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Banks of a Feather: The Informational Advantage of Being Alike

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 opaque loan portfolios, which do not obtain credit from dissimilar peers.

JEL codes: E50, G11, G20, G21
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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 tight-

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ening 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 portfolios. Leaning on Flannery (1996), we hypothesize that this informational advantage implies that 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 borrowing banks with opaque portfolios. 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 (Pérignon, Thesmar, and Vuillemey 2018), and (iii) how information asymmetries can be overcome in the interbank market (Heider, Hoerova, and Holthausen 2015).

Our analysis is built on quarterly, bilateral bank-to-bank and bank-to-firm exposure of more than 2,000 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, that is, 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 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 (Afonso, Kovner, and Schoar 2011, Craig, Fecht, and Tümer-Alkan 2015), the NPL ratio does not capture the default risk inherent in the *current* loan portfolio, but the one of the past.

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 2.

We also include a new measure of portfolio opacity building on banks' disagreement about the PD of the same firm, that is, 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 (Braeuning and Fecht 2017, Morgan 2002).[3]

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 affect 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) (cf. 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 similar loan portfolios lend significantly more to each other, with a particularly strong effect on the intensive margin. While the average quarterly change in interbank lending is 0.41%, banks that are one standard deviation more similar in terms of industry exposure increase their quarterly lending by 218 basis points, whereas banks with one standard deviation higher regional similarity increase it by up to 121 basis points. The effect on the extensive margin is also significant but smaller in magnitude: while the unconditional probability of lending is 26.5%, a one standard deviation higher similarity in loan portfolios with respect to industries is associated with a 4-basis-point higher probability of forming a lending relationship. The corresponding increase associated with one standard deviation higher regional similarity is 14 basis points. Lending between similar banks proves to be particularly important for borrowers with opaque loan portfolios. In this context, we show that while portfolio opacity is generally associated with lower interbank lending volumes, this negative relationship does not apply to interbank relationships where portfolio similarity between banks exceeds three stan-

3. External ratings are subject to the policies of the rating agencies. They stabilize ratings over time so as to underscore the predictive power. Hence, rating developments are biased. In addition, external ratings exist for large, listed companies only. In the case of Germany, the number of externally rated firms is fairly small. In contrast, PDs are confidential and therefore not biased by publication concerns. Yet, a financial institution may bias its PD estimates with regard to the implications for supervision and regulation. Supervisors restrain this behavior by checking the PD-estimation models.

dard deviations above the mean. Our findings hold after controlling for relationship lending, established bank networks, characteristics of both the lending and borrowing banks, market conditions, as well as fixed effects for lender, borrower, lender × borrower, and time (i.e., quarter-year) fixed effects.

We ensure that our findings are driven by changes in interbank credit supply, rather than demand, by following the credit supply identification methodology proposed by Khwaja and Mian (2008). When including borrowing bank × quarter fixed effects, which absorb all borrower-related variation in each time period, we replicate all our core findings.[4]

Economically, preferential lending between similar banks holds similar significance to relationship lending, which is one of the most important determinants of interbank lending in the literature (Braeuning and Fecht 2017). Both variables are robust predictors of the existence of an interbank loan and the amounts lent. However, we find evidence of informational advantages for similar banks, as they make lending contingent on the forward-looking assessment of portfolio quality, but not for those in long-standing relationships. As such, similarity and relationship appear to measure two relevant but distinct dimensions of interbank dynamics: portfolio similarity aids in assessing private information from a peer, even in the absence of a previous lending relationship, while relationship lending builds trust, thereby increasing the likelihood of subsequent lending relationships. Our results thus suggest that portfolio similarity and relationship lending are not competing but are rather complementary drivers 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 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, Thesmar, and Vuillemey (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, above all, how they obtain this information.

4. In the Online Appendix, we also show that our results are robust to using an alternative approach for identifying credit supply that is also based on absorbing interbank credit demand variation via fixed effects but uses a less restrictive framework. This approach that leans on similar identification schemes presented in Berton et al. (2018), Greenstone, Mas, and Nguyen (2020), Degryse et al. (2019), and Degryse, Karas, and Schoors (2019) presumes 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 once the corresponding fixed effects for the borrowing bank are introduced can thus be interpreted as a supply response to characteristics of the borrowing bank.

Our paper is also related to the strand of literature that emphasizes the importance of repeated interactions to obtain information on an interbank counterparty. Affinito (2012), Braeuning and Fecht (2017), Cocco, Gomes, and Martins (2009), Hatzopoulos et al. (2015), and Temizsoy, Iori, and Montes-Rojas (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 results suggest that portfolio similarity can be an important, yet so far overlooked, complement to interbank relationships as a mechanism allowing banks to obtain information about potential interbank borrowers.

To this end, we specifically differentiate our work from Braeuning and Fecht (2017), who also explore the German interbank market but are exclusively focused on pre-existing interbank relationships as a source of information about peers. While we confirm that relationships play a role in facilitating interbank exposures, we enrich the picture by demonstrating that similarity plays an important role as well. Moreover, by horse-racing similarity and relationships, we find that even though the two can partially overlap, there is still a relevant and significant contribution of similarity that goes beyond and above that of relationships in shaping interbank exposures. Additionally, we demonstrate that not only relationships but also similarity can contribute to overcoming the particular challenges that banks with opaque portfolios face when trying to access the interbank market.

Fecht, Nyborg, and Rocholl (2011) presume that correlated liquidity shocks may reduce banks' propensity to lend to each other. Following this reasoning, banks are expected to lend less to other banks with similar loan portfolios, as this would be associated with correlated liquidity shocks. Our results, however, indicate that the opposite is the case and that the correlated liquidity shocks channel is not important enough to challenge the robust, positive relation between portfolio similarity and interbank lending in our data.

When analyzing the importance of similarity, we saturate our models with a wide range of control variables whose relevance has been shown by several papers investigating the role of lender and borrower characteristics and market conditions for interbank lending decisions (Furfine 2001, Afonso, Kovner, and Schoar 2011, Angelini, Nobili, and Picillo 2011, Fecht, Nyborg, and Rocholl 2011, Brossard and Saroyan 2016). Hence, we contribute to this strand of the literature by including in the analysis the similarity as a 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). Moreover, in contrast to 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, Gomes, and Martins 2009, Ladley 2013). Regardless of their interbank connections, banks with a similar loan portfolio are exposed to the risk of indirect contagion, for example, by fire sales or feedback effects with the real sector (Allen, Babus, and Carletti 2012, Diamond and Rajan 2011, Silva, Alexandre, and Tabak 2017). 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, Georg, and Hazell (2021) rationalize this socially suboptimal 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 nonfavorable 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 trade-off is similar to the conflict between focus and diversification in corporate lending analyzed by Acharya, Hasan, and Saunders (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 2 presents our data. In Section 3, we show that banks lend preferably to similar peers and that they react to private information on the peer's portfolio quality–something dissimilar banks seem unable to do. Section 4 concludes.

1. 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, Nyborg, and Rocholl (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 databases from providers, like Bloomberg, which all banks can access. All lenders can thus incorporate accurate information on the peer's capital, liquidity, and profitability to a similar degree. Changes in the asset quality, in contrast, are reflected in the financial report only with a substantial delay. Timely information on a peer's asset quality is, therefore, private and thus more costly to obtain (Morgan 2002).

We presume, however, that for banks with a similar portfolio, the costs of obtaining information about the asset quality of a potential borrowing bank are lower than for banks with less similar portfolios. This presumption is based on assuming that a lender can assess the quality of a peer's loan portfolio by leveraging information about the specific default risks in the industries and regions to which the peer is exposed. For banks with exposure to the same industries and/or regions, tracking the time-varying default risks of these sectors is less costly, as most relevant information has already been acquired in the process of granting loans to firms in these areas. Consequently, lending conditions between similar banks should more accurately reflect the borrower bank's asset quality. Moreover, lenders should be aware of their informational advantage toward similar peers and prefer to lend to similar counterparties.

This line of argument requires that the lender can observe the portfolio similarity with peer banks, at least imperfectly. More specifically, while we do not assume that all banks have access to perfect information about the portfolio composition of all other banks, we do assume that banks are aware of whether their portfolio is similar or dissimilar to that of a peer. Several arguments support this assumption. First, banks are aware of their competitors. They can gauge the similarity to peers' portfolios based on the information they have about where their potential borrowers ultimately obtain loans. This is particularly true in Germany, where most banks have a strong geographic focus and many industries are clustered geographically (Fink et al. 2016, Tente, von Westernhagen, and Slopek 2017).[5] Moreover, syndicated lending, which in Germany often involves relatively stable sets of participating banks, allows banks to observe a significant portion of the portfolios of other banks within these syndicates. Finally, bank risk is held disproportionately by other banks, forcing banks to gain as much knowledge as possible on peers, including information on their portfolio (Bekaert and Breckenfelder 2019). In other words, even though information about bank portfolios is not publicly available, banks can infer the portfolio composition of banks with overlapping exposures to the same industries or regions and thus gauge the degree of similarity. This assumption of the observability of close peers' portfolios aligns with the literature on specialization and segmentation in bank lending (see, e.g., Acharya, Hasan, and Saunders 2006, Blickle, Parlatore, and Saunders 2023, and Paravisini, Rappoport, and Schnabl 2023), where similar types of observability are assumed.

