijt}}$	52,375	-0.360	0.103	-0.420	-0.300
LPI$_{\mathrm{ijt}}$	52,375	0.102	0.261	0.002	0.027
BPI$_{\mathrm{ijt}}$	52,375	0.811	0.323	0.669	1
Excess Reserves$_{\mathrm{it}}$ (Lender) [in €mn]	52,143	1.110	2.373	0.209	1.237
Excess Reserves$_{\mathrm{jt}}$ (Borrower) [in €mn]	50,198	137.8	1,236	0.361	11.56
Dummy German Loan$_{\mathrm{ijt}}$	52,375	0.922	0.268	1	1
Dummy Institutional Loan$_{\mathrm{ijt}}$	52,375	0.823	0.382	1	1
Dummy Non-Institutional German Loan$_{\mathrm{ijt}}$	52,375	0.099	0.299	0	0
Dummy Domestic Loan$_{\mathrm{ijt}}$	52,375	0.955	0.208	1	1
Dummy Cross-Border Loan$_{\mathrm{ijt}}$	52,375	0.045	0.208	0	0
Dummy German Lender$_{\mathrm{it}}$	52,375	0.924	0.265	1	1

Descriptive Statistics: Panel C reports summary statistics of unsecured, overnight interbank loans within Germany as well as Germany's COVID-19 statistics. Panel D shows loans of German non-institutional banks and Panel E those of institutional banks. An institutional loan is clarified by trading between two banks within the subsectors of corporate banks or savings/federal state banks. Panel F represents loans of the Eurozone, excluding Germany.

Panel C: Germany	N	Mean	SD	p25	p75
Loan Amount$_{ijt}$ [in €mn]	48,291	41.70	50.34	8	52
Log(Loan Amount)$_{ijt}$	48,291	3.099	1.242	2.197	3.970
Loan Rate$_{ijt}$	48,291	-0.357	0.074	-0.420	-0.300
LPI$_{ijt}$	48,291	0.055	0.180	0.002	0.020
BPI$_{ijt}$	48,291	0.850	0.282	0.875	1
Excess Reserves$_{it}$ (Lender) [in €mn]	48,114	1.101	1.892	0.246	1.248
Excess Reserves$_{jt}$ (Borrower) [in €mn]	46,229	28.27	274.2	0.210	8.391
Dummy Institutional Loan$_{ijt}$	48,291	0.892	0.310	1	1
Dummy Non-Institutional German Loan$_{ijt}$	48,291	0.108	0.310	0	0
COVID Cases$_{t}$	48,291	1142.846	1712.712	0	1304
14-Day Incidence$_{t}$(per 100.000)	48,291	18.605	26.260	0.005	33.815
Deaths$_{t}$	48,291	54.076	82.456	0	92
Panel D: German Non-Institutionals	N	Mean	SD	p25	p75
Loan Amount$_{ijt}$ [in €mn]	5,200	43.97	53.15	10	50
Log(Loan Amount)$_{ijt}$	5,200	-0.364	0.112	-0.450	-0.320
Loan Rate$_{ijt}$	5,200	3.159	1.259	2.398	3.932
LPI$_{ijt}$	5,200	0.276	0.372	0.00737	0.446
BPI$_{ijt}$	5,200	0.528	0.340	0.224	0.984
Excess Reserves$_{it}$ (Lender) [in €mn]	5,200	0.337	1.061	0.00802	0.264
Excess Reserves$_{jt}$ (Borrower) [in €mn]	5,090	32.41	152.3	0.00872	16.25
Panel E: German Institutional Loans	N	Mean	SD	p25	p75
Loan Amount$_{ijt}$ [in €mn]	43,091	41.42	49.98	7.500	54
Log(Loan Amount)$_{ijt}$	43,091	3.091	1.240	2.140	4.007
Loan Rate$_{ijt}$	43,091	-0.356	0.068	-0.420	-0.300
LPI$_{ijt}$	43,091	0.028	0.114	0.002	0.017
BPI$_{ijt}$	43,091	0.889	0.247	1	1
Excess Reserves$_{it}$ (Lender) [in €mn]	42,914	1.193	1.948	0.293	1.361
Excess Reserves$_{jt}$ (Borrower) [in €mn]	41,139	27.76	285.7	0.258	7.820
Network F: Eurozone w.o. Germany	N	Mean	SD	p25	p75
Loan Amount$_{ijt}$ [in €mn]	3,466	35.11	96.48	0.200	19
Log(Loan Amount)$_{ijt}$	3,466	1.987	1.718	0.182	2.996
Loan Rate$_{ijt}$	3,466	-0.430	0.255	-0.580	-0.400
relAB$_{ijt}$	3,466	18.60	4.938	18	22
LPI$_{ijt}$	3,466	0.740	0.359	0.490	1
BPI$_{ijt}$	3,466	0.291	0.383	0.0146	0.440
Excess Reserves$_{it}$ (Lender) [in €mn]	3,411	0.963	4.875	2.09e-05	0.221
Excess Reserves$_{jt}$ (Borrower) [in €mn]	3,369	1,497	4,230	161.6	1,199
Dummy Domestic Loan$_{ijt}$	3,466	0.495	0.500	0	1
Dummy Cross-Border (Eurozone)$_{ijt}$	3,466	0.505	0.500	0	1

