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Banks of a feather: The informational advantage of being alike

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Non-technical summary

Research question

Can banks effectively monitor their peers? This question is of central importance, given the relevance of banks' ability to monitor their peers for functioning interbank markets and, thereby, financial markets. In this paper, we investigate how a similar loan portfolio of the lending and borrowing bank can help to overcome information asymmetries in the interbank market.

Contribution

Based on proprietary, regulatory data about the quality of banks’ loan portfolio, our paper contributes to the literature on peer monitoring of banks in an environment characterized by asymmetric information. It argues that, the more similar the loan portfolio of a lending and borrower bank, the better their ability to assess private information about the counterparty’s solvency. Introducing portfolio similarity into the analysis of interbank lending allows us to reconcile two seemingly opposing positions in the literature: On the one hand, we confirm that peer monitoring works: A large fraction of lending banks, i.e., banks with a similar portfolio, react to a deterioration of the counterparty's asset quality, even though this information is private. On the other hand, we confirm that peer-monitoring fails under asymmetric information: A just as large fraction of lending banks, i.e., banks with a dissimilar portfolio, prove unable to react to private information on the deterioration of the counter-party's asset quality.

Results

We show that banks can be good monitors, albeit only of very similar peers. Interbank lenders grant credit less frequently and in smaller amounts after a deterioration of the quality of a borrowing bank's loan portfolio. However, lending banks only do so for borrowing banks that have outstanding credit to similar industries and regions. Dissimilar bank pairs, in contrast, do not adjust their lending to a deterioration of the quality of the counterparty's loan portfolio. Instead, dissimilar peers react to the backward-looking NPL ratio, which only imperfectly proxies forward-looking credit risk. Aware of their informational advantage, banks with a similar loan portfolio lend significantly more to each other, both at the extensive and the intensive margin. Lending between similar banks proves to be particularly important for borrowers with an opaque loan portfolio.

Nichttechnische Zusammenfassung

Fragestellung

Können Banken andere Banken effektiv kontrollieren? Für einen funktionierenden Interbanken- und Finanzmarkt ist diese Frage von größter Bedeutung. In dieser Studie untersuchen wir die Rolle, die die Ähnlichkeit des Kreditportfolios zweier Banken bei der Überwindung von Informationsasymmetrien am Interbankenmarkt spielt.

Beitrag

Mithilfe interner, aufsichtsrechtlicher Daten zur Qualität des Kreditportfolios von Banken tragen wir zum tieferen Verständnis der Frage bei, wie gut Banken sich unter asymmetrischer Information gegenseitig kontrollieren können. Je ähnlicher die Kreditportfolien der kreditgebenden und kreditnehmenden Bank, so unsere Hypothese, desto besser können Banken die Solvenz des Gegenübers einschätzen. Ein Einbezug der Ähnlichkeit der Kreditportfolios zweier Banken in die Untersuchung der Interbank-Kreditvergabe löst einen in der Literatur existierenden Widerspruch: Auf der einen Seite bestätigen wir, dass gegenseitige Kontrolle zwischen Banken funktioniert: Ein Teil der kreditgebenden Banken, nämlich der mit einem ähnlichen Kreditportfolio wie die kreditnehmende Bank, reagiert auf eine Verschlechterung des Kreditportfolios des Gegenübers mit einer Einschränkung der Kreditvergabe, obwohl die Information über die Portfolioqualität nicht öffentlich zugänglich ist. Auf der anderen Seite bestätigen wir, dass gegenseitige Kontrolle unter asymmetrischer Information scheiten kann: Ein ebenso großer Teil der kreditgebenden Banken, nämlich der mit einem sehr unterschiedlichen Kreditportfolio wie die kreditnehmende Bank, reagiert nicht auf private Informationen über die Qualität des Kreditportfolios des Gegenübers.

Ergebnisse

Wir zeigen, dass Banken andere Banken gut kontrollieren können, allerdings nur, wenn diese sich ähnlich sind. Kreditgebende Banken vergeben weniger Kredite und kleinere Summen am Interbankenmarkt, wenn sich die Portfolioqualität des Gegenübers verschlechtert. Allerdings tun Banken das nur für Kreditnehmer, welche Kredite in ähnliche Bereiche der Realwirtschaft vergeben. Banken mit Krediten in anderen Bereichen der Realwirtschaft reagieren im Gegensatz dazu nicht auf private Informationen über die Portfolioqualität. Stattdessen verringern sie ihre Kreditvergabe in Reaktion auf eine Erhöhung der notleidenden Kredite, welche das vorausschauende Kreditrisiko nur unzureichend approximieren. Wissend um ihren Informationsvorsprung leihen sich ähnliche Banken am Interbankenmarkt signifikant häufiger und signifikant höhere Summen. Kreditbeziehungen zwischen ähnlichen Banken sind besonders für intransparente Banken wichtig, welche andernfalls Schwierigkeiten haben, sich am Interbankenmarkt zu refinanzieren.

Deutsche Bundesbank Discussion Paper No 09/2023

Banks of a Feather: The Informational Advantage of Being Alike*

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Abstract

Banks lend more to banks that are similar to them. Using data from the German credit register and proprietary supervisory data on the quality of banks' loan portfolio, we show that a similar portfolio of the lending and borrowing bank helps to overcome information asymmetries in interbank markets. While interbank lenders generally do not adjust their lending to information on the counterparty's portfolio quality, banks with an exposure to similar industries and regions strongly react to this private information. Lending between similar banks is particularly important for borrowers with an opaque loan portfolio, which do not obtain credit from dissimilar peers.

JEL codes: E50; G11; G20; G21

Keywords: Peer monitoring; interbank markets; asymmetric information; portfolio quality; portfolio similarity; systemic risk and contagion

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1 Introduction

Can banks effectively monitor their peers? This question is of central importance, given the relevance of banks' monitoring ability for functioning interbank markets and, by implication, financial markets. With the tightening of monetary policies starting in the early 2020s and the associated regaining relevance of liquidity provision via interbank markets, understanding the mechanisms behind peer monitoring has become a pressing concern.[1] The degree to which banks can accurately assess the solvency of other banks under asymmetric information has important implications for central bank policy. If banks monitor effectively, central banks can reduce their involvement to a night-watchman role (Goodfriend and King 1988). If, in contrast, banks systematically fail to identify solvent counterparties, central banks should be more active (Freixas and Jorge 2008).

We argue that portfolio similarity between two banks is key to understanding their reciprocal monitoring ability. We hypothesize that banks use private information on their own loan portfolio to evaluate the quality of the loan portfolio of a peer. A lending bank will then be better informed about a borrowing bank, the more similar their exposure. Aware of this informational advantage, a bank should prefer lending to similar peers. The mitigation of information asymmetries through similar portfolios should be particularly relevant when information is scarce, that is, for opaque borrowers. Introducing portfolio similarity to the analysis of interbank lending and peer monitoring thus improves our understanding of (i) how lending banks obtain private information on peers, (ii) why lending banks differ in their ability to monitor peers (see Pérignon et al. 2018), and (iii) how information asymmetries can be overcome in the interbank market (see Heider et al. 2015).

Our analysis is built on quarterly, bilateral bank-to-bank and bank-to-firm exposure of more than 2000 banks from the German credit register between 2009 and 2018. We introduce a novel measure for the private quality of a bank's loan portfolio based on the bank's confidential risk evaluation of every outstanding loan. We obtain this information from proprietary supervisory data on the probability of default (PD), which banks need to report for each of their borrowers.[2] To capture the time-varying quality of the loan portfolio of a bank, we calculate its portfolio-weighted PD and deduct this value from one, i.e. from a hypothetical portfolio without any default risk. We confirm the relevance of our measure as a forward-looking assessment for portfolio quality by showing its predictive

[1] Even in our sample, which covers the period between 2009 and 2018 when central banks were actively providing liquidity through expansionary monetary policies, interbank exposure represents 21% of German banks' total borrowing and 20% of banks' total lending, respectively. Decisions about lending and borrowing in interbank markets therefore have always remained of high relevance for German banks.

[2] For detailed information, see Section 3.3

power for the bank's non-performing loans (NPL) ratio in the next quarter up to the next 2 years. We show that our measure is, indeed, confidential as most peers do not adjust their lending when the portfolio quality of a borrowing bank worsens. Instead, banks adjust their lending to inferior, backward-looking proxies for portfolio quality, like the NPL ratio. Though easily accessible and commonly used in the literature (e.g. Afonso et al. 2011 and Craig et al. 2015), the NPL ratio does not capture the default risk inherent in the *current* loan portfolio, but the one of the past.

We also include a new measure of portfolio opacity building on banks' disagreement about the PD of the same borrowing firm, i.e. the standard deviation of PDs assigned to the same firm by different banks. A bank's portfolio-weighted standard deviation of PDs captures the divergence of peers' evaluations of the bank's loan portfolio. It measures portfolio opacity as gauged by banks themselves and, therefore, more directly as compared to the disagreement of rating agencies or the volatility of credit default swap (CDS) spreads used in the literature (e.g. Braeuning and Fecht 2017, Morgan 2002).

To measure the similarity between the loan portfolio of the lending and the borrowing bank, we compute the cosine similarity between their real exposure to different industries and regions. Building on these measures, we estimate how the quality and opacity of a borrowing bank's loan portfolio affects lending between banks with different levels of similarity. To capture the extensive and intensive margin of interbank lending and account for the fact that entering a lending relationship is not random, we use a sample selection model similar to Heckman (1977) (see Braeuning and Fecht 2017).

Our results draw a nuanced picture of banks' ability to monitor peers. We show that banks can be good monitors, albeit only of very similar peers. Interbank lenders grant credit less frequently and in smaller amounts when a borrowing bank's loan portfolio deteriorates. However, lending banks only do so for borrowing banks with outstanding loans to similar industries and regions like themselves. Dissimilar bank pairs, in contrast, do not adjust their lending to a deterioration of the counterparty's loan portfolio. Instead, dissimilar peers react to the backward-looking NPL ratio, which only imperfectly proxies forward-looking credit risk.

In line with our theoretical argument, banks with a similar loan portfolio lend significantly more to each other, both at the extensive and the intensive margin. Economically, preferential lending between similar banks is of similar relevance as relationship lending, one of the most important determinants of interbank lending in the literature (Braeuning and Fecht 2017). Lending between similar banks proves to be particularly important for borrowers with an opaque loan portfolio. Our findings hold after controlling for relationship lending, established bank networks, characteristics of the lending and the borrowing bank, market conditions, lender, borrower and time fixed effects.

We ensure that our findings are driven by changes in interbank credit supply, rather than demand, by identifying changes in liquidity supply in an adapted version of Degryse et al. (2019)'s methodology. The intuition behind our approach is that banks of the same class (i.e. private, cooperative, or public banks of similar size), which concentrate on the same industries and regions should have similar liquidity needs in a given quarter. The distinct liquidity provision towards different borrowing banks of the same type can thus be interpreted as a supply response to characteristics of the borrowing bank, like its portfolio quality or opacity.[3] Disentangling supply from demand effects offers additional insights on how interbank borrowers cope with restricted access to the interbank market: Borrowing banks with a deteriorated loan portfolio obtain less liquidity by similar peers, which are well-informed about their (bad) portfolio quality. To compensate the lack of lending by similar peers, they turn to less informed, dissimilar lenders, which grant them interbank loans. Borrowing banks with an opaque loan portfolio obtain less liquidity by dissimilar peers, which cannot assess their portfolio adequately. To compensate the lack of lending by dissimilar peers, they turn to better informed, similar lenders, which grant them interbank loans.

Finally, we explore how relevant the different determinants of interbank lending are. Following Lemmon et al. (2008), we decompose the variance in interbank lending into the variance attributable to characteristics of the lending bank, characteristics of the borrowing bank, common characteristics of both banks, and market characteristics. In our specifications, common characteristics of the counterparties explain 98.0 percent of the variation in the extensive margin, and 18.9 percent of the variation in the intensive margin of interbank lending. In contrast, borrower, lender, or market characteristics only explain 0.8, 1.2 and 0.1 percent of the variation in the extensive, and 44.2, 35.6, and 9.1 percent of the variation in the intensive margin of interbank lending, respectively. This finding substantiates the importance of including common characteristics of the lending and borrowing bank, like portfolio similarity, in the analysis of interbank lending.

Our paper contributes to several strands of literature. First, we extend the literature on peer monitoring of banks in an environment characterized by asymmetric information. Goodfriend and King (1988) argue that peers are particularly capable of assessing the solvency of banks and Rochet and Tirole (1996) show that they have an incentive to apply this ability. Flannery and Sorescu (1996) and Furfine (2001) provide empirical support

[3] Our procedure to identify liquidity supply provides us with borrower-level changes in liquidity supply. As such, the approach helps us to support the supply-based interpretation, but cannot substitute the bank-pair-level analysis as it does not allow us to include bank-pair characteristics like portfolio similarity.

and conclude that banks can identify other banks' risk better than other institutions, given their similar business model. We take their analysis one step further by showing that, even among banks, the more similar a lender, the better its monitoring ability. This is in line with Pérignon et al. (2018) who highlight the heterogeneity between informed and uninformed lenders in interbank markets. By identifying "informed lenders" as banks with a similar loan portfolio, we shed light on which lenders can gain access to the borrowing bank's private information and how they obtain this information.

A related strand of literature highlights the importance of repeated interactions to obtain information on a counterparty. Affinito (2012), Braeuning and Fecht (2017), Cocco et al. (2009), Hatzopoulos et al. (2015), and Temizsoy et al. (2015) show that banks form stable and persistent relationships in interbank markets. The authors rationalize this finding by bilateral information generation, which facilitates monitoring and screening. Our analysis reveals one kind of information banks want to obtain through such relationships – information on the quality of the counterparty's real exposure. In contrast to the previous literature, we show that, given a similar loan portfolio, no long-standing relationship is needed to receive this information.

Concerns about the effectiveness of peer monitoring are particularly high for opaque banks and during insecure periods, when market information is less reliable (Flannery and Sorescu 1996). Braeuning and Fecht (2017) show that less transparent institutions, which have more difficulties refinancing themselves on interbank markets, rely on long-standing relationships to secure access. We show that, in addition to long-standing relationships, portfolio similarity mitigates the problem of hampered interbank access of opaque banks.

Several papers investigate the importance of lender and borrower characteristics and market conditions for interbank lending decisions (Afonso et al. 2011, Angelini et al. 2011, Brossard and Saroyan 2016, Fecht et al. 2011, Furfine 2001). Controlling for established lender, borrower, and market characteristics, we incorporate portfolio similarity and thereby augment the analysis with common characteristics of the borrowing and lending bank. In network analysis terms, we extend the analysis of ego covariates (lender characteristics), alter covariates (borrower characteristics) and network covariates (market characteristics) by dyadic covariates (common characteristics of lender and borrower).

One consequence of portfolio similarity discussed in the literature are correlated liquidity shocks (Fecht et al. 2011): Banks with a similar loan portfolio should have fewer opportunities to lend to each other. While correlated liquidity shocks might play a role in our analysis, this role is not important enough to challenge the robust, positive relation between portfolio similarity and interbank lending in our data.

Unless existing research on interbank lender and borrower characteristics, we use granular data on banks' real exposure to industries and regions. This allows us to look behind aggregated bank-level ratios and explicitly incorporate banks' real credit exposure, which is indispensable to properly judging banks' asset quality. Drawing on proprietary, supervisory data on banks' self-assessed borrower-specific risk, we can analyze peers' reaction to confidential information of the bank.

Finally, our findings contribute to the literature on systemic risk and contagion in interbank markets (Allen and Gale 2000, Brusco and Castiglionesi 2007, Castiglionesi and Wagner 2013, Craig and Ma 2022, Cocco et al. 2009, Ladley 2013). Regardless of their interbank connections, banks with a similar loan portfolio are exposed to the risk of indirect contagion, e.g. by fire sales or feedback effects with the real sector (Allen et al. 2012, Diamond and Rajan 2011, Silva et al. 2017a). Banks with a similar portfolio should consequently avoid running the additional risk of direct contagion by interbank lending. We show that banks do not avoid this risk and, instead, expose themselves over-proportionally to similar counterparties. Elliott et al. (2018) rationalize this socially sub-optimal pattern by arguing that banks deliberately create systemic risk to be able to realize gains in a favorable state and increase their probability of being saved in a non-favorable state. Their study highlights the trade-off between hedging risk by financial connections, on the one hand, while propagating shocks through exactly these connections, on the other. While we do not aim to rule out the presence of risk shifting, we show that lending banks and the social planner face at least one additional trade-off: The strong connection between similar counterparties alleviates information asymmetries and, hence, increases interbank markets' efficiency, however, at the costs of increased systemic risk. This tradeoff is similar to the conflict between focus and diversification in corporate lending analyzed by Acharya et al. (2006).

The remainder of this paper is structured as follows. The next section explores the theoretical links between peer monitoring, private information on the quality of a borrowing bank's loan portfolio, and portfolio similarity. Section 3 presents our data. In Section 4, we demonstrate that the average bank does not restrict interbank lending to peers with a lower-quality loan portfolio, but significantly to peers with a higher NPL ratio. Section 5 shows that banks with a similar portfolio, however, restrict lending to peers after a deterioration of their loan portfolio, while reacting significantly less to similar peers' NPL ratio. We endorse that our results are driven by supply effects in Section 6 and rule out that our results are driven by the correlated portfolio quality of similar peers in Section 7. In Section 8, we show that common characteristics, like portfolio similarity, are highly relevant for interbank lending decisions by disentangling the fraction of variation in interbank lending attributable to lender, borrower, bank-pair, and market characteristics. Section 9 concludes.