In order to analyze the role of portfolio similarity and opacity on the extensive margin and the intensity of interbank relationships, we draw on a seminal model of interbank lending proposed by Flannery (1996). This model examines lending equilibria in a simple setting with two potential lenders (*Bank A* and *Bank B*), where

5. Anecdotal evidence we gathered from supervisors suggests that bank executives demonstrate a very good knowledge of the competitors of their banks.

one lender has more precise information about the borrower's asset quality than the other, and both lenders are aware of their informational (dis)advantage. The setup of the model is straightforward: there are many potential borrowing banks, some with a low PD (their net worth V_G is sufficient to repay the loan provided the interest is not too high) and some with a high PD (their net worth V_B is insufficient to repay the loan). Each of the potential lenders i observes a signal $\hat{V}_j$ of the jth borrowing bank.

$$\begin{aligned} &\text{if } \hat{V}_j = 1 \text{ then } Pr(V_j = V_G) = p_i \text{ and} \\ &\qquad\qquad Pr(V_j = V_B) = 1 - p_i \\ &\text{if } \hat{V}_j = 0 \text{ then } Pr(V_j = V_B) = p_i \text{ and} \\ &\qquad\qquad Pr(V_j = V_G) = 1 - p_i. \end{aligned} \tag{1}$$

The differing quality of the signal is represented by the difference between the p_i observed by lenders A and B. Assume that $p_A > p_B$, implying that *Bank A* has a more precise estimate of the jth borrower's portfolio quality than *Bank B*. *Bank A* is aware of its informational advantage and sets the lending rate R_A accordingly:

$$\begin{aligned} &1 < (1 + R_A)p_A + 0(1 - p_A) \text{ or} \\ &\qquad R_A > (1/p_A) - 1. \end{aligned} \tag{2}$$

Bank B, aware of its informational disadvantage, would offer a lending rate R_B similarly, such that $R_B > (1/p_B) - 1$. Since $p_A > p_B$, the interest rate offered by *Bank B* is higher than that offered by *Bank A*. Consequently, *Bank B* knows it will only be approached by borrowing banks that have been rejected by *Bank A*—either because they genuinely have a high PD or because *Bank A* has incorrectly assessed their default probability as high. Therefore, the interest rate that *Bank B* will offer must comply with:

$$\begin{aligned} &1 < (1 + R_B)p_B(1 - p_A) + 0 \text{ or} \\ &\quad R_B > 1/(p_B(1 - p_A)) - 1. \end{aligned} \tag{3}$$

The comparison between R_A and R_B suggests that *Bank A*, which has more precise information about the borrower's portfolio quality (and hence the PD), will offer better lending conditions. Consequently, *Bank A* has a higher probability of forming an interbank relationship and is expected to provide more interbank lending.

Applying the results of the model to our setting, where banks with similar portfolios have more precise information about portfolio quality and, hence, default probabilities, leads to the following hypothesis[6]:

6. In all our hypotheses, we 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 data set does not include interest rates and therefore does not allow for an analysis of price effects.

Hypothesis 1. Bank pairs with similar loan portfolios lend more to each other in interbank markets.

We can also employ the setup by Flannery (1996) to derive theoretical predictions about how interbank lending changes when the borrowing bank changes its type from a good bank to a bad bank (i.e., a deterioration of asset quality). While the more similar lender will observe this change (from V_G to V_B) with high precision and will discontinue lending, the less similar lender (who has less precise information about the quality of the bank) will have a higher probability of not observing the change in the signal. This results in the following:

Hypothesis 2. Lenders with a similar loan portfolio reduce lending when the borrower's portfolio quality deteriorates. Lenders with a dissimilar loan portfolio are less sensitive to borrower's portfolio deterioration than lenders with a similar portfolio.

We can further extend Flannery's framework to account for the difference between lending to banks with more or less opaque asset portfolios. We argue that the mitigation of information asymmetries through similar portfolios should be particularly relevant for borrowing banks with more opaque portfolios. In the model's framework, this implies that for these borrowing banks, the quality of the signal received by both lenders will be lower, that is, both p_A and p_B will decrease. Consequently, banks with opaque portfolios will generally face worse borrowing conditions. Additionally, the difference in signal precision between *Bank A* and *Bank B* will be more pronounced ($p_A - p_B$ will be larger) compared to the situation where the borrowing bank's portfolio is less opaque. In other words, since it is particularly difficult for lenders without inside information to judge the quality of opaque portfolios, the advantage of lenders with a similar portfolio in assessing these portfolios should be particularly strong. As a result, banks with more opaque portfolios should be more likely to borrow from more similar lenders (both in terms of the intensive and extensive margin), allowing us to formulate our final hypothesis:

Hypothesis 3. Banks with a more opaque loan portfolio receive more loans from peers with a similar loan portfolio.

2. DATA AND VARIABLES

2.1 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

TABLE 1

Banks and Interbank Credit Relations

Bank type	Lending banks	Borrowing banks
Large private banks	6	6
Smaller private banks	199	185
Head institutes of cooperative & saving banks	14	14
Saving banks	472	472
Cooperative banks	1,381	1,379
Other/not classified	22	21
Total	2,094	2,084
Lender-borrower combinations in 40 quarters	2,860,121	
True credit relations	757,974	
- between banks of same network (saving or cooperative banks)	111,969	
- between banks of same holding company	2,202	

Note: 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 combinations* 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 that do actually have outstanding bilateral exposure in a given quarter.

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. This exposure to the real economy includes micro, small, mid-cap, and large companies, allowing us to conduct an analysis that is not tilted toward loans taken by large companies, as is often the case with other frequently used data sources, such as syndicated loan data.[7]

The credit register provides additional information about each borrower of a bank's loan portfolio. Most importantly, it includes the borrower's 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 2,094 lending and 2,084 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, that is, regional heads of the savings banks network ("Landesbanken") or head institutes of the cooperative financial services

7. 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 do 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.

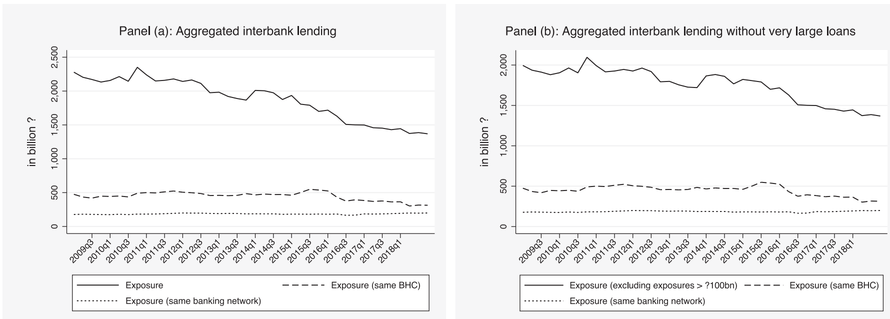

Fig. 1. Interbank Lending in Germany, 2009 to 2018.

NOTES: 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. Panel A aggregates all interbank exposures. Panel B only aggregates exposures below € 100bn.

network.[8,9] 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 2,860,121 lender-borrower-quarter combinations.[10]

2.2 *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 757,974 interbank credit relations, out of which 111,969 are between banks from the same banking network, for example, between two savings banks or two cooperative banks, 2,202 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 (Allen et al. 2020), the market has slightly shrunk over our sample period, in particular for very large loans. However, with an average quarterly credit exposure of about 1.4

8. For further details on the German banking sector, we refer to Braeuning and Fecht (2017).

9. 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, but never borrowed from the interbank market. See also endnote 9.

10. 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, that is, the finding that most German banks do never lend to each other directly (Craig and von Peter 2014).

trillion euros by the end of 2018, interbank exposure still represents 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, that is, if to lend or borrow at all, and the intensive margin of credit, that is, how much to lend or borrow. To address both dimensions, we construct two dependent variables: the binary variable $Credit\ relation_{i,j,t}$ 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.[11]

To capture the intensive margin of interbank lending, we calculate the percentage change in on-balance bilateral exposure[12] between lending bank i and borrowing bank j from quarter-year $t-1$ to quarter-year t ($\Delta Exposure_{i,j,t}$). We interpret $\Delta Exposure_{i,j,t}$ as the provision of additional or reduced liquidity by lender i to borrowing bank j during quarter t. We use gross, rather than net exposure, as a bank's lending decision should depend on the granting of new loans, regardless of whether old loans have been repaid (by the borrowing bank to the lending bank or vice versa) in a given month.[13] We calculate the (approximate) percentage change in bilateral exposure as:

$$\Delta Exposure_{i,j,t} = ln(Exposure_{i,j,t}) - ln(Exposure_{i,j,t-1}). \tag{4}$$

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 eval-

11. 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).

12. While off-balance exposure could also be significant in interbank markets, we focus on on-balance exposure as it is closest to interbank loans and therefore aligns most closely with the theoretical mechanism we envision. However, we show that our findings are robust when using both on- and off-balance exposures, as demonstrated in Table D4 in the Online Appendix D.

13. To ensure that our results are not driven by reciprocal effects of extending or reducing interbank loans, we control for the change in reverse exposures in all our specifications. When we run our analysis on net exposure, rather than gross exposure (see Table D5 in Online Appendix D), the effects on the extensive margin remain the same, with minor changes due to the exclusion of reverse exposure as a control variable when using net exposures. However, results for the intensive margin change, with most effects becoming insignificant. This is because netting exposures is equivalent to merging two observations in our data-one where bank A acts as a lender and bank B as a borrower, and another where bank B acts as a lender and bank A as a borrower. This is problematic in all cases where both bank A and bank B extend or reduce lending during (and probably on different days of) the quarter. An extension or reduction by both banks is then misinterpreted as a zero change—something that should happen more frequently for similar than for dissimilar banks.

uation of the counterparty's creditworthiness is most relevant for long-term exposure, the German data provide an excellent setting to study peer monitoring. Given the low share of overnight lending in the German market, our quarterly data capture the most important variation in interbank lending.