Descriptive Statistics: Borrower Level reports an aggregated dataset at the borrower level. Tender Level shows a cross sectional dataset of interbank lending the week before the tender is announced (March 9 to 13, 2020) or variables of the TLTRO III (announcement date: March 16, 2020)

Borrower Level	N	Mean	SD	p25	p75
Volwgt. Borrowing Rate per Day$_{\mathrm{jt}}$	45,954	-0.361	0.0941	-0.421	-0.260
Total Borrowing per Day$_{\mathrm{jt}}$	45,954	58.83	115.4	7.600	63
Log(Total Borrowing)$_{\mathrm{jt}}$	45,954	3.053	1.619	2.028	4.143
Number of Loans per Day$_{\mathrm{jt}}$	45,954	1.288	1.220	1	1
BPI (Volwgt.)$_{\mathrm{jt}}$	45,954	0.896	0.230	1	1
BPI (Volwgt.)$_{\mathrm{jt}}$|German borrower	43,449	0.913	0.207	1	1
LPI (Volwgt.)$_{\mathrm{jt}}$	45,954	0.078	0.216	0.002	0.023
LPI (Volwgt.)$_{\mathrm{jt}}$|German borrower	43,449	0.052	0.173	0.002	0.019
Dummy ECB Borrower$_{\mathrm{jt}}$	45,954	0.055	0.228	0	0
Dummy Large BBK Borrower$_{\mathrm{jt}}$	45,954	0.018	0.131	0	0
Dummy Institutional Loan$_{\mathrm{jt}}$	45,954	0.849	0.349	1	1
German Lender Share$_{\mathrm{jt}}$	45,954	0.922	0.267	1	1
Tender Level	N	Mean	SD	p25	p75
Fit (Probability Loan|BPI)$_{\mathrm{b}}$	474	0.906	0.190	0.999	0.999
Fit (Probability Loan|LPI)$_{\mathrm{b}}$	474	0.647	0.203	0.576	0.595
Volwgt. Borrowing Rate Week$_{\mathrm{b}}$	474	-0.392	0.071	-0.427	-0.350
Total Borrowing Week$_{\mathrm{b}}$	474	295.1	591.9	35	315.5
Log(1+Total Borrowing Week)$_{\mathrm{b}}$	474	4.686	1.540	3.584	5.757
Dummy Interbank$_{\mathrm{b}}$	565	0.839	0.368	1	1
Dummy Tender$_{\mathrm{b}}$	565	0.202	0.402	0	0
Settlement Amount$_{\mathrm{b}}$ [in bn. EUR]	114	1.01	2.702	0.025	0.800
Log(1+Settlement Amount)$_{\mathrm{b}}$	114	0.400	0.616	0.025	0.588

Table 2: Variable Description

Variable	Definition
	Interbank Market-Specific Variables
Loan Amount$_{\mathrm{ijt}}$ [in €mn]	Loan amount of an overnight interbank loan between lender i and borrower j at day t.
Log(Loan Amount)$_{\mathrm{ijt}}$	Logarithm of loan amount.
Loan Rate$_{\mathrm{ijt}}$	Volume-weighted loan rate of an overnight interbank loan between lender i and borrower j at day t.
Loan Preference Index$_{\mathrm{ijt}}$ (LPI)	Amount lent by lender i to borrower j during the last 30 days preceding day t divided by overall amount lent by lender i during the days preceding day t. LPI reflects the importance of a borrower j for a lender i.
Borrower Preference Index$_{\mathrm{ijt}}$ (BPI)	Amount borrowed by borrower j from lender i during the last 30 days preceding day t divided by overall amount borrowed by borrower j during the days preceding day t. BPI reflects the importance of a lender i for a borrower j.
Excess Reserves$_{\mathrm{ijt}}$ [in €mn]	Actual reserve holdings of bank i (j) at day t minus the minimum reserve requirement of bank i (j) within the maintenance period divided by the days left within the maintenance minimum reserve period.
Dummy Eurozone Loan$_{\mathrm{ijt}}$	Dummy Variable equals one for a Eurozone loan and zero otherwise.
Dummy German Loan$_{\mathrm{ijt}}$	Dummy Variable equals one for a German loan and zero otherwise.
Dummy Institutional Loan$_{\mathrm{ijt}}$	Dummy Variable equals one for an institutional loan. Institutional loans are characterised by trades within the corporate banks or savings-/federal state banks subsectors and are zero otherwise.
Dummy Non-Institutional German Loan$_{\mathrm{ijt}}$	Dummy Variable equals one for a German loan and zero otherwise.
Dummy Domestic Loan$_{\mathrm{ijt}}$	Dummy Variable equals one for a domestic loan within countries of the Eurozone and zero otherwise.
Dummy Cross-Border Loan$_{\mathrm{ijt}}$	Dummy Variable equals one for a cross-border loan where the location of the lender and borrower are different and zero otherwise.
Dummy German Lender$_{\mathrm{it}}$	Dummy Variable equals one for a German lender and zero otherwise.
Dummy Eurozone Lender$_{\mathrm{it}}$	Dummy Variable equals one for a Eurozone lender and zero otherwise.
Dummy Non-Eurozone Lender$_{\mathrm{it}}$	Dummy Variable equals one for a lender outside the Eurozone and zero otherwise.
Post Covid$_{\mathrm{t}}$	Dummy Variable equals one after the outbreak of COVID-19, between March 12 and the end of the sample June 9, 2020 and zero otherwise.