2 Peer monitoring, portfolio quality, and portfolio similarity

To fulfill their role as peer-monitors, interbank market participants must distinguish between illiquid and insolvent peers. According to Fecht et al. (2011), lending banks make this distinction based on information on (i) the peer's capital position, (ii) its liquidity position, (iii) its profitability, and (iv) its asset quality. Weighing the costs and benefits of obtaining information on these positions, a lending bank will determine the optimal level of information it generates on each item.

Information costs are different for these four positions: A lending bank can easily research a peer's capital, liquidity, and profitability, drawing on commercial data bases from providers, like Bloomberg, which all banks can access. All lenders should thus incorporate accurate information on the peer's capital, liquidity, and profitability to a similar degree.

Information on a peer's asset quality is, in contrast, private and thus more costly to obtain (Morgan 2002). We hypothesize that a lender proxies the quality of a peer's loan portfolio by the average quality of industries and regions of the peer's exposure.[4] Tracking the time-varying default risks of these industries and regions, however, requires costly information gathering. To facilitate information generation, a lending bank can draw on its own private information, i.e. on information the lender itself has generated when granting loans to different industries and regions. Costs of information generation are consequently lower for a peer with a similar portfolio. Ceteris paribus, a similar lender should thus obtain more information on the borrowing bank. Lending conditions between similar banks should therefore more accurately reflect a borrower's asset quality. Moreover, lenders should be aware of their informational advantage towards similar peers and prefer to lend to similar counterparties.

We therefore test the following hypotheses:[5]

[4] We assume that the lender can observe the peer's exposure to different industries and regions, at least imperfectly. This assumption is in line with the literature on specialization and segmentation in bank lending, see, e.g. Acharya et al. 2006, Blickle et al. 2021, and Paravisini et al. 2021.

[5] Our hypotheses focus on the effect of portfolio quality, portfolio opacity, and portfolio similarity on *the amount of bilateral interbank lending*, rather than on its price. While price effects are certainly important in our setting, our dataset does not entail interest rates and does therefore not allow for an analysis of price effects.

Hypothesis 1: Lenders with a similar loan portfolio reduce lending when the borrower's portfolio quality deteriorates. Lenders with a dissimilar loan portfolio do not reduce lending when the borrower's portfolio quality deteriorates.

Hypothesis 2: Bank pairs with a similar loan portfolio lend more to each other in interbank markets.

Generating information on the time-varying quality of a peer's credit exposure is more costly if the peer's portfolio is opaque, which increases the value of the lending bank's pre-existing private information. Therefore, the informational advantages of similar portfolios should be higher, the less transparent a borrower (c.f. Braeuning and Fecht 2017). Preferential lending between similar peers should, consequently, be more pronounced, the less transparent the borrowing bank's loan portfolio.

We therefore test the following hypotheses:

Hypothesis 3: Banks with a less transparent loan portfolio receive less interbank loans.

Hypothesis 4: Banks with a less transparent loan portfolio receive more loans from peers with a similar loan portfolio.

3 Data and variables

3.1 Data sources and sample construction

Our unit of analysis are quarter-bank-pairs. As interbank loans are decided on the level of the bank, rather than on the level of the bank holding company, our level of observation is a pair between two banks, rather than between two bank holding companies. We obtain bilateral bank-to-bank and bank-to-firm exposure from the German credit register for the years between 2009 and 2018. The credit register is administered by the Deutsche Bundesbank and contains information on German banks' credit exposure to firms, including to financial firms (i.e. other banks). Banks have to report any loan granted to a firm whose total outstanding loans to German financial institutions add up to at least €1.5 million. The reporting requirement also includes loans below €1.5 million if the borrower's total debt exceeds the threshold of €1.5 million. Due to this low reporting threshold, our sample covers the complete universe of interbank exposure and all relevant exposure to the real economy.[6]

[6] For details, see https://www.bundesbank.de/resource/blob/882918/897f226302c2462141dc6c5ee21aa621/mL/2021-12-27-dkp-52-data.pdf (Section 2.2). Unfortunately, our data does not entail information about interest rates for interbank loans. We therefore focus on the existence of a bilateral lending relation and lending quantities as outcome variables, rather than on prices.

The credit register provides additional information about each borrower of a bank's loan portfolio. Most importantly, it includes the borrower's probability of default (PD) as reported by the credit granting bank, and each borrower's industry and region. We use this information to construct our main explanatory variables (for details, see below). Information on the PD is only available from 2009 on, which therefore marks the start of our analysis. To control for relevant bank characteristics, we add information on the lending and borrowing bank balance sheet from supervisory data of the Deutsche Bundesbank.

Table 1 shows the banks and interbank relations used in our analysis. Our sample of 2,054 lending and 2,035 borrowing banks reflects the German banking system, which is dominated by a few, large private banks (with a market share of about 30%), many savings banks (market share about 30%) and cooperative banks (market share about 20%), as well as their head institutes, i.e, regional heads of the savings banks network ("Landesbanken") or head institutes of the cooperative financial services network.[7] [8] We create a balanced sample by extending the bank-pairs that enter a lending relationship at least once during our sample period over all quarters. This procedure results in 2,644,640 lender-borrower-quarter combinations.[9]

3.2 Dependent variables: Extensive and intensive margin of interbank lending

We identify an interbank credit relation between two banks by credit register entries of the lending bank indicating an outstanding exposure to the borrowing bank. As reported in Table 1, our sample includes 701,533 interbank credit relations, out of which 102,044 are between banks from the same banking network, e.g. between two savings banks or two cooperative banks, 2,087 credit relations are between banks from the same holding company.

Figure 1 shows the aggregated amount of quarterly interbank exposure between banks of our sample from 2009 to 2018. In accordance to previous studies (e.g. Allen et al. 2020), the market has slightly shrunk over our sample period, in particular for very large

[7] For further details on the German banking sector, we refer to Braeuning and Fecht (2017)

[8] The small difference between the number of lending and borrowing banks is due to the fact that most banks appear both as a lender and a borrower in the interbank market, few banks of our sample have, however, only lent to, not borrowed from the interbank market. See also Footnote 6.

[9] We decide against the alternative of including any possible bank-pair combination to avoid to inflate our sample artificially by including bank-pairs that have never entered a bilateral lending relationship (and will, most likely, not do so in the future). We thereby capture all bank pairs that could realistically lend to each other. However, we ignore those bank pairs that could theoretically lend to each other, but will not do so in reality. This is in line with the empirical evidence of tiered interbank markets, i.e. the finding that most German banks do never lend to each other directly (Craig and von Peter 2014).

loans. However, with an average quarterly credit exposure of about 1.4 trillion euros by the end of 2018, interbank exposure still represent 21% of German banks' total borrowing and 20% of banks' total lending, respectively. Decisions about lending and borrowing in interbank markets therefore remain of high relevance for German banks.

A bank's decision to lend or borrow in the interbank market involves a decision about the extensive margin of credit, i.e. if to lend or borrow at all, and the intensive margin of credit, i.e. how much to lend or borrow. To address both dimensions, we construct two dependent variables: The binary variable $Creditrelation_{i,j,t}$ captures the extensive margin of interbank lending. It assumes the value of one, if lending bank i has an outstanding loan to borrowing bank j at the end of quarter t, or if the borrowing bank j has paid back the loan in quarter t. It is zero for all other lender-borrower combinations.[10]

To capture the intensive margin of interbank lending, we calculate the percentage change in on-balance bilateral exposure between lending bank i and borrowing bank j from quarter $t-1$ to quarter t ($\Delta Exposure_{i,j,t}$). We interpret $\Delta Exposure_{i,j,t}$ as the granting of additional, respectively less liquidity by lender i to a borrowing bank j during quarter t. We calculate the (approximate) percentage change in bilateral exposure as:

$$\Delta Exposure_{i,j,t} = ln(Exposure_{i,j,t}) – ln(Exposure_{i,j,t-1}) \quad (1)$$

Craig and Ma (2022) show that the majority of loans in the German interbank market are long-term. About 45% of loans maturities are even longer than a year and overnight loans make up for only 15% of total interbank lending. As a thorough evaluation of the counterparty's creditworthiness is most relevant for long-term exposure, the German data provides an excellent setting to study peer monitoring. Given the low share of overnight lending in the German market, our quarterly data captures the most important variation in interbank lending.

3.3 Explanatory variables

In the following section, we introduce our explanatory variables of interest measuring the private information on a bank's *Portfolio quality*, a bank's *Portfolio opacity* and the *Portfolio similarity* between two banks. Moreover, we introduce the control variables used in our analysis.

[10] Almost all banks appear both as a borrower and as a lender in the interbank market. For our sample, we therefore include each bank-pair twice, once with bank A as a lender and bank B as a borrower, once with bank B as a lender, bank A as a borrower. An exception are banks that have never lent or never borrowed in interbank markets in our sample period. We include those banks only in the role which they assume at least once during our sample period (i.e. only as a lender or only as a borrower).

Private information on quality of the bank's loan portfolio

Judging a lending bank's ability to observe private information of a potential borrowing bank requires us (i) to identify information on a borrowing bank that is private, and (ii) to ensure this information is indeed relevant for the lending decision. In the following, we introduce our measure of *Portfolio quality*. We confirm its relevance for the interbank lending decision and its privacy in Section 4.

We measure the quality of a bank's loan portfolio by aggregating bank internal information about the credit risk of each of its borrowers. We obtain this information from quarterly regulatory filings, in which banks report the probability of default (PD) of each borrower to the regulator, which uses this information to quantify banks' credit risk, and, in turn, determine their capital requirement. The PD is a bank internal estimate of the likelihood that a counterparty will default on a loan or off-balance sheet financial contract within a year. Banks need to estimate the PD in accordance to data quality and methodological standards specified in the Capital Requirement Regulation (CRR, Article 180). Banks update their PD estimate quarterly for all counterparties, incorporating any new information obtained about borrowers' creditworthiness.[11]

Only banks using the Internal Rating-Based Approach need to report PDs. For banks using the Credit Risk Standardised Approach, PD reporting is not required.[12] To avoid a biased sample, we construct our measure of portfolio credit quality for all banks, including those following the Credit Risk Standardised Approach. To be able to do so, we obtain a borrower-specific PD, using the quarterly median PD reported for each borrower. For example, if firm A has outstanding credit to banks B and C, who use the Internal Rating-Based Approach, and to bank D who uses the Credit Risk Standardised Approach, we use the median of the PDs reported for firm A by banks B and C. This approach allows us to include PDs of all borrowers, except for those who only have exposure to banks following the Credit Risk Standardised Approach.

To construct a measure of *Portfolio quality*, we first calculate a bank's average portfolio PD as the exposure-weighted average of the PD of each borrower k, out of the bank's K different borrowers at the end of quarter t. 'Borrower', in this context, refers to both counterparties with a loan on the bank's balance sheet and counterparties with an off-balance sheet financial contract, as both are relevant for a bank's portfolio quality. We then deduct the portfolio-weighted PD from the value of one. Thereby, we obtain

[11] For more details on the regulatory context of the PD, see the Capital Requirement Regulation (CRR), in particular Article 180.

[12] According to CRR, banks can decide if to use the Credit Risk Standardised Approach, for which the regulator assigns risk-weights based on asset class, or the Internal Rating-Based approach, for which the regulator estimates risk-weights based on bank-reported PDs for each borrower.

a measure between zero - the quality of a hypothetical loan portfolio containing only borrowers with a PD of 1 - and one - the quality of a hypothetical loan portfolio containing only borrowers with a PD of 0:

$$Portfolio\,quality_t = 1 - \frac{1}{\sum_{k \in K} Exposure_{k,t}} \sum_{k \in K} Exposure_{k,t} \times PD_{k,t} \tag{2}$$

In line with the regulatory intention, our measure of *Portfolio quality* is a forward-looking proxy for a bank's credit risk: Regressing banks' *Non-performing loans (NPL) ratio* on lagged values of *Portfolio quality* in Table 2 shows that *Portfolio quality* negatively and significantly predicts *NPL ratio*s of the next quarter up to the next 2 years, both in the cross-section of different banks (models in column (1)) and within each bank (models in column (2)). The variation in *Portfolio quality* explains between 16 and 17% of the cross-sectional variation of *NPL ratio*s in our sample (column (1)), and between 71% and 77% when including fixed effects (column (2)). A panel Granger causality test following Juodis et al. (2021) confirms that *Portfolio quality* precedes a bank's *NPL ratio* and that this negative relationship is highly significant for the next 5 to 50 quarters (Pooled Wald test statistics based on the Half Panel Jackknife procedure Dhaene and Jochmans (2015) > 300; Dumitrescu and Hurlin (2012)'s Z statistics < -50).[13]

Much of banks' loan exposure is long term, in particular the exposure to the real economy. Consequently, both the series of *Portfolio quality* and *NPL ratio* are persistent to a certain extent. The presented analyses should thus be considered with caution. However, we take them as gentle evidence that *Portfolio quality* is indeed more forward-looking than the *NPL ratio* or that, at the very least, bank agents perceive it as such.

We will demonstrate that our measure of *Portfolio quality* is relevant for the lending decision and unobserved by the average counterparty when estimating the impact of *Portfolio quality* on interbank lending in Section 4.

The informative value and privacy of a supervisory measure to assess a counterparty is also supported by the literature: DeYoung et al. (1998) show that proprietary regulatory bank data contains useful private information about bank safety and soundness and that this information is unknown by other financial markets participants. This holds true even for banks that are extensively followed and analyzed by private investors and rating agencies. Similarly, Berger et al. (2000) find that supervisors produce valuable information on bank conditions, which is complementary to information produced in the financial market.

[13]Coefficients from regressing the first differences of *NPL ratio* on *Portfolio quality* are insignificant and can be found in Table B1 in Appendix B .

Portfolio opacity

As we observe several PD assessments for borrowers, we build our measure of *Portfolio opacity* on peers' disagreement about a bank's *Portfolio quality*. For each borrower k at quarter t, we determine the level of disagreement about its PD by the standard deviation of all PDs assigned to it in a quarter ($SD_{k,t}$). We then define a bank's *Portfolio opacity* as the quarterly, exposure-weighted average of these standard deviations:

$$Portfolio\,Opacity_t = \frac{1}{\sum_{k \in K} Exposure_{k,t}} \sum_{k \in K} Exposure_{k,t} \times SD_{k,t} \tag{3}$$

Portfolio opacity captures asset opacity from the perspective of peers. For the decision on interbank credit, this should be more relevant than external measures that have been used in the literature, e.g. the disagreement of rating agencies or the volatility of credit default swap (CDS) spreads (e.g. Braeuning and Fecht 2017, Morgan 2002).

Portfolio similarity

With our measure of *Portfolio similarity* between a lending and borrowing bank, we aim at capturing how similar the firms are to which both banks have granted a loan or an off-balance sheet financial contract. As we assume that knowledge about a firm's situation requires knowledge about its industry and region, we consider a sectoral and a regional dimension of *Portfolio similarity*. We compute the cosine similarity between the loan portfolio of the lending and the borrowing bank based on banks' exposure towards different industries and regions.

To construct this cosine similarity measure, we first aggregate the on- and off-balance sheet exposure to different industries, respectively regions, for each bank in every quarter. For the sectoral exposure, we group loans to firms based on firms' principal activity. We classify the principal activity according to the first digit of *WZ 73*, the official industry classification scheme of the Federal statistical office of Germany.[14] This classification results in exposure to 10 distinct industries per bank. For robustness, we also include analyses based on the *WZ 73* two-digit classification code, resulting in 100 industries in Appendix B. To measure regional exposure, we group loans based on the first digit of the firms' zip code, resulting in exposure to a maximum of 9 distinct regions per bank.

For sectoral exposure, we construct the vectors $X_{i,t}$ and $X_{j,t}$ containing the exposure to each industry p (out of $P = 10$ industries) of lending bank i, respectively borrowing bank

[14]Unfortunately, we cannot use a more standard classification, like the NACE or SIC codes, as the credit register uses the *WZ 73* classification. More information on the industry classification can be found here: https://www.destatis.de/DE/Methoden/Klassifikationen/Gueter-Wirtschaftsklassifikationen/klassifikation-wz-2008.html

j, at quarter t in euros. Similarly, for regional exposure, we construct the vectors $Y_{i,t}$ and $Y_{j,t}$ containing the exposure to each region q (out of $Q = 9$ regions) in euros. For each lender-borrower pair in quarter t, the cosine similarity between the two vectors is then defined as:

$$Portfolio\,Similarity\,(industries)_{i,j,t} = \frac{X_{i,t} \cdot X_{j,t}}{||X_{i,t}||||X_{j,t}||} = \frac{\sum_{p=1}^{P} x_{i,p,t}x_{j,p,t}}{\sum_{p=1}^{P} x_{i,p,t}^2 \sum_{p=1}^{P} x_{j,p,t}^2} \tag{4}$$

$$Portfolio\,Similarity\,(regions)_{i,j,t} = \frac{Y_{i,t} \cdot Y_{j,t}}{||Y_{i,t}||||Y_{j,t}||} = \frac{\sum_{q=1}^{Q} x_{i,q,t}x_{j,q,t}}{\sum_{q=1}^{Q} x_{i,q,t}^2 \sum_{q=1}^{Q} x_{j,q,t}^2} \tag{5}$$

The cosine of the angle between the two vectors $X_{i,t}$ and $X_{j,t}$, and $Y_{i,t}$ and $Y_{j,t}$, respectively, quantifies the extent to which the vectors point in the same direction. *Portfolio similarity* assumes a value of one if the two vectors are parallel, i.e. both banks possess exactly the same fraction of each industry or region. It assumes a value of zero for orthogonal vectors, that is, when the overlap between the industry or regional exposure of the two banks is zero. Since a bank cannot lend a negative amount, the measure ranges between zero and one for all other levels of similarity. As a scaled measure, it is independent of the vectors' length, respectively, of the total loan volume of a bank.