2.3 Explanatory Variables

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

2.3.1 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 toward 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 Table D1 in Online Appendix D. To measure regional exposure, we group loans based on the first digit of the firms' zip code, resulting in exposure to a maximum of nine distinct regions per bank.

For sectoral exposure, we construct the vectors $X_{i,t}$ and $X_{j,t}$ containing the lending bank's loan exposure $x_{i,p,t}$ to each industry p (out of $P = 10$ industries) at quarter t in euros and the borrowing bank's loan exposure $x_{j,p,t}$ to industry p at quarter t, respectively. Similarly, for regional exposure, we construct the vectors $Y_{i,t}$ and $Y_{j,t}$ containing the lending bank's loan exposure $x_{i,q,t}$ to each region q (out of $Q = 9$ regions) at quarter t in euros and the borrowing bank's loan exposure $x_{j,q,t}$ to region q at quarter t, respectively. For each lender-borrower pair in quarter t, the cosine similarity between the two vectors is then defined as:

$$\textit{Portfolio Similarity (industries)}_{i,j,t} = \frac{X_{i,t} \cdot X_{j,t}}{||X_{i,t}||||X_{j,t}||} = \frac{\sum_{p=1}^{P} x_{i,p,t} x_{j,p,t}}{\sum_{p=1}^{P} x_{i,p,t}^2 \sum_{p=1}^{P} x_{j,p,t}^2}, \tag{5}$$

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.

$$\textit{Portfolio Similarity (regions)}_{i,j,t} = \frac{Y_{i,t} \cdot Y_{j,t}}{||Y_{i,t}||||Y_{j,t}||} = \frac{\sum_{q=1}^{Q} x_{i,q,t} x_{j,q,t}}{\sum_{q=1}^{Q} x_{i,q,t}^2 \sum_{q=1}^{Q} x_{j,q,t}^2}. \quad (6)$$

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, that is, 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.

2.3.2 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 to (i) identify information about a borrowing bank that is private and (ii) ensure that this information is indeed relevant for the lending decision. In the following, we introduce our measure of *Portfolio quality* and confirm its relevance for privately assessing a peer's asset quality.

We measure the quality of a bank's loan portfolio by aggregating internal information about the credit risk of each of its borrowers. This information is obtained from quarterly regulatory filings, in which banks report the PD of each borrower to the regulator. The regulator uses this information to quantify banks' credit risk and determine their capital requirements. The PD is an internal bank estimate of the likelihood that a counterparty will default on a loan or an off-balance sheet financial contract within a year. Banks are required to estimate the PD in accordance with the data quality and methodological standards specified in the Capital Requirements Regulation (CRR, Article 180). Banks update their PD estimates quarterly for all counterparties, incorporating any new information obtained about borrowers' creditworthiness.[15]

Only banks using the Internal Rating-Based Approach (IRB banks) are required to report PDs. For banks using the Credit Risk Standardised Approach (SA banks), PD reporting is not mandatory but is still often conducted.[16] Of our sample of 2,084 borrowing banks, 135 report PDs during our sample period, including 56 IRB banks and 79 SA banks. Reporting banks tend to be larger and consistently involved in interbank markets over our sample period. As a result, they account for 45% of our quarterly lender-borrower links (including both actual credit relations and instances where potential lenders do not lend to potential borrowers in a given quarter). To

15. For more details on the regulatory context of the PD, see the CRR, particularly Article 180. For the estimation of PDs by IRBA banks see next paragraph, Art. 171 Abs. 2 CRR and European Banking Authority (2017).

16. According to the CRR, banks can choose to use either the Credit Risk Standardised Approach, where the regulator assigns risk-weights based on asset class, or the IRB Approach, where the regulator estimates risk-weights based on bank-reported PDs for each borrower.

avoid bias when focusing only on this selective subsample, we derive information on nonreporting banks' loan portfolios from PDs of reporting banks. Specifically, we obtain a borrower-specific PD using the quarterly median PD reported for each borrower. For example, if firm A has outstanding credit with banks B and C, which report PDs, and with bank D, which does not report PDs, we use the median of the PDs reported for firm A by banks B and C. This approach allows us to include PDs for all borrowers, except those who only have exposure to banks that do not report PDs. To ensure our results are valid when considering only PD-reporting borrowers, we provide robustness tests that include only PD-reporting borrowers in Table D7 in Appendix D, which yield qualitatively similar results.

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 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:

$$Portfolio\ quality_t = 1 - \frac{1}{\sum_{k \in K} Exposure_{k,t}} \sum_{k \in K} Exposure_{k,t} \times PD_{k,t}. \tag{7}$$

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 (column (1)) and within each bank (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, Karavias, and Sarafidis (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's (2012) Z statistics < -50.

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 analyses presented in Table 2 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.

Portfolio quality is not only a relevant measure of a bank's asset quality but also a private one. We will provide evidence for the measure's privateness in the

TABLE 2

Predicting Nonperforming Loans (NPL) Ratios with Portfolio Quality

	Dependent variable: NPL ratio (t)	
	(1)	(2)
Portfolio quality (t)	−0.370***	−0.118***
	(0.00)	(0.00)
R^2	0.16	0.70
N	57,942	57,925
Portfolio quality ($t-1$)	−0.368***	−0.104***
	(0.00)	(0.00)
R^2	0.16	0.71
N	55,701	55,656
Portfolio quality ($t-2$)	−0.365***	−0.089***
	(0.00)	(0.00)
R^2	0.17	0.73
N	53,513	53,494
Portfolio quality ($t-3$)	−0.360***	−0.071***
	(0.00)	(0.00)
R^2	0.17	0.73
N	51,433	51,400
Portfolio quality ($t-4$)	−0.356***	−0.052***
	(0.00)	(0.00)
R^2	0.17	0.73
N	49,405	49,375
Portfolio quality ($t-5$)	−0.352***	−0.039***
	(0.00)	(0.00)
R^2	0.17	0.74
N	47,414	47,343
Portfolio quality ($t-6$)	−0.349***	−0.026***
	(0.00)	(0.00)
R^2	0.17	0.75
N	45,459	45,435
Portfolio quality ($t-7$)	−0.346***	−0.020***
	(0.00)	(0.00)
R^2	0.17	0.75
N	43,586	43,548
Bank fixed effects	No	Yes

Note: This table shows coefficients from OLS regressions of a bank's 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 2,094 banks between 2009 and 2018. Regressions in column (2) include bank fixed effects. Appendix A in the Online Appendix provides a detailed variable description. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

next chapter, where we show that the average interbank peer does not react to changes in *portfolio quality*, indicating that the measure is unobserved by the average counterparty.

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 contain 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, Davies, and Flannery (2000) find that supervisors produce valuable information on bank conditions, which is complementary to information produced in the financial market.

2.3.3 Portfolio opacity. We observe diverse PD assessments for the same corporate borrowers by different banks, indicating that banks often disagree about the creditworthiness of corporate borrowers. We build our measure of *Portfolio opacity* on this disagreement among peers about a bank's *Portfolio quality*. For each borrower k at quarter t, we determine the level of disagreement about its PD by calculating the standard deviation of all PDs assigned to it in that quarter ($SD_{k,t}$). We then define a bank's *Portfolio opacity* as the quarterly, exposure-weighted average of these standard deviations:

$$Portfolio\ Opacity_t = \frac{1}{\sum_{k \in K} Exposure_{k,t}} \sum_{k \in K} Exposure_{k,t} \times SD_{k,t}, \tag{8}$$

Portfolio opacity captures asset opacity from the perspective of peers. For interbank credit decisions, this measure should be more relevant than external measures used in the literature, such as the disagreement of rating agencies or the volatility of CDS spreads (Braeuning and Fecht 2017, Morgan 2002).

2.3.4 Control variables. Corresponding to the argument in Section 1, 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 nonsimilar pairs (see Appendix B in the Online Appendix).

Long-standing lending relationships are an important determinant of interbank lending (Braeuning and Fecht 2017, Cocco, Gomes, and Martins 2009). To avoid confusing the impact of *Portfolio similarity* and relationship lending, we control for the frequency of previous interactions over a 2-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.

$$Relationship\ lending_{i,j,t} = ln(1 + \sum_{t'=1}^{T} I(Credit\ relation_{i,j,t'} = 1)). \tag{9}$$

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.

$$Reverse\ relationship\ lending_{i,j,t} = ln(1 + \sum_{t'=1}^{T} I(Credit\ relation_{j,i,t'} = 1)). \tag{10}$$

A similar portfolio should go along with similar liquidity shocks (Fecht, Nyborg, and Rocholl 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:

$$\begin{aligned} Difference\ in\ liquidity\ surplus_{i,j,t} &= Liquidity\ surplus_{i,t} - Liquidity\ surplus_{j,t} \\ &= Liquidity\ ratio_{i,t} - \overline{Liquidity\ ratio_{i}} \\ &\quad - (Liquidity\ ratio_{j,t} - \overline{Liquidity\ ratio_{j}}), \end{aligned} \tag{11}$$

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, that is, there is preferred lending between savings banks or cooperative banks (Fecht, Nyborg, and Rocholl 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. To ensure that our results are not driven by peculiar lending behavior between banks from the same network, we repeat our analyses for the subsample of lending relations between banks from different networks. The results, presented in Table D6 in Online Appendix D, yield qualitatively similar estimates.

