Assortative Matching, Interbank Markets, and Monetary Policy[†]

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August 2025

Abstract

We develop a quantitative macroeconomic framework with heterogeneous financial intermediaries and liquidity management. Banks manage idiosyncratic deposit withdrawal risk through an iterative over-the-counter interbank market with endogenous intensive and extensive margins and equilibrium positive-assortative matching based on balance sheet size. We validate our framework using administrative data from Germany encompassing the universe of bank-to-bank exposures. Our findings strongly support the presence of positive-assortative matching in the data, thereby confirming the model's key mechanism. We show that assortative matching is stable but inefficient relative to the constrained-efficient benchmark, leading to reduced trading volumes and a broader region of inaction in the interbank market, a smaller and riskier banking sector, and lower aggregate demand. Using our empirically validated framework, we study the transmission of monetary policy, secular trends in interbank trading and banking concentration, and the role of deposit market power.

JEL classification: E44, E52, G20, G21
Keywords: heterogeneous banks, interbank markets, monetary policy, liquidity policy.

[†]We thank Manuel Amador, Javier Bianchi, Saki Bigio, V. V. Chari, Dean Corbae, Pablo D'Erasmo, Mishel Ghassibe, Paymon Khorrami, Tobias König, Jan-Pieter Krahnen, Yi Li (discussant), Christodoulos Louca, Guillermo Ordoñez, Fabrizio Perri, Linda Schilling (discussant), Quentin Vandeweyer, as well as seminar participants at the 2024 EFA Annual Meeting, Cyprus University of Technology, the 2024 Macroeconomic Policy Perspectives Conference at the Minneapolis Fed, and the 2024 CEPR Paris Symposium for useful comments and suggestions. Saidi acknowledges funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy (EXC 2126/1 – 390838866) and through CRC TR 224 (Project C03). This research was conducted under Bundesbank research project number 2024\0040. The views expressed are those of the authors and do not necessarily reflect those of the Bundesbank or the Eurosystem. First draft: May 2024.

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1 Introduction

This paper studies the bank lending channel of monetary policy transmission in a quantitative framework where heterogeneous banks manage their liquidity under a dynamic interest rate corridor rule and a frictional interbank market. Theoretically, we build on the influential contribution of Bianchi and Bigio (2022) who develop a rich theory of banks' liquidity management and the credit channel of monetary policy in an environment with a representative intermediary. Our contribution is to introduce ex-ante heterogeneity into the financial sector of this standard model. In the presence of permanent differences in bank efficiency and size, many appealing aggregation properties disappear as a distribution of banks arises in equilibrium. The combination of bank heterogeneity and liquidity frictions yields novel theoretical and policy-relevant conclusions that we support and validate with administrative micro-data from Germany.

Our main focus is to document and analyze—empirically, theoretically, and quantitatively—assortative matching in the interbank market. Empirically, we leverage the administrative quarterly credit registry from Germany over 2002-2019 and find that large lenders not only trade more but also tend to match with large borrowers. Matching is *positive*-assortative (PAM) based on balance sheet size.

Theoretically, we obtain PAM as an equilibrium outcome via an iterative trading algorithm where banks trade sequentially in a frictional over-the-counter market. We show that—while PAM is the unique stable outcome of this algorithm—this allocation does not coincide with the planner's constrained-efficient (CE) solution that maximizes joint surplus.

Quantitatively, we show that our model with PAM can match the empirical impulse responses to monetary policy shocks, while the CE version cannot. We also quantitatively verify that the empirically consistent PAM allocation is inefficient relative to both the CE and the frictionless benchmarks, leading to significantly less interbank trading, a smaller and riskier banking sector, and lower aggregate demand. Finally, we show that the state of the interbank market impacts the transmission of monetary policy, with PAM amplifying the real effects of monetary shocks in the short run.

Empirics. To provide empirical motivation for our model, we leverage the quarterly administrative credit registry from Germany that spans the period from 2002 to 2019 and covers, on average, 1,800 banks and 28,429 interbank connections per quarter. We document several relevant facts. First, there is strong evidence pointing to size-based trading and a positive correlation between interbank trading volume and bank balance sheet size. Second, and this is our key finding, there is positive-assortative matching in the interbank market: large banks do not only trade more but they are also much more likely to match with other big banks.

Third, following identified contractionary shocks to the monetary policy rate of the European Central Bank (ECB), German banks *increase* the amount of lending and the number of connections in the interbank market. Fourth and finally, we uncover significant heterogeneous effects suggesting that assortative matching strengthens following positive monetary policy shocks.

Model. In our quantitative model, financial intermediaries are ex-ante heterogeneous in monitoring efficiency (Stiglitz and Weiss, 1981), which in equilibrium yields a positive association between efficiency and size (net worth). Banks face idiosyncratic deposit withdrawal risk and a minimum reserve requirement rule. They can manage liquidity risk and cover any shortage of reserves by borrowing either from the over-the-counter interbank market or from the discount window of the lender of last resort. The monetary authority controls the interest rate corridor by setting the discount and deposit facility rates. The interbank rate is determined by the relative bargaining power of market participants. There are variable and fixed costs of match formation.

Because interbank borrowing may be expensive and due to a possible stigma associated with turning to the discount window, deposit withdrawal risk generates endogenous liquidity premia that vary with bank characteristics and are priced into the cross-section of retail deposit rates. At the franchise level, banks source funding from households in the form of time deposits and hold claims on the capital stock which—in conjunction with household labor supply—is used to produce the final good. Thus, interbank market frictions can have first-order effects on the macroeconomy since costly liquidity management impacts the evolution of bank profitability, the propensity to lend to firms and, thus, aggregate production.

Solving for equilibrium allocations in the frictional two-sided interbank market is the key challenge of our model analysis. We consider two alternative solution concepts. First, we propose an iterative trading algorithm that generates positive-assortative matching (PAM), consistent with the data. This approach is similar to solving the entry problem with heterogeneous foreign firms and sectors (Atkeson and Burstein, 2008). The algorithm gives precedence to large, efficient intermediaries on a "first-come, first-served" basis: small, less efficient banks solve the liquidity management problem last, and by the time their turn arrives, suitable counterparties may no longer be available. Those left out must turn to the lender of last resort, borrow at a penalty rate, and bear the associated stigma. Because bank-level trade pay-offs are functions of both sides' types and everyone prefers high-type counterparties, equilibrium PAM arises naturally, as in the classic matching model of Becker (1973). Second, we solve for the global, joint surplus-maximizing allocation. This constitutes a constrained-efficient (CE), or second-best, outcome that does not necessarily achieve PAM but serves as a very useful efficiency benchmark.

Besides assortative matching in the interbank market, the model offers two additional testable predictions. First, there is a positive association between interbank trading volume and balance sheet size (e.g., total assets or total net worth). Second, in response to a contractionary monetary policy shock—which constitutes a simultaneous increase in the deposit facility rate and a widening of the corridor spread—the interbank market expands while the real economy shrinks. Both of these moments are in line with the data. As the discount window rate rises, the outside option for borrowers becomes less attractive, which causes an expansion in interbank trading along both the intensive and extensive margins. In addition, tightening of liquidity conditions puts upward pressure on retail deposit rates through rising liquidity premia. The endogenously higher cost of external financing reduces lending to non-financial firms, leading to a decline in aggregate output.

Quantitative experiments. We use our calibrated and empirically validated model to conduct several quantitative experiments. First, we leverage the model to explain the secular decline in interbank lending in Germany over the past 20 years. Based on anecdotal evidence that can be motivated with various institutional features of the ECB, we conjecture that the stigma associated with discount window borrowing in the euro area has declined over time. We find that a twofold reduction in the stigma is enough to explain the measured 30% decline in aggregate interbank trading.

Second, we study how the state of interbank markets impacts monetary policy transmission. We find that the model with PAM amplifies the effects of non-systematic monetary policy shocks relative to both the CE and frictionless benchmarks. The amplification affects both aggregate demand and bank leverage—a key financial-fragility metric—potentially pointing to stronger trade-offs between macroeconomic and financial stabilization. Importantly, we also find that the CE model variant cannot match the correct response of interbank trading volume following a monetary contraction. While trading is pro-cyclical in the data and in the model with PAM, it is counter-cyclical in the CE version. Thus, the baseline model with PAM is likely to be the correct representation of the German data.

Third, the number of active credit institutions has been steadily declining in Germany over the past decades. This pattern is part of a broader worldwide trend of consolidation in the banking industry (Corbae and D'Erasmo, 2020). A back-of-the-envelope calculation suggests that by 2035 the number of active banks in Germany will drop to 1,000 from fewer than 1,500 as of 2020. We use our framework to show that this predicted change will likely have a marginally positive effect on the financial sector and the real economy through a double dividend in the form of enhanced efficiency and financial stability.