Control variables

Corresponding to our theoretical argument, we control for other indicators of bank solvency. Public information on a peer's capital position, liquidity position, and profitability should impact a lending decision, and could proxy loan portfolio risk. We therefore control for the borrowing bank's *Capital ratio* calculated as Equity/Risk-weighted-assets, its *Liquidity ratio* calculated as Liquid assets/Total assets, and its profitability measured by (risk-weighted) *Return on assets (ROA)*, calculated as net income divided by risk-weighted bank assets. To prevent that these values are affected by the availability of interbank loans in quarter t, we lag these control variables by one quarter.

For a bank pair with a high level of *Portfolio similarity*, the lending bank's solvency will resemble the borrower's solvency. We therefore also control for variables measuring the lender's solvency. In particular, we include the lender's *Portfolio quality*, *Portfolio opacity*, its *NPL ratio*, its *Liquidity ratio*, *Capital ratio*, and *ROA* in our analyses. However, the relatively high correlation between the *Portfolio quality* of similar peers poses another problem to our analysis: If a lending bank lends less in response to a deterioration of *its own portfolio*, we could misinterpret this as a response to the deterioration of the borrowing bank's similar portfolio. To make sure that the correlated *Portfolio quality* of similar bank pairs does not drive our results, we run additional analyses on a matched sample for which this correlation is the same for similar and non-similar pairs (see Section 8).

Long-standing lending relationships are an important determinant of interbank lending (Cocco et al. 2009, Braeuning and Fecht 2017). To avoid confusing the impact of *Portfolio similarity* and relationship lending, we control for the frequency of previous interactions over a two-year window. Following Petersen and Rajan (1994) and Braeuning and Fecht (2017), we compute relationship lending as the logged sum of quarters t' out of the last $T = 8$ quarters in which the lending bank i has lent to the borrowing bank j.

$$Relationship\,lending_{i,j,t} = ln(1 + \sum_{t'=1}^{T} I(Credit\,relation_{i,j,t'} = 1)) \tag{6}$$

Analogously, we compute reverse relationship lending as the logged sum of quarters in which the borrowing bank j has lent to the lending bank i.

$$Reverse\,relationship\,lending_{i,j,t} = ln(1 + \sum_{t'=1}^{T} I(Credit\,relation_{j,i,t'} = 1)) \tag{7}$$

A similar portfolio should go along with similar liquidity shocks (Fecht et al. 2011). As interbank lending requires one bank to have more, one to have less liquidity as compared to their desired level, similar banks should less often make a good lender-borrower match in the interbank market. We therefore control for the *Difference in liquidity surplus* between the lender and borrower. For each borrower-lender pair at the end of a quarter t, the variable is calculated as follows:

$$\begin{aligned} Difference\,in\,liquidity\,surplus_{i,j,t} &= Liquidity\,surplus_{i,t} - Liquidity\,surplus_{j,t} \\ &= Liquidity\,ratio_{i,t} - \overline{Liquidity\,ratio_i} \\ &- (Liquidity\,ratio_{j,t} - \overline{Liquidity\,ratio_j}) \end{aligned} \tag{8}$$

where $\overline{Liquidity\,ratio_i}$ is the lender's average liquidity ratio and $\overline{Liquidity\,ratio_j}$ is the borrower's average liquidity ratio.

Banks allocate liquidity within established banking networks, i.e. there is preferred lending between savings banks or cooperative banks (Fecht et al. 2011). As banks from the same network could also have similar credit exposure, we include a dummy variable indicating if lender and borrower are part of the same banking network, and if lender and borrower belong to the same bank holding company. Moreover, following the literature, we include the *Size* of the lending and borrowing bank as measured by ln(Total Assets) (Angelini et al. 2011, Ashcraft et al. 2011, Fecht et al. 2011, Furfine 2001, Gabrieli 2011, Iori et al. 2015). To control for unobserved, stable bank-specific characteristics, we include lender and borrower fixed effects. To account for changing macroeconomic conditions which affect all banks (Angelini et al. 2011), we also include quarter-year fixed effects.

Our mechanism of interest is driven by the supply of interbank credit. To control for interbank credit demand, we capture a bank's need for liquidity by including its *Loans-to-assets* calculated by total loans over total assets as a control. As this control variable alone cannot rule out that demand effects, rather than supply effects could explain our findings, we perform additional analyses on the changes of interbank supply in Section 7).

Table 3 reports descriptive statistics for all relevant bank and interbank characteristics of our analysis.

4 How do interbank lenders react to a change in the borrower's portfolio quality?

This section analyzes if banks incorporate forward-looking information on a peer's *Portfolio quality* in their decision to grant an interbank loan. We first discuss our empirical approach to estimate both the extensive and the intensive margin of interbank lending in a two-stage procedure. We then confirm the relevance and privacy of our *Portfolio quality* measure and find that, on average, banks with a lower *Portfolio quality* do not receive less funding, but banks with a higher *NPL ratio* do.

4.1 Methodological considerations

A lender's choice to supply liquidity to a bank in need involves two decisions: In a first step, the bank decides whether to lend at all (extensive margin). In a second step, it decides on the size of the loan (intensive margin).[15] Information on bilateral exposure, however, only exists for the subsample of bank pairs that have established a lending relation. To control for this non-random selection into our sample, we follow a two-step approach, as suggested by Heckman (1977) and used for the interbank market by Braeuning and Fecht

[15] Of course, these two decisions are interrelated, both temporally (i.e. they can be done simultaneously) and logically (i.e. the first decision can depend on the second). We separate between the two steps for analytical reasons. The second step involves more decisions such as the interest rate, the maturity of the loan or the requirement of collateral. However, this paper limits its attention to the size of the loan.

(2017). We model the two steps by two equations, the selection equation and the outcome equation.

The selection equation defines the extensive margin of interbank lending. In the first stage of our regression, we estimate whether a bilateral loan ($Credit\,relation_{i,j,t}$) exists between lending bank i and borrowing bank j at quarter t using the following Probit model:

First Stage (Probit):

$$
\begin{aligned}
P(Credit\ Relation_{i,j,t} = 1) = \Phi(&\beta_0 \\
&+ \beta_1 Portfolio\,quality_{j,t} + \beta_2 NPL\,ratio_{j,t} + \beta_3 Portfolio\,opacity_{j,t} \\
&+ \beta_4 Portfolio\,quality_{i,t} + \beta_5 NPL\,ratio_{i,t} + \beta_6 Portfolio\,opacity_{j,t} \\
&+ \beta_7 Credit\ Relation_{i,j,t-1} + Controls + FE_i + FE_j + FE_t + \epsilon_{i,j,t})
\end{aligned}
\tag{9}
$$

The outcome equation defines the intensive margin of interbank lending. It models the amount lent ($\Delta Exposure_{i,j,t}$) as a function of the covariates of interest. However, regressing $\Delta Exposure_{i,j,t}$ on our non-random sample would yield biased estimates. We therefore include information on the non-existing pairs by controlling for the hazard of not entering into a lending relationship. This "non-selection hazard" is measured by the inverse Mills ratio (IMR), which we obtain from the first-stage Probit regression.

The IMR must contain some information that is not yet included in the second-stage estimation (exclusion restriction). Therefore, at least one variable should serve as an instrument: It should predict the matching between borrower and lender at the first stage, but be irrelevant for the change in exposure estimated at the second stage. We use $Credit\,relation_{i,j,t-1}$, i.e. the existence of a credit relation in $t-1$ as an instrument (c.f. Arellano and Bond 1991). As bilateral exposure often last longer than three months, this variable is highly predictive for the existence of a credit relation in t. However, a credit relation in $t-1$ bears no information about whether the bilateral exposure will increase or decrease over the next quarter. In the second stage, we estimate the following equation by OLS:

Second Stage (OLS):

$$
\begin{aligned}
\Delta Exposure_{i,j,t} = &\beta_0 \\
&+ \beta_1 Portfolio\,quality_{j,t} + \beta_2 NPL\,ratio_{j,t} + \beta_3 Portfolio\,opacity_{j,t} \\
&+ \beta_4 Portfolio\,quality_{i,t} + \beta_5 NPL\,ratio_{i,t} + \beta_6 Portfolio\,opacity_{j,t} \\
&+ \beta_7 IMR_{First\,Stage} + Controls + FE_i + FE_j + FE_t + \epsilon_{i,j,t}
\end{aligned}
\tag{10}
$$

4.2 Results

Table 4 reports the results of the Heckman sample selection model, estimating the effect of *Portfolio quality*, *Portfolio opacity*, and *NPL ratio* on the matching probability between two banks (Model (1)), on the changes in bilateral interbank exposure in the cross-section (Model (2)), on the changes in bilateral interbank exposure within a lending or borrowing bank (Model(3)) and on the changes in bilateral interbank exposure within a lending or borrowing bank, controlling for quarter-specific effects (Model (4)). To be able to compare coefficient sizes, we standardize all independent variables, except for binary variables.

Interbank lending and borrower's portfolio quality and opacity

In contrast to the idea that interbank lending should be restricted for banks with a worse asset quality, coefficients on the borrowing bank's *Portfolio quality* are negative and mostly insignificant. At the extensive margin, banks with a better loan portfolio are even *less* likely to form an interbank relationship (Model (1)). Setting all other variables to the average and binary variables to zero, a one standard deviation decrease in *Portfolio quality* is associated with a 82 basis points lower probability of being an interbank borrower, compared to an unconditional probability of being an interbank borrower of 26.53 percent. At the intensive margin, there is no significant difference between banks with different levels of portfolio quality (Model (2)) and banks do not receive less interbank liquidity after a deterioration of their *Portfolio quality* (Model (3)), also not after controlling for quarter-year specific effects (Model (4)).

A higher *NPL ratio*, however, significantly decreases both a borrowing bank's probability of forming a lending relationship and the magnitude of a loan. A one-standard deviation increase in the borrowing bank's *NPL ratio* decreases its probability of receiving a loan by 118 basis points, holding all other variables at their mean and binary variables at zero (Model(1)). The amount of liquidity received by a bank with a one standard deviation higher *NPL ratio* is 236 basis points lower, compared to the cross section (Model (2)). Similarly, a borrower receives between 133 (Model (3)) and 154 basis points (Model(4)) less interbank liquidity with a one standard deviation increase in its *NPL ratio*. This is a relevant reduction, compared to the average quarterly change in bilateral interbank exposure of 1.46 percent (considering only banks with a lending relationship).

These findings are in line with the interpretation that the forward-looking *Portfolio quality* is unobserved by the average market participant. Therefore, banks resort to the backward-looking, though observable, information on peers' *NPL ratio*. Given the predictive power of a bank's *Portfolio quality* for *NPL ratios* in the following quarters reported in Section

3, the average lending bank thereby uses an inferior, though easily accessible proxy to assess the borrower's asset quality.

An opaque portfolio of the borrower has a significantly negative effect on interbank lending. Banks with a less transparent portfolio receive fewer and smaller loans. For banks with a one-standard deviation higher *Portfolio opacity*, the likelihood of receiving an interbank loan decreases by 38 basis points (Model (1)) and the amount of liquidity received decreases by 111 basis points (Model (2)). A bank's one-standard deviation increase of *Portfolio opacity* results in a reduction in interbank liquidity by 59 (Model (3)), or 57 basis points, when also controlled for quarter-specific effects (Model (4)), respectively.

Lenders' reluctance to grant loans to peers with a less transparent portfolio is in line with the expectation that opacity makes it harder to judge a counterparty's portfolio as it increases the risk of evaluating the peer's portfolio quality incorrectly.

Interbank lending and lender's portfolio quality

In line with existing research (e.g. Acharya and Merrouche 2013), lenders lend significantly less when their *own* asset quality worsens. For a lender with a one standard deviation lower *Portfolio quality*, the likelihood to start a new lending relationship is reduced by 29 basis points (Model (1)), the amount of liquidity provided is reduced by 89 basis points (Model (2)), compared to an unconditional probability to lend of 26.53 percent. In the cross-section, the economic magnitude of the effect is rather small. However, the effect of changes of one bank's *Portfolio quality* over time is large, compared to the average quarterly change in bilateral exposure of 1.46 percent: A one-standard deviation decrease in *Portfolio quality* reduces the amount provided in interbank markets by 226 (Model (3)), or 215 basis points, when controlled for quarter-specific effects (Model(4)), respectively.

While, on average, banks with a higher *NPL ratio* lend less in interbank markets, banks do not react negatively to an increase in their own *NPL ratio*: In the cross-section, banks with a one-standard deviation higher *NPL ratio* have a 44 basis points lower likelihood to lend in interbank markets (Model (1), compared to an unconditional probability to lend of 26.53 percent) and lend 49 basis points less (Model (2), compared to the average bilateral change in exposure of 1.46 percent). Within a potential lending bank, however, an increase in the *NPL ratio* shows no clear impact on the amount lent (Model (3) and Model (4)).

These results further support our interpretation that *Portfolio quality* is a relevant and private measure of asset quality. A lending bank, which can observe its own *Portfolio quality*, therefore responds to a change in this private measure and less to the inferior, but publicly available *NPL ratio*.

Other variables and quality of the model

Our results hold after controlling for established bank and relationship characteristics, for bank network affiliation, for belonging to the same bank holding company and for having (un)correlated liquidity shocks. The direction of included controls is in line with the existing literature: Larger banks borrow more in interbank markets and, even though appearing more often as a lender, lend less in interbank markets. Established relationship characteristics also show large effects in the expected direction.

Model (1) in Table 4 further shows that our first-stage instrument, the lagged existence of a credit relation, has a strong impact on the existence of a credit relation in quarter t (t-statistic of 335), ruling out concerns about a weak instrument in our first-stage regression.

To sum up, the average lending bank does not react to a deterioration in the forward-looking *Portfolio quality*, even though it is predictive for future *NPL ratios*. Instead, lenders rely on current *NPL ratios*, an inferior measure capturing the "damage already done", not the one to expect in upcoming quarters. The stark reduction of lending after a deterioration of bank's own *Portfolio quality*, indicates that, in line with our analyses in Section 3, banks consider *Portfolio quality* a useful metric for its asset quality.

5 How do interbank lenders with a (dis)similar portfolio react to changes in the borrower's portfolio quality?

We now investigate which role *Portfolio similarity* plays in interbank lending. In particular, we evaluate (i) whether banks with a similar loan portfolio lend more or less to each other, (ii) whether banks with different levels of similarity react differently to a change in peers' asset quality as measured by *Portfolio quality* and the *NPL ratio*, and (iii) whether banks with different levels of similarity react differently to a change in the *Portfolio opacity* of peers. We first explain our specification and then report our results.

5.1 Methodological considerations

As in the previous section, we estimate bilateral matching probabilities and changes in the interbank exposure between bank pairs, controlling for sample selection issues with a Heckman sample selection model. In this section, however, we include *Portfolio similarity* between the lending and borrowing bank in our analysis. With the base effect of *Portfolio similarity*, we investigate whether banks with a similar loan portfolio lend more or less to each other. To test if similar banks react differently to the different measures of asset quality, we interact *Portfolio similarity* with *Portfolio quality* and *NPL ratio*. To identify a divergence in the reaction to *Portfolio opacity*, based on different similarity levels of the lending and borrowing bank, we also include the interaction between *Portfolio similarity* and *Portfolio opacity.* We do so for both the sectoral and regional dimension of *Portfolio similarity.* In particular, we estimate the following two equations. For simplicity, $Portfolio\,Similarity_{i,j,t}$ refers to both the sectoral and the regional similarity measure.