Variable Description

Variable	Definition
	Borrowers Level
Total $\text{Borrowing}_{\text{jt}}$	Aggregated borrowing per borrower j and day t.
$\text{Log(Total Borrowing)}_{\text{jt}}$	Logarithm of total borrowing.
Number of Loans_{jt}	Number of loans of borrower j per day t.
BPI_{jt} (Volwgt.)	Volume-weighted average BPI per borrower j and day t.
LPI_{jt} (Volwgt.)	Volume-weighted average LPI per borrower j and day t.
Dummy ECB $\text{Borrower}_{\text{j}}$	Dummy variable equals one for an ECB MMSR reporting agent and zero otherwise.
Dummy Large BBK $\text{Borrower}_{\text{j}}$	Dummy variable equals one for an ECB and BBK MMSR reporting agent and zero otherwise.
Institutional Loan_{jt}	The share of institutional loans per borrower. An institutional loan is characterised if both lender and borrower are saving banks and/or federal state or corporate banks.
German Lender Share_{jt}	The share of German lender of borrower j at day t.
	Tender Level
$\text{Fit(Probability Loan\|BPI)}_{\text{b}}$	$\hat{\text{Y}}$ of the first-stage regression of BPI on the probability of receiving a loan for borrower j on day t at the interbank market.
$\text{Fit(Probability Loan\|LPI)}_{\text{b}}$	$\hat{\text{Y}}$ of the first-stage regression of LPI on the probability of receiving a loan for borrower j on day t at the interbank market.
Volwgt. Borrowing Rate_{b} (Week)	Volume-weighted average borrowing rate the week before the tender is settled (March 9 to 13, 2020).
Total $\text{Borrowing}_{\text{b}}$ (Week)	Total borrowing on the interbank market the week before the tender is settled (March 9 to 13, 2020).
$\text{Log(1+Total Borrowing Week)}_{\text{b}}$	Logarithm of total borrowing.
Dummy $\text{Interbank}_{\text{b}}$	Dummy variable equals one for borrower j participates in the interbank market the week before the tender is settled (March 9 to 13, 2020).
Dummy Tender_{b}	Dummy variable equals one if borrower j participates in the tender.
Settlement Amount_{b}	The amount settled for borrower j by the Eurosystem.
$\text{Log(1+Settlement Amount)}_{\text{b}}$	Logarithm of one plus the settlement amount.

Table 3: Baseline Regression: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. *Post Covid*$_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. The dependent variable is either *Loan Rate*$_{ijt}$, the price of a loan, *Log(Total Amount)*$_{ijt}$ the logarithm of the amount of a loan or *Loan Dummy*$_{ijt}$, a dummy variable which equals one if bank i and j trade on day t and zero otherwise. All regressions include lender and borrower fixed effects and use panel A. Standard errors are double-clustered at the date and bank-pair level.

	(1) Loan Rate$_{\mathrm{ijt}}$	(2) Log(Total Amount)$_{\mathrm{ijt}}$	(3) Loan Dummy$_{\mathrm{ijt}}$
Post Covid$_{\mathrm{t}}$	0.0594***	-0.0887***	-0.0003***
	(23.19)	(-3.35)	(-2.78)
Observations	60,516	60,516	22,893,480
R^2	0.943	0.857	0.109
Lender Fixed Effects	Yes	Yes	Yes
Borrower Fixed Effects	Yes	Yes	Yes
Borrower×Day Fixed Effects	No	No	No
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	All	All	All

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Fixed Effects Variation: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. $Post\ Covid_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. The dependent variable is $Loan\ Rate_{ijt}$, the price of a loan. The regressions vary in the set of fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)
			Loan $\mathrm{Rate_{ijt}}$			
Post $\mathrm{Covid_t}$	0.0556***	0.0593***	0.0556***	0.0602***	0.0594***	0.0602***
	(15.95)	(22.48)	(19.37)	(23.11)	(23.19)	(22.94)
Observations	60,576	60,546	60,543	60,430	60,516	60,430
R^2	0.056	0.835	0.763	0.952	0.943	0.952
Lender Fixed Effects	No	Yes	No	No	Yes	Yes
Borrower Fixed Effects	No	No	Yes	No	Yes	Yes
Borrower-Lender (Pair) Fixed Effects	No	No	No	Yes	No	Yes
Borrower×Day Fixed Effects	No	No	No	No	No	No
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	All	All	All	All	All	All