Fourth, we depart from the assumption of perfect competition in the deposit market and allow banks to charge mark-downs over the competitive deposit rate. We find that deposit market power has significant effects on the overall banking sector and the aggregate economy but little impact on the intensive or extensive margins of the interbank market.

Related literature. Our paper relates to several strands of the literature. First, a burgeoning literature studies macroeconomic implications of heterogeneity in the financial sector (e.g., Corbae and D'Erasmo, 2021; Elenev et al., 2021; Begenau and Landvoigt, 2021; Coimbra and Rey, 2023; Goldstein et al., 2024; Bellifemine et al., 2024). In particular, our framework is most closely related to Jamilov and Monacelli (2025) and introduces a frictional interbank market. Our model can nest the canonical Gertler and Kiyotaki (2010), Gertler and Karadi (2011) macro-banking model with a representative intermediary as a special case.

Second, our paper relates to the literature on monetary policy transmission and banks' liquidity management (Poole, 1968; Keister and McAndrews, 2009; Bech and Monnet, 2016; Armenter and Lester, 2017; Allen et al., 2020; Anderson et al., 2020; Bianchi and Bigio, 2022). Our contribution is the introduction of persistent, ex-ante bank heterogeneity which yields a stationary distribution of bank size. Our quantitative and empirical emphasis on assortative matching builds on the classic literature on two-sided matching (Gale and Shapley, 1962; Demange and Gale, 1985; Demange, 1987), search-and-matching with heterogeneous agents (Becker, 1973; Morgan, 1994; Smith, 2006), and sorting (Chade et al., 2017; Wright et al., 2021). In particular, our environment features a standard stationary environment, as opposed to a non-stationary situation where characteristics of participating agents evolve over time (Boneton and Sandmann, 2025). Our definition of constrained efficiency follows Dávila et al. (2012) and the general-equilibrium macro literature, computing the optimal allocations of a planner who cannot undo market frictions but takes them as given.

Third, we contribute to the vast literature on banks and the macroeconomic effects of financial crises (e.g., Diamond and Dybvig, 1983; Diamond, 1984; Bernanke and Blinder, 1988; Bernanke and Gertler, 1995; Allen and Gale, 1998; Bernanke et al., 1999; Allen and Gale, 2004; Brunnermeier and Sannikov, 2014; Gertler et al., 2016, 2019; Nuño and Thomas, 2017; Bigio and Sannikov, 2023; Amador and Bianchi, 2024; Faccini et al., 2024; Begenau et al., 2025). Our imperfect-competition extension builds on the deposits channel of monetary policy (Drechsler et al., 2017, 2021, 2025; Egan et al., 2017; Wang et al., 2022).

Finally, we contribute to the applied literature that studies monetary policy transmission in the euro area. Some important studies include, among others, Maddaloni and Peydró (2011), Giannone et al. (2012), Ciccarelli et al. (2014), Altavilla et al. (2014), Altavilla et al. (2019), Heider et al. (2019), Elliott et al. (2021), and Bittner et al. (2023). Our contribution is to provide novel empirical evidence on the largest eurozone economy and to supplement it with a micro-founded macroeconomic framework with bank heterogeneity and liquidity management.

2 Empirical Analysis

This section discusses our data, empirical methodology, and presents the main empirical results for interbank lending patterns.

2.1 Data Description

Our dataset consists of two general parts. First, to study the interbank market we obtain bank-to-bank linked exposure data from the BAKIS-M administrative credit-registry database for Germany (Schmieder, 2006). Banks that are domiciled in Germany are required to report any exposure that exceeds €1 million.[1] The dataset contains outstanding bilateral exposures on a quarterly basis. The sample runs from 2002 to 2019 and is comprised of, on average, about 1,800 banks in the role of either lender or borrower in the interbank market. We have, on average, 28,429 interbank connections per quarter, of which 1,740 are new links, whereas 1,451 are being terminated. Panel A of Table 1 provides summary statistics for the interbank portion of the dataset. In addition, Table B.1 in the Appendix presents lender-borrower exposures by bank type (commercial banks, savings banks, state banks, cooperative banks, mortgage banks, and other banks).

Second, we use monthly balance sheet statistics (BISTA)[2] with the coverage of banks'

[1] In January 2015, the reporting threshold was reduced from €1.5 million. Note that this reporting requirement applies to all borrowers, including those with less credit exposure, as long as the total loan amount of a given borrower's parent and all affiliated units is equal to or exceeds the threshold at any point in time during the reporting period.

[2] Data ID: 10.12757/BBk.BISTA.99Q1-19Q4.01.01

Table 1: Summary Statistics

Panel A: Interbank market level	Mean	SD	p25	p75	*N*
Number of borrowers	1,786	223	1,652	1,923	72
Number of lenders	1,861	228	1,718	1,990	72
Number of links	28,429	5,632	24,190	32,436	72
New links	1,740	748	1,247	2,045	71
Terminated links	1,451	575	1,026	1,701	71
Panel B: Bank level (average)	Mean	SD	p25	p75	*N*
Assets [€ mn.]	3,309	21,289	142	1,213	2,585
Liquid assets / assets	0.238	0.118	0.160	0.301	2,585
Non-bank lending / assets	0.572	0.173	0.504	0.682	2,585
Bank lending / assets	0.140	0.143	0.063	0.154	2,585
Bank funding / assets	0.170	0.145	0.092	0.194	2,585
Non-bank funding / assets	0.675	0.180	0.651	0.778	2,585
Non-bank funding / capital	12.934	4.830	10.782	15.332	2,585
Capital / assets	0.062	0.038	0.047	0.065	2,585
Profits / assets	0.033	0.011	0.029	0.029	2,585
Market share [in %]	0.046	0.351	0.001	0.013	2,585

Notes: This table provides summary statistics for the main variables used in the empirical analysis. The top panel considers aggregated interbank-market statistics at the quarterly level, and the bottom panel shows summary statistics for the main bank balance-sheet characteristics averaged by bank. The sample is 2002:q1-2019:q4.

asset and liability positions (Gomolka et al., 2020) alongside annual income and expense information (GuV)[3] with the coverage of banks' profit and loss accounts (Stahl and Scheller, 2023). Panel B of Table 1 shows summary statistics for the main balance sheet characteristics averaged by bank.

2.2 Assortative Matching and Other Facts

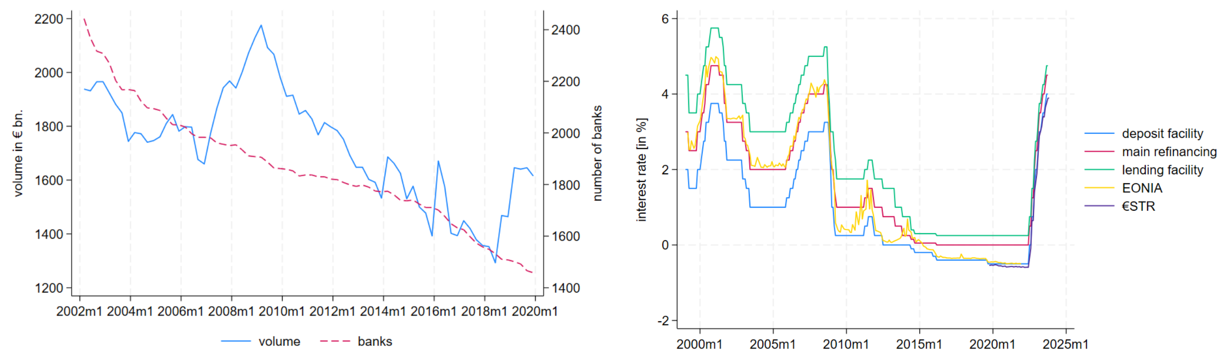
We start by establishing several stylized facts on quantities and prices that are relevant for our analysis. First, Figure 1a shows the aggregate time-series for the German interbank market. Both the total volume of transactions (intensive margin) and the number of active participants (extensive margin) have been trending down steadily over the past 20 years. This is a fact that we will later replicate with our quantitative model.

In Figure 1b we plot the time-series of the ECB interest rate corridor—the deposit facility rate, the main refinancing rate, and the lending facility rate—along with the Euro Overnight Index Average (EONIA) rate, which is the main interbank interest rate on unsecured overnight lending in the euro area. We notice that the pass-through from movements in the refinancing rate to the EONIA rate is almost complete. Statistically, the

[3] Data ID: 10.12757/BBk.GuV.9922.01.01

Figure 1: German Interbank Market and Interest Rates

(a) Interbank Market **(b)** Interest Rates



Notes: Panel (a) plots the time-series of the total volume of transactions in the interbank market (straight line) and the number of active participants in the interbank market (dashed line) in Germany. Panel (b) plots the time-series of the deposit facility, main refinancing, lending facility, interbank (EONIA) and the euro short-term interest rates. Source: European Central Bank.

correlation between the two rates is over 99%.