First Stage (Probit):

$$
\begin{aligned}
P(Credit\ Relation_{i,j,t} = 1) = \Phi(&\beta_0 + \beta_1 Portfolio\,Similarity_{i,j,t} \\
&+ \beta_2 Portfolio\,quality_{j,t} + \beta_3 Portfolio\,quality_{j,t} \times Portfolio\,Similarity_{i,j,t} \\
&+ \beta_4 NPL\,ratio_{j,t} + \beta_5 NPL\,ratio_{j,t} \times Portfolio\,Similarity_{i,j,t} \\
&+ \beta_6 Portfolio\,opacity_{j,t} + \beta_7 Portfolio\,opacity_{j,t} \times Portfolio\,Similarity_{i,j,t} \\
&+ \beta_8 Portfolio\,quality_{i,t} + \beta_9 NPL\,ratio_{i,t} + \beta_{10} Portfolio\,opacity_{i,t} \\
&+ \beta_{11} Credit\ Relation_{i,j,t-1} + Controls + FE_i + FE_j + FE_t + \epsilon_{i,j,t})
\end{aligned}
\tag{11}
$$

Second Stage (OLS):

$$
\begin{aligned}
\Delta Exposure_{i,j,t} = &\beta_0 + \beta_1 Portfolio\,Similarity_{i,j,t} \\
&+ \beta_2 Portfolio\,quality_{j,t} + \beta_3 Portfolio\,quality_{j,t} \times Portfolio\,Similarity_{i,j,t} \\
&+ \beta_4 NPL\,ratio_{j,t} + \beta_5 NPL\,ratio_{j,t} \times Portfolio\,Similarity_{i,j,t} \\
&+ \beta_6 Portfolio\,opacity_{j,t} + \beta_7 Portfolio\,opacity_{j,t} \times Portfolio\,Similarity_{i,j,t} \\
&+ \beta_8 Portfolio\,quality_{i,t} + \beta_9 NPL\,ratio_{i,t} + \beta_{10} Portfolio\,opacity_{i,t} \\
&+ \beta_{11} IMR_{First\,Stage} + Controls + FE_i + FE_j + FE_t + \epsilon_{i,j,t}
\end{aligned}
\tag{12}
$$

5.2 Results

Table 5 and 6 report the results of estimating Equation (11) (Model (1)) and Equation (12) (Models (2) to (4)), including bank fixed effects in Model (3) and bank and quarter-year fixed effects in Model (4). To be able to compare coefficient sizes, all independent variables, except for binary variables, are standardized.

Interbank lending, borrower's portfolio quality, and portfolio similarity

As in the previous section, the base effect of *Portfolio quality* on interbank lending is negative at the extensive, and mostly insignificant at the intensive margin. The significantly positive coefficients for the interaction between *Portfolio quality* and *Portfolio similarity*, however, show that the effect differs considerably for bank-pairs with different levels of *Portfolio similarity.* Table 6 reports marginal effects for the regressions of Table 5. "High" similarity refers to bank pairs with a 3 standard deviation higher similarity than the average, "low" similarity to bank pairs with a 3 standard deviation lower similarity than the average. We report marginal effects for these relatively extreme values of portfolio similarity to demonstrate how different a bank's most similar peers (i.e. the few banks with almost the same business model) react, compared to a bank's most dissimilar peers (i.e. the few banks specialized on completely different industries and regions).

For the interpretation of marginal effects in Table 6, note that the variable *Credit relation* assumes either the value 0 or the value 1; a coefficient of 1 in the Probit model (Model (1)), therefore, means an increase in 100 percentage points. The variable Δ *Exposure*, in contrast, is reported in percentage points; a coefficient of 1 in the OLS model (Model (2) to Model (4)), therefore, means an increase in one percentage point.

Considering only bank pairs with a high level of similarity (Table 6, row "Portfolio quality (both similarities high)"), a one standard deviation increase in *Portfolio quality increases* the likelihood to enter a lending relationship by 50 basis points (Model (1)), compared to an unconditional probability of lending of 26.53 percent. Given a high level of similarity, a lending bank thus picks those peers with better asset quality. Similarly, for the intensive margin, bank pairs with a high level of similarity lend 408 basis points more to banks with a better asset quality (Model(2)). Moreover, for similar bank pairs, a deterioration of a bank's loan portfolio is associated with a significant reduction of interbank lending. In particular, a one standard deviation decrease in *Portfolio quality* leads to a 368 basis points decrease in interbank liquidity obtained (Model (3)), or a 348 basis points decrease in interbank liquidity, when controlling for quarter specific effects (Model (4)). These effects are strong, given the average change in bilateral exposure between similar banks of 10.95 percent.

For banks with very different portfolios (Table 6, row "Portfolio quality (both similarities low)"), in contrast, the likelihood of entering a lending relationship is 80 basis points lower for a one standard deviation increase in *Portfolio quality* (Model (1)). Similarly, in the intensive margin, the amount lent between dissimilar banks is 563 basis points lower for banks with an additional standard deviation of *Portfolio quality* (Model (2)), compared to an average change in exposure of -2.91 percent for banks with a very different portfolio. For dissimilar bank pairs, lending *increases* after a deterioration of the borrower's *Portfolio quality* by 370, respectively 342 basis points (Model (3) and Model (4)). We show in Section 6 that this effect is due to the higher liquidity demand from borrowers with a low *Portfolio quality.*

Like in the previous section, the average bank lends significantly less often and lower amounts to banks with a higher *NPL ratio.* The positive terms for the interaction between

NPL ratio and *Portfolio similarity* in Table 5 and the marginal effects in Table 6 show that this effect vanishes for very similar bank pairs: For very similar bank pairs (Table 6, row "NPL ratio (both similarities high)", Model (1)), a higher *NPL ratio* is not associated with a significant decrease in the likelihood of entering a lending relationship, compared to a significant decrease of 60 basis points for very dissimilar banks pairs (Table 6, row "NPL ratio (both similarities low)", Model(1)). In the intensive margin, the effect is also insignificant for very similar bank pairs: Banks with a higher *NPL ratio* do neither receive less interbank lending from very similar lenders (Model (2)), nor do similar lenders decrease their loans after an increase of their *NPL ratio* (Model(3)) and (Model (4)).

These results support Hypothesis 1. In line with the notion that lending banks with a very similar portfolio can adequately access borrowers' private quality of the loan portfolio, they adjust their lending to the superior, forward-looking information on *Portfolio quality*. Therefore, similar banks need to rely less on the inferior backward looking *NPL ratio*.[16]

Interbank lending, borrower's portfolio opacity, and portfolio similarity

Like in Section 4, the effect of the borrower's *Portfolio opacity* is negative for a bank pair of average similarity, both at the extensive and the intensive margin. The significantly positive coefficients on the interaction effect between *Portfolio opacity* and the similarity measures reveal that this negative effect becomes weaker, the more similar the portfolio of the lending and borrowing bank: The marginal effects reported in Table 6 (row "Portfolio opacity (both similarities high)") show that bank pairs with a similarity level of 3 standard deviations above average are even 23 basis points *more* likely to form a lending relationship with one additional standard deviation of *Portfolio opacity* (Model (1)). They grant 129 basis points *more* loans to banks with a one standard deviation higher *Portfolio opacity* (Model (2)), compared to the average quarterly change in lending between similar banks of 10.95 percent. A bank that becomes less transparent by one standard deviation obtains 149 basis points (Model (3)), respectively 162 (Model (4)) basis points more loans by very similar banks.

These results support Hypotheses 3 and 4. While borrowers with an opaquer portfolio, on average, face difficulties to refinance themselves in interbank markets, interbank lenders "dare to" lend borrowers with an opaque portfolio if this portfolio is similar to their own.

Interbank lending and portfolio similarity

Table 5 shows that *Portfolio similarity* itself, both its sectoral and regional dimension, has a significantly positive effect at the extensive and intensive margin of lending. Bank

[16]So far, one might think that these findings are a pure artifact of the high correlation between similar banks *Portfolio quality*. We show in Section 7 that this is not the case.

pairs with a one standard deviation more similar loan portfolio with respect to industries are 2 basis points more likely to form a lending relationship; banks pairs with a one standard deviation more similar loan portfolio with respect to regions are 14 basis points more likely to form a lending relationship (Model (1)). Compared to the unconditional probability to lend of 26.53 percent, these effects on the extensive margin are rather small, but significant.

In the intensive margin, banks with a one standard deviation more similar industry exposure increase their quarterly lending, on average, by 100 basis points, banks with an additional standard deviation of regional similarity by 84 basis points (Model (2)). Increasing *Portfolio similarity* between two banks by one standard deviation increases their granted lending by 259 basis points for sectoral similarity, and by 94 basis points for regional similarity (Model(3)). Controlling for quarter specific shocks, obtained interbank liquidity increases by 211 basis points after a one standard deviation increase of sectoral similarity and by 114 basis points after a one standard deviation increase in regional similarity (Model (4)).

These effect sizes are large, compared to the average quarterly change in interbank lending of 1.46 percent. Coefficients of both similarities for the intensive margin add up to an effect of similar size as relationship lending, the variable identified as the strongest predictor for interbank lending in the literature (e.g. Braeuning and Fecht 2017). In other words, a one standard deviation increase in *Portfolio similarity* in regional and sectoral terms increases interbank lending as much as having a one standard deviation longer relationship.

These results support Hypothesis 2. In line with the interpretation that banks with a similar portfolio are well aware about their informational advantage regarding the peer's *Portfolio quality*, they prefer lending to peers with a similar portfolio.

The results also demonstrate that, empirically, positive effects of *Portfolio similarity* dominate potential negative effects outlined in the introduction, i.e. reduced lending out of diversification concerns or reduced lending in the case of correlated liquidity shocks. However, while our results imply that informational advantages are important drivers of preferential lending between similar peers, we cannot rule our that the latter is also driven by risk shifting, i.e. by banks deliberately exposing themselves to banks with correlated risk to increase profits in the case of success and increase the probability of being rescued in case of failure.

Other variables and quality of the model

Our findings hold with the inclusion of control variables. Moreover, the coefficients of $Credit\ relation_{i,j,t-1}$ and $IMR_{firststage}$ in Table 5 are reassuring that our instrument is not too weak (t = 293).

Table 5, however, leaves two questions unanswered: First, why should dissimilar lenders, ceteris paribus, lend *more* to borrowers with a lower *Portfolio quality*? If the lending bank is, indeed, unable to observe the counterparty's *Portfolio quality*, it should not react to this information at all. In the next section, we will separate supply and demand effects to demonstrate that the negative coefficient of *Portfolio quality* for dissimilar banks is a result of a demand effect: Banks with a lower *Portfolio quality* have a greater demand for interbank liquidity, dissimilar lenders satisfy this demand.

A second concern is that the positive interaction effect of *Portfolio similarity* and borrower's *Portfolio quality* could be an artifact of the high correlation of the *Portfolio quality* of banks with a similar portfolio. Our analysis could then misinterpret a lending bank's reaction to a change *in its own Portfolio quality* as a reaction to the *Portfolio quality* of a similar borrower. We will show that this is not the case by running our analysis on a matched sample in Section 7.

6 Do demand effects drive our results?

We hypothesize that interbank lenders adjust their lending in response to changes in the *Portfolio quality* or *Portfolio opacity* of the borrowing bank. Our theoretical argument thus speaks to supply effects. Empirically, however, we can only observe equilibrium lending, that is, the exposure which the lending and borrowing bank have agreed on. To rule out demand-driven interpretations, this chapter investigates how interbank credit *supply* changes with different levels of the borrowing bank's *Portfolio quality*, *NPL ratio*, and *Portfolio opacity*. Our procedure to identify liquidity supply shocks provides us with borrower-level shocks. As such, the shocks help us to support the supply-based interpretation, but cannot substitute the bank-pair-level analysis from Section 5 and 6 as it does not allow us to include bank pair characteristics, like *Portfolio similarity*. In the following, we first explain our approach to disentangle supply effects from the observed equilibrium level of interbank lending and then present our results.

6.1 Methodological considerations

We identify liquidity supply shocks building on Degryse et al. (2019). In particular, we borrow the idea that the average credit demand of firms of the same type in the same quarter is a proxy for a firm's credit demand and that supply effects can be estimated with the help of lending bank-time fixed effects.

We start with an adjusted definition of change in bilateral credit exposure $\Delta Exposure'_{i,j,t}$, which, by limiting the range of values between -2 to 2, incorporates both the extensive and the intensive margin of lending (see Chodorow-Reich (2014); Davis and Haltiwanger (1992)).

$$\Delta Exposure'_{i,j,t} = \frac{Exposure_{i,j,t} - Exposure_{i,j,t-1}}{0.5(Exposure_{i,j,t} + Exposure_{i,j,t-1}} \tag{13}$$

To detect the change in interbank exposure attributable to changes in supply, we then regress $\Delta Exposure'_{i,j,t}$ on *lending bank-time fixed effects*, proxying liquidity supply, and *borrowing bank class-industry-region-time fixed effects*, proxying liquidity demand. We obtain the latter fixed effects by classifying borrowing banks by their bank class, which includes information on the size of the bank (see Table 1), their industry focus, classified by the first digit of *WZ 73*, and their regional focus, classified by the first digit of the zip code. We proxy industry and regional focus by the industry/region to which the bank lends most in a given quarter. We exclude loans to the financial and the public sector, as those represent the highest share of loans for almost every bank.

$$\Delta Exposure'_{i,j,t} = FE_{j,t} + FE_{class_j,industry_j,region_j,t} + \epsilon_{i,j,t} \tag{14}$$

Assuming that a borrowing bank's liquidity demand is homogeneous across lending banks, the inclusion of $FE_{class,industry,region,t}$ deducts all changes in $\Delta Exposure'_{i,j,t}$ attributable to changes in demand of borrowing bank j.[17] $FE_{i,t}$ then accounts for time-specific changes in liquidity supply of lending bank i. In contrast to most other fixed effects regressions, we are interested in the effect sizes of $FE_{i,t}$, as they depict the actual changes in liquidity supply. In practice, we estimate fixed effects by including bank-time dummies for all but one bank. $FE_{i,t}$ is therefore fixed to zero for the omitted bank. To obtain comparable values for liquidity supply shocks for all banks, which we can later aggregate on the borrowing bank level, we deduct the time-specific mean from the estimate:

[17] As a borrowing bank should not care about which other bank provides them with liquidity, as long as they offer the same conditions, the assumption of homogeneous demand is reasonable in our setting.

$$F\tilde{E}_{i,t} = F\hat{E}_{i,t} - F\bar{E}_t \tag{15}$$

We aggregate the liquidity supply shock experienced by borrowing bank j from all its I lenders at quarter t to obtain:

$$\Delta Liquidity\ supply_{j,t} = \sum_{i \in I} F\tilde{E}_{i,t} \tag{16}$$

Note that, here, our intuition deviates from Degryse et al. (2019). While Degryse et al. (2019) aim to identify a credit supply shock which is exogenous to a borrower, we are interested in whether this credit supply shock depends on the solvency of different borrowers the bank has lent to in the interbank market. Therefore, Equation (16) aggregates shocks of lending banks on the level of the borrowing bank. The shock experienced by a borrowing bank consequently depends on the liquidity provision of its lenders. To assess if lenders' change in liquidity provision depends on the borrower's *Portfolio quality*, *NPL ratio* and *Portfolio opacity*, we estimate the following regression:

$$\begin{aligned} \Delta\ Liquidity\ supply_{j,t} = \beta_0 &+ \beta_1 Portfolio\, quality_{j,t} + \beta_2 NPL\, ratio_{j,t} \\ &+ \beta_3 Portfolio\, opacity_{j,t} + Controls + FE_j + \epsilon_{j,t} \end{aligned} \tag{17}$$

6.2 Results

Table 7 reports the results of regressing changes in interbank supply on characteristics of the borrowing bank based on equation (17). Like in previous tables, all explanatory variables are standardized for comparability. As the dependent variable is constructed in such a way to include both the extensive and the intensive margin of lending, we cannot interpret effect sizes in a meaningful way and will only interpret direction and significance of the coefficient.[18]

Disentangling supply effects reveals that, on average, liquidity supply is restricted when banks' *Portfolio quality* deteriorates and when their *NPL ratio* increases. Borrowers receive also less liquidity after their portfolio gets opaquer. These results show that, from a borrowing bank's perspective, a deteriorated loan portfolio actually reduces access to interbank market liquidity.

[18] As we can only interpret Δ *Liquidity supply* at the level of a bank over time, we do not report the model without borrowing bank fixed effects.

The results also reveal that the negative impact of *Portfolio quality* for lending between dissimilar banks reported in previous regressions (Table 4 and Table 5) is driven by demand effects: Banks with a lower or lowered *Portfolio quality* demand more interbank loans. However, they face difficulties receiving these loans, because they are shun by lenders with a similar portfolio. Consequently, they turn to dissimilar lenders, resulting in a negative association between *Portfolio quality* and interbank lending for dissimilar bank pairs.

The reverse is true for borrowers with an opaque portfolio: Opaque borrowers receive fewer and smaller loans as dissimilar lenders do not like to lend to them. To circumvent these constraints, opaque banks turn to their similar peers to obtain interbank liquidity.

7 Does the portfolio quality of lending banks drive our results?

Banks with a similar portfolio will also have a similar *Portfolio quality*.[19] A bank that reduces lending as a response to the deterioration of its own portfolio could thus appear to react on the deterioration of the portfolio of a similar peer. To rule out that the lender's reaction on its own *Portfolio quality* is driving our results, we rerun our analyses from Section 6 on a matched subsample of our data. In this subsample, we force the correlation between lender's and borrower's *Portfolio quality* to being independent of *Portfolio similarity*. In the following, we first describe our matching strategy and then report our results.

7.1 Matched sample

To force the correlation between lender's and borrower's *Portfolio quality* to being independent of *Portfolio similarity*, we create a subsample of our sample, in which the within-pair correlation of *Portfolio quality* is at a comparable level for similar and dissimilar banks pairs. If, in fact, banks only reacted to their own *Portfolio quality*, coefficients on the interaction between our similarity measures and *Portfolio quality* should be insignificant for this sample.