As being part of the same banking holding company could also drive lending patterns, we include a dummy variable for banks belonging to the same bank holding company in all our regressions. Moreover, following the literature, we include the *Size* of the lending and borrowing bank as measured by ln(Total Assets) (Angelini, Nobili, and Picillo 2011, Ashcraft, McAndrews, and Skeie 2011, Fecht, Nyborg, and Rocholl 2011, Furfine 2001, Gabrieli 2009, Iori, Kapar, and Olmo 2015). To control for unobserved, stable bank-specific characteristics, we include lender and borrower fixed effects. To account for changing macro-economic conditions that affect all banks (Angelini, Nobili, and Picillo 2011), we also include quarter-year fixed effects. To check which part of our effect can be traced back to time-varying similarity (i.e., two banks

TABLE 3

Bank and Interbank Characteristics

	Observations	Unit	Mean	SD	p5	Median	p95
Interbank lending							
Credit relation	2,860,121	Dummy	0.27	0.44	0.00	0.00	1.00
Δ Exposure	2,837,718	%	−0.41	35.39	−3.83	0.00	2.51
Portfolio similarity							
Portfolio similarity (industries)	2,860,121	%	91.61	14.57	63.23	97.10	99.79
Portfolio similarity (industries, fine classification)	2,860,121	%	73.90	21.73	28.94	79.20	98.40
Portfolio similarity (regions)	2,860,121	%	38.75	25.41	4.99	34.64	89.18
Bank characteristics							
Interbank borrowing/total borrowing	2,859,774	%	20.94	20.74	2.52	14.39	51.85
Interbank lending/total lending[a]	2,859,777	%	19.62	13.95	2.34	16.57	45.22
Portfolio quality	2,860,121	%	97.94	2.79	92.24	98.78	99.91
Portfolio opacity	2,860,121	%	1.80	1.67	0.30	1.29	4.99
NPL ratio	2,860,121	%	2.22	2.50	0.06	1.59	6.11
Capital ratio ($t-1$)	2,854,737	%	24.09	32.76	11.67	18.75	35.33
Liquidity ratio ($t-1$)	2,859,774	%	24.09	32.76	11.67	18.75	35.33
ROA ($t-1$)	2,854,745	%	1.37	2.35	−0.32	1.56	3.47
Loans-to-assets ($t-1$)	2,859,734	%	53.05	19.27	13.41	56.22	79.88
Size ($t-1$)	2,859,774	log	8.97	2.39	5.44	8.76	12.74
Relationship characteristics							
Relationship lending	2,860,121		2.13	3.31	0.00	0.00	8.00
Reverse relationship lending	2,860,121		2.11	3.30	0.00	0.00	8.00
Δ Reverse exposure	2,860,121	%	−0.40	35.56	−4.07	0.00	2.68
Same network	2,860,121	Dummy	0.12	0.32	0.00	0.00	1.00
Difference in liquidity surplus ($t-1$)	2,859,430	ppt	0.00	49.53	−9.23	0.00	9.24

Notes: This table reports summary statistics of the bank and interbank characteristics of our sample. All variables are defined in Appendix A in the Online Appendix.
[a]Interbank borrowing/total borrowing does not equal interbank lending/total lending as German banks can also lend to and borrow from foreign banks.

becoming more or less similar over time), we include lender-borrower fixed effects in one specification per table.

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* ratio, calculated as total loans over total assets, as a control. More importantly, we demonstrate that all our results hold when using credit supply shocks, as suggested by Khwaja and Mian (2008k), instead of the total amount of bilateral interbank lending. These supply shocks are accounted for by including $Borrower \times quarter - year$ fixed effects and are explained in detail in Section 3.

Table 3 reports descriptive statistics for all relevant bank and interbank characteristics included in our analysis. Appendix A in the Online Appendix provides a summary of the definitions and sources of all variables used in this study.

3. INTERBANK LENDERS' REACTION TO CHANGES IN THE BORROWER'S PORTFOLIO QUALITY: THE ROLE OF PORTFOLIO SIMILARITY

In this section, we investigate the role that *Portfolio similarity* plays in interbank lending. Specifically, we focus on testing Hypotheses 1–3 and evaluate (i) whether banks with similar loan portfolios lend more or less to each other; (ii) whether banks with different levels of similarity react differently to changes in their peers' asset quality, as measured by *portfolio quality* and the *NPL ratio*; and (iii) how *Portfolio opacity* affects banks' access to interbank funding and whether the impact of opacity is modified by the portfolio similarity between lending and borrowing banks. We begin this section with a discussion of our empirical strategy and then elaborate on the results of the estimation.

3.1 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 interbank loan (intensive margin).[17] Information on bilateral exposure, however, only exists for the subsample of bank pairs that have established a lending relation. To control for this nonrandom 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 (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. It represents the first stage of our regression, where we estimate whether a bilateral loan ($Credit\ relation_{i,j,t}$) exists between lending bank i and borrowing bank j at quarter-year t using the following Probit model.

$$
\begin{aligned}
Pr(Credit\ Relation_{i,j,t} = 1) = \Phi(&\beta_0 + \beta_1 Portfolio\ Similarity_{i,j,t} \\
&+ \beta_2 Portfolio\ quality_{j,t} + \beta_3 Portfolio\ quality_{j,t} \\
&\times Portfolio\ Similarity_{i,j,t} + \beta_4 NPL\ ratio_{j,t} \\
&+ \beta_5 NPL\ ratio_{j,t} \times Portfolio\ Similarity_{i,j,t} \\
&+ \beta_6 Portfolio\ opacity_{j,t} + \beta_7 Portfolio\ opacity_{j,t} \\
&\times Portfolio\ Similarity_{i,j,t} + \beta_8 Portfolio\ quality_{i,t} \\
&+ \beta_9 NPL\ ratio_{i,t} + \beta_{10} Portfolio\ opacity_{i,t} \\
&+ \beta_{11} Credit\ Relation_{i,j,t-1} + Controls \\
&+ FE_i + FE_j + FE_t + \epsilon_{i,j,t}).
\end{aligned} \tag{12}
$$

17. 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.

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. As highlighted by Heckman (1977), regressing $\Delta Exposure_{i,j,t}$ on our nonrandom sample would yield biased estimates. We therefore include information on the nonexisting 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 $Credit\ relation_{i,j,t-1}$, that is, the existence of a credit relation in quarter-year $t-1$ as an instrument (Arellano and Bond 1991). As bilateral exposure often lasts longer than 3 months, this variable is highly predictive for the existence of a credit relation in the subsequent quarter t. However, a credit relation in quarter-year $t-1$ bears no information about whether the bilateral exposure will increase or decrease over the next quarter. In the second stage, we therefore estimate the following equation by ordinary least squares (OLS):

$$\begin{aligned}\Delta Exposure_{i,j,t} = {} & \beta_0 + \beta_1 Portfolio\ Similarity_{i,j,t} \\ & + \beta_2 Portfolio\ quality_{j,t} + \beta_3 Portfolio\ quality_{j,t} \\ & \times Portfolio\ Similarity_{i,j,t} + \beta_4 NPL\ ratio_{j,t} \\ & + \beta_5 NPL\ ratio_{j,t} \times Portfolio\ Similarity_{i,j,t} \\ & + \beta_6 Portfolio\ opacity_{j,t} + \beta_7 Portfolio\ opacity_{j,t} \\ & \times Portfolio\ Similarity_{i,j,t} + \beta_8 Portfolio\ quality_{i,t} \\ & + \beta_9 NPL\ ratio_{i,t} + \beta_{10} Portfolio\ opacity_{i,t} \\ & + \beta_{11} IMR_{First\ Stage} + Controls + FE_i + FE_j + FE_t + \epsilon_{i,j,t}.\end{aligned} \tag{13}$$

The key explanatory variables in both the selection and the outcome equations reflect our focus on estimating the effect of *Portfolio similarity*[18] between the lending and borrowing bank on the interbank lending relationship. More specifically, with the base effect of *Portfolio similarity*, we test Hypothesis 1 and investigate whether banks with a similar loan portfolio lend more or less to each other. We test Hypothesis 2 by exploring whether similar banks adjust interbank lending more to changes in asset quality. For this purpose, we interact *Portfolio similarity* with the two alternative quality measures (*Portfolio quality* and *NPL ratio*) and trace the differences between the results with the *NPL ratio* that is observable for all lenders and those with *Portfolio quality* that is more likely to be observed by lenders with a similar

18. For simplicity, $Portfolio\ Similarity_{i,j,t}$ refers to both the sectoral and the regional similarity measure.

portfolio. Finally, we test Hypothesis 3. To this end, we first examine the relation between *Portfolio opacity* and interbank lending, then we also include the interaction between *Portfolio similarity* and *Portfolio opacity*. We do so for both the sectoral and regional dimension of *Portfolio similarity*.

As explained in Section 2, we include various fixed effects to control for fixed lender, borrower, lender-borrower, and quarter-year characteristics in the outcome equation. Moreover, we make sure that our results are driven by supply, rather than demand effects, following the identification approach proposed by Khwaja and Mian (2008). Khwaja and Mian (2008) assume that borrower × quarter-year fixed effects capture all variation in credit demand, leaving any remaining variation in observable credit volumes driven by credit supply. Including borrower × quarter-year fixed effects means the estimation is based solely on the variation in credit supply that the same borrower receives from different lenders. In our case, this estimation focuses on interbank lending relationships where the borrowing bank borrows from multiple lenders in the same quarter. While this focus on multiple lenders can be a limitation in bank-firm lending settings, it is less problematic in our interbank lending setup since most banks borrow from multiple interbank lenders. Indeed, the average borrowing in our sample has outstanding interbank loans to 11.3 different lending banks in a given quarter. Nonetheless, Table C1 in Online Appendix C shows that our results are robust to using an alternative identification scheme, similar to those used in recent studies by Berton et al. (2018), Greenstone, Mas, and Nguyen (2020), Degryse et al. (2019), and Degryse, Karas, and Schoors (2019). That approach disentangles demand from supply effects using a range of fixed effects as demand and supply proxies, respectively, and is explained in detail in Online Appendix C.