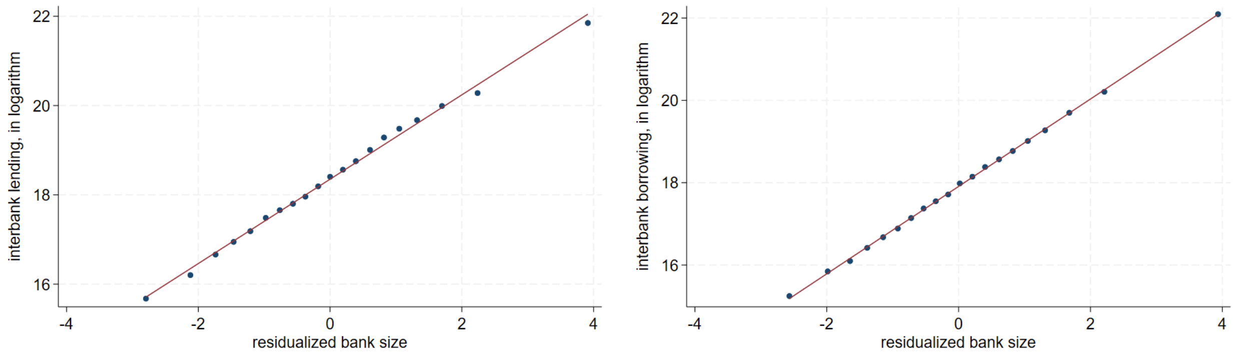
The second stylized fact involves cross-sectional patterns in the banking and interbank sectors. Figure 2 presents (binned) scatter plots for banks' balance sheet size (proxied with the log of total assets) and interbank trading volumes as lender and borrower in Panels (a) and (b), respectively. Both relationships are residualized from time fixed effects. In both panels, we observe an almost perfectly linear positive association in logarithms. In order for our macro-banking model to be consistent with the micro-data, it is important that the model can generate the same cross-sectional pattern.

The third fact is a key empirical finding of the paper regarding the matching patterns in the interbank market. Figure 3 shows matrix-like graphs with size deciles of borrowers and size deciles of lenders on the horizontal and the vertical axis, respectively. Size is defined as total assets but results are quantitatively the same if we use total deposits or total equity. We consider the entire sample between 2002 and 2019. The intensity of lender-borrower matches is represented by the size of circles. Panel (a) uses lender-borrower interactions weighted by the number of matches, and Panel (b) uses lender-borrower interactions weighted by the volume of transactions.

We highlight two important observations. First, a strong, robust pattern of the data is size-based trading and *positive-assortative* matching by size: large lenders lend more and tend to match with large borrowers. This can be seen from the top-right directed concentration of both number-weighted and volume-weighted matches. The reverse also holds true, i.e., large borrowers borrow more and tend to match with large lenders. Notice that there is a bit more variation in terms of the size of the lenders from which the largest

Figure 2: Interbank Exposures and Bank Size in the German Data

(a) Interbank Lending **(b)** Interbank Borrowing



Notes: Binned scatterplots of (log) lending and (log) borrowing in the interbank market on the vertical axes of Panels (a) and (b), respectively, as well as residuals on the horizontal axes obtained from regressing (log) assets on year-quarter fixed effects. The quarterly sample is 2002:q1-2019:q4.

borrowers source credit.[4]

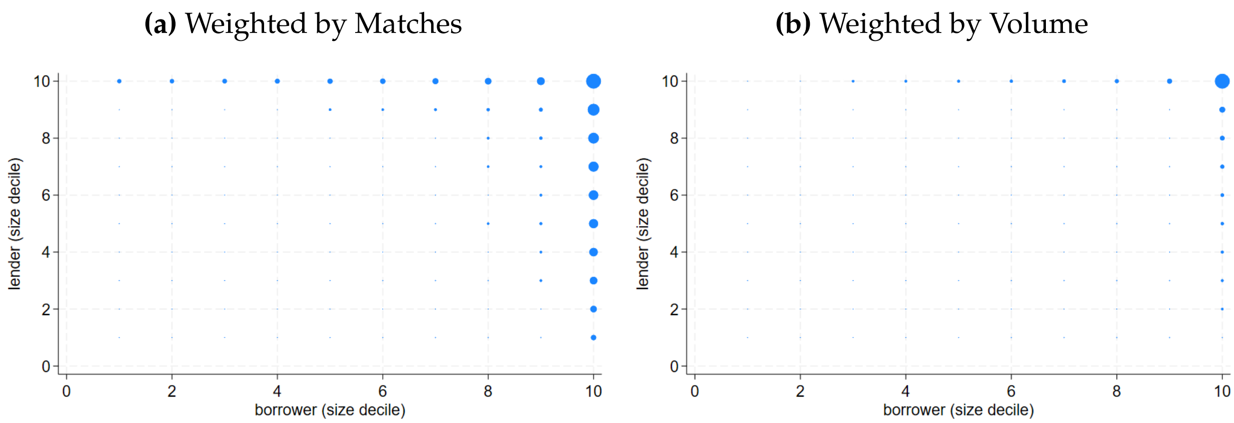
We can document the size-based trading and assortative matching result more formally in a bank-counterparty-year-level panel regression, thus accounting for time-varying unobserved heterogeneity at both the lender and the borrower levels. In Table B.2 in the Appendix, the main independent variable is $Entity_{bt}$, an indicator variable for a bank b that is in the top decile of lenders (for columns 1 and 3) or borrowers (for columns 2 and 4) based on balance sheet size. $Counterparty_{ct}$ variable refers to borrowers for columns 1 and 3 and to lenders for columns 2 and 4. The dependent variable, $Match_{bct}$, is an indicator variable that takes the value of one in case of a relationship between a lender and a borrower in a given year t, and 0 otherwise. The dependent variable is weighted by the natural logarithm of the exposure volume in columns 3 and 4.

The key takeaway is that the magnitude and significance of the coefficients increase as we move down the rows (and, thus, up in the size distribution). That is, conditional on being a lender in the top decile of the size distribution, an interbank market match is much more likely with a counterparty that is also in the top decile of the size distribution. This is true from the perspective of lenders (columns 1 and 3) and borrowers (columns 2 and 4), irrespective of whether matches are weighted (columns 3 and 4) or not (columns 1 and 2).

Figure 3 also speaks to another important fact: interbank market activity is almost

[4]The patterns of size-based trading and assortative matching are highly robust over time and to various sub-periods (see Figure B.3). In addition, this result is robust to the exclusion of building societies and development banks (see Figure B.4).

Figure 3: Assortative Matching in the German Interbank Market



Notes: Bank-to-bank linkages in the German interbank market over 2002:q1-2019:q4. Size deciles of borrowers and size deciles of lenders are on the horizontal and vertical axes, respectively. The intensity of lender-borrower matches is represented by the size of circles. Panel (a) weights lender-borrower interactions by the number of matches, and Panel (b) weights lender-borrower interactions by the volume of transactions.

zero in the lowest size deciles. We interpret this as evidence of *rationing out* of the smallest banks. Our model will be able to speak to this through the lens of a sequential, "first-come, first-served" matching algorithm. While the notion that banks systematically sort into borrowers of preferred profiles and build persistent relationships is ubiquitous (Degryse and Van Cayseele, 2000; Chodorow-Reich, 2013; Chang et al., 2023), we document a particular form of sorting—positive-assortative matching by size—in the context of interbank transactions for the largest euro area economy.

2.3 Local Projections with ECB Monetary Policy Shocks

In this section, we trace out the impact of identified ECB monetary policy shocks on the intensive and extensive margins of the German interbank market. We will use these important moments for model validation in the later sections. The monetary policy shock series is depicted in Figure B.1 in the Appendix. The shocks are identified with the high-frequency approach of Jarociński and Karadi (2020), building on Gurkaynak et al. (2005), Gertler and Karadi (2015), and Nakamura and Steinsson (2018).