To create the matched sample, for each bank pair, we first determine the correlation between *Portfolio quality* of the borrower and lender over time. We then define bank pairs to be "similar", if their similarity measure is higher than the 75th percentile for both sectoral and regional similarity in the first quarter of 2009. We classify bank pairs as "dissimilar"

[19] In our sample, the correlation of *Portfolio quality* of two banks with an above-average level of similarity is 0.0499, while the correlation of *Portfolio quality* of two banks with a below-average level of similarity is only 0.0150.

if their similarity measure is lower than the 25th percentile for both sectoral and regional similarity in the first quarter of 2009. We then select our subsample by nearest-neighbour matching: To each "similar" bank pair, we assign those three "dissimilar" bank pairs which have the closest value for the correlation in *Portfolio quality.* We keep only the matched pairs in our sample and exclude banks for which we do not find an adequate match. As the sample consists only of very similar and very dissimilar bank pairs, we redefine similarity as a binary variable, which is 1 for "similar" and 0 for "dissimilar" banks. Appendix C reports details on our matched sample and on our matching success. We run all analyses described in Section 5 on the matched sample.

7.2 Results

Table 8 presents the results of the Heckman sample selection model from Equation (11) (Model (1)) and Equation (12) (Models (2) to (4)) on our matched sample. Model (1) estimates the likelihood of forming a relationship based on our variables of interest, Model (2) estimates the additional loan granted between bank pairs, Model (3) includes lending and borrowing bank fixed effect in this estimation, and Model (4) adds quarter-year effects. To be able to compare coefficient sizes, all independent variables, except for binary variables, are standardized.

As our sample is very selective and only entails a non-random fraction of the variation in *Portfolio similarity* and *Portfolio quality*, our interpretation focuses on interaction effects and ignores base effects. Moreover, due to the non-randomness of our sample, we do not interpret coefficient sizes.

Table 8 shows that the effect reported in the previous sections is also present in the matched sample: Even for the subset of bank pairs for which the similarity level does not imply anything for the correlation between the lender's and the borrower's *Portfolio quality*, the interaction term between the different measures of similarity and *Portfolio quality* is positive and mostly significant, so is the interaction term between the different measures of portfolio similarity and *NPL ratio*. Like in previous regressions, the interaction between the different measures of similarity and *Portfolio opacity* is also positive, though not always significantly. However, the non-significant coefficients in Model (3) and (4) are of comparable size to our coefficients in Table 5, indicating that the lower significance is mainly a consequence from the smaller sample size.

These results are reassuring regarding our previous interpretation: Similar banks avoid lending to low *Portfolio quality* borrowers; these borrowers turn to dissimilar banks. Dissimilar banks avoid lending to high NPL and opaque borrowers; these borrowers turn to similar banks.

8 Decomposition of explanatory power

From our analyses, we conclude that *Portfolio similarity* is an important determinant for forming interbank lending relationships and for the size of interbank loans. In contrast to the existing literature, which focuses on characteristics of the lender, the borrower, their relationship or on market factors, we thereby draw the attention to *common characteristics* of the lending and borrowing bank. To put this novelty into perspective, we provide an estimate of the relative importance of the different factors determining lending patterns. Similar to Lemmon et al. (2008), we decompose the variation in interbank lending attributable to lender characteristics, borrower characteristics, bank-pair (i.e. common and relationship) characteristics and market characteristics.

8.1 Methodological considerations

We use analysis of covariance (ANCOVA) to decompose the variation in lending attributable to different factors. We do so by estimating the following equations capturing the extensive and intensive margin of interbank lending:

$$\begin{aligned}
Credit\ relation_{i,j,t} = \beta_0 + \\
&\beta_1 Lender\ characteristics\ (varying)_{i,t} + \beta_2 Lender\ characteristics\ (fixed)_i + \\
&\beta_3 Borrower\ characteristics\ (varying)_{j,t} + \beta_4 Borrower\ characteristics\ (fixed)_j + \\
&\beta_5 Bank\ pair\ characteristics\ (varying)_{i,j,t} + \beta_6 Bank\ pair\ characteristics\ (fixed)_{i,j} + \\
&\beta_7 Market\ characteristics_t + \epsilon_{i,j,t}
\end{aligned} \tag{18}$$

$$\begin{aligned}
\Delta Exposure_{i,j,t} = \beta_0 + \\
&\beta_1 Lender\ characteristics\ (varying)_{i,t} + \beta_2 Lender\ characteristics\ (fixed)_i + \\
&\beta_3 Borrower\ characteristics\ (varying)_{j,t} + \beta_4 Borrower\ characteristics\ (fixed)_j + \\
&\beta_5 Bank\ pair\ characteristics\ (varying)_{i,j,t} + \beta_6 Bank\ pair\ characteristics\ (fixed)_{i,j} + \\
&\beta_7 Market\ characteristics_t + \epsilon_{i,j,t}
\end{aligned} \tag{19}$$

where:

- $Lender characteristics (varying)_{i,t}$ include the lending bank's *Portfolio quality*, *NPL ratio*, *Portfolio opacity*, lagged *Capital ratio*, lagged *Liquidity ratio*, lagged *ROA*, lagged *Loans-to-assets*, and lagged *Size*.

- $Lender\ characteristics\ (fixed)_i$ include the lending bank's *Bank class* and lender fixed effects.

- $Borrower characteristics (varying)_{j,t}$ include the borrowing bank's *Portfolio quality*, *NPL ratio*, *Portfolio opacity*, lagged *Capital ratio*, lagged *Liquidity ratio*, lagged *ROA*, lagged *Loans-to-assets*, and lagged *Size*.

- $Borrower\ characteristics\ (fixed)_j$ include the borrowing bank's *Bank class* and borrower fixed effects.

- $Bank pair characteristics (varying)_{i,j,t}$ include the variables *Portfolio similarity (industries)*, *Portfolio similarity (regions)*, *Relationship lending*, *Reverse relationship lending*, *Δ reverse exposure*, *Difference in liquidity surplus.*

- $Bank\ pair\ characteristics\ (fixed)_{i,j}$ include the dummies if banks are part of the same bank network and/or part of the same bank holding company.

- $Market\ characteristics_t$ are quarter-year fixed effects.

We obtain the fraction of the model sum of squares attributable to the each variable like follows: First, we divide the Type III partial sum of squares of this variable by the aggregate partial sum of squares for all variables to calculate the fraction of *total variance in lending* attributable to each variable.[20] Second, we scale this number by the fraction of overall variance explained by our model to obtain the variable's contribution to total *explained variance* by our model. We then aggregate the variables into varying and fixed lender, borrower, bank-pair and market fixed effects.[21]

8.2 Results

Table 10 presents the results of the variance decomposition for the extensive and intensive margin of interbank lending. The rows of the table, except for the last row, correspond

[20]Following Lemmon et al. (2008), we use Type III sum of squares as Type I sum of squares is sensitive to the variable's order (c.f. Scheffé 1959).

[21]For market characteristics, we do not distinguish between varying and fixed effects as they change over time per definition.

to the fraction of Type III partial sum of squares for different model specifications. Intuitively, the table shows the fractions of the model sum of squares attributable to the different "characteristics", i.e. borrower, lender, market and bank-pair characteristics. The last row of Table 10 presents the adjusted R-square of each specification. For example, to explain the extensive margin of interbank lending, in the model without fixed effects, about 0.14% (=0.09%+0.05%) of the variation in interbank lending is attributable to lender characteristics (in network terms: ego covariates), about 0.25% are attributable to borrower characteristics (alter covariates), and about 99.60% are attributable to bank pair characteristics (dyadic covariates).

The results of the partitioning corroborate the relevance of common characteristics and relationship characteristics for interbank lending. When determining who enters an interbank lending relation at all (Panel (A)), more than 97% of the variation can be explained by bank pair characteristics. The explanatory power comes almost exclusively from varying bank-pair characteristics, like relationship lending or *Portfolio similarity*, and only marginally from fixed characteristics, like having the same bank holding company or being part of the same banking network. Market, lender, and borrower characteristics *together* are responsible for less that 3% of the variation. Out of this fraction, borrower characteristics are most important, explaining a between 0.25 and 1.18% of the total explained variation. From the characteristics of the lending and borrowing bank, fixed determinants, captured by bank fixed effects, are more relevant than varying determinants, like the bank's *Capital ratio* or other balance-sheet based variables.

For the variation in the size of interbank loans (Panel (B)), the characteristics of the lending and borrowing bank are more decisive: Between 21 and 44% of the variation in credit amounts can be traced back to lender characteristics, between 29 and 36% to borrower characteristics. Fixed bank characteristics captured by the included fixed effects are significantly more relevant than varying bank characteristics captured by the different balance sheet variables. At the intensive margin, market characteristics captured by the quarter-year fixed effects explain about 9% of the total explained variation. With fractions of explained variance ranging between 19 and 51%, bank pair characteristics also explain a considerable fraction of interbank loan sizes.

Interestingly, the explained variance for the extensive margin is considerably higher than for the intensive margin. Variables of our model, including the fixed effects, seem to be much better in explaining which bank-pair forms a credit relation than in explaining how much additional credit is granted.

These results are re-assuring, both for our analysis and for the focus of the recent literature: When trying to explain interbank lending patterns, relationship characteristics -

the focus of recent studies - and common characteristics - the focus of our study - do, indeed, matter most.

9 Conclusion

By allowing banks to manage, pool and redistribute funds, the interbank market allocates liquidity around the financial system and provides insurance against idiosyncratic liquidity shocks. It serves as an important transmission channel of monetary policy. Understanding the mechanisms within this market is thus of central importance for prudential regulation and adequate monetary policy.

This paper builds on research on banks' ability to monitor peers, adding a further puzzle piece to our understanding of the interbank market. It reconciles two seemingly opposing positions: On the one hand, we confirm that peer monitoring works: A large fraction of lending banks reacts to a deterioration of the counterparty's asset quality, even though this information is private. On the other hand, we confirm that peer-monitoring fails under asymmetric information: A just as large fraction of lending banks proves unable to react to private information on the deterioration of the counterparty's asset quality. These banks substitute private, forward-looking measures on the borrowing bank's asset quality by inferior, backward-looking, but publicly available measures.

Most importantly, we shed light on which banks have access to private information on the counterparty, and which do not. We show that the ability for effective peer-monitoring is restricted to similar bank pairs, that is, banks with a similar loan portfolio. This reveals a new channel of information generation in interbank markets: Banks use private information about their own portfolio to assess a peer in the interbank market. Given the superior information on peers with a similar loan portfolio, credit relations between similar banks are more frequent and involve larger sums.

Preferential lending between banks with a similar real exposure is paralleled by a lack of diversification and, consequently, induces risks to financial stability (Silva et al. 2017a, Silva et al. 2017b). Our findings reveal trade-offs at both the micro and the macro level: From a lending bank's perspective, lending to a similar institution is associated with a better-informed risk-assessment. However, lending to a bank that is already exposed to similar industries and regions impedes portfolio diversification. From a market and societal perspective, lending between similar counterparties increases informational efficiency and monitoring in interbank markets. At the same time, the above-average direct interbank exposure between banks with a similar real exposure could multiply systemic risks and too-interconnected-to-fail concerns.

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Figures and tables

Figure 1: Interbank lending in Germany, 2009 to 2018

This figure shows the total amount of quarterly interbank lending between German banks. The solid line depicts total interbank exposure. The dotted line shows lending between banks of the same banking network. The dashed line shows lending between banks that belong to the same bank holding company.

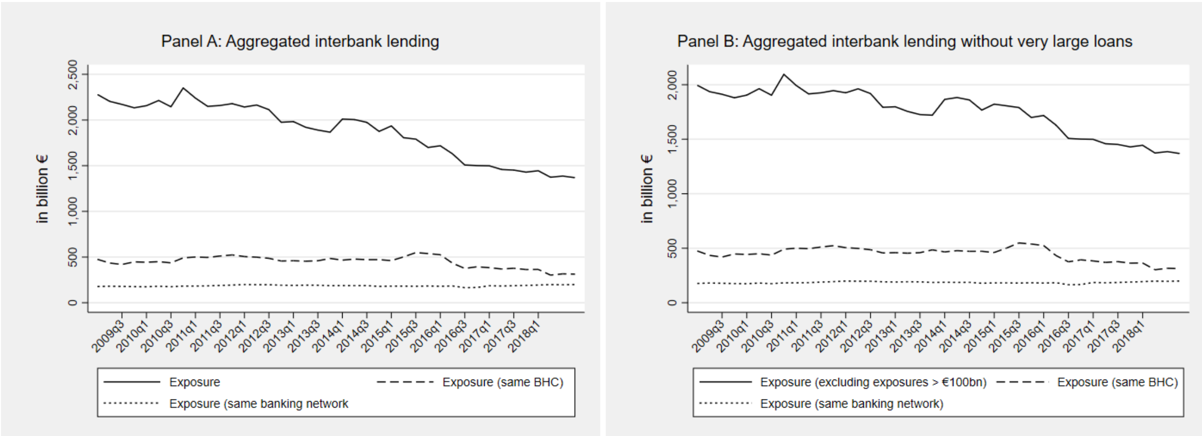

Table 1: Banks and interbank credit relations

This table reports the type of banks that lend and borrow in the interbank market in our sample and the number of credit relations between these banks. *Lender-borrower relations* are all possible quarterly bank-to-bank combinations between banks which have entered a lending relationship at least once in our sample, *True Credit relations* are those bank-to-bank relationships which do actually have outstanding bilateral exposure in a given quarter.

Bank type	**Lending banks**	**Borrowing banks**
Large private banks	6	6
Smaller private banks	198	182
Head institutes of cooperative & saving banks	14	14
Saving banks	467	467
Cooperative banks	1,347	1,345
Other/Not classified	22	21
Total	2,054	2,035
Lender-borrower relations in 40 quarters	2,644,640	
True credit relations	701,533	
- Credit relations between banks of same network (saving or cooperative banks)	102,044	
- Credit relations between banks of same holding company	2,087	

Table 2: Predicting non-performing loans ratios with portfolio quality

This table shows coefficients from OLS regressions of a bank's non-performing loans (NPL) ratios on its (lagged) *Portfolio quality*. Each cell shows the beta coefficient, standard error, R^2, and number of observations of regressing the *NPL ratio* at time t on *Portfolio quality* at time t, (t-1),(t-2), (t-3), (t-4), (t-5), (t-6), **or** (t-7), respectively. The sample consists of quarterly bank observations of 2054 banks between 2009 and 2018. Regressions in column (2) include bank fixed effects. Appendix A provides a detailed variable description.

	Dependent variable: NPL ratio (t)	
	(1)	(2)
Portfolio quality (t)	-0.362***	-0.098***
	(0.00)	(0.00)
R^2	0.16	0.71
N	53,200	53,174
Portfolio quality (t-1)	-0.360***	-0.084***
	(0.00)	(0.00)
R^2	0.16	0.72
N	51,003	50,945
Portfolio quality (t-2)	-0.358***	-0.068***
	(0.00)	(0.00)
R^2	0.16	0.74
N	48,871	48,848
Portfolio quality (t-3)	-0.354***	-0.050***
	(0.00)	(0.00)
R^2	0.16	0.74
N	46,863	46,829
Portfolio quality (t-4)	-0.350***	-0.030***
	(0.00)	(0.00)
R^2	0.16	0.75
N	44,908	44,882
Portfolio quality (t-5)	-0.347***	-0.018***
	(0.00)	(0.00)
R^2	0.17	0.76
N	42,988	42,926
Portfolio quality (t-6)	-0.344***	-0.007
	(0.00)	(0.00)
R^2	0.17	0.77
N	41,099	41,080
Portfolio quality (t-7)	-0.341***	-0.000
	(0.00)	(0.00)
R^2	0.17	0.77
N	39,284	39,245
Bank Fixed Effects	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Bank and interbank characteristics

This table reports summary statistics of the bank and interbank characteristics of our sample. All variables are defined in Appendix A.