3.2 Results

Table 4 reports the results of estimating the first-stage Probit model (equation (12), column (1) of Table 4) and second-stage OLS model (equation (13), columns (2) to (5) of Table 4). The specification in column (2) includes bank fixed effects, column (3) presents results with bank and quarter-year fixed effects, and column (4) shows the results when adding lender-borrower relationship fixed effects. Finally, column (5) includes borrower × quarter-year fixed effects to provide evidence that the observed relationships between interbank lending and similarity are driven by the supply rather than by the demand for interbank funds (Khwaja and Mian 2008). We standardize all independent variables, except for binary variables in all models, to facilitate the comparison of the magnitudes of the estimated coefficients. The coefficients of the control variables will not be discussed as they are consistent with the existing literature. Moreover, the coefficients of $Credit\ relation_{i,j,t-1}$ and $IMR_{firststage}$ in Table 4 are reassuring that our instrument is not too weak ($t = 356$).

3.2.1 Interbank lending and portfolio similarity. The results presented in Table 4 (with marginal effects[19] in Table 5) show that *portfolio similarity*, in both its sectoral

19. We calculate average marginal effects, meaning we take the derivative of our variable of interest for all sample observations and then average the resulting marginal effects. We use Stata's *margins* command

TABLE 4

Interbank Lending, Portfolio Similarity, and Credit Portfolio Quality

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
Common characteristics					
Portfolio similarity (industries)	0.011***	2.350***	1.968***	3.496***	2.181***
	(0.00)	(0.65)	(0.65)	(1.01)	(0.79)
Portfolio similarity (regions)	0.031***	0.925***	1.102***	0.709**	1.121***
	(0.00)	(0.19)	(0.20)	(0.31)	(0.18)
Borrower characteristics					
Portfolio quality	−0.032***	−0.007	−0.003	0.148	
	(0.00)	(0.56)	(0.65)	(0.86)	
Portfolio quality × Portfolio similarity (industries)	0.020***	0.543**	0.416	0.785**	1.076**
	(0.00)	(0.25)	(0.26)	(0.35)	(0.51)
Portfolio quality × Portfolio similarity (regions)	0.017***	0.499***	0.521***	−0.043	0.661***
	(0.00)	(0.13)	(0.14)	(0.18)	(0.13)
NPL ratio	−0.061***	−1.280***	−1.557***	−1.659***	
	(0.00)	(0.41)	(0.50)	(0.61)	
NPL ratio × Portfolio similarity (industries)	−0.000	0.102	−0.136	−0.157	0.328
	(0.00)	(0.23)	(0.22)	(0.31)	(0.48)
NPL ratio × Portfolio similarity (regions)	0.015***	0.384***	0.359***	−0.220	0.525***
	(0.00)	(0.13)	(0.13)	(0.21)	(0.15)
Portfolio opacity	−0.018***	−0.586**	−0.577*	−0.504	
	(0.00)	(0.23)	(0.30)	(0.35)	
Portfolio opacity × Portfolio similarity (industries)	0.011***	0.212	0.198	0.062	0.609**
	(0.00)	(0.14)	(0.14)	(0.17)	(0.26)
Portfolio opacity × Portfolio similarity (regions)	0.005**	0.256*	0.317**	0.177	0.442***
	(0.00)	(0.13)	(0.14)	(0.15)	(0.14)
Capital ratio ($t-1$)	−0.022***	−1.368*	−0.158	0.049	
	(0.00)	(0.77)	(0.72)	(0.87)	
Liquidity ratio ($t-1$)	−0.003	−8.294	−8.770	−8.156	
	(0.00)	(7.69)	(7.19)	(8.03)	
ROA ($t-1$)	0.095***	2.475***	2.162***	2.201**	
	(0.00)	(0.65)	(0.70)	(0.87)	
Loans-to-assets ($t-1$)	0.054***	2.432**	2.858***	4.365***	
	(0.00)	(0.97)	(0.84)	(1.03)	
Size ($t-1$)	0.209***	0.200	−0.155	12.656*	
	(0.01)	(5.52)	(5.16)	(6.55)	
Lender characteristics					
Credit portfolio quality	0.015***	2.076***	1.917***	2.298***	1.762***
	(0.00)	(0.48)	(0.52)	(0.55)	(0.53)
NPL ratio	−0.018***	1.081***	0.046	−0.370	−0.085
	(0.00)	(0.34)	(0.41)	(0.45)	(0.40)
Portfolio opacity	0.015***	0.516***	0.682***	0.695***	0.718***
	(0.00)	(0.16)	(0.16)	(0.22)	(0.16)
Capital ratio ($t-1$)	−0.097***	−2.073**	0.132	−0.404	0.021
	(0.01)	(0.99)	(1.03)	(1.37)	(1.00)
Liquidity ratio ($t-1$)	0.021***	5.684	4.507	2.643	1.210
	(0.00)	(7.66)	(7.26)	(8.08)	(5.76)

(*Continued*)

TABLE 4
(CONTINUED)

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
ROA $(t-1)$	0.039***	2.326***	1.465***	1.876***	1.649***
	(0.00)	(0.57)	(0.54)	(0.60)	(0.48)
Loans-to-assets $(t-1)$	−0.114***	1.057	2.626**	1.911	2.640***
	(0.00)	(1.07)	(1.05)	(1.38)	(1.00)
Size $(t-1)$	0.028***	−13.395***	−6.793	1.029	−10.979**
	(0.00)	(4.36)	(4.27)	(5.40)	(4.34)
Relationship characteristics					
Relationship lending	0.368***	3.124***	3.223***	−1.364***	3.385***
	(0.00)	(0.55)	(0.54)	(0.52)	(0.50)
Reverse relationship lending	0.073***	1.512***	1.456***	1.384**	1.413***
	(0.00)	(0.26)	(0.26)	(0.60)	(0.26)
Δ Reverse exposure	0.019***	2.450***	2.404***	2.368***	2.206***
	(0.00)	(0.42)	(0.41)	(0.43)	(0.39)
Same BHC	0.503***	14.082***	13.883***	22.750**	12.709***
	(0.06)	(2.23)	(2.23)	(10.53)	(2.16)
Same network	0.387***	6.773***	6.922***	−7.719*	7.485***
	(0.01)	(1.39)	(1.40)	(4.21)	(1.34)
Difference in liquidity surplus $(t-1)$	−0.001	−31.058	−30.196	−26.518	−14.197
	(0.00)	(29.46)	(27.74)	(31.03)	(21.61)
Heckman controls					
Credit relation $(t-1)$	2.932***				
	(0.01)				
IMR		61.090***	61.141***	67.145***	60.848***
		(2.02)	(2.01)	(2.21)	(1.94)
Observations	2,760,542	710,751	710,751	708,850	692,722
Controls	Yes	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	Yes	Yes	Yes	Yes
Quarter-year FEs	No	No	Yes	Yes	Yes
Lender-borrower relation FEs	No	No	No	Yes	No
Quarter × borrower FEs (Khwaja and Mian 2008)	No	No	No	No	Yes
R-squared	0.83	0.15	0.15	0.19	0.21

NOTE: This table shows the coefficients of a two-stage Heckman sample selection model. The sample consists of quarterly bank-pair observations of 2,094 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 (column (1), Probit), and the percentage change of interbank exposure between lender i and borrower j over the period $(t-1)$ to t, respectively (columns (2) to (5), OLS). Column (2) includes lender and borrower fixed-effects, column (3) adds quarter-year fixed-effects, column (4) adds borrower-lender relation fixed effects and column (5) adds borrower × quarter-year fixed effects following the approach introduced by Khwaja and Mian (2008k). Coefficients are standardized except for binary variables. Standard errors are clustered on the borrower and lender level. All variables are defined in Appendix A in the Online Appendix. Standard errors (two-way clustered by borrower and lender) in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

and regional dimensions, has a significantly positive effect on both the extensive and intensive margins of lending across all specifications. Bank pairs with a one standard deviation more similar loan portfolio with respect to industries are 4 basis points more likely to form a lending relationship; bank pairs with a one standard deviation more similar loan portfolio with respect to regions are 14 basis points more likely (Table 5,

for this calculation, and the relevant effects are reported in Table 5. In the OLS model, the average marginal effects are equivalent to the reported beta coefficients, except when interaction terms are involved.