Our empirical specification is a lag-augmented local projection, which we run on the full quarterly sample over 2002-2019 (Jordà, 2005; Montiel Olea and Plagborg-Møller, 2021). We denote the interbank exposure of lender i to borrower j in quarter t by $y_{i,j,t}$, ϵ_t is the monetary policy surprise, and h the impact horizon. The baseline specification estimating the average effect of monetary policy surprises is:

$$y_{i,j,t+h} = \alpha_i + \alpha_j + \beta_h \epsilon_t + \gamma_h y_{i,j,t-1} + \omega_h^1 \boldsymbol{X}_{i,t-1} + \omega_h^2 \boldsymbol{X}_{j,t-1} + e_{i,j,t+h}, \tag{1}$$

where $y_{i,j,t}$ is either the natural logarithm of the exposure volume between i and j in year-quarter t (intensive margin, conditional on non-zero volume) or an indicator variable for any non-zero exposure between the two parties (extensive margin). α_i and α_j denote lender and borrower fixed effects, respectively, which capture time-invariant characteristics. $\boldsymbol{X_{it}}$ and $\boldsymbol{X_{jt}}$ denote vectors of time-varying lender and borrower characteristics, namely the natural logarithm of total assets, the deposits to equity ratio, and the liquid assets to total assets ratio.[5] The inclusion of these controls addresses concerns with the omitted variable bias and ensures that our results are not driven by bank size, leverage, or liquidity. The coefficient of interest is β_h. To the extent that ϵ_t is exogenously assigned, $\hat{\beta}_h$ is identified. Standard errors are three-way clustered at the year-quarter, lender, and borrower levels. As the dependent variable may be serially correlated, we also control for its lags (Ramey, 2016).

We are also interested in understanding the heterogeneous effects of ECB monetary policy shocks across banks of different size. To this end, we introduce a size interaction: an indicator $s_{i,t}$ which equals one if lender i is in the top decile of the total assets distribution as of quarter t, and similarly for borrowers ($s_{j,t}$). The specification now takes on the following form:

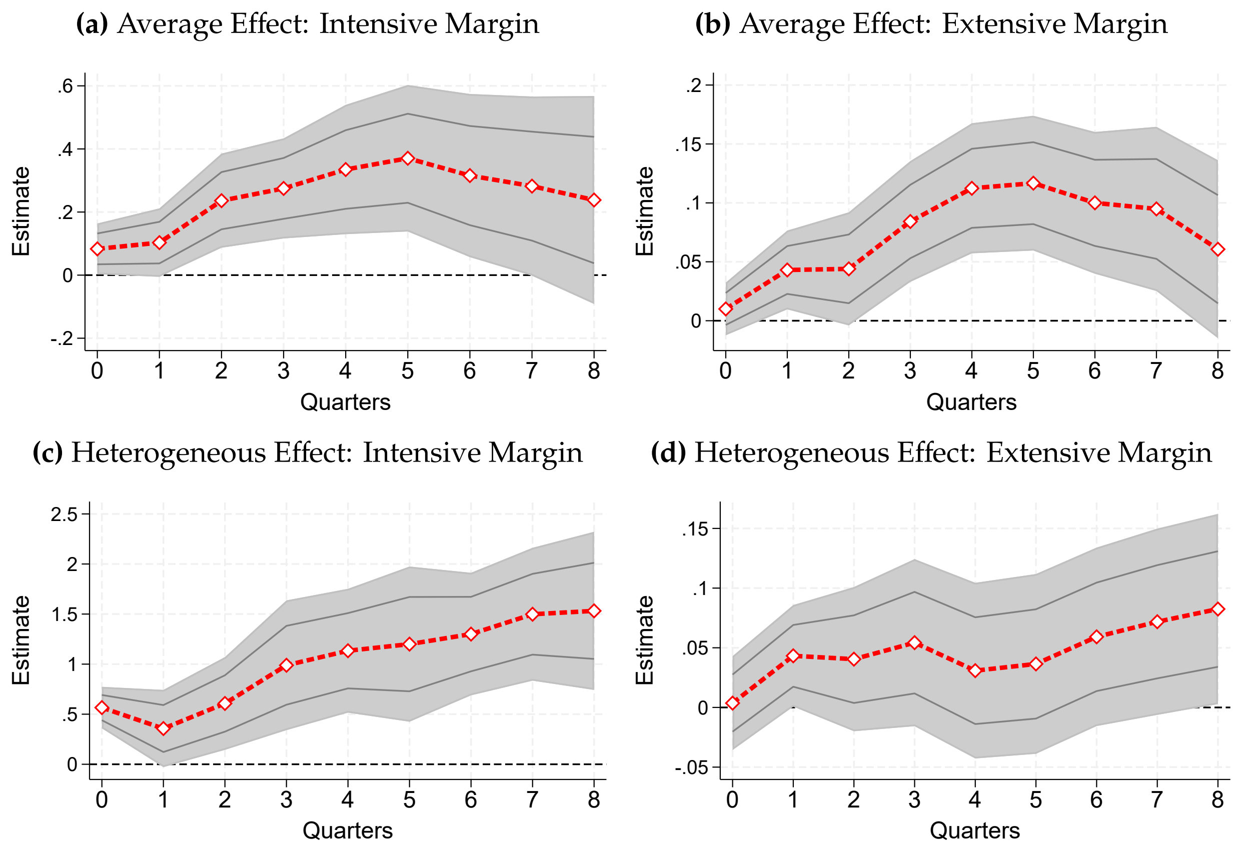
$$y_{i,j,t+h} = \alpha_{i,t} + \alpha_{j,t} + \phi_h s_{i,t} \times s_{j,t} \times \epsilon_t + \nu_h s_{i,t} \times s_{j,t} + \gamma_h y_{i,j,t-1} + e_{i,j,t+h}, \tag{2}$$

where ϕ_h is the coefficient of interest. It captures the triple interaction between monetary policy shocks, lenders being large in size (top decile), and borrowers being large in size (top decile). Note that this specification can no longer identify the average effect due to the presence of lender by quarter and borrower by quarter fixed effects, $\alpha_{i,t}$ and $\alpha_{j,t}$. However, our interest now lies in the *relative* effects.

Figure 4 presents the results in two stages. Panels (a) and (b) show dynamic estimates of $\hat{\beta}_h$ for $h \in [0, 8]$, varying the dependent variable to reflect either the intensive or extensive margin of interbank connections in specification (1). We document that positive (contractionary) ECB monetary policy shocks cause an expansion in the interbank market along the intensive and extensive margins: banks establish more connections *and* lend more in already existing relationships. In other words, the interbank market activity is procyclical with respect to monetary policy changes.

[5] Results without lender and borrower control variables are shown in Figure B.5 in the Appendix.

Figure 4: Local Projections



Notes: Local projections with respect to identified monetary policy shocks (shown in Figure B.1). The quarterly sample is 2002:q1-2019:q4. Panels (a) and (b) show $\hat{\beta}_h$ for $h \in [0, 8]$, varying the dependent variable to reflect either the intensive or extensive margin of interbank connections in specification (1). For the same dependent variables, Panels (c) and (d) show $\hat{\phi}_h$, i.e., the coefficient on the triple interaction term in specification (2). Gray lines and shaded areas correspond to 68% and 90% confidence intervals, respectively. Standard errors are three-way clustered at the year-quarter, lender, and borrower levels.

Panels (c) and (d) of Figure 4 show dynamic estimates of $\hat{\phi}_h$, i.e., the coefficient on the triple interaction term in specification (2). We find that the expansion in the intensive margin is concentrated among matches between large lenders and large borrowers. A positive and significant coefficient in Panel (c) suggests that interbank lending goes up by *more* if both lenders and borrowers belong to the top size decile. In Panel (d), we also observe an increase in interbank lending along the extensive margin, i.e., the largest lenders expand their lending to the largest borrowers if they did not already lend to them before, albeit this effect is more noisy.[6]

Before proceeding with our model, we take stock of our motivating empirical evidence. Our findings suggest that there is a strong interaction between financial intermediary balance sheet size and interbank market activities: larger banks lend more and have more

[6]Results are robust to the exclusion of building societies and development banks (Figure B.6).

connections in general. Larger banks also tend to lend more to other large banks, i.e., there is evidence of positive-assortative matching. Smaller banks, on the other hand, are more likely to be rationed out. Finally, the interbank market response to monetary policy shocks is procyclical and concentrated on the matches between large lenders and large borrowers. Thus, it seems that a good general equilibrium model of banks' liquidity management should contain (i) realistic bank size heterogeneity and (ii) an active interbank market with flexible intensive and extensive margins that correlate with balance sheet size.

3 A Heterogeneous-Bank Model with Liquidity Management

This section presents our quantitative model. Time is discrete and infinite. The environment consists of a continuum of banks that are ex-ante heterogeneous and indexed by $j \in [0, 1]$, a representative household, a representative capital good producer, a representative final good producer, and a monetary authority.

3.1 Interest Rate Policy

We start with the monetary authority which operates an interest rate corridor policy that all agents in the economy take as given. The net interest rates on the lending facility, r^l_t, and reserves, r^s_t, constitute the corridor ceiling and floor, respectively. The interest rates satisfy the following restriction due to the absence of arbitrage: $r^l_t \geq r^s_t$. The rate at which banks will trade in the interbank market, r^i_t, is a weighted average of r^l_t and r^s_t, and its determination is described in detail later below.