	Observations	Unit	Mean	SD	p5	Median	p95
Interbank Lending							
Credit relation	2,644,640	Dummy	0.27	0.44	0.00	0.00	1.00
Δ Exposure	2,623,392	%	-0.41	36.08	-4.01	0.00	2.59
Portfolio Similarity							
Portfolio similarity (industries)	2,644,640	%	91.92	14.27	65.13	97.28	99.80
Portfolio similarity (industries, fine classification)	2,644,640	%	74.51	21.54	29.49	79.86	98.48
Portfolio similarity (regions)	2,644,640	%	38.42	25.50	4.83	34.10	89.29
Bank characteristics							
Interbank borrowing/total borrowing	2,644,397	%	21.32	21.13	2.68	14.70	52.08
Interbank lending/total lending[22]	2,644,398	%	20.02	13.95	2.49	17.07	45.70
Portfolio quality	2,644,640	%	97.90	2.82	92.13	98.73	99.91
Portfolio opacity	2,644,640	%	1.81	1.68	0.31	1.30	5.00
NPL ratio	2,644,640	%	2.29	2.53	0.06	1.64	6.20
Capital ratio	2,639,307	%	23.58	31.92	11.52	18.54	33.92
Liquidity ratio	2,644,397	%	18.50	12.81	4.72	15.75	40.27
ROA	2,637,317	%	1.39	2.44	-0.30	1.58	3.49
Loans-to-assets	2,644,357	%	52.85	19.20	13.45	56.02	79.73
Size	2,644,397	Log	8.97	2.39	5.43	8.78	12.73
Relationship characteristics							
Relationship lending	2,644,640		2.13	3.30	0.00	0.00	8.00
Reverse relationship lending	2,644,640		2.11	3.29	0.00	0.00	8.00
Δ Reverse exposure	2,644,640	%	-0.40	36.25	-4.26	0.00	2.77
Same network	2,644,640	Dummy	0.12	0.32	0.00	0.00	1.00
Same BHC	2,644,640	Dummy	0.00	0.03	0.00	0.00	0.00
Difference in liquidity surplus	2,644,155	ppt	0.00	52.14	-9.28	0.00	9.28

Table 4: Interbank lending, portfolio quality, and portfolio opacity

This table shows the coefficients of a two-stage Heckman sample selection model. The sample consists of quarterly bank-pair observations of 2054 banks between 2009 and 2018. The dependent variables are the existence of a loan between lender i and borrower j at end-of-quarter t (Model 1, Probit), and the percentage change of interbank exposure between lender i and borrower j over the period $t-1$ to t, respectively (Model 2 to 4, OLS). Model (3) includes lender and borrower fixed-effects, model (4) includes lender, borrower, and time fixed-effects. Coefficients are standardized, except for binary variables. Standard errors are clustered on the borrower and lender level. Control variables include the lagged values of ln(total assets), liquid assets/total assets, equity/risk-weighted assets, *ROA*, and (non interbank) *Loans-to-assets* of the borrowing and lending bank. Controls for the bank class, for being part of the same bank network, and of the same bank holding company are also included. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Borrower characteristics				
Portfolio quality	-0.046***	-0.996	-0.029	-0.014
	(0.00)	(0.75)	(0.48)	(0.60)
NPL ratio	-0.066***	-2.360***	-1.331***	-1.536***
	(0.00)	(0.50)	(0.39)	(0.49)
Portfolio opacity	-0.021***	-1.106***	-0.593**	-0.567*
	(0.00)	(0.32)	(0.24)	(0.30)
Capital ratio (t-1)	-0.021***	-0.194	-1.923***	-0.324
	(0.00)	(0.54)	(0.74)	(0.70)
Liquidity ratio (t-1)	-0.005**	-1.385**	2.315	1.293
	(0.00)	(0.65)	(2.49)	(2.52)
ROA (t-1)	0.102***	3.861***	2.906***	2.395***
	(0.00)	(0.66)	(0.79)	(0.83)
Loans-to-assets (t-1)	0.050***	1.794***	1.925*	2.837***
	(0.00)	(0.56)	(1.07)	(0.93)
Size (t-1)	0.208***	2.481***	-0.660	-0.940
	(0.01)	(0.86)	(6.10)	(5.66)
Lender characteristics				
Portfolio quality	0.017***	0.892***	2.257***	2.154***
	(0.00)	(0.27)	(0.52)	(0.55)
NPL ratio	-0.025***	-0.488*	1.421***	0.136
	(0.00)	(0.26)	(0.39)	(0.40)
Portfolio opacity	0.016***	0.553***	0.586***	0.766***
	(0.00)	(0.17)	(0.16)	(0.17)
Capital ratio (t-1)	-0.094***	-1.942***	-2.447**	0.110
	(0.01)	(0.43)	(1.02)	(1.04)
Liquidity ratio (t-1)	0.023***	-1.158***	-5.355**	-6.052**
	(0.00)	(0.31)	(2.48)	(2.52)
ROA (t-1)	0.038***	1.661***	2.384***	1.357**
	(0.00)	(0.42)	(0.60)	(0.57)
Loans-to-assets (t-1)	-0.114***	-3.041***	0.612	2.776**
	(0.00)	(0.34)	(1.18)	(1.16)
Size (t-1)	0.028***	-0.657	-15.839***	-6.973
	(0.00)	(0.50)	(5.14)	(5.00)

Table 4: (continued) Interbank lending, portfolio quality, and portfolio opacity

Relationship characteristics				
Relationship lending	0.360***	3.528***	3.115***	3.260***
	(0.00)	(0.57)	(0.56)	(0.56)
Reverse relationship lending	0.077***	1.282***	1.661***	1.621***
	(0.00)	(0.28)	(0.29)	(0.29)
Log reverse exposure	0.019***	2.631***	2.588***	2.536***
	(0.00)	(0.44)	(0.45)	(0.44)
Same BHC	0.502***	13.735***	14.969***	14.873***
	(0.06)	(2.16)	(2.31)	(2.31)
Same network	0.391***	9.348***	7.796***	7.957***
	(0.01)	(1.46)	(1.40)	(1.39)
Difference in liquidity surplus (t-1)	0.000	-0.529**	11.229	9.988
	(0.00)	(0.25)	(9.78)	(9.88)
Heckman controls				
Credit relation (t-1)	2.929***			
	(0.01)			
IMR		60.919***	61.761***	61.817***
		(2.04)	(2.05)	(2.04)
Observations	2,545,319	655,517	655,493	655,493
Bank class controls	Yes	Yes	No	No
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes
(Pseudo) R-squared	0.83	0.14	0.15	0.15

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Interbank lending, portfolio similarity, and credit portfolio quality

This table shows the coefficients of a two-stage Heckman sample selection model on a matched sample. The sample consists of quarterly bank-pair observations of 2054 banks between 2009 and 2018. Bank pairs with a high-similarity in both regional and sectoral terms are matched to bank pairs of similar correlation between the lender's and the borrower's credit portfolio quality but with a low similarity both regional and sectoral terms. The dependent variables are the existence of a loan between lender i and borrower j at end-of-quarter t (Model 1, Probit), and the percentage change of interbank exposure between lender i and borrower j over the period (t-1) to t, respectively (Model 2 to 4, OLS). Model (3) includes lender and borrower fixed-effects, model (4) includes lender, borrower, and time fixed-effects. Coefficients are standardized, except for binary variables. Standard errors are clustered on the borrower and lender level. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Common characteristics				
Portfolio similarity (industries)	0.007**	0.999*	2.587***	2.109***
	(0.00)	(0.51)	(0.68)	(0.68)
Portfolio similarity (regions)	0.031***	0.843***	0.943***	1.142***
	(0.00)	(0.23)	(0.20)	(0.21)
Borrower characteristics				
Portfolio quality	-0.034***	-0.773	-0.012	0.036
	(0.00)	(0.60)	(0.54)	(0.63)
Portfolio quality × Portfolio similarity (industries)	0.022***	0.921**	0.735***	0.638**
	(0.00)	(0.43)	(0.27)	(0.27)
Portfolio quality × Portfolio similarity (regions)	0.017***	0.698***	0.496***	0.511***
	(0.00)	(0.19)	(0.14)	(0.14)
NPL ratio	-0.063***	-2.376***	-1.257***	-1.661***
	(0.00)	(0.47)	(0.43)	(0.52)
NPL ratio × Portfolio similarity (industries)	-0.000	0.071	0.114	-0.158
	(0.00)	(0.31)	(0.23)	(0.23)
NPL ratio × Portfolio similarity (regions)	0.016***	0.569***	0.401***	0.370***
	(0.00)	(0.19)	(0.14)	(0.14)
Portfolio opacity	-0.021***	-1.122***	-0.672***	-0.648**
	(0.00)	(0.31)	(0.25)	(0.31)
Portfolio opacity × Portfolio similarity (industries)	0.016***	0.594***	0.485***	0.462***
	(0.00)	(0.17)	(0.12)	(0.13)
Portfolio opacity × Portfolio similarity (regions)	0.006***	0.210	0.235*	0.293**
	(0.00)	(0.15)	(0.14)	(0.14)
Capital ratio (t-1)	-0.018***	0.114	-1.450*	0.022
	(0.00)	(0.59)	(0.77)	(0.73)
Liquidity ratio (t-1)	-0.006**	-1.340**	2.438	1.443
	(0.00)	(0.65)	(2.49)	(2.53)
ROA (t-1)	0.100***	3.762***	2.808***	2.385***
	(0.00)	(0.66)	(0.76)	(0.81)
Loans-to-assets (t-1)	0.053***	2.036***	2.322**	3.015***
	(0.00)	(0.58)	(1.08)	(0.91)
Size (t-1)	0.210***	2.518***	-0.468	-1.101
	(0.01)	(0.86)	(6.03)	(5.58)
Lender characteristics				
Portfolio quality	0.016***	0.808***	2.224***	2.118***
	(0.00)	(0.28)	(0.51)	(0.54)
NPL ratio	-0.022***	-0.416*	1.430***	0.239
	(0.00)	(0.25)	(0.39)	(0.42)

Table 5: (continued) Interbank lending, portfolio similarity, and portfolio quality

Portfolio opacity	0.015***	0.556***	0.613***	0.791***
	(0.00)	(0.16)	(0.16)	(0.17)
Capital ratio (t-1)	-0.093***	-1.845***	-2.156**	0.300
	(0.01)	(0.41)	(1.04)	(1.05)
Liquidity ratio (t-1)	0.022***	-1.105***	-5.495**	-6.189**
	(0.00)	(0.32)	(2.49)	(2.53)
ROA (t-1)	0.039***	1.676***	2.335***	1.375**
	(0.00)	(0.41)	(0.60)	(0.56)
Loans-to-assets (t-1)	-0.113***	-2.907***	0.978	2.961**
	(0.00)	(0.36)	(1.22)	(1.18)
Size (t-1)	0.027***	-0.672	-14.539***	-6.333
	(0.00)	(0.50)	(5.08)	(5.02)
Relationship characteristics				
Relationship lending	0.359***	3.507***	3.074***	3.206***
	(0.00)	(0.57)	(0.56)	(0.56)
Reverse relationship lending	0.073***	1.129***	1.508***	1.440***
	(0.00)	(0.27)	(0.29)	(0.28)
Δ Reverse exposure	0.019***	2.626***	2.577***	2.526***
	(0.00)	(0.44)	(0.44)	(0.44)
Same network	0.388***	9.436***	7.702***	7.887***
	(0.01)	(1.46)	(1.41)	(1.41)
Same BHC	0.487***	13.595***	14.507***	14.321***
	(0.06)	(2.15)	(2.33)	(2.33)
Difference in liquidity surplus (t-1)	0.000	-0.525**	11.797	10.585
	(0.00)	(0.25)	(9.77)	(9.90)
Heckman controls				
Credit relation (t-1)	2.929***			
	(0.01)			
IMR		60.981***	61.814***	61.870***
		(2.03)	(2.04)	(2.04)
Observations	2,545,319	655,517	655,493	655,493
Bank class controls	Yes	Yes	No	No
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes
R-squared	0.83	0.14	0.15	0.15

Standard errors (twoway clustered by borrower and lender) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The impact of portfolio quality, NPL ratio, and portfolio opacity on interbank lending for different values of similarity (marginal effects)

This table reports marginal effects for the regression reported in Table 5. "Low similarity" refers to a similarity of 3 standard deviation below the variable mean, "high similarity" refers to a similarity of 3 standard deviations above the variable mean. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Portfolio quality (both similarities low)	-0.008***	-5.629***	-3.706***	-3.410***
	(0.00)	(1.65)	(0.87)	(1.00)
Portfolio quality (industry dissimilar, region similar)	-0.003***	-1.441	-0.728	-0.346
	(0.00)	(1.65)	(0.93)	(1.05)
Portfolio quality (industry similar, region dissimilar)	-0.001	-0.105	0.704	0.418
	(0.00)	(1.43)	(1.13)	(1.14)
Portfolio quality (both similarities high)	0.005***	4.082***	3.682***	3.481***
	(0.00)	(1.44)	(1.25)	(1.20)
NPL ratio (both similarities low)	-0.006***	-4.295***	-2.801***	-2.296***
	(0.00)	(1.16)	(0.69)	(0.79)
NPL ratio (industry dissimilar, locality similar)	-0.001	-0.884	-0.395	-0.076
	(0.00)	(1.37)	(0.87)	(0.85)
NPL ratio (industry similar, locality dissimilar)	-0.006***	-3.867***	-2.118*	-3.245***
	(0.00)	(1.22)	(1.11)	(1.18)
NPL ratio (both similarities high)	-0.001	-0.456	0.287	-1.025
	(0.00)	(0.95)	(0.97)	(0.95)
Portfolio opacity (both similarities low)	-0.004***	-3.535***	-2.832***	-2.913***
	(0.00)	(0.77)	(0.63)	(0.67)
Portfolio opacity (industry dissimilar, locality similar)	-0.003***	-2.277***	-1.419***	-1.156**
	(0.00)	(0.63)	(0.50)	(0.55)
Portfolio opacity (industry similar, locality dissimilar)	0.000	0.032	0.076	-0.141
	(0.00)	(0.81)	(0.69)	(0.77)
Portfolio opacity (both similarities high)	0.002***	1.290	1.488**	1.616***
	(0.00)	(0.80)	(0.61)	(0.60)
Observations	2,545,319	655,517	655,493	655,493
Other variables included (see table 5)	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Interbank lending supply and borrower's solvency

This table shows the coefficients from an OLS regression of the change in liquidity supply on characteristics of the borrowing bank. The sample consists of 2054 banks between 2009 and 2018. Liquidity supply shocks are calculated following Degryse et al. (2019), controlling for the extensive margin of lending. *Change in liquidity supply* is estimated following equation (16). All other variables are defined in Appendix A.

	Dependent variable: Change in liquidity supply
Portfolio quality	0.034*
	(0.020)
NPL ratio	-0.318***
	(0.019)
Portfolio opacity	-0.073***
	(0.011)
Capital ratio (t-1)	0.211***
	(0.024)
Liquidity ratio (t-1)	0.244***
	(0.029)
ROA (t-1)	0.024
	(0.019)
Loans-to-assets (t-1)	-0.026
	(0.039)
Size (t-1)	1.267***
	(0.145)
Observations	115,968
Borrower FEs	Yes
R-squared	0.73

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Interbank lending, portfolio similarity, and portfolio quality (matched sample)

This table shows the coefficients of a two-stage Heckman sample selection model. The sample consists of quarterly bank-pair observations of 2054 banks between 2009 and 2018. The dependent variables are the existence of a loan between lender i and borrower j at end-of-quarter t (Model 1, Probit), and the percentage change of interbank exposure between lender i and borrower j over the period (t-1) to t, respectively (Model 2 to 4, OLS). Model (3) includes lender and borrower fixed-effects, model (4) includes lender, borrower, and time fixed-effects. Coefficients are standardized except for binary variables. Standard errors are clustered on the borrower and lender level. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Common characteristics				
Portfolio similarity (industries)	-0.005	0.037	1.048	0.539
	(0.01)	(0.46)	(0.73)	(0.65)
Portfolio similarity (regions)	0.050***	1.398***	1.490**	1.390**
	(0.01)	(0.41)	(0.59)	(0.56)
Borrower characteristics				
Portfolio quality	-0.054***	-1.007	0.007	-0.368
	(0.01)	(0.72)	(0.88)	(0.95)
Portfolio quality × Portfolio similarity (industries)	0.043***	1.257***	0.850*	0.994**
	(0.01)	(0.36)	(0.49)	(0.44)
Portfolio quality × Portfolio similarity (regions)	0.011	1.081**	0.650	0.597
	(0.01)	(0.46)	(0.55)	(0.53)
NPL ratio	-0.068***	-2.195***	-1.327*	-2.407***
	(0.01)	(0.48)	(0.73)	(0.64)
NPL ratio × Portfolio similarity (industries)	0.015**	0.631*	0.422	0.162
	(0.01)	(0.34)	(0.43)	(0.40)
NPL ratio × Portfolio similarity (regions)	0.026**	1.074**	0.780	0.515
	(0.01)	(0.45)	(0.51)	(0.50)
Portfolio opacity	0.006	0.147	0.198	0.180
	(0.01)	(0.49)	(0.46)	(0.54)
Portfolio opacity × Portfolio similarity (industries)	0.030***	0.708**	0.540	0.601
	(0.01)	(0.31)	(0.38)	(0.40)
Portfolio opacity × Portfolio similarity (regions)	0.011	0.330	0.478	0.506
	(0.01)	(0.59)	(0.69)	(0.68)
Capital ratio (t-1)	-0.036***	-1.380***	-1.819***	-0.342
	(0.01)	(0.48)	(0.69)	(0.75)
Liquidity ratio (t-1)	0.009	-1.235*	3.722	2.093
	(0.01)	(0.72)	(7.43)	(7.28)
ROA (t-1)	0.054***	2.396***	3.154***	2.672***
	(0.01)	(0.41)	(0.72)	(0.78)
Loans-to-assets (t-1)	0.078***	2.563***	2.203	3.354*
	(0.01)	(0.58)	(1.48)	(1.72)
Size (t-1)	0.220***	2.846***	5.041	7.460
	(0.02)	(0.93)	(9.35)	(8.83)
Lender characteristics				
Portfolio quality	0.017	1.241**	1.335*	1.421*
	(0.01)	(0.53)	(0.79)	(0.83)
NPL ratio	-0.012	-0.073	1.467**	0.111
	(0.01)	(0.41)	(0.74)	(0.76)
Portfolio opacity	0.003	0.382*	0.433*	0.717***
	(0.01)	(0.22)	(0.23)	(0.26)