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Fragmentation–Eurozone and Germany: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender *i* and borrower *j*, trading with each other at day *t* with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. *Post Covid*$_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. *German Loan*$_{ijt}$ and *Institutional Loan*$_{ijt}$ are both dummy variables, which equal one for, respectively, a German loan and an institutional loan. The dependent variable is either *Loan Rate*$_{ijt}$, the price of a loan, *Log(Total Amount)*$_{ijt}$ the logarithm of the amount of a loan or *Loan Dummy*$_{ijt}$, a dummy variable which equals one if bank *i* and *j* trade on day *t* and zero otherwise. All regressions include lender and time-varying borrower-day fixed effects. Columns (1), (3) and (5) use panel B while Columns (2), (4) and (6) use panel C. All regressions include lender and time-varying borrower and date fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan Rate$_{ijt}$		Log(Total Amount)$_{ijt}$		Loan Dummy$_{ijt}$	
German Loan$_{ijt}$	0.0196**		1.8289***		0.0193***	
	(2.03)		(6.03)		(11.47)	
Post Covid$_t$ ×German Loan$_{ijt}$	0.0091**		0.2288		-0.0012***	
	(2.19)		(1.53)		(-3.20)	
German Institutional Loan$_{ijt}$		-0.0460***		0.6069***		0.0294***
		(-4.85)		(3.68)		(21.73)
Post Covid$_t$ ×Institutional Loans$_{ijt}$		0.0319***		-0.1175		-0.0032***
		(5.71)		(-1.02)		(-2.69)
Observations	12,764	10,226	12,764	10,226	10,751,682	5,420,700
R^2	0.983	0.905	0.898	0.789	0.138	0.172
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	No	No	No
Borrower×Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	Eurozone	Germany	Eurozone	Germany	Eurozone	Germany

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Fragmentation–Cross-Border Trading: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. $Post\ Covid_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. $Cross\text{-}Border_{ijt}$ and $Non\text{-}Eurozone\ Lender_{it}$ are both dummy variables, which equal one for an cross-border loan, where both parties are located in different countries, or a non-Eurozone lender, a lender outside the Eurozone. The dependent variable is either $Loan\ Rate_{ijt}$, the price of a loan, $Log(Total\ Amount)_{ijt}$ the logarithm of the amount of a loan or $Loan\ Dummy_{ijt}$, a dummy variable which equals one if bank i and j trade on day t and zero otherwise. All regressions use German borrowing and include lender and time-varying borrower and date fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan $Rate_{ijt}$		Log(Total $Amount)_{ijt}$		Loan $Dummy_{ijt}$	
Post $Covid_t \times$Cross-$Border_{ijt}$	0.0635***		0.0169		0.0013***	
	(3.65)		(0.06)		(3.33)	
Post $Covid_t \times$Non-Eurozone $Lender_{it}$		0.0326**		0.1498		0.0007***
		(2.36)		(0.99)		(3.54)
Observations	11,826	11,826	11,826	11,826	19,135,128	19,135,128
R^2	0.954	0.954	0.802	0.802	0.151	0.151
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	No	No	No
Borrower×Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	German Borrower	German Borrower	German Borrower	German Borrower	German Borrower	German Borrower

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Liquidity Endowment: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. *Post Covid*$_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. *Excess Reserves*$_{ijt\text{-}1}$ are the lender banks' excess reserves, defined in equation 3. The dependent variable is either *Loan Rate*$_{ijt}$, the price of a loan, *Log(Total Amount)*$_{ijt}$ the logarithm of the amount of a loan or *Loan Dummy*$_{ijt}$, a dummy variable which equals one if bank i and j trade on day t and zero otherwise. Columns (1), (3) and (5) use panel A, while (2), (4) and (6) use panel C. All regressions include lender and time-varying borrower and date fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan Rate$_{ijt}$		Log(Total Amount)$_{ijt}$		Loan Dummy$_{ijt}$	
Excess Reserve$_{it\text{-}1}$	-0.0039***	-0.0038***	0.0340	0.0314	0.0001	0.0005*
	(-2.90)	(-2.81)	(1.49)	(1.37)	(1.24)	(1.68)
Post Covid$_t$ $\times$Excess Reserves$_{it\text{-}1}$	0.0040***	0.0042**	-0.0462*	-0.0530**	-0.0001*	-0.0011**
	(2.83)	(2.44)	(-1.95)	(-2.01)	(-1.94)	(-2.50)
Observations	9,201	7,288	9,201	7,288	8,964,180	3,982,140
R^2	0.983	0.892	0.902	0.784	0.123	0.161
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	No	No	No
Borrower$\times$Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	All	Germany	All	Germany	All	Germany

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Relationship Lending I: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. $\textit{Post Covid}_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. LPI_{ijt} is the lending preference index, defined in equation 1. The dependent variable is either $\textit{Loan Rate}_{ijt}$, the price of a loan, $\textit{Log(Total Amount)}_{ijt}$ the logarithm of the amount of a loan or $\textit{Loan Dummy}_{ijt}$, a dummy variable which equals one if bank i and j trade on day t and zero otherwise. Columns(1), (3) and (5) use panel A while (2), (4) and (6) use panel C. All regressions include lender and time-varying borrower and date fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan Rate_{ijt}		Log(Total $\text{Amount})_{\text{ijt}}$		Loan $\text{Dummy}_{\text{ijt}}$	
LPI_{ijt}	0.0049	0.0178	0.8248***	0.9155***	0.6620***	0.9337***
	(0.58)	(1.16)	(6.67)	(4.23)	(21.99)	(13.83)
Post $\text{Covid}_{\text{t}} \times \text{LPI}_{\text{ijt}}$	-0.0049	-0.0532***	0.0072	0.8748**	-0.0521	-0.1119
	(-0.77)	(-2.68)	(0.05)	(2.35)	(-1.62)	(-1.55)
Observations	19,248	10,226	19,248	10,226	22,893,480	5,420,700
R^2	0.983	0.903	0.895	0.797	0.204	0.205
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	No	No	No
Borrower×Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	All	Germany	All	Germany	All	Germany