3.2 Firms

There is a continuum of measure unity of competitive non-financial firms that are indexed by i. A firm that wishes to finance new investment issues state-contingent equity-like claims on the returns from aggregate capital, which depreciates fully every period. Let L_t be the total amount of such claims. We assume that the full quantity of claims is intermediated by the banking sector such that $L_t = \int l_{j,t} dj$, where $l_{j,t}$ are claims held at the bank level, and $K_{t+1} = L_t$ is the evolution of capital in the economy.

On the supply side, production of new capital is determined by $K_{t+1} = \Phi(I_t)$, where $\Phi(.)$ is an increasing and concave function and I_t is aggregate investment. Each firm solves the following problem:

$$\max_{I_t(i)} = Q_t \Phi(I_t(i)) - I_t(i). \tag{3}$$

The problem above is symmetric and its solution determines the price of capital, Q_t, as a function of investment:

$$Q_t = [\Phi'(I_t)]^{-1}. \tag{4}$$

Thus, the cross-section of bank-level assets, $\int l_{j,t}$, determines the aggregate demand for capital and, in equilibrium, its production and price.

In addition to the above, there is a representative firm that rents labor, H_t, and capital, K_t, in order to produce the final good with a constant returns to scale production technology:

$$Y_t = K_t^{\alpha} H_t^{1-\alpha}, \tag{5}$$

where $0 < \alpha < 1$. Finally, the return on aggregate capital, which banks take as given, is as follows:

$$R_{t+1}^k = \frac{\alpha K_{t+1}^{\alpha-1} H_{t+1}^{1-\alpha}}{Q_t}. \tag{6}$$

3.3 Households

Households discount the future with $\beta \in (0,1)$ and derive utility from consumption, C_t. Labor hours, H_t, are supplied inelastically and normalized to unity. Preferences are given by:

$$\max \mathbb{E}_t \sum_{k=0}^{\infty} \beta^k U\Big(C_{t+k}\Big). \tag{7}$$

The period utility flow is as follows:

$$U(C_t) = \begin{cases} \frac{1}{1-\psi} C_t^{1-\psi} & , \psi \neq 1 \\ \ln C_t & , \psi = 1, \end{cases} \tag{8}$$

where ψ is the coefficient of relative risk aversion.

Households can save via time deposits, $b_{j,t}$, which are one-period bonds that pay out non-contingent gross returns $R_{j,t}^b$. The sequence of household balance sheet constraints is:

$$C_t + \int_0^1 b_{j,t} \leq \int_0^1 R_{j,t}^b b_{j,t-1} + W_t + \text{Div}_t + T_t, \tag{9}$$

where W_t is the competitive wage rate, Div_t are lump-sum transfers of bank dividends from exiting banks, and T_t are any remaining lump-sum transfers. Retail deposit rates do not equalize due to liquidity risk premia that vary by bank, to be defined below.

3.4 Banks

The role of banks in our model is to source time deposits, $b_{j,t}$, from households and—in combination with their own net worth, $n_{j,t}$—to invest in claims, $l_{j,t}$, on aggregate capital. Banks are ex-ante and permanently heterogeneous in efficiency, κ_j, which is a cost shifter that impacts their ability to obtain cheaper funding. Lower values of κ_j henceforth mean *higher* efficiency. κ_j is drawn by nature from a normal distribution $\mathcal{N}(1, \sigma_\kappa)$. Banks also hold reserves, $s_{j,t}$, which is a cash-like risk-free asset. The bank balance sheet constraint binds every period and is as follows:

$$b_{j,t} + n_{j,t} = Q_t l_{j,t} + s_{j,t}. \tag{10}$$

Due to moral hazard frictions as in Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), banks face a leverage constraint of the form:

$$\lambda Q_t l_{j,t} \leq v_{j,t}, \tag{11}$$

where $v_{j,t}$ is the franchise value and λ is a fraction of divertible bank assets.

A minimum reserves rule is given by:

$$s_{j,t} \geq \omega b_{j,t}, \tag{12}$$

where ω is the reserve requirement ratio. It is a policy choice for the monetary authority.

The law of motion of net worth with *lending-stage* (before idiosyncratic shocks are realized) variables is:

$$n_{j,t+1} = R^k_{t+1} Q_t l_{j,t} + R^s_{t+1} s_{j,t} - (1 + \kappa_j r^b_{j,t+1}) b_{j,t} - \nu_1 l^{\nu_2}_{j,t}, \tag{13}$$

where the pair $\{\nu_1, \nu_2\}$ captures non-interest expenses. Whenever $\nu_2 > 1$, the scale-invariance property that is inherent to the standard model is broken, which in turn makes bank size matter. Recall that R^s is the gross interest rate on reserves—a policy choice for the monetary authority. Also, notice how a higher value of κ_j increases the net retail deposit rate, $r^b_{j,t+1}$, at the bank level.

Finally, we assume that banks are risk-neutral, cannot operate with non-positive net worth, and exit with an exogenous probability $1 - \sigma$. The latter assumption also captures a fixed dividend payout rule because, upon exit, all accumulated bank earnings are transferred to the household.

3.5 Interbank Market

After lending decisions are locked in, banks face idiosyncratic deposit withdrawal shocks, $\xi_{j,t}$.[7] $\xi_{j,t}$ are drawn from a mean-zero normal distribution with variance σ_ξ^2 and are i.i.d. over time. Unexpected arrival of $\xi_{j,t}$ generates a liquidity problem for banks. Their tool of liquidity risk management is in the form of borrowing or lending reserves, $s_{j,t}$. A negative realization of $\xi_{j,t}$ creates a deficit in reserve holdings. On the other hand, a positive realization creates excess reserves, which the bank can lend to the other banks or hold at the central bank.

The surplus/deficit in reserves is denoted by $\Delta_{j,t}$ and can be defined as follows:

$$\Delta_{j,t} \equiv \omega b_{j,t} + \frac{\left(1+\kappa_j r^b_{j,t+1}\right)}{R^s_{t+1}} \xi_{j,t} b_{j,t} - \omega b_{j,t}\left(1+\xi_{j,t}\right). \tag{14}$$

The first two terms in (14) summarize the reserve balance and the third term the required reserves level after the shock $\xi_{j,t}$, respectively. Following Bianchi and Bigio (2022), we adopt the convention that the bank pays interest on deposits no matter if they are withdrawn, and therefore any transfer is settled with $\frac{\left(1+\kappa_j r^b_{j,t+1}\right)}{R^s_{t+1}}$ reserves. In the absence of $\xi_{j,t}$ shocks, there are no surpluses or deficits.

Interbank borrowing is costly. Denote with b and l the integer ranks of borrowers and lenders, respectively, based on their efficiency indicator κ_j. Each borrower's objective is to minimize total borrowing costs associated with establishing a match. Each potential match is subject to convex variable costs that are parameterized by the pair $\{\varphi_1, \varphi_2\}$, with $\varphi_1 > 0$ and $\varphi_2 > 1$. These are akin to portfolio settlement frictions (Bianchi and Bigio, 2023) or monitoring costs (Diamond, 1984). These costs are *match-specific* and scale not only with the volume of the transaction but also with the ranks b and l. The total variable cost for a transaction of volume q between borrower b and lender l is as follows:

$$VC_{bl} = b \times l \times \varphi_1 q_{bl}^{\varphi_2}. \tag{15}$$

In our baseline quantitative analysis, we assume that variable costs are borne by the

[7] Suppose that households are subject to preference shocks as in Diamond and Dybvig (1983), which require them to suddenly become impatient and withdraw deposits from bank j in order to save in a different financial vehicle.

borrowers.[8] In addition, each potential transaction must be greater than the minimum trade threshold $\underline{q}$. This parameter is akin to a "fixed cost" and helps with establishing a region of inaction (extensive margin) in the market. The total cost of a singular transaction for the borrower—subject to the outside option (the discount window of the central bank)—is:

$$TC_{bl} = q_{bl} \times \left(R_t^i - R_t^l\right) + VC_{bl}. \tag{16}$$

Optimal trade volume, q_{bl}^*, must satisfy the capacity constraints: $q_{bl}^* = \min\left[\min\left(|\Delta_l|, |\Delta_b|\right), \tilde{q}_{bl}\right]$, where $\tilde{q}_{bl}$ is the desired volume. That is, q_{bl}^* cannot surpass the absolute value of either the deficit of the borrower or the surplus of the lender. Finally, q_{bl}^* must be above the minimum threshold $\underline{q}$.

How are lenders and borrowers matched in the interbank market? Section 4.2 describes two distinct matching algorithms, discusses their efficiency and stability properties, and shows when and how assortative matching—which we observe in the German data—can be obtained in equilibrium.