TABLE 5

THE IMPACT OF PORTFOLIO QUALITY, NPL RATIO, AND PORTFOLIO OPACITY ON INTERBANK LENDING FOR DIFFERENT VALUES OF SIMILARITY (MARGINAL EFFECTS)

	Probit Credit relation	OLS Δ Exposure		
	(1)	(2)	(3)	(4)
Portfolio similarity (industries), average marginal effects	0.0004***	See Table 4 (OLS coefficients equal marginal effects)		
	(0.000)			
Portfolio similarity (industries), average marginal effects	0.0014***			
	(0.000)			
Portfolio quality (both similarities low)	−0.007***	−3.133***	−2.812***	−2.079*
	(0.00)	(0.83)	(0.97)	(1.15)
Portfolio quality (industry dissimilar, region similar)	−0.005***	−0.137	0.314	−2.335
	(0.00)	(0.91)	(1.07)	(1.46)
Portfolio quality (industry similar, region dissimilar)	−0.002***	0.122	−0.319	2.632
	(0.00)	(1.11)	(1.12)	(1.73)
Portfolio quality (both similarities high)	−0.004***	3.119**	2.807**	2.376
	(0.00)	(1.21)	(1.16)	(1.46)
NPL (both similarities low)	−0.005***	−2.739***	−2.227***	−0.528
	(0.00)	(0.69)	(0.79)	(1.06)
NPL (industry dissimilar, region similar)	−0.003***	−0.435	−0.071	−1.848
	(0.00)	(0.85)	(0.84)	(1.22)

(*Continued*)

TABLE 5

(CONTINUED)

	Probit Credit relation	OLS Δ Exposure		
	(1)	(2)	(3)	(4)
NPL (industry similar, region dissimilar)	−0.001	−2.125**	−3.043***	−1.471
	(0.00)	(1.06)	(1.11)	(1.42)
NPL (both similarities high)	−0.005***	0.179	−0.887	−2.790**
	(0.00)	(0.93)	(0.92)	(1.38)
Portfolio opacity (both similarities low)	−0.003***	−1.992***	−2.122***	−1.220
	(0.00)	(0.64)	(0.66)	(0.79)
Portfolio opacity (industry dissimilar, region similar)	−0.002***	−0.454	−0.222	−0.158
	(0.00)	(0.56)	(0.56)	(0.61)
Portfolio opacity (industry similar, region dissimilar)	−0.002***	−0.717	−0.933	−0.850
	(0.00)	(0.72)	(0.79)	(0.88)
Portfolio opacity (both similarities high)	−0.002***	0.821	0.967	0.212
	(0.00)	(0.61)	(0.60)	(0.75)
Observations	2,760,542	710,751	710,751	708,850
Controls	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	Yes	Yes	Yes
Quarter-year FEs	No	No	Yes	Yes
Lender-borrower relation FEs	No	No	No	Yes

NOTE: This table reports marginal effects for the regression reported in Table 4. “Low similarity” refers to a similarity of three standard deviation below the variable mean, “high similarity” refers to a similarity of three standard deviations above the variable mean. All variables are defined in Appendix A in the Online Appendix. Standard errors (two-way clustered by lender and borrower) in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

column (1)). Compared to the unconditional probability of lending, which is 26.5% (see Table 3), these effects on the extensive margin are small but significant.

In the intensive margin, lender-borrower combinations with a one standard deviation more similar industry exposure increase their quarterly lending by 235 basis points, while banks with additional regional similarity increase it by 93 basis points in the model with borrower and lender fixed effects (Table 4, column (2)). The effects remain significant and become slightly smaller when adding time fixed characteristics (Table 4, column (3)), and stronger when only considering changes within a given bank-pair, respectively (Table 4, column (4)). Controlling for borrower × quarter-year specific shocks in Table 4, column (5) shows that interbank liquidity supply increases by 218 basis points with one additional standard deviation of sectoral similarity and by 112 basis points with one additional standard deviation of regional similarity. These effect sizes are large, compared to the average quarterly change in interbank lending of 0.41%.

These results support Hypothesis 1. Consistent with the interpretation that banks with similar portfolios are aware of their informational advantage regarding a peer's *Portfolio quality*, they prefer lending to peers with a similar portfolio.

The results also demonstrate that, empirically, the positive effects of *portfolio similarity* dominate the potential negative effects of similarity, for example, the potentially reduced lending in the case of correlated liquidity shocks (Fecht, Nyborg, and Rocholl 2011). While our findings suggest that informational advantages are important drivers of preferential lending between similar peers, we cannot rule our that this behavior is also driven by risk shifting, that is, 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 (Elliott, Georg, and Hazell (2021)).

3.2.2 Interbank lending, borrower's portfolio quality, and portfolio similarity. The base effect of our forward-looking measure of the borrower's *Portfolio quality* on interbank lending is negative and significant at the extensive margin, but insignificant at the intensive margin. In contrast, the base effect of the borrower's *NPL ratio* is significantly negative at both the extensive and intensive margins. These findings indicate that the forward-looking *Portfolio quality* is indeed private information and generally not observable by the average interbank lender. It appears that banks mainly rely on the observable, backward-looking information on peers' asset quality, as depicted by the *NPL ratio*. Given the predictive power of a bank's *Portfolio quality* for *NPL ratios* in subsequent quarters, as reported in Section 2, the average lending bank uses an inferior but easily accessible proxy to assess the borrower's asset quality.

However, consistent with our Hypotheses 1 and 2, these base effects of asset quality are strongly moderated by the similarity between lending and borrowing banks. The significantly positive coefficients for the interaction between *Portfolio quality* and *Portfolio similarity* in both the selection and outcome models indicate that *Portfolio similarity* is associated with a significantly higher sensitivity of interbank lending to the borrower's asset quality. To facilitate the inference of the economic magnitude of the estimated relationships in Table 4, we report the marginal effects for the regressions in Table 5.

These marginal effects are reported for various levels of similarities between the lending and borrowing banks in terms of the industrial composition of their portfolios and location: "High similarity" refers to bank pairs with a three standard deviation higher similarity than the average, while "low similarity" refers to bank pairs with a three standard deviation lower similarity than the average. We report marginal effects for these relatively extreme values of portfolio similarity to demonstrate the differing reactions of a bank's most similar peers (i.e., those with almost the same business model) compared to its most dissimilar peers (i.e., those specialized in completely different industries and regions).[20]

For the interpretation of marginal effects in Table 5, note that the variable *Credit relation* assumes either the value 0 or 1; thus, a coefficient of 1 in the Probit model (column (1)) of Table 5 signifies an increase of 100 percentage points. In contrast, the variable Δ *Exposure* is reported in percentage points; hence, a coefficient of 1 in the OLS model (columns (2) to (5)) indicates an increase of 1 percentage point.

Considering only bank pairs with a high level of similarity (Table 5, row "Portfolio quality (both similarities high)"), such bank pairs lend between 238 and 312 basis points more following a one-standard deviation improvement in the peer's *Portfolio quality* (column (2) to column (4)). While the impact of *Portfolio quality* appears negative at the extensive margin, this negative effect is significantly reduced for more similar peers (column (1)).

For banks with very different portfolios (Table 5, row "Portfolio quality (both similarities low)"), the amount lent increases by 208 to 313 basis points after a deterioration of the borrower's *Portfolio quality* (columns (2) to (4)), as dissimilar, uninformed lenders make up for the reduced amount in lending by similar, informed ones.

The results regarding the *NPL ratio* are quite different. While the average bank lends significantly less frequently and in lower amounts to banks with a higher *NPL ratio*, the positive interaction terms between *NPL ratio* and *Portfolio similarity* in Table 4, as well as the marginal effects in Table 5, show that this effect vanishes for very similar bank pairs. For very similar bank pairs (Table 5, row "NPL ratio (both similarities high)," column (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 for very dissimilar bank pairs (Table 5, row "NPL ratio (both similarities low)," column (1)). At the intensive margin, banks with a higher *NPL ratio* do not receive less interbank lending nor do similar lenders decrease their loans after an increase in their *NPL ratio* (columns (2) to (4)). In contrast, dissimilar lenders strongly restrict lending in reaction to an increased *NPL ratio*.

These results are consistent with our Hypothesis 2. In line with the notion that lending banks with a very similar portfolio can adequately access borrowers' private

20. We report marginal effects for all specifications, except for the one including borrower $\times$ quarter-year effects, as the latter absorbs all base effects of *Portfolio quality*, *Portfolio opacity*, and *NPL ratio*. The marginal effects on similarity can be straightforwardly taken from Table 4 since this is a linear model.

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*.[21]

3.2.3 Interbank lending, borrower's portfolio opacity, and portfolio similarity. We next focus on discussing the results regarding our tests of Hypothesis 3. We begin by noting that the effect of the borrower's *Portfolio opacity* is negative for a bank pair of average similarity, both at the extensive and intensive margins. The significantly positive coefficients on the interaction effect between *Portfolio opacity* and the similarity measures indicate that this negative effect becomes weaker as the portfolio similarity between the lending and borrowing bank increases. The marginal effects reported in Table 5 (row "Portfolio opacity (both similarities high)") show that, while bank pairs with a similarity level of three standard deviations still reduce lending at the extensive margin (column (1)), they do not seem to be concerned about their peer's *Portfolio opacity* or how it has changed over time when deciding about loan volumes (columns (2) to (4)).

In sum, these results are consistent with Hypothesis 3. While borrowers with a more opaque portfolio, on average, face difficulties refinancing themselves in interbank markets, interbank lenders are more willing to lend to borrowers with an opaque portfolio if this portfolio is similar to their own.

3.2.4 Portfolio similarity and relationship lending. The coefficients of both similarities for the intensive margin combine to an effect similar in size to relationship lending, identified as a key predictor for interbank lending (Braeuning and Fecht 2017). In other words, a one standard deviation increase in *portfolio similarity* in both regional and sectoral terms increases interbank lending as much as having a one standard deviation longer relationship.

This confirms the relevance of portfolio similarity in the dynamics of interbank lending. However, how do our findings on similarity relate to established findings about relationship lending in interbank markets, conceptually? As discussed in the introduction, other papers (e.g., Braeuning and Fecht 2017) have argued that information asymmetry in the interbank market can be mitigated by a pre-existing relationship between lenders and borrowers. In the following, we provide two tests to explore the interplay between portfolio similarity and relationship lending. First, we examine whether our findings on informational advantage apply similarly to relationship lending. Second, we investigate whether portfolio similarity provides additional explanatory power beyond that of relationship variables in understanding interbank lending.