Table 8: (continued) Interbank lending, portfolio similarity, and portfolio quality (matched sample)

Capital ratio (t-1)	-0.086***	-1.976***	-3.795***	-1.452
	(0.01)	(0.48)	(1.00)	(1.07)
Liquidity ratio (t-1)	0.001	-1.635**	-7.023	-7.007
	(0.01)	(0.64)	(7.89)	(7.72)
ROA (t-1)	0.021**	0.863***	0.651	-0.304
	(0.01)	(0.33)	(0.54)	(0.56)
Loans-to-assets (t-1)	-0.112***	-2.382***	-0.270	2.070
	(0.01)	(0.48)	(2.00)	(1.86)
Size (t-1)	0.011	-1.150*	-16.750**	-10.899*
	(0.02)	(0.67)	(6.60)	(6.35)
Relationship characteristics				
Relationship lending	0.420***	5.418***	3.558***	3.788***
	(0.01)	(1.12)	(0.99)	(1.00)
Reverse relationship lending	0.068***	1.152**	2.396***	2.326***
	(0.01)	(0.50)	(0.61)	(0.61)
Δ Reverse exposure	0.025***	2.292***	2.224***	2.128***
	(0.01)	(0.57)	(0.56)	(0.54)
Same network	0.391***	6.468***	5.961**	6.040**
	(0.03)	(1.65)	(2.81)	(2.81)
Same BHC	0.548***	12.989**	6.708	6.791
	(0.18)	(5.18)	(4.27)	(4.19)
Difference in liquidity surplus (t-1)	0.026***	-0.053	2.116	1.776
	(0.01)	(0.48)	(3.39)	(3.31)
Heckman controls				
Credit relation (t-1)	2.883***			
	(0.03)			
IMR		61.691***	64.628***	64.614***
		(2.96)	(3.02)	(3.02)
Observations	226,190	69,509	69,452	69,452
Bank class controls	Yes	Yes	No	No
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes
R-squared	0.84	0.12	0.14	0.14

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: The effect of portfolio quality, NPL ratio, and portfolio opacity on interbank lending for different values of similarity (marginal effects, matched sample)

This table reports marginal effects for the regression on our matched sample reported in Table 8. ”Low similarity” refers to a similarity of 3 standard deviation below the variable mean, ”high similarity” refers to a similarity of 3 standard deviations above the variable mean. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Portfolio quality (both similarities low)	-0.011***	-8.021***	-4.492**	-5.141***
	(0.00)	(1.34)	(1.84)	(1.59)
Portfolio quality (industry dissimilar, locality similar)	-0.009***	-1.532	-0.591	-1.562
	(0.00)	(1.97)	(2.37)	(2.35)
Portfolio quality (industry similar, locality dissimilar)	0.002	-0.481	0.606	0.825
	(0.00)	(2.29)	(2.54)	(2.57)
Portfolio quality (both similarities high)	0.006***	6.008***	4.506*	4.404*
	(0.00)	(1.80)	(2.64)	(2.42)
NPL ratio (both similarities low)	-0.010***	-7.308***	-4.932***	-4.436***
	(0.00)	(1.26)	(1.33)	(1.29)
NPL ratio (industry dissimilar, locality similar)	-0.002**	-0.867	-0.251	-1.348
	(0.00)	(2.04)	(2.38)	(2.27)
NPL ratio (industry similar, locality dissimilar)	-0.005**	-3.524	-2.403	-3.466
	(0.00)	(2.16)	(2.57)	(2.41)
NPL ratio (both similarities high)	0.003	2.918**	2.279	-0.378
	(0.00)	(1.46)	(2.05)	(1.92)
Portfolio opacity (both similarities low)	-0.006***	-2.968**	-2.855	-3.139
	(0.00)	(1.42)	(1.87)	(1.95)
Portfolio opacity (industry dissimilar, locality similar)	-0.003	-0.987	0.012	-0.105
	(0.00)	(2.34)	(2.71)	(2.73)
Portfolio opacity (industry similar, locality dissimilar)	0.003*	1.281	0.384	0.466
	(0.00)	(2.73)	(3.13)	(3.12)
Portfolio opacity (both similarities high)	0.007***	3.262**	3.251**	3.499**
	(0.00)	(1.33)	(1.55)	(1.58)
Observations	226,190	69,509	69,452	69,452
Other variables included (see table 8)	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Variance decompositon of interbank lending

This table presents a variance decomposition for several different model specifications of the extensive and intensive margin of interbank lending, with adjusted R -squares at the bottom. We compute the Type III partial sum of squares for each effect in the model and then normalize each estimate by the sum across the effects, forcing each column to sum to one. For example, at the extensive margin (Panel A) with all fixed effects (last column), 0.09% of the explained sum of squares captured by the included covariates can be attributed to macroeconomic shocks. Firm FE are firm fixed effects. Time FE are quarter fixed effects (c.f.Lemmon et al. 2008).

Panel A: Extensive margin

	Model without FE	Borrower & lender FE	Borrower, lender & time FE
Lender characteristics (Ego covariates)			
Varying characteristics	0.09%	0.03%	0.02%
Fixed characteristics	0.05%	0.77%	0.77%
Borrower characteristics (Alter covariates)			
Varying characteristics	0.17%	0.05%	0.06%
Fixed characteristics	0.08%	1.13%	1.12%
Bank-pair characteristics (Dyadic covariates)			
Varying characteristics	99.56%	97.98%	98.01%
Fixed characteristics	0.04%	0.02%	0.02%
Market characteristics (Network covariates)			0.09%
Adj. R-squared	75.33%	75.98%	76.01%

Panel B: Intensive margin

	Model without FE	Borrower & lender FE	Borrower, lender & time FE
Lender characteristics (Ego covariates)			
Varying characteristics	13.19%	3.72%	4.05%
Fixed characteristics	7.77%	39.62%	40.23%
Borrower characteristics (Alter covariates)			
Varying characteristics	14.89%	1.16%	1.16%
Fixed characteristics	13.89%	34.96%	35.40%
Bank-pair characteristics (Dyadic covariates)			
Varying characteristics	47.71%	20.26%	18.89%
Fixed characteristics	2.54%	0.29%	0.27%
Market characteristics (Network covariates)			9.11%
Adj. R-squared	0.68%	1.06%	1.19%

A Variable Descriptions and Sources

Variable	Definition	Source
	Panel A: Bank-quarter level	
Portfolio quality	1 - portfolio-weighted average of borrowers' probability of default, see Equation (2)	Bundesbank credit register
NPL ratio	Non-performing loans/Total loans outstanding	Bundesbank monthly balance sheet statistics
Portfolio opacity	Portfolio-weighted standard deviation of borrowers' probabilities of default, see Equation (3)	Bundesbank credit register
Capital ratio	Equity/Risk-weighted assets	Bundesbank monthly balance sheet statistics
Liquidity ratio	Liquid assets/Total assets	Bundesbank monthly balance sheet statistics
ROA	Return on risk-weighted assets	Bundesbank monthly balance sheet statistics
Loans-to-assets	Loans/Total assets	Bundesbank monthly balance sheet statistics
Size	Log total assets	Bundesbank monthly balance sheet statistics
	Panel B: Bank level	
Bank class	Dummy for each of the bank classes listed in Table 1	Bundesbank monthly balance sheet statistics
	Panel C: Bank-pair-quarter level	
Credit relation	Binary variable that is one if there is outstanding credit between lending and borrowing bank at the end of the quarter	Bundesbank credit register
Δ Exposure	Percentage change in credit amount from lending to borrowing bank, see Equation (1)	Bundesbank credit register
Δ Reverse exposure	Percentage change in credit amount from borrowing to lending bank, see Equation (1)	Bundesbank credit register
Portfolio similarity (industries)	Cosine similarity between credit exposures of lending and borrowing bank to 10 different industries, see Equation (4)	Bundesbank credit register
Portfolio similarity (industries, fine)	Cosine similarity between credit exposures of lending and borrowing bank to 100 different industries, see Equation (4)	Bundesbank credit register
Portfolio similarity (regions)	Cosine similarity between credit exposures of lending and borrowing bank to 9 different regions, see Equation (5)	Bundesbank credit register
Relationship lending	Logged sum of quarters out of the last 8 quarters in which the lending bank has lent to the borrowing bank, see Equation (6)	Bundesbank credit register
Reverse relationship lending	Logged sum of quarters out of the last 8 quarters in which the borrowing bank has lent to the lending bank, see Equation (7)	Bundesbank credit register
Difference in liquidity surplus	Difference between lender's abnormal liquidity and borrower's abnormal liquidity, see Equation (8)	Bundesbank monthly balance sheet statistics
IMR	Inverse Mill's ratio calculated from the first-stage Probit regression	1st-stage Probit regression
	Panel D: Bank-pair level	
Same BHC	Binary variable indicating if lending and borrowing bank are part of the same bank holding company	Bundesbank monthly balance sheet statistics
Same network	Binary variable indicating if lending and borrowing bank are part of the same bank network	Bundesbank monthly balance sheet statistics

B Relationship Between Portfolio quality and NPL ratio

Table B1: Regression of first differences of portfolio quality on NPL ratio, and NPL ratio on portfolio quality

This table shows coefficients from OLS regressions of a bank's *NPL ratio* on its *Portfolio quality* and vice versa, both in first differences. Standard errors are clustered on the bank level and shown in parenthesis. The sample consists of quarterly bank observations of 2054 banks between 2009 and 2018. Regressions in column (2) and (4) include bank fixed effects. Appendix A provides a detailed variable description.

	Dependent variable: NPL ratio (first difference)		Dependent variable: Portfolio quality (first difference)	
	(1)	(2)	(3)	(4)
Portfolio quality (first difference)	0.002	0.004		
	(0.00)	(0.00)		
NPL ratio (first difference)			0.006	0.009
			(0.01)	(0.01)
Observations	62,390	62,388	62,390	62,388
Bank FEs	No	Yes	No	Yes

Standard (clustered on bank level) errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Finer Measure of Portfolio Similarity

This Appendix reports the analyses from Table 5, Table 6, Table 8 and Table 9 with the finer measure of sectoral portfolio similarity. Instead of using 10 different industries in calculating the similarity measure of equation 4, we use 100 industries here.

Table C1: Interbank lending, portfolio similarity (fine), and portfolio quality

This table shows the coefficients of a two-stage Heckman sample selection model on a matched sample. The sample consists of quarterly bank-pair observations of 2054 banks between 2009 and 2018. Bank pairs with a high-similarity in both regional and sectoral terms are matched to bank pairs of similar correlation between the lender's and the borrower's credit portfolio quality but with a low similarity both regional and sectoral terms. The dependent variables are the existence of a loan between lender i and borrower j at end-of-quarter t (Model 1, Probit), and the percentage change of interbank exposure between lender i and borrower j over the period (t-1) to t, respectively (Model 2 to 4, OLS). Model (3) includes lender and borrower fixed-effects, model (4) includes lender, borrower, and time fixed-effects. Coefficients are standardized, except for binary variables. Standard errors are clustered on the borrower and lender leve All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Common characteristics				
Portfolio similarity (industries, fine)	0.019***	0.711*	1.859***	1.291***
	(0.00)	(0.41)	(0.42)	(0.41)
Portfolio similarity (regions)	0.031***	0.864***	0.978***	1.178***
	(0.00)	(0.23)	(0.20)	(0.21)
Borrower characteristics				
Portfolio quality	-0.057***	-1.326**	-0.338	-0.283
	(0.00)	(0.59)	(0.50)	(0.62)
Portfolio quality × Portfolio similarity (industries, fine)	-0.003	0.026	0.327	0.058
	(0.00)	(0.47)	(0.26)	(0.25)
Portfolio quality × Portfolio similarity (regions)	0.017***	0.713***	0.509***	0.525***
	(0.00)	(0.20)	(0.14)	(0.14)
NPL ratio	-0.066***	-2.490***	-1.462***	-1.761***
	(0.00)	(0.44)	(0.42)	(0.50)
NPL ratio × Portfolio similarity (industries, fine)	0.001	-0.254	0.014	-0.396
	(0.00)	(0.44)	(0.25)	(0.26)
NPL ratio × Portfolio similarity (regions)	0.016***	0.575***	0.415***	0.385***
	(0.00)	(0.20)	(0.14)	(0.14)
Portfolio opacity	-0.023***	-1.285***	-0.695***	-0.687**
	(0.00)	(0.31)	(0.24)	(0.30)
Portfolio opacity × Portfolio similarity (industries, fine)	0.016***	0.622***	0.308**	0.298**
	(0.00)	(0.15)	(0.13)	(0.13)
Portfolio opacity × Portfolio similarity (regions)	0.005**	0.231	0.235*	0.298**
	(0.00)	(0.15)	(0.14)	(0.14)
Capital ratio (t-1)	-0.017***	-0.094	-1.625**	-0.147
	(0.00)	(0.56)	(0.75)	(0.71)
Liquidity ratio (t-1)	-0.004	-1.300**	2.400	1.384
	(0.00)	(0.65)	(2.50)	(2.53)
ROA (t-1)	0.102***	3.899***	2.889***	2.446***
	(0.00)	(0.66)	(0.79)	(0.83)
Loans-to-assets (t-1)	0.057***	2.121***	2.742**	3.321***
	(0.00)	(0.63)	(1.12)	(0.97)

Table C1: (continued) Interbank lending, portfolio similarity (fine), and portfolio quality

Size (t-1)	0.207***	2.509***	-0.096	-1.046
	(0.01)	(0.85)	(6.02)	(5.57)
Lender characteristics				
Portfolio quality	0.016***	0.840***	2.169***	2.085***
	(0.00)	(0.29)	(0.51)	(0.54)
NPL ratio	-0.023***	-0.448*	1.382***	0.181
	(0.00)	(0.26)	(0.39)	(0.41)
Portfolio opacity	0.016***	0.564***	0.601***	0.790***
	(0.00)	(0.17)	(0.16)	(0.17)
Capital ratio (t-1)	-0.091***	-1.857***	-2.183**	0.247
	(0.01)	(0.42)	(1.03)	(1.04)
Liquidity ratio (t-1)	0.022***	-1.144***	-5.416**	-6.114**
	(0.00)	(0.31)	(2.49)	(2.53)
ROA (t-1)	0.039***	1.689***	2.330***	1.354**
	(0.00)	(0.41)	(0.60)	(0.57)
Loans-to-assets (t-1)	-0.111***	-2.919***	1.087	3.034**
	(0.00)	(0.36)	(1.23)	(1.19)
Size (t-1)	0.025***	-0.707	-14.586***	-6.477
	(0.00)	(0.51)	(5.05)	(4.99)
Relationship characteristics				
Relationship lending	0.358***	3.474***	3.067***	3.198***
	(0.00)	(0.57)	(0.56)	(0.56)
Reverse relationship lending	0.074***	1.163***	1.527***	1.456***
	(0.00)	(0.27)	(0.29)	(0.28)
Δ Reverse exposure	0.019***	2.628***	2.578***	2.528***
	(0.00)	(0.44)	(0.44)	(0.44)
Same network	0.392***	9.580***	7.598***	7.856***
	(0.01)	(1.43)	(1.42)	(1.41)
Same BHC	0.490***	13.493***	14.544***	14.339***
	(0.06)	(2.15)	(2.30)	(2.30)
Difference in liquidity surplus (t-1)	0.000	-0.518**	11.592	10.358
	(0.00)	(0.25)	(9.75)	(9.88)
Heckman controls				
Credit relation (t-1)	2.930***			
	(0.01)			
IMR		60.962***	61.812***	61.868***
		(2.04)	(2.05)	(2.04)
Observations	2,545,319	655,517	655,493	655,493
Bank class controls	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes
R-squared	0.83	0.14	0.15	0.15

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C2: The impact of portfolio quality, NPL ratio, and portfolio opacity on interbank lending for different values of similarity (marginal effects)

This table reports marginal effects for the regression reported in Table C1. "Low similarity" refers to a similarity of 3 standard deviation below the variable mean, "high similarity" refers to a similarity of 3 standard deviations above the variable mean. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Portfolio quality (both similarities low)	-0.005***	-3.542**	-2.848***	-2.031**
	(0.00)	(1.76)	(0.96)	(0.94)
Portfolio quality (industry dissimilar, locality similar)	0.000	0.733	0.208	1.117
	(0.00)	(1.71)	(1.05)	(1.03)
Portfolio quality (industry similar, locality dissimilar)	-0.006***	-3.385**	-0.884	-1.684
	(0.00)	(1.64)	(1.03)	(1.15)
Portfolio quality (both similarities high)	-0.001	0.890	2.172**	1.464
	(0.00)	(1.36)	(1.05)	(1.09)
NPL ratio (both similarities low)	-0.006***	-3.453**	-2.748***	-1.727*
	(0.00)	(1.43)	(0.79)	(0.88)
NPL ratio (industry dissimilar, locality similar)	-0.001*	-0.004	-0.257	0.583
	(0.00)	(1.64)	(0.93)	(0.96)
NPL ratio (industry similar, locality dissimilar)	-0.006***	-4.977***	-2.667**	-4.105***
	(0.00)	(1.69)	(1.10)	(1.22)
NPL ratio (both similarities high)	-0.001	-1.528	-0.176	-1.796*
	(0.00)	(1.32)	(0.97)	(1.01)
Portfolio opacity (both similarities low)	-0.004***	-3.845***	-2.323***	-2.476***
	(0.00)	(0.80)	(0.70)	(0.71)
Portfolio opacity (industry dissimilar, locality similar)	-0.003***	-2.459***	-0.916*	-0.685
	(0.00)	(0.59)	(0.53)	(0.57)
Portfolio opacity (industry similar, locality dissimilar)	0.000	-0.112	-0.473	-0.690
	(0.00)	(0.69)	(0.64)	(0.73)
Portfolio opacity (both similarities high)	0.002***	1.274*	0.934	1.101*
	(0.00)	(0.72)	(0.61)	(0.58)
Observations	2,545,319	655,517	655,493	655,493
All other variables included (see Table C5)	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Interbank lending, portfolio similarity, and credit portfolio quality (matched sample)