Interbank rate determination. The interbank market rate, r_t^i, is determined as a weighted average between the interest on reserves and the lending facility rate:

$$r_t^i = \eta r_t^s + (1 - \eta) r_t^l, \tag{17}$$

where η is the bargaining power of the side that is in deficit. A larger η, everything else equal, lowers r_t^i and brings it closer to the corridor floor. In Section 5, η will be calibrated to match the measured average interbank market rate in Germany.

End-of-period net worth. We can now characterize bank net worth *after* the closure of the interbank market. Denote by $q_{j,t}^a$ and $q_{j,t}^b$ the amount of reserves allocated to the interbank market and central bank, respectively, let $VC_{j,t}$ be the total monitoring cost paid by the borrower, and let $\hat{x}$ denote *end-of-period* variables. Thus, the evolution of net worth, $\hat{n}_{j,t+1}$, is as follows:

$$\hat{n}_{j,t+1} = \begin{cases} n_{j,t+1} - r_t^i q_{j,t}^a - r_t^l q_{j,t}^b - VC_{j,t}, & \text{if} \quad \xi_{j,t} < 0 \\ n_{j,t+1} + r_t^i q_{j,t}^a + r_t^s q_{j,t}^b, & \text{if} \quad \xi_{j,t} > 0. \end{cases} \tag{18}$$

Because of frictional interbank trading activities, end-of-period net worth could be lower, everything else equal, than in the frictionless benchmark. And since net worth is a state

[8] This assumption does not affect any of our theoretical results. See Section 4.2 for more details.

variable, this can translate into less lending to non-financial firms and lower output. Clearly, absent idiosyncratic deposit withdrawal shocks, $n_{j,t+1}$ and $\hat{n}_{j,t+1}$ equalize.

Liquidity risk premia. A sufficiently negative return on over-the-counter trading activities can potentially lead a bank to illiquidity if $\hat{n}_{j,t+1}$ falls below zero. In other words, the bank's cash on hand at the end of the period can become negative. Since its lending-stage net worth, $n_{j,t+1}$, is positive, the bank is illiquid but otherwise solvent. Liquidity risk is competitively priced into the retail deposit contract in the form of a premium. Conditional on the bank being in a liquidity crisis, we assume that the household recovers nothing. Thus, deposits are not insured.[9] The solution to the household problem determines the risky retail deposit rate as follows:

$$1 = \Big[(1 - p_{j,t})\mathbb{E}_t\Lambda_{t+1}\Big] \times R^b_{j,t+1}, \tag{19}$$

where $p_{j,t}$ is given by $p_{j,t} = \mathbb{E}_t\Big(Pr\Big(\hat{n}_{j,t+1} < 0\Big)\Big)$ and $\Lambda_{t+1} \equiv \beta\Big(\frac{C_{t+1}}{C_t}\Big)^{\psi}$ is the stochastic discount factor. Observe that both $p_{j,t}$ and $R^b_{j,t+1}$ vary by bank due to ex-ante heterogeneity in κ_j. The interest on reserves and the discount factor are linked through the household Euler equation for riskless bonds that are in zero net supply, $\mathbb{E}_t\left(\Lambda_{t+1}R^s_t\right) = 1$.

3.6 General Equilibrium

A steady-state equilibrium is characterized by a stationary distribution of bank net worth and permanent types, a vector of exogenous government policies $\{R^s, R^l, \omega\}$, endogenous aggregate prices $\{R^i, Q, R^k, W\}$, bank-level policies and value functions $\{v_j, l_j, b_j, n_j, s_j, q^a_j, q^b_j, \hat{n}_j\}$, and endogenous bank-level risk premia and interest rates $\{p_j, R^b_j\}$ such that (i) bank policies and the value function solve the banks' optimization problem; (ii) households and firms optimize; (iii) the distribution of banks is consistent with the decision rules; (iv) all markets clear.[10]

[9] In the United States, around half of all bank deposits are not insured (Egan et al., 2017).

[10] To close the model, we must also keep track of banks' non-interest expenses. Our baseline approach is to assume that these expenses are deducted from aggregate output, yielding a flow variable that is aggregate consumption. However, it is also possible to assume that expenses are rebated back to the household in the form of lump-sum payments for "financial services". The two assumptions do not materially affect our results but could influence normative, welfare-centric statements since the level and cyclicality of (net) consumption and welfare would differ across these two approaches.

4 Theoretical Analysis

In this section, we provide more theoretical details on the lending and interbank-trading stages of the bank problem.

4.1 Recursive Bank Lending Problem

To analyze the banks' lending-stage dynamic problem, we adopt recursive notation. The state vector includes the permanent efficiency type, κ, and net worth state, n. Recall that individual net worth is a state variable due to scale variance. Hence, we can write the banks' dynamic lending problem as follows:

$$v_t(n,\kappa) = \max_{\{l,b,s\}\geq 0} \left\{ \beta \mathbb{E}_t \Big[(1-\sigma) n_{t+1} + \sigma v_{t+1}(n,\kappa) \Big] \right\} \tag{20}$$

subject to:

$$\begin{aligned}
& n_{t+1} = R^k_{t+1} l + R^s_{t+1} s - \Big(1 + \kappa r^b_{t+1}(n,\kappa)\Big) b - \nu_1 l^{\nu_2} \\
& b + n = Q_t l + s \\
& \lambda Q_t l \leq v_t(n,\kappa) \\
& s \geq \omega b \\
& 1 = (1 - p_t(n,\kappa)) \mathbb{E}_t \Lambda_{t+1} (1 + r^b_{t+1}).
\end{aligned}$$

Marginal propensity to lend. Because banks are risk-neutral, they will always lever up until the leverage constraint is binding. Similarly, the reserve requirement constraint holds with equality due to the absence of a precautionary savings motive. The policy function for bank-level lending is the following implicit function of the choice variable:

$$l^*_t(n,\kappa) = \frac{\mathbb{E}_t \Big\{ \tilde{\Lambda}_{t+1} \Big(\frac{(1+\kappa r^b_{t+1}(n,\kappa)) - R^s_{t+1}\omega}{1-\omega} n - \nu_1 l_t(n,\kappa)^{\nu_2} \Big) \Big\}}{Q_t \Big(\lambda - \mathbb{E}_t \Big\{ \tilde{\Lambda}_{t+1} \Big(R^k_{t+1} - \frac{(1+\kappa r^b_{t+1}(n,\kappa)) - R^s_{t+1}\omega}{1-\omega} \Big) \Big\} \Big)}, \tag{21}$$

where $\tilde{\Lambda}_{t+1} \equiv \Lambda_{t+1}(1 - \sigma + \sigma v_{t+1})$ is an augmented discount factor.

In (21), the numerator is the expected discounted cost of a unit of bank deposits or the cost saving from exchanging internal finance for deposit finance. This cost incorporates the reserve requirements constraint and convex non-interest expenses. The denominator of (21) captures the expected discounted excess return on bank assets relative to deposits.

Following Jamilov and Monacelli (2025), we can now characterize the marginal propensity to lend (MPL), an object that succintly summarizes the sensitivity of the banking sector towards exogenous shocks. The MPL is defined as the elasticity of bank-level lending to marginal changes in bank-level net worth:

$$\mathrm{MPL}_t(n,\kappa) = \frac{\mathbb{E}_t\left\{\tilde{\Lambda}_{t+1}\left(\frac{(1+\kappa r^b_{t+1}(n,\kappa))-R^s_{t+1}\omega}{1-\omega}\right)\right\}}{Q_t\left(\lambda - \mathbb{E}_t\left\{\tilde{\Lambda}_{t+1}\left(R^k_{t+1} - \frac{(1+\kappa r^b_{t+1}(n,\kappa))-R^s_{t+1}\omega}{1-\omega}\right)\right\} + \nu_1\nu_2 l_t(n,\kappa)^{\nu_2-1}\right)}. \tag{22}$$

Notice how the MPL varies by bank type, κ, and implicitly by size, through l. In the representative-bank benchmark of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), the MPL is independent from bank-level characteristics. Thus, in our framework the *sensitivity* of bank-level responses to aggregate shocks or policy shifts is not distributed uniformly across the banking distribution. Moreover, this sensitivity depends explicitly on liquidity frictions.

4.2 Interbank Market Matching

How is the interbank market settled? We consider two alternatives. First, iterative sequential trading. Each borrower and lender is ranked according to a perfectly observable characteristic. The ranks of counterparties determine ordinal preferences, and trading opportunities arise based on a predefined order. Second, global surplus maximization. This allocation is akin to a social planner's solution that equalizes the net marginal surplus across all possible lender-borrower links.