To explore the extent to which relationship lending follows a mechanism similar to portfolio similarity, Table 6 includes the interaction between *Relationship lending* and *Reverse relationship lending* with the borrower's *Portfolio quality*, *NPL ratio*, and *Portfolio opacity*. While the interaction terms remain significant for our two

21. One might think that these findings are a pure artifact of the high correlation between similar banks *Portfolio quality*. We show in Online Appendix B that this is not the case.

TABLE 6

Relationship Lending and Portfolio Similarity

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
Similarity					
Portfolio similarity (industries)	0.022***	3.222***	2.680***	4.568***	3.022***
	(0.00)	(0.84)	(0.84)	(1.24)	(0.99)
Portfolio similarity (regions)	0.029***	0.927***	1.116***	0.730**	1.115***
	(0.00)	(0.21)	(0.22)	(0.35)	(0.18)
Relationship					
Relationship lending	0.358***	3.380***	3.500***	−1.751***	3.715***
	(0.00)	(0.63)	(0.62)	(0.57)	(0.60)
Reverse relationship lending	0.073***	1.476***	1.389***	1.416***	1.344***
	(0.00)	(0.25)	(0.25)	(0.54)	(0.24)
Borrower characteristics					
Credit portfolio quality	−0.057***	−1.276	−1.527	1.907	
	(0.00)	(1.34)	(1.39)	(1.29)	
Portfolio quality × Portfolio similarity (industries)	0.025***	0.610**	0.412	0.789**	1.347**
	(0.00)	(0.31)	(0.32)	(0.38)	(0.61)
Portfolio quality × Portfolio similarity (regions)	0.012***	0.385***	0.418***	−0.001	0.499***
	(0.00)	(0.13)	(0.13)	(0.21)	(0.11)
Portfolio quality × Relationship lending	0.067***	1.135	1.193*	−0.702	1.201
	(0.00)	(0.72)	(0.72)	(0.67)	(0.80)
Portfolio quality × Reverse relationship lending	−0.016***	−0.008	−0.113	−0.299	−0.075
	(0.00)	(0.23)	(0.23)	(0.42)	(0.26)
NPL ratio	−0.076***	−3.282**	−3.513**	−0.135	
	(0.00)	(1.41)	(1.47)	(1.39)	
NPL ratio × Portfolio similarity (industries)	0.001	−0.172	−0.480*	−0.407	0.403
	(0.00)	(0.30)	(0.27)	(0.35)	(0.63)
NPL ratio × Portfolio similarity (regions)	0.013***	0.324**	0.328**	−0.288	0.471***
	(0.00)	(0.15)	(0.15)	(0.22)	(0.15)
NPL ratio × Relationship lending	0.050***	1.316*	1.301*	−0.785	1.347
	(0.00)	(0.78)	(0.77)	(0.71)	(0.83)
NPL ratio × Reverse relationship lending	0.009***	0.131	−0.063	0.060	−0.110
	(0.00)	(0.22)	(0.21)	(0.36)	(0.23)

(*Continued*)

TABLE 6
(Continued)

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
Portfolio opacity	−0.013***	−0.144	−0.619	−1.691**	
	(0.00)	(0.60)	(0.62)	(0.69)	
Portfolio opacity × Portfolio similarity (industries)	0.016***	0.551***	0.398*	0.381	1.035***
	(0.00)	(0.21)	(0.21)	(0.26)	(0.37)
Portfolio opacity × Portfolio similarity (regions)	0.002	0.194	0.282*	0.019	0.387**
	(0.00)	(0.16)	(0.16)	(0.17)	(0.15)
Portfolio opacity × Relationship lending	−0.008***	−0.298	−0.204	0.684*	−0.396
	(0.00)	(0.34)	(0.34)	(0.37)	(0.38)
Portfolio opacity × Reverse relationship lending	0.010***	0.102	0.143	−0.237	0.356*
	(0.00)	(0.16)	(0.19)	(0.22)	(0.18)
Capital ratio ($t-1$)	−0.023***	−0.800	0.541	0.668	
	(0.00)	(0.60)	(0.57)	(0.69)	
Liquidity ratio ($t-1$)	−0.006**	0.372	−0.446	−2.705	
	(0.00)	(4.14)	(4.06)	(4.42)	
ROA ($t-1$)	0.086***	1.948***	1.708***	2.082***	
	(0.00)	(0.61)	(0.65)	(0.79)	
Loans-to-assets ($t-1$)	.050***	2.430**	2.866***	4.084***	
	(0.00)	(0.96)	(0.78)	(1.01)	
Size ($t-1$)	0.212***	0.883	0.727	11.865*	
	(0.00)	(5.44)	(5.14)	(6.21)	
Lender characteristics					
Credit portfolio quality	0.018***	1.997***	1.715***	2.329***	1.606***
	(0.00)	(0.48)	(0.52)	(0.51)	(0.53)
NPL ratio	−0.015***	1.048***	0.019	−0.450	−0.171
	(0.00)	(0.34)	(0.39)	(0.43)	(0.40)
Portfolio opacity	0.016***	0.983***	0.987***	1.000***	0.999***
	(0.00)	(0.23)	(0.18)	(0.22)	(0.19)
Capital ratio ($t-1$)	−0.096***	−2.322**	−0.071	−0.323	−0.056
	(0.01)	(1.01)	(1.03)	(1.32)	(0.99)
Liquidity ratio ($t-1$)	0.023***	−1.793	−3.223	−2.134	8.234*
	(0.00)	(4.39)	(4.37)	(4.73)	(4.67)

(*Continued*)

TABLE 6
(Continued)

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
ROA ($t-1$)	0.034***	2.364***	1.624***	1.868***	1.790***
	(0.00)	(0.52)	(0.46)	(0.53)	(0.41)
Loans-to-assets ($t-1$)	−0.113***	0.417	1.842*	1.279	1.946*
	(0.00)	(1.09)	(1.06)	(1.35)	(1.02)
Size ($t-1$)	0.022***	−16.083***	−9.015**	−1.129	−12.443***
	(0.00)	(4.24)	(4.11)	(4.97)	(4.11)
Relevant bilateral measures					
Δ Reverse exposure	0.018***	2.204***	2.162***	2.142***	1.981***
	(0.00)	(0.37)	(0.37)	(0.38)	(0.35)
Same BHC	0.523***	13.434***	13.299***	23.819***	11.966***
	(0.06)	(2.09)	(2.10)	(9.15)	(2.02)
Same network	0.380***	6.733***	6.863***	−8.677**	7.459***
	(0.01)	(1.45)	(1.46)	(3.65)	(1.37)
Difference in liquidity surplus ($t-1$)	0.253	1931.565	3347.170	−14865.481	−101529.640**
	(3.80)	(42131.44)	(41782.70)	(45241.29)	(44616.77)
Heckman controls					
Credit relation ($t-1$)	2.932***				
	(0.01)				
IMR		62.760***	62.805***	68.434***	62.481***
		(1.91)	(1.90)	(2.05)	(1.83)
Observations	2,965,986	765,121	765,121	763,000	745,714
Controls	Yes	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	Yes	Yes	Yes	Yes
Quarter-year FEs	No	No	Yes	Yes	Yes
Lender-borrower relation FEs	No	No	No	Yes	No
Quarter-year × borrower FEs (Khwaja and Mian 2008)	No	No	No	No	Yes
R-squared	0.83	0.15	0.15	0.19	0.22

Note: This table shows the coefficients of a two-stage Heckman sample selection model, comparing the effect of similarity and relationship lending. The sample consists of quarterly bank-pair observations of 2,094 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 (column (1), Probit), and the percentage change of interbank exposure between lender i and borrower j over the period ($t-1$) to t, respectively (columns (2) to (5), OLS). Column (2) includes lender and borrower fixed-effects, column (3) adds quarter-year fixed-effects, column (4) adds borrower-lender relation fixed effects and column (5) adds borrower × quarter-year fixed effects following the approach introduced by Khwaja and Mian (2008). Coefficients are standardized except for binary variables. Standard errors are clustered on the borrower and lender level. All variables are defined in Appendix A in the Online Appendix. Standard errors (two-way clustered by borrower and lender) in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

similarity measures, all interactions between the variables capturing relationship lending and the borrower's asset quality and opacity are insignificant. This indicates that, even though relationship lending is highly relevant for the formation and maintenance of interbank lending, an established relationship does not provide the lender with private knowledge about the peer's portfolio. Instead, preferential lending after a long-standing relationship could be driven by mutual trust or the convenience of repeating established lending patterns.

To determine whether portfolio similarity remains relevant even when excluding all components of relationship lending it might entail, Table 7 presents the results of re-estimating the models of Table 4, using an orthogonalized version of the similarity measures with respect to relationship lending. The main explanatory variables here are the residuals of regressions where the similarity variables are regressed on the interbank relationship variables. The results presented in this table qualitatively match those illustrated in Table 4. This demonstrates that portfolio similarity is not just a peculiar subdimension of relationship lending, but has explanatory power over and beyond what we can learn from interbank relationships.

3.2.5 Additional tests. Does the portfolio quality of lending banks drive the results? Banks with a similar portfolio will also have a similar *Portfolio quality*.[22] 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 baseline results 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*. The matching strategy and the results, which confirm that our estimation outcomes are not driven by the dynamics of the lenders' portfolio quality, are reported in Online Appendix B.