This table shows the coefficients of a two-stage Heckman sample selection model on a matched sample. The sample consists of quarterly bank-pair observations of 2054 banks between 2009 and 2018. Bank pairs with a high-similarity in both regional and sectoral terms are matched to bank pairs of similar correlation between the lender's and the borrower's *Credit portfolio quality* but with a low similarity both regional and sectoral terms. The dependent variables are the existence of a loan between lender i and borrower j at end-of-quarter t (Model 1, Probit), and the percentage change of interbank exposure between lender i and borrower j over the period (t-1) to t, respectively (Model 2 to 4, OLS). Model (3) includes lender and borrower fixed-effects, model (4) includes lender, borrower, and time fixed-effects. Coefficients are standardized, except for binary variables. Standard errors are clustered on the borrower and lender level. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Common characteristics				
Portfolio similarity (industries, fine)	0.031***	1.092***	2.197***	1.495**
	(0.01)	(0.41)	(0.58)	(0.64)
Portfolio similarity (regions)	0.045***	1.378***	1.518***	1.407**
	(0.01)	(0.40)	(0.58)	(0.55)
Borrower characteristics				
Portfolio quality	-0.094***	-2.156***	-0.792	-1.252
	(0.01)	(0.72)	(0.80)	(0.87)
Portfolio quality × Portfolio similarity (industries, fine)	-0.013	-0.128	-0.096	-0.259
	(0.01)	(0.47)	(0.62)	(0.60)
Portfolio quality × Portfolio similarity (regions)	0.030***	1.559***	0.900*	0.915*
	(0.01)	(0.43)	(0.52)	(0.50)
NPL ratio	-0.067***	-2.245***	-1.469**	-2.248***
	(0.01)	(0.49)	(0.66)	(0.60)
NPL ratio × Portfolio similarity (industries, fine)	-0.002	0.114	0.096	-0.268
	(0.01)	(0.40)	(0.42)	(0.41)
NPL ratio × Portfolio similarity (regions)	0.033***	1.305***	0.820*	0.579
	(0.01)	(0.43)	(0.50)	(0.48)
Portfolio opacity	0.001	-0.041	0.152	0.134
	(0.01)	(0.49)	(0.48)	(0.58)
Portfolio opacity × Portfolio similarity (industries, fine)	0.014**	0.129	-0.103	-0.090
	(0.01)	(0.35)	(0.40)	(0.42)
Portfolio opacity × Portfolio similarity (regions)	0.018**	0.640	0.729	0.781
	(0.01)	(0.52)	(0.64)	(0.64)
Capital ratio (t-1)	-0.032***	-1.218**	-1.597**	-0.307
	(0.01)	(0.49)	(0.66)	(0.74)
Liquidity ratio (t-1)	0.010	-1.148	3.840	2.352
	(0.01)	(0.75)	(7.38)	(7.30)
ROA (t-1)	0.055***	2.445***	3.159***	2.674***
	(0.01)	(0.42)	(0.74)	(0.79)
Loans-to-assets (t-1)	0.082***	2.789***	3.129**	3.856**
	(0.01)	(0.62)	(1.51)	(1.79)
Size (t-1)	0.221***	2.824***	6.089	8.332
	(0.02)	(0.94)	(9.23)	(8.78)
Lender characteristics				
Portfolio quality	0.013	1.122**	1.176	1.274
	(0.01)	(0.54)	(0.76)	(0.81)
NPL ratio	-0.017*	-0.208	1.287*	0.073
	(0.01)	(0.40)	(0.74)	(0.76)

Table C3: (continued) Interbank lending, portfolio similarity, and credit portfolio quality (matched sample)

Portfolio opacity	0.005	0.430*	0.466**	0.747***
	(0.01)	(0.22)	(0.23)	(0.26)
Capital ratio (t-1)	-0.081***	-1.764***	-3.540***	-1.368
	(0.01)	(0.49)	(1.01)	(1.06)
Liquidity ratio (t-1)	0.000	-1.608**	-6.970	-7.081
	(0.01)	(0.64)	(7.79)	(7.68)
ROA (t-1)	0.020**	0.823**	0.545	-0.339
	(0.01)	(0.33)	(0.53)	(0.56)
Loans-to-assets (t-1)	-0.106***	-2.186***	0.378	2.324
	(0.01)	(0.48)	(2.01)	(1.83)
Size (t-1)	0.007	-1.279*	-14.500**	-9.332
	(0.02)	(0.67)	(6.51)	(6.37)
Relationship characteristics				
Relationship lending	0.421***	5.442***	3.633***	3.832***
	(0.01)	(1.12)	(0.99)	(1.00)
Reverse relationship lending	0.069***	1.221**	2.447***	2.371***
	(0.01)	(0.50)	(0.62)	(0.61)
Δ Reverse exposure	0.025***	2.293***	2.219***	2.127***
	(0.01)	(0.57)	(0.56)	(0.54)
Same BHC	0.564***	12.910**	6.929	6.976*
	(0.18)	(5.09)	(4.24)	(4.18)
Same network	0.391***	6.762***	5.743**	5.925**
	(0.03)	(1.62)	(2.84)	(2.83)
Difference in liquidity surplus (t-1)	0.028***	-0.012	2.158	1.852
	(0.01)	(0.48)	(3.35)	(3.29)
Heckman controls				
Credit relation (t-1)	2.885***			
	(0.03)			
IMR		61.645***	64.609***	64.591***
		(2.95)	(3.01)	(3.02)
Observations	226,190	69,509	69,452	69,452
Bank class controls	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes
R-squared	0.84	0.12	0.14	0.14

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C4: The effect of portfolio quality, NPL ratio, and portfolio opacity on interbank lending for different values of similarity (marginal effects, matched sample)

This table reports marginal effects for the regression on our matched sample reported in Table C8. "Low similarity" refers to a similarity of 3 standard deviation below the variable mean, "high similarity" refers to a similarity of 3 standard deviations above the variable mean. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Portfolio quality (both similarities low)	-0.008***	-6.451***	-3.205	-3.222
	(0.00)	(1.81)	(2.52)	(2.23)
Portfolio quality (industry dissimilar, locality similar)	0.002	2.905	2.197	2.270
	(0.00)	(2.19)	(2.60)	(2.52)
Portfolio quality (industry similar, locality dissimilar)	-0.012***	-7.217***	-3.781	-4.774*
	(0.00)	(2.26)	(2.35)	(2.51)
Portfolio quality (both similarities high)	-0.003	2.140	1.622	0.718
	(0.00)	(1.91)	(2.79)	(2.67)
NPL ratio (both similarities low)	-0.008***	-6.502***	-4.217***	-3.182**
	(0.00)	(1.49)	(1.50)	(1.45)
NPL ratio (industry dissimilar, locality similar)	0.002	1.330	0.701	0.292
	(0.00)	(1.95)	(2.47)	(2.38)
NPL ratio (industry similar, locality dissimilar)	-0.009***	-5.820***	-3.640*	-4.788**
	(0.00)	(2.08)	(2.18)	(2.14)
NPL ratio (both similarities high)	0.002	2.013	1.279	-1.313
	(0.00)	(1.74)	(1.96)	(1.83)
Portfolio opacity (both similarities low)	-0.005***	-2.347	-1.726	-1.938
	(0.00)	(1.67)	(2.23)	(2.34)
Portfolio opacity (industry dissimilar, locality similar)	0.001	1.493	2.649	2.748
	(0.00)	(2.19)	(2.46)	(2.43)
Portfolio opacity (industry similar, locality dissimilar)	-0.000	-1.575	-2.344	-2.480
	(0.00)	(2.30)	(2.70)	(2.71)
	(0.00)	(1.76)	(1.96)	(1.99)
Portfolio opacity (both similarities high)	0.006***	2.265	2.031	2.206
	(0.00)	(1.47)	(1.79)	(1.86)
Observations	226,190	69,509	69,452	69,452
Other variables included (see table C8)	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes

Standard errors (twoway clustered by lender and borrower) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Analyses on Matched Sample

This Appendix reports details on our matched sample and runs the analysis of Table 4 on our matched sample. The matching procedure is explained in Section 7.

Table D1: Characteristics of similar and non-similar bank pairs in the matched sample

This table compares relevant covariates of similar and non-similar bank pairs in our matched sample. The sample consists of quarterly bank-pair observations of 2054 banks between 2009 and 2018. Bank pairs with a high-similarity in both regional and sectoral terms are matched to bank pairs of similar correlation between the lender's and the borrower's *Portfolio quality* but with a low similarity both regional and sectoral terms. All variables are defined in Appendix A. The normalized difference is calculated as suggested by Imbens and Wooldridge (2009).

	Portfolio similarity (industries)	Portfolio similarity (regions)	Credit relation	Δ Exposure	Credit portfolio quality	NPL ratio	Portfolio opacity
Similar bank pairs							
(N=523,766)							
Mean	97.86	63.25	0.31	-0.06	98.61	2.33	2.34
Median	99.45	99.45	0	0	99.16	1.61	2.03
SD	6.20	6.20	0.461	43.47	1.78	3.13	2.05
Non-similar bank-pairs							
(N=251,560)[23]							
Mean	81.34	18.05	0.19	-0.05	97.54	3.17	2.76
Median	88.15	11.86	0	0	99.04	2.25	2.49
SD	17.98	18.42	0.394	30.13	3.84	3.85	2.22
Normalized difference (Imbens/Woolridge)	0.869	2.326	0.198	-0.000	0.253	-0.169	-0.139

Table D2: Bank and interbank characteristics

This table reports summary statistics of the bank and interbank characteristics of our matched sample. All variables are defined in Appendix A.

	Observations	Unit	Mean	SD	p5	Median	p95
Interbank Lending							
Credit relation	234,944	Dummy	0.31	0.46	0.00	0.00	1.00
Δ Exposure	232,945	%	-0.38	38.39	-9.81	0.00	7.41
Portfolio Similarity							
Portfolio similarity (industries)	234,944	%	92.27	13.00	66.76	98.22	99.90
Portfolio similarity (industries, fine classification)	234,944	%	78.51	19.23	38.69	83.71	99.09
Portfolio similarity (regions)	234,944	%	48.77	31.41	3.49	50.41	97.21
Bank characteristics							
Interbank borrowing/total borrowing	234,927	%	5.24	7.43	0.00	2.76	16.39
Interbank lending/total lending[24]	234,927	%	5.02	7.10	0.00	2.25	20.64
Portfolio quality	234,944	%	98.07	2.77	91.49	98.92	99.92
Portfolio opacity	234,944	%	1.74	1.63	0.30	1.22	5.01
NPL ratio	234,944	%	2.05	2.12	0.08	1.51	6.20
Capital ratio	234,655	%	22.28	14.97	12.15	19.35	37.61
Liquidity ratio	234,927	%	19.23	14.04	4.39	16.21	41.94
ROA	234,433	%	1.71	1.23	0.15	1.62	3.69
Loans-to-assets	234,918	%	50.21	19.46	11.90	53.42	77.76
Size	234,927	Log	9.09	2.48	5.42	8.98	13.19
Relationship characteristics							
Relationship lending	234,944		2.49	3.49	0.00	0.00	8.00
Reverse relationship lending	234,944		2.47	3.48	0.00	0.00	8.00
Δ Reverse exposure	234,944	%	-0.38	38.43	-10.18	0.00	7.68
Same BHC	234,944	Dummy	0.00	0.05	0.00	0.00	0.00
Same network	234,944	Dummy	0.10	0.30	0.00	0.00	1.00
Difference in liquidity surplus (t-1)	234,910	ppt	0.00	6.15	-9.60	0.00	9.60

Table D3: Interbank lending, portfolio quality, and portfolio opacity (matched sample)

This table shows the coefficients of a two-stage Heckman sample selection model on a matched sample. The sample consists of quarterly bank-pair observations of 2054 banks between 2009 and 2018. Bank pairs with a high-similarity in both regional and sectoral terms are matched to bank pairs of similar correlation between the lender's and the borrower's *Portfolio quality* but with a low similarity both regional and sectoral terms. The dependent variables are the existence of a loan between lender i and borrower j at end-of-quarter t (Model 1, Probit), and the percentage change of interbank exposure between lender i and borrower j over the period (t-1) to t, respectively (Model 2 to 4, OLS). Model (3) includes lender and borrower fixed-effects, model (4) includes lender, borrower, and time fixed-effects. Coefficients are standardized, except for binary variables. Standard errors are clustered on the borrower and lender level. All variables are defined in Appendix A.

	(1) Probit **Credit relation**	(2) OLS **Δ Exposure**	(3) OLS **Δ Exposure**	(4) OLS **Δ Exposure**
Borrower characteristics				
Portfolio quality	-0.072***	-1.745**	-0.195	-0.916
	(0.01)	(0.86)	(0.83)	(0.87)
NPL ratio	-0.080***	-2.447***	-1.642**	-2.161***
	(0.01)	(0.52)	(0.64)	(0.53)
Portfolio opacity	0.000	0.125	0.315	0.269
	(0.01)	(0.51)	(0.44)	(0.53)
Capital ratio (t-1)	-0.038***	-1.442***	-2.015***	-0.452
	(0.01)	(0.47)	(0.70)	(0.72)
Liquidity ratio (t-1)	0.011	-1.145	3.776	2.046
	(0.01)	(0.71)	(7.44)	(7.32)
ROA (t-1)	0.055***	2.388***	3.160***	2.540***
	(0.01)	(0.42)	(0.69)	(0.77)
Loans-to-assets (t-1)	0.072***	2.242***	1.846	3.224*
	(0.01)	(0.59)	(1.49)	(1.72)
Size (t-1)	0.213***	2.599***	4.484	7.360
	(0.02)	(0.91)	(9.52)	(9.03)
Lender characteristics				
Portfolio quality	0.022*	1.284**	1.339*	1.454*
	(0.01)	(0.53)	(0.79)	(0.83)
NPL ratio	-0.019*	-0.264	1.425**	-0.048
	(0.01)	(0.40)	(0.72)	(0.76)
Portfolio opacity	0.006	0.441*	0.460**	0.721***
	(0.01)	(0.23)	(0.23)	(0.26)
Capital ratio (t-1)	-0.088***	-2.045***	-4.041***	-1.535
	(0.01)	(0.47)	(1.00)	(1.08)
Liquidity ratio (t-1)	0.001	-1.688***	-6.967	-6.891
	(0.01)	(0.65)	(7.86)	(7.71)
ROA (t-1)	0.020**	0.853***	0.734	-0.300
	(0.01)	(0.32)	(0.54)	(0.56)
Loans-to-assets (t-1)	-0.114***	-2.435***	-0.562	1.948
	(0.01)	(0.48)	(2.02)	(1.86)
Size (t-1)	0.008	-1.313**	-17.029**	-10.598
	(0.02)	(0.65)	(6.76)	(6.45)
Relationship characteristics				
Relationship lending	0.421***	5.388***	3.575***	3.844***
	(0.01)	(1.12)	(1.00)	(1.01)
Reverse relationship lending	0.072***	1.410***	2.509***	2.441***

Table D3: (continued) Interbank lending, portfolio quality, and portfolio opacity(matched sample)

	(0.01)	(0.50)	(0.61)	(0.61)
Log Reverse exposure	0.025***	2.299***	2.229***	2.133***
	(0.01)	(0.57)	(0.56)	(0.54)
Same BHC	0.569***	12.476**	7.135*	7.120*
	(0.18)	(5.03)	(4.21)	(4.17)
Same network	0.412***	6.484***	6.297**	6.357**
	(0.03)	(1.68)	(2.76)	(2.77)
Difference in liquidity surplue (t-1)	0.028***	-0.009	2.113	1.723
	(0.01)	(0.49)	(3.39)	(3.31)
Heckman controls				
Credit relation (t-1)	2.887***			
	(0.03)			
IMR		61.572***	64.529***	64.532***
		(2.95)	(3.01)	(3.02)
Observations	226,190	69,509	69,452	69,452
Bank class controls	Yes	Yes	No	No
Lender & borrower FEs	No	No	Yes	Yes
Time FEs	No	No	No	Yes
(Pseudo) R-squared	0.84	0.12	0.14	0.14

Standard errors (twoway clustered by lending and borrowing bank) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$