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Relationship Lending II: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. $Post\ Covid_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. LPI_{ijt} is the lending preference index, defined in equation 1. $German\ Loan_{ijt}$ and $Institutional\ Loan_{ijt}$ are both dummy variables, which equal one for a German loan and an institutional loan. The dependent variable is either $Loan\ Rate_{ijt}$, the price of a loan, $Log(Total\ Amount)_{ijt}$ the logarithm of the amount of a loan or $Loan\ Dummy_{ijt}$, a dummy variable which equals one if bank i and j trade on day t and zero otherwise. Columns(1), (3) and (5) use panel A, while (2), (4) and (6) use panel C. All regressions include lender and time-varying borrower and date fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan Rate$_{ijt}$		Log(Total Amount)$_{ijt}$		Loan Dummy$_{ijt}$	
LPI$_{ijt}$	0.0002	-0.0247*	0.8108***	0.9398***	0.5916***	0.9015***
	(0.02)	(-1.84)	(5.73)	(2.96)	(17.59)	(12.61)
Post Covid$_t$ ×LPI$_{ijt}$	0.0064	-0.0424**	-0.1543	0.8609*	-0.0391	-0.1006
	(1.09)	(-2.01)	(-1.07)	(1.83)	(-1.19)	(-1.40)
German Loan$_{ijt}$	-0.0532		1.5379***		0.0102***	
	(-0.69)		(3.47)		(19.92)	
German Loan$_{ijt}$ ×Post Covid$_t$	-0.0175		-1.1686***		-0.0012***	
	(-0.71)		(-2.83)		(-3.22)	
German Loan$_{ijt}$ ×LPI$_{ijt}$	0.0248		0.0791		0.3310***	
	(1.36)		(0.31)		(4.35)	
German Loan$_{ijt}$ ×LPI$_{ijtijt}$ ×Post Covid$_t$	-0.0548***		1.0619***		-0.0726	
	(-2.69)		(2.74)		(-0.96)	
Institutionals$_{ijt}$		-0.0562***		0.7317***		0.0278***
		(-5.77)		(4.10)		(21.59)
Institutionals$_{ijt}$ ×Post Covid$_t$		0.0258***		-0.0810		-0.0031***
		(4.00)		(-0.60)		(-2.73)
Institutionals$_{ijt}$ ×LPI$_{ijt}$		0.0862***		-0.0071		0.0481
		(3.52)		(-0.01)		(0.33)
Institutionals$_{ijt}$ ×LPI$_{ijt}$ ×Post Covid$_t$		0.0074		0.0965		-0.0271
		(0.35)		(0.15)		(-0.19)
Observations	19,248	10,226	19,248	10,226	22,893,480	5,420,700
R^2	0.983	0.911	0.896	0.798	0.208	0.216
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	No	No	No
Borrower×Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	Eurozone	Germany	Eurozone	Germany	Eurozone	Germany

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Relationship Lending III: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender *i* and borrower *j*, trading with each other at day *t* with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. *Post Covid*$_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. *LPI*$_{ijt}$ is the lending preference index, defined in equation 1. *Non-Eurozone Lender*$_{it}$ and *Cross-Border*$_{ijt}$ are both dummy variables, which equal one for, respectively, a lender outside the Eurozone and a cross-border loan. The dependent variable is either *Loan Rate*$_{ijt}$, the price of a loan, *Log(Total Amount)*$_{ijt}$ the logarithm of the amount of a loan or *Loan Dummy*$_{ijt}$, a dummy variable which equals one if bank *i* and *j* trade on day *t* and zero otherwise. All regressions use a subsample of panel C. All regressions include lender and time-varying borrower and date fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan Rate$_{ijt}$		Log(Total Amount)$_{ijt}$		Loan Dummy$_{ijt}$	
LPI$_{ijt}$	0.0212	0.0175	0.9500***	0.9233***	0.9230***	0.9204***
	(1.44)	(1.15)	(4.56)	(4.27)	(13.58)	(13.44)
Post Covid$_t$ ×LPI$_{ijt}$	-0.0492***	-0.0504**	0.7910**	0.9222**	-0.1531**	-0.1117
	(-2.95)	(-2.60)	(2.56)	(2.57)	(-2.04)	(-1.51)
Non-Eurozone Lender$_{it}$	0.0084		0.6061***		0.0007***	
	(0.68)		(2.66)		(3.39)	
Non-Eurozone Lender$_{it}$ ×LPI$_{ijt}$	-0.0171		-0.4705*		-0.5235***	
	(-1.09)		(-1.74)		(-5.74)	
Non-Eurozone Lender$_{it}$ ×LPI$_{ijt}$ ×Post Covid$_t$	0.0505***		-0.6618*		0.1331	
	(2.93)		(-1.91)		(1.42)	
Cross-Border$_{ijt}$		0.0156		0.9279**		0.0012***
		(0.62)		(2.24)		(3.25)
Cross-Border$_{ijt}$ ×LPI$_{ijt}$		-0.0137		-0.4443		-0.5087***
		(-0.85)		(-1.63)		(-5.56)
Cross-Border$_{ijt}$ ×LPI$_{ijt}$ ×Post Covid$_t$		0.0569***		-0.7564*		0.0753
		(2.80)		(-1.90)		(0.82)
Observations	11,826	11,826	11,826	11,826	19,135,128	19,135,128
R^2	0.955	0.955	0.810	0.811	0.202	0.202
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	No	No	No
Borrower×Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	German Borrower	German Borrower	German Borrower	German Borrower	German Borrower	German Borrower