Observable proxies of similarity

While our similarity measure is sophisticated and potentially only partially observable by peers (see Section 1), there could be observable clues by which peers can infer similarity. If these clues are correlated with other determinants of interbank lending, we might misinterpret the effect of these determinants as an effect of portfolio similarity. To ensure this is not the case, we conduct additional analyses. First, we check whether our effects are driven by observable similarity measures, particularly size similarity, geographical proximity, being part of the same bank network (e.g., whether both banks are savings banks), and being part of the same bank holding company, by including them and potential interactions in our baseline analysis. Second, we orthogonalize our similarity measures with respect to size similarity, geographical proximity, being part of the same bank network, and the same bank holding

22. 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.

TABLE 7

Interbank Lending, Portfolio Similarity Orthogonalized on Relationship Variables, and Credit Portfolio Quality

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
Common characteristics					
Portfolio similarity (industries), orthogonalized	−0.024***	2.879***	2.314***	5.823***	2.607***
	(0.00)	(0.81)	(0.81)	(1.31)	(0.95)
Portfolio similarity (regions), orthogonalized	0.023***	0.973***	1.160***	1.325***	1.149***
	(0.00)	(0.21)	(0.21)	(0.39)	(0.18)
Borrower characteristics					
Credit portfolio quality	−0.021***	−0.044	−0.270	0.140	
	(0.00)	(0.60)	(0.66)	(0.84)	
Credit portfolio quality × Portfolio similarity (industries), orthogonalized	0.006**	0.349	0.154	0.774**	0.822
	(0.00)	(0.30)	(0.30)	(0.39)	(0.74)
Credit portfolio quality × Portfolio similarity (regions), orthogonalized	0.011***	0.408***	0.006	0.499***	
	(0.00)	(0.13)	(0.22)	(0.12)	
NPL ratio	−0.059***	−1.672***	−2.028***	−1.950**	
	(0.00)	(0.53)	(0.60)	(0.81)	
NPL ratio × Portfolio similarity (industries), orthogonalized	−0.012***	−0.225	−0.543**	−0.304	0.179
	(0.00)	(0.29)	(0.28)	(0.41)	(0.76)
NPL ratio × Portfolio similarity (regions), orthogonalized	0.017***	0.563***	0.375**	−0.290	0.498***
	(0.00)	(0.22)	(0.15)	(0.25)	(0.16)
Portfolio opacity	−0.012***	−0.355	−0.705*	−0.512	
	(0.00)	(0.24)	(0.36)	(0.43)	
Portfolio opacity × Portfolio similarity (industries), orthogonalized	0.015***	0.536**	0.359*	0.257	0.899**
	(0.00)	(0.22)	(0.22)	(0.27)	(0.39)
Portfolio opacity × Portfolio similarity (regions), orthogonalized	0.001	0.155	0.251	−0.081	0.380**
	(0.00)	(0.16)	(0.17)	(0.18)	(0.15)
Capital ratio ($t-1$)	−0.030***	−1.022	0.423	0.691	

(*Continued*)

TABLE 7
(Continued)

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
	(0.00)	(0.63)	(0.58)	(0.69)	
Liquidity ratio ($t-1$)	−0.012***	0.362	−0.500	−2.985	
	(0.00)	(4.26)	(4.16)	(4.50)	
ROA ($t-1$)	0.081***	1.855***	1.561**	2.012**	
	(0.00)	(0.62)	(0.66)	(0.80)	
Loans-to-assets ($t-1$)	0.047***	2.113**	2.647***	3.728***	
	(0.00)	(0.98)	(0.79)	(1.07)	
Size ($t-1$)	0.280***	0.610	0.568	9.604	
	(0.01)	(5.59)	(5.29)	(6.92)	
Lender characteristics					
Credit portfolio quality	0.025***	2.087***	1.813***	2.469***	1.692***
	(0.00)	(0.48)	(0.53)	(0.52)	(0.53)
NPL ratio	−0.017***	1.172***	0.076	−0.125	−0.150
	(0.00)	(0.34)	(0.39)	(0.44)	(0.40)
Portfolio opacity	0.008***	0.935***	0.889***	0.979***	0.892***
	(0.00)	(0.23)	(0.18)	(0.24)	(0.19)
Capital ratio ($t-1$)	−0.099***	−2.339**	0.086	0.079	0.123
	(0.01)	(1.03)	(1.03)	(1.40)	(0.98)
Liquidity ratio ($t-1$)	0.009***	−1.931	−3.363	−1.953	8.450*
	(0.00)	(4.51)	(4.46)	(4.80)	(4.70)
ROA ($t-1$)	0.035***	2.383***	1.613***	1.884***	1.767***
	(0.00)	(0.52)	(0.46)	(0.52)	(0.40)
Loans-to-assets ($t-1$)	−0.130***	0.199	1.750*	0.935	1.925*
	(0.00)	(1.10)	(1.06)	(1.37)	(1.02)
Size ($t-1$)	0.085***	−16.162***	−8.537**	−3.246	−11.735***
	(0.00)	(4.29)	(4.16)	(5.04)	(4.17)

(*Continued*)

TABLE 7

(Continued)

	Probit Credit relation	OLS Δ Exposure			
	(1)	(2)	(3)	(4)	(5)
Relationship characteristics					
Same BHC	0.649***	15.023***	14.860***	24.454***	13.541***
	(0.06)	(2.20)	(2.21)	(9.05)	(2.15)
Same network	0.428***	7.890***	8.038***	−8.733**	8.668***
	(0.01)	(1.58)	(1.58)	(3.70)	(1.49)
Δ Reverse exposure	0.012***	2.134***	2.094***	2.080***	1.913***
	(0.00)	(0.37)	(0.36)	(0.37)	(0.34)
Difference in liquidity surplus ($t-1$)	−1.109	2479.9	3472.5	−16151.5	−104850.9**
	(4.23)	(43279.76)	(42699.91)	(45922.28)	(44897.61)
Heckman controls					
Credit relation ($t-1$)	3.560***				
	(0.01)				
IMR		58.373***	58.345***	65.443***	57.947***
		(1.72)	(1.72)	(1.91)	(1.67)
Observations	2,965,986	765,121	765,121	763,000	745,714
Controls	Yes	Yes	Yes	Yes	Yes
Lender & borrower FEs	No	Yes	Yes	Yes	Yes
Quarter-year FEs	No	No	Yes	Yes	Yes
Lender-borrower relation FEs	No	No	No	Yes	No
Quarter-year × borrower FEs (Khwaja and Mian 2008)	No	No	No	No	Yes
R-squared	0.82	0.15	0.15	0.19	0.22

Note: This table shows the coefficients of a two-stage Heckman sample selection model, where *Portfolio similarity (regions)*, and *Portfolio similarity (industries)* are orthogonalized on *Relationship lending* and *Reverse relationship lending*. The sample consists of quarterly bank-pair observations of 2,094 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 (column (1), Probit), and the percentage change of interbank exposure between lender i and borrower j over the period ($t-1$) to t, respectively (columns (2) to (5), OLS). Column (2) includes lender and borrower fixed-effects, column (3) adds quarter-year fixed-effects, column (4) adds borrower-lender relation fixed effects and column (5) adds borrower × quarter-year fixed effects following the approach introduced by Khwaja and Mian (2008). “Portfolio similarity (industries), orthogonalized” and “Portfolio similarity (regions), orthogonalized” are the residuals from regressing *Portfolio similarity (industries)* and *Portfolio similarity (regions)*, respectively, on *Relationship lending* and *Reverse relationship lending*. Coefficients are standardized except for binary variables. Standard errors are clustered on the borrower and lender level. All variables are defined in Appendix A in the Online Appendix. Standard errors (two-way clustered by lender and borrower) in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

company. The results, which support our main findings, are reported and discussed in Table D2 and Table D3 in Online Appendix D.

Decomposition of explanatory power

From our baseline analyses, we conclude that *Portfolio similarity* is an important determinant for forming interbank lending exposure at the extensive and the intensive margin. 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 also provide a set of additional tests that estimate the relative importance of the different factors determining lending patterns. Our approach and its results, which corroborate the importance of the *common characteristics*, are presented in Section E of the Online Appendix.

4. 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, Alexandre, and Tabak 2017, Silva, da Silva, and Tabak 2017). Our findings reveal trade-offs at both the micro- and the macrolevel: 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 raises too-interconnected-to-fail concerns.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table A1: Variable descriptions and sources

Table B1: Characteristics of similar and non-similar bank pairs in the matched sample

Table B2: Bank and interbank characteristics (matched sample)

Table B3: Interbank lending, portfolio similarity, and portfolio quality (matched sample)

Table B4: The effect of portfolio quality, NPL ratio, and portfolio opacity on interbank lending for different values of similarity (marginal effects, matched sample)

Table C1: Interbank lending supply and borrower's solvency

Table D1: Interbank lending, portfolio similarity (fine classification), and portfolio quality

Table D2: Interbank lending, portfolio similarity, observable proxies of similarity, and portfolio quality

Table D3: Interbank lending, portfolio similarity orthogonalized on observable similarity proxies, and portfolio quality

Table D4: Interbank lending including off-balance sheet items, portfolio similarity, and portfolio quality

Table D5: Net interbank lending, portfolio similarity, and portfolio quality

Table D6: Interbank lending outside of banking network, portfolio similarity, and portfolio quality

Table D7: Interbank lending to PD reporting banks, portfolio similarity, and portfolio quality

Table E1: Variance decomposition of interbank lending