Iterative settlement algorithm. We start with the iterative settlement algorithm. The setup is most similar to the classic heterogeneous-agent matching model in which payoffs are a function of both sides' types and everyone strictly prefers higher types (Becker, 1973; Smith, 2006). Our environment is also related to the canonical two-sided matching problem in Gale and Shapley (1962), the common-ranking two-sided problem in Richter and Rubinstein (2024), and the discrete firm entry problem in Atkeson and Burstein (2008). The interbank market is settled in rounds. All potential lenders—banks with realizations of $\xi_{j,t} > 0$—and potential borrowers—banks with realizations of $\xi_{j,t} < 0$—are ranked in descending order according to their efficiency indicator κ_j, which is perfectly observable. We assume that the most efficient banks get to choose first. In equilibrium, κ_j heterogeneity—in combination with scale variance—will lead to a positive correlation between the lending-stage net worth choice $n_{j,t+1}$ and (the inverse of) κ_j. Thus, the most efficient banks are also the largest.

A degree of freedom in our algorithm is whether the market is borrower- or lender-driven, i.e., who gets to solve the portfolio problem. We assume that it is *borrowers* who approach lenders in an iterative manner and, as such, the market is *demand-driven*. While this assumption impacts individual trade-level allocations, it does not affect our results qualitatively.

Denote borrowers with $\mathcal{B} = \{1, \ldots, N\}$, and lenders with $\mathcal{L} = \{1, \ldots, N\}$ which are indexed by ranks b and l, respectively, with 1 being most efficient. A *matching* μ is a bijection $\mu : \mathcal{B} \to \mathcal{L}$. Following Gale and Shapley (1962), μ is *stable* if there is no blocking pair (b, l) that can deviate while making each party strictly better off than under μ.

Is the iterative trading algorithm stable? Is the equilibrium matching pattern assortative, as in the data? Proposition 1 provides answers to these questions.

Proposition 1. *With identical strict preferences* $1 \succ 2 \succ \cdots \succ N$ *on both sides, non-transferable surplus, with or without the minimum trade rule* $\underline{q}$, *and regardless of how the monitoring costs are split, the unique stable matching is the positive-assortative identity matching*

$$\mu^{\star}(b) = b \quad \textit{for all} \quad b = 1, \ldots, N.$$

Proof. Appendix A.1. □

We have shown that the sequential trading algorithm leads to a matching that is stable. In other words, no lender-borrower pair has a profitable deviation from equilibrium. Moreover, the matching is PAM, meaning that the first borrower matches with the first lender, the second borrower with the second lender, and so on. Intuitively, this outcome is natural because pay-offs are super-modular in types, i.e. the match cost falls whenever the quality of the matching partner rises. Importantly, the stability property is not impacted by the presence of the minimum quantity threshold $\underline{q}$ or by the assumption on cost-splitting.

Observe that, in our model, surplus is non-transferable as in Smith (2006) because each transaction is executed under a common offer rate r^i and the division of the surplus is pre-determined exogenously by the combination of the known minimum threshold $\underline{q}$ and the matching cost split. In other words, no pair of banks can shift the individual transaction-level utility with side payments *after* trading quantities have been chosen. As shown by Shapley and Shubik (1972), the core solution—that which cannot be improved upon by any coalition of banks—generally excludes these third-party payments.

Joint surplus maximization. The iterative matching algorithm, while capable of matching the German data very well (as we show in Section 5), is not *constrained-efficient*.

In other words, this algorithm is a not a global maximizer of joint surplus and the economy as a whole can do better in terms of aggregate output while taking frictions as given.

We now discuss the constrained-efficient outcome in the interbank market. This outcome is achieved by a social-planner-like programme that equalizes net marginal surplus across all active borrower-lender links. Borrowers $\mathcal{B} = \{1, \ldots, N\}$ each face a liquidity gap $\Delta_b^- > 0$, and lenders $\mathcal{L} = \{1, \ldots, N\}$ each hold excess reserves $\Delta_l^+ > 0$. As before, all trades occur at the interbank rate r^i, the rate on the lending facility alternative is r^l, and interest on reserves is r^s. The variable matching cost is defined in (15). Trades are subject to the same minimum threshold $\underline{q}$, and utilities are still non-transferable.

For a given quantity q, the borrower's linear gain is $R^l - R^i$ while the lender's linear gain is $R^i - R^s$. The *joint* linear gain is $R^l - R^s$. The planner's program is as follows:

$$
\begin{aligned}
\max_{q,z} \quad & \sum_{b,l} \Big[(R^l - R^s)\, q_{bl} - \varphi_1\, bl\, q_{bl}^{\varphi_2} \Big] \\
\text{s.t.} \quad & \sum_{b} q_{bl} \leq \Delta_l^+, \quad \sum_{l} q_{bl} \leq \Delta_b^-, \\
& \underline{q}\, z_{bl} \leq q_{bl} \leq \bar{q}_{bl}\, z_{bl}, \qquad \bar{q}_{bl} := \min\{\Delta_l^+, \Delta_b^-\}, \\
& z_{bl} \in \{0, 1\}.
\end{aligned}
$$

The above program achieves an allocation that equalizes joint marginal surplus across all active links. An allocation is *pairwise-stable* as per the definition below.

Definition 1 (Pairwise stability)**.** *An allocation (q, z) is pairwise-stable if for every borrower-lender pair (b, l) the following holds:*

(a) If $z_{bl} = 1$ (the link is already active): no $\delta \in (0, \bar{q}_{bl} - q_{bl}]$ makes both agents strictly better off.

(b) If $z_{bl} = 0$ (the link is inactive): no $\delta \in [\underline{q}, \bar{q}_{bl}]$ makes both agents strictly better off.

Finally, the proposition below details the stability property of the planner's allocation (q^*, z^*).

Proposition 2. *For any $\varphi_2 \geq 1$, the planner's solution $(q^\star, z^\star)$ is pairwise-stable.*

Proof. Appendix A.2. □

Thus, the joint surplus-maximizing allocation is pairwise-stable. Any feasible extra trade δ would raise the lender's benefit by $(r^i - r^s)\delta$ but raise the borrower's cost by at least $(r^i - r^s)\delta$. Since side-payments are not allowed, the pair cannot make both sides better off. Because every bilateral deviation is blocked, no larger coalition can profitably deviate either—the allocation is in the grand-coalition core. Note that this result does not change if we (i) dispose of the minimum trading requirement, since $\underline{q}$ does not alter ordinal preferences; (ii) alter the monitoring cost split, because the program optimizes over *joint* surplus, not individual pay-offs.

To summarize, in this section we have discussed two benchmark interbank market matching algorithms. Sequential matching yields a unique, stable, positive-assortative matching (PAM) allocation. While having superior quantitative properties and matching the German data well, as we discuss below, this algorithm does not align with the constrained-efficient solution. It is, therefore, inefficient relative to a social planner allocation that is achieved through global joint-surplus maximization. The latter ensures that the economy can not be better off, given the cost structure. It, however, fails to match the data along several dimensions.

4.3 Discussion

Before proceeding with the quantification of our framework, we briefly discuss several key modeling assumptions.

Endogenous intermediation efficiency. Ex-ante heterogeneity in κ_j is a crucial departure from the standard representative-bank benchmark models. At the bank franchise level, a possible interpretation for κ_j is differences in monitoring "devices" (Stiglitz and Weiss, 1981). The transformation of the same unit of external financing onto next-period net worth varies across franchises. In the meantime, the order of portfolio allocation in the iterative matching algorithm is also determined by κ_j. While we do not micro-found the origins of κ_j in this context explicitly, the intuition is that the rate of arrival of trading opportunities is not distributed equally, and that some banks are permanently more effective, i.e., faster, at identifying them (Wallace, 1988). It is natural to have a single parameter be responsible for both forces through net worth being the unifying characteristic. Low-κ banks are more efficient at the franchise level and are therefore larger in equilibrium. For larger banks, in turn, trading opportunities arrive quicker on average.

Search and matching in the interbank market. Recall that the interbank market rate is determined by the relative bargaining power of borrowers, η. While we calibrate η in order to match the measured interbank interest rate in the euro area, we do not micro-found it. A possible micro-foundation for η involves a search and matching structure in the spirit of Bianchi and Bigio (2022) and Afonso and Lagos (2015), according to which η

would be driven by potentially aggregate state-dependent forces of demand and supply for reserves.

Insolvency risk and bank run risk. Finally, our framework takes into account the pass-through of liquidity risk premia to retail deposit rates. In particular, both risk premia and market rates vary across the distribution of banks, which by itself is an endogenous object. Our model, however, abstracts from endogenous bank-level insolvency that is driven by credit risk and not by liquidity problems (Bellifemine et al., 2024). In addition, we do not allow for bank runs and/or fire sales—fundamental or non-fundamental extreme illiquidity events—as in Diamond and Dybvig (1983) or Bryant (1980). In our model, the probability of a fundamentals-based bank run would in principle vary by bank net worth, a non-trivial extension that we leave for future research.