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: The Eurosystems Tender Participation: The Table reports a two stage regression. Stage 1 uses a balanced panel at the borrower bank-day level, *jt*, which represent interbank borrowing, the week before the TLTRO III is settled (March 9 to 13, 2020). LPI_{jt}, the volume-weighted average lender preference index of a borrower's lender, reflects the average importance of a borrower for its counterpart and BPI_{jt}, the volume-weighted average borrower preference index of a borrower, reflects the average importance of a lender for borrower banks. The dependent variable is $Loan\ Dummy_{jt}$, a dummy variable which equals one if borrower j is active in borrowing and zero otherwise. Stage 2 use a cross section at borrower bank level b. $Log(Total\ Borrowing)_b$ and $Borrowing\ Rate_b$ represent the aggregated borrowing and the volume-weighted average borrowing rate of a bank during March 9 to 13, 2020, respectively. $Estimated\ Prob_b$ reflects the estimated probability of trading dependent on underlying relationship measures LPI_{jt} or BPI_{jt} from stage 1. The dependent variable $Tender\ Dummy_b$ is a dummy variable which equals one for a bank's participation in a tender and zero otherwise. Stage 1 includes borrower fixed effects. Standard errors are clustered at the borrower and day level.

	(1)		(2)	
	Loan $\mathrm{Dummy_{jt}}$	Tender $\mathrm{Dummy_b}$	Loan $\mathrm{Dummy_{jt}}$	Tender $\mathrm{Dummy_b}$
$\mathrm{BPI_{jt}}$	0.8481***			
	(12.78)			
$\mathrm{LPI_{jt}}$			0.9313***	
			(8.73)	
$\mathrm{Log(Total\ Borrowing)_b}$		0.0163**		0.0197***
		(2.40)		(2.83)
Borrowing $\mathrm{Rate_b}$		0.4703**		0.4678**
		(2.18)		(2.00)
Estimated Prob $\mathrm{(Loan\|Volwgt\ BPI)_b}$		-0.1017		
		(-1.46)		
Estimated Prob $\mathrm{(Loan\|Volwgt\ LPI)_b}$				0.0771
				(1.12)
Observations	3,520	474	3,520	474
R^2	0.980	0.031	0.924	0.029
Borrower FE	Yes	No	Yes	No
Stage	1	2	1	2
Standard Error Clustering	Borrower and Date	Borrower and Date	Borrower and Date	Borrower and Date

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Borrower Level–Borrowing Rate I: The sample is an aggregated panel at the borrower bank and day level *jt*. A borrower bank is defined as a bank which is active in the interbank market between January 2 and June 9, 2020 at least once; observations are daily. *Post Covid*$_t$ is a dummy variable which equals one between March 12 and June 9, 2020 and zero otherwise. *ECB Borrower*$_{jt}$, is a dummy variable which equals one if the borrower bank is a reporting agent based on ECB criteria (largest 47 European banks) and zero otherwise. *Large BBK Borrower*$_{jt}$ is a dummy variable if the borrower bank is German and fulfils the ECB criteria (largest 14 German banks) and zero otherwise. *German Lender*$_{jt}$ and *Institutional Loans*$_{jt}$ express the share, respectively of German lenders and institutional loans in a bank's daily total borrowing. The dependent variable is *Borrowing Rate*$_{jt}$, the volume-weighted average borrowing rate of a bank. All regressions include borrower and time fixed effects and vary in terms of the underlying dataset. Standard errors are double-clustered at the date and borrower level.

Borrowing Rate$_{jt}$	(1)	(2)	(3)	(4)	(5)
Post Covid$_t$	0.0688***				
	(23.03)				
Post Covid$_t$×ECB Borrower$_j$		-0.0787***			
		(-7.46)			
Post Covid$_t$×Large BBK Borrower$_j$			-0.0585***		
			(-6.10)		
Post Covid$_t$×German Lender$_{jt}$				0.0672***	
				(9.16)	
Post Covid$_t$×Institutional Loans$_{jt}$					0.0244**
					(2.46)
Observations	45,934	45,934	43,438	43,438	42,197
R^2	0.902	0.924	0.912	0.914	0.926
Borrower FE	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes
Standard Error Clustering	Borrower and Date	Borrower and Date	Borrower and Date	Borrower and Date	Borrower and Date
Sample	All	All	German Borrower	German Borrower	German Loans

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Borrower Level–Total Borrowing I: The sample is an aggregated panel at the borrower bank and day level *jt*. A borrower bank is defined as a bank which is active in the interbank market between January 2 and June 9, 2020 at least once, observations are daily. *Post Covid*$_t$ is a dummy variable which equals one between March 12 and June 9, 2020 and zero otherwise. *ECB Borrower*$_{jt}$, is a dummy variable which equals one if the borrower bank is a reporting agent based on ECB criteria (largest 47 European banks) and zero otherwise. *Large BBK Borrower*$_{jt}$ is a dummy variable if the borrower bank is German and fulfils the ECB criteria (largest 14 German banks) and zero otherwise. *German Lender*$_{jt}$ and *Institutional Loans*$_{jt}$ express the share, respectively of German lenders and institutional loans in a bank's daily total borrowing. The dependent variable is *Log(Total Borrowing)*$_{jt}$, the total borrowing per borrower bank *j* per day *t*. All regressions include borrower and time fixed effects and vary in terms of the underlying dataset. Standard errors are double-clustered at the date and borrower level.

Log (Total Amount)$_{jt}$	(1)	(2)	(3)	(4)	(5)
Post Covid$_t$	-0.1508***				
	(-4.18)				
Post Covid$_t$ ×ECB Borrower$_{jt}$		0.2157*			
		(1.76)			
Post Covid$_t$ ×Large BBK Borrower$_{jt}$			0.2158		
			(1.30)		
Post Covid$_t$ ×German Lender$_{jt}$				-0.1822	
				(-1.37)	
Post Covid$_t$ ×Institutional Loans$_{jt}$					0.0727
					(0.75)
Observations	45,934	45,934	43,438	43,438	42,197
R^2	0.874	0.882	0.881	0.881	0.886
Borrower FE	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes
Standard Error Clustering	Bank and Date	Bank and Date	Bank and Date	Bank and Date	Bank and Date
Sample	All	All	German Borrower	German Borrower	Germans

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Borrower Level–Borrowing Rate II: The sample is an aggregated panel at the borrower bank and day level *jt*. A borrower bank is defined as a bank which is active in the interbank market between January 2 and June 9, 2020 at least once, observations are daily. *Post Covid*$_t$ is a dummy variable which equals one between March 12 and June 9, 2020 and zero otherwise. LPI_{ijt} is the volume-weighted average lending preference index and BPI_{ijt} is the volume-weighted average borrowing preference index, both per borrower j and day t. The dependent variable is *Log(Total Borrowing)*$_{jt}$, the total borrowing per borrower bank j per day t. All regressions include borrower and time fixed effects and vary in terms of the underlying dataset. Standard errors are double-clustered at the date and borrower level.

Borrowing Rate_{jt}	(1)	(2)	(3)	(4)
LPI	0.0345*	0.0460***		
	(1.94)	(2.73)		
Post $\text{Covid}_\text{t} \times \text{LPI}_{\text{jt}}$	-0.1083***	-0.0948***		
	(-9.02)	(-13.13)		
BPI_{jt}			-0.0373***	-0.0167**
			(-3.44)	(-2.58)
Post $\text{Covid}_\text{t} \times \text{BPI}_{\text{jt}}$			0.0792***	0.0550***
			(7.50)	(6.60)
Observations	45,934	42,291	45,934	42,291
R^2	0.929	0.934	0.923	0.931
Borrower FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Standard Error Clustering	Bank and Date	Bank and Date	Bank and Date	Bank and Date
Sample	All	German Borrower	All	German Borrower

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 15: Borrower Level–Total Borrowing II: The sample is an aggregated panel at the borrower bank and day level *jt*. A borrower bank is defined as a bank which is active in the interbank market between January 2 and June 9, 2020 at least once, observations are daily. $Post\ Covid_t$ is a dummy variable which equals one between March 12 and June 9, 2020 and zero otherwise. LPI_{ijt} is the volume-weighted average lending preference index and BPI_{ijt} is the volume-weighted average borrowing preference index, both per borrower j and day t. The dependent variable is $Borrowing\ Rate_{jt}$, the volume-weighted average borrowing rate of a bank. All regressions include borrower and time fixed effects and vary in terms of the underlying dataset. Standard errors are double-clustered at the date and borrower level.

$\text{Log(Total Amount)}_{\text{jt}}$	(1)	(2)	(3)	(4)
LPI_{jt}	-0.1666	0.3061		
	(-0.59)	(1.03)		
$\text{Post Covid}_{\text{t}} \times \text{LPI}_{\text{jt}}$	0.2892***	0.1032		
	(2.79)	(1.01)		
BPI_{jt}			0.1225	-0.3528***
			(0.80)	(-3.37)
$\text{Post Covid}_{\text{t}} \times \text{BPI}_{\text{jt}}$			0.0128	0.2878**
			(0.10)	(2.47)
Observations	45,934	42,291	45,934	42,291
R^2	0.882	0.886	0.882	0.886
Borrower FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Standard Error Clustering	Bank Date	Bank Date	Bank Date	Bank Date
Sample	All	German Borrower	All	German Borrower