5 Quantitative Analysis

In this section, we begin to take our model to the data. First, we parameterize the model by targeting select moments from the German data. Second, we present policy functions and inspect the main model mechanisms. Third, we validate the model by showing that it predicts cross-sectional relationships that are in line with our micro-data.

5.1 Calibration

Table 2 reports our model parameterization along with the sources and targets used. Model frequency is one quarter. We discuss our calibration approach block by block, beginning with the macro parameters. For the capital share, α, the risk aversion parameter, ψ, and the discount factor, β, we assign standard values from the literature. The capital production function takes on the form $\Phi(L_t) = a(L_t)^{1-b}$. We calibrate the parameter a internally in order to hit the aggregate price of capital, Q_t, of unity in the stationary steady state. Parameter b is chosen so as to yield the elasticity of the price of capital to bank lending of 0.25, which corresponds to typical values for the elasticity of the price of capital to firm investment (Gilchrist and Himmelberg, 1995). Finally, we set the number of operating banks to $\mathcal{N} = 1,500$, which corresponds to the number of operational credit institutions in Germany as of 2020, as can be seen from Figure 1a.

We now turn to the interbank market. The bargaining power parameter, η, is calibrated internally in order to hit 2.78% p.a, which is the average EONIA rate over 2003q1-2008q4, the period that we refer to as the "normal" years before the onset of the zero lower bound

Table 2: Model Parameterization

Parameter		Description	Target/Source
		Macro	
α	0.36	Capital share	Standard
ψ	1	Risk Aversion	Standard
β	0.995	Discount factor	Standard
a	3.05	Capital technology	$Q = 1$
b	0.75	Capital technology	Elasticity of Q wrt $L = 0.25$
$\mathcal{N}$	1,500	Number of banks in the economy	Germany in 2020
		Interbank Market	
η	0.86	Bargaining power of borrowers	EONIA rate $R^i = 2.78\%$
$\underline{q}$	0.032	Minimum quantity cutoff	Fraction of transactions active = 10%
φ_1	4.5E-6	Match variable cost, linear	Net worth-IB lending elasticity = 0.95
φ_2	2	Match variable cost, quadratic	Normalization
		Bank Balance Sheets	
σ_κ	0.011	Permanent heterogeneity dispersion	Standard deviation of returns on assets = 1.1%
σ	0.973	Dividend payout frequency	Gertler and Kiyotaki (2010)
ν_1	8E-4	Non-interest expense, linear	Non-interest expenses / bank assets = 3%
ν_2	2	Non-interest expense, quadratic	Normalization
σ_ξ	1.8	Stochastic deposit withdrawal volatility	Interbank market volume / bank assets = 13%
λ	0.09	Capital requirement ratio	Bank assets / bank net worth = 10
		Policy and Interest Rates	
ω	1.62%	Reserve requirement ratio	ECB data
R^s	1.82%	Interest on reserves	ECB data
R^l	8.78%	Lending facility rate	Stigma = 5% (Bianchi and Bigio, 2022)

(ZLB) period. The minimum trade threshold parameter, $\underline{q}$, is calibrated internally in order to target the *region of action*, which is defined as the fraction of active interbank links over the total number of possible links. Figure 3 shows that most of the trading activity in the German interbank market is concentrated in the upper deciles of the distribution. Thus, we calibrate $\underline{q}$ so that the region of action is 10%. Parameter φ_1, which governs the linear component of the variable interbank match cost function, controls the relationship between bank size and interbank trading intensity. Using our data, we run a linear regression with (log) interbank borrowing as the dependent variable and (log) bank assets as the independent variable. We also include time fixed effects. The resulting elasticity is 0.95. We then calibrate φ_1 in order to achieve the same elasticity in the model. We normalize φ_2, i.e., the power component of the match cost function, to 2.

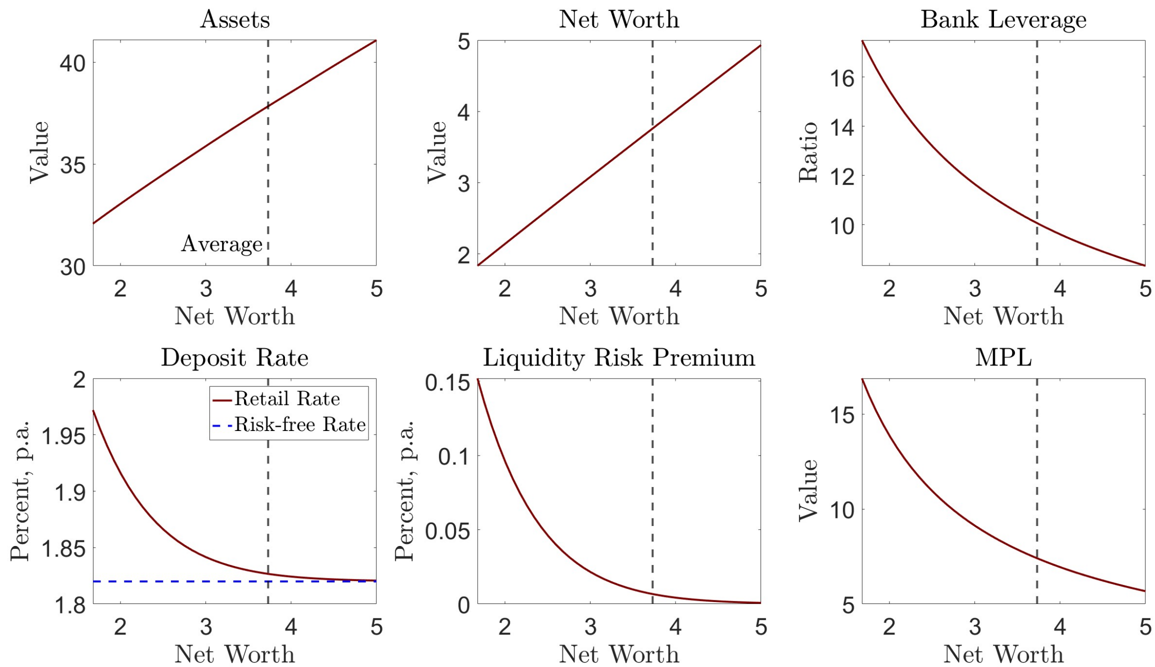
There are several parameter choices that must be made for the bank balance sheets block. Volatility of permanent heterogeneity in efficiency, σ_κ, is set to 1.1%, which corresponds to the cross-sectional standard deviation of profits over assets, as seen from Table 1, and captures variability in profitability. The exogenous survival probability, σ, is set to 0.973 (per quarter) following Gertler and Kiyotaki (2010), which implies that banks live on average for around 9.25 years. The pair of parameters $\{\nu_1, \nu_2\}$ is important as it determines convex non-interest expenditures and, as a result, the departure from scale invariance. We normalize ν_2 to 2. To calibrate ν_1, we compute the average ratio of non-interest expenses to assets in the German data. We define assets as total loans to non-banking institutions since this is the correct object in the model. The ratio is around 3%, on average, which we use as the target. This target is in the ballpark of values typically used in the literature (Corbae and D'Erasmo, 2021). Volatility of the stochastic deposit withdrawal process, σ_ξ, is important for determining the strength of the liquidity risk problem. We reverse engineer σ_ξ such that the interbank volume to total assets ratio is 13%, which corresponds to the average value across time in our German data. The final component of the bank balance sheets block is λ, a parameter that determines the fraction of divertible assets and, thus, the moral hazard friction in the banking sector. We calibrate λ so that the average leverage ratio in the model is equal to 10, which corresponds to average bank leverage in our data. As with non-interest expense ratios, we define leverage as total credit to non-banks over total equity.

The final block involves the government's policy choices. For this block, we leverage publicly available ECB data. The reserve requirement ratio is set to 1.62%, which is the average over our sample. The interest on reserves is set to 1.82% per year, which is the average over 2003q1-2008q4. Finally, the lending facility rate is set conditional on two assumptions. First, the average measured rate over the normal years was 3.78% p.a. Second, we allow for the well-documented stigma that is associated with discount window borrowing. Following Bianchi and Bigio (2022), we set the value of the stigma to 5% p.a. In Section 6, we study the impact of a persistent decline in the stigma on equilibrium allocations.

5.2 Policy Functions

We begin to analyze our calibrated model with the presentation of select policy functions in Figure 5. Each plot showcases a bank-level choice on the y-axis as a function of beginning-of-period net worth, $n_{j,t}$, on the x-axis. The dashed vertical line corresponds to the average level of net worth in the ergodic distribution. Due to the balance sheet constraint, banks with greater $n_{j,t}$ choose to purchase more firm claims, $l_