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Robustness I–Continuous COVID Shock: The sample is a panel at the transactional, bank-pair and date level ijt. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. *COVID Cases*$_t$ reports the number of the COVID-19 cases per day in Germany. *Incidence*$_t$ report the 14-days incidence of COVID-19 cases per 100,.000 inhabitants per day in Germany while *Deaths*$_t$ reports the number of deaths with or due to COVID-19 in Germany. *Excess Reserves*$_{it\text{-}1}$ reflects the first lag of a lender banks' excess reserves. The dependent variable is either *Loan Rate*$_{ijt}$, the price of a loan, *Log(Total Amount)*$_{ijt}$ the logarithm of the amount of a loan or *Loan Dummy*$_{ijt}$, a dummy variable which equals one if bank i and j trade on day t and zero otherwise. All regressions include lender and time-varying borrower-day fixed effects and use network C. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Loan Rate$_{ijt}$			Log(Total Amount)$_{ijt}$			Loan Dummy$_{ijt}$	
Excess Reserves$_{it\text{-}1}$	-0.003347***	-0.003339***	-0.002847***	0.016105	0.015614	0.012310	-0.000071	0.000046	0.000088
	(-3.49)	(-3.81)	(-4.69)	(0.99)	(1.10)	(1.00)	(-0.13)	(0.12)	(0.42)
COVID Cases$_t$ ×Excess Reserves$_{it\text{-}1}$	0.000004***			-0.000029			-0.000000		
	(2.69)			(-1.55)			(-0.25)		
Incidence$_t$ ×Excess Reserves$_{it\text{-}1}$		0.000229***			-0.001749*			-0.000027	
		(4.14)			(-1.68)			(-0.70)	
Deaths$_t$ ×Excess Reserves$_{it\text{-}1}$			0.000032***			-0.000252*			-0.000006*
			(3.92)			(-1.89)			(-1.68)
Observations	7,288	7,288	7,288	7,288	7,288	7,288	3,982,140	3,982,140	3,982,140
R^2	0.892	0.892	0.892	0.784	0.784	0.784	0.161	0.161	0.161
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	No	No	No	No	No	No
Borrower×Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	Germany	Germany	Germany	Germany	Germany	Germany	Germany	Germany	Germany

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Robustness II–Placebo Test: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. Columns (1) and (2) contains overnight unsecured interbank loans between January 2 and June 9, 2017, January 2 and June 9, 2018 as well as January 2 and June 9, 2019. Column 3 contains the period January 2 and June 9, 2019. $Placebo_t$ is a dummy variable that equals one from March 12 to June 9 of the corresponding year. $Excess\ Reserves_{it\text{-}1}$ reflects the first lag of a lender banks' excess reserves. The dependent variable is either $Loan\ Rate_{ijt}$, the price of a loan, $Log(Total\ Amount)_{ijt}$ the logarithm of the amount of a loan or $Loan\ Dummy_{ijt}$, a dummy variable which equals one if bank i and j trade on day t and zero otherwise. All regressions include lender and time-varying borrower-day fixed effects and use network A. Standard errors are double-clustered at the date and bank-pair level.

	(1) Loan $\text{Rate}_{\mathbf{ijt}}$	(2) Log(Total $\text{Amount})_{\text{ijt}}$	(3) Loan $\text{Dummy}_{\text{ijt}}$
Excess $\text{Reserves}_{\text{it-1}}$	0.0001	-0.0045	-0.000071
	(1.12)	(-0.88)	(-0.13)
$\text{Placebo}_\text{t}\times$Excess $\text{Reserves}_{\text{it-1}}$	-0.0000	0.0071	-0.000000
	(-0.76)	(1.00)	(-0.25)
Observations	20,745	20,745	3,982,140
R^2	0.958	0.877	0.161
Lender Fixed Effects	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No
Borrower×Day Fixed Effects	Yes	Yes	Yesy
Standard Error Clustering	Date and Pair Level	Date and Pair Level	Date and Pair Level
Sample	2017-2019	2017-2019	2019

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Robustness III–Specialisation of Shocks: The sample is a panel at the transactional, bank-pair and date level *ijt*. A bank-pair is defined as two banks, lender i and borrower j, trading with each other at day t with daily frequency. It contains overnight unsecured interbank loans between January 2 and June 9, 2020. $Post\ Covid_t$ is a dummy variable which equals one between March 12 and June 9 2020 and zero otherwise. $Specialisation_{ijt}$ is a dummy variable which equals one if a borrower j bank actively borrows within at least one subnetwork in which the lender bank is active within a rolling window of 30 days *and* the lending amount of the corresponding lender i is within either the second (Q2), third (Q3) or fourth (Q4) quantile, and zero otherwise. The dependent variable is $Loan\ Rate_{ijt}$. The regressions include lender and borrower×day fixed effects. Standard errors are double-clustered at the date and bank-pair level.

	(1)	(2)
	Loan Rate	
Specialisation $\text{Dummy}_{\text{ijt}}$ Q2	-0.0033	-0.0051
	(-1.24)	(-1.66)
Specialisation $\text{Dummy}_{\text{ijt}}$ Q3	0.0061**	0.0079**
	(2.44)	(2.25)
Specialisation $\text{Dummy}_{\text{ijt}}$ Q4	-0.0031	-0.0044*
	(-1.12)	(-1.66)
Post Covid_{t} ×Specialisation $\text{Dummy}_{\text{ijt}}$ Q2		0.0032
		(1.22)
Post Covid_{t} ×Specialisation $\text{Dummy}_{\text{ijt}}$ Q3		-0.0041
		(-1.15)
Post Covid_{t} ×Specialisation $\text{Dummy}_{\text{ijt}}$ Q4		0.0018
		(0.49)
Observations	18,252	18,252
R^2	0.975	0.975
Lender Fixed Effects	Yes	Yes
Borrower Fixed Effects	No	No
Borrower-Lender (Pair) Fixed Effects	No	No
Borrower×Day Fixed Effects	Yes	Yes
Standard Error Clustering	Date and Pair Level	Date and Pair Level
Sample	All	All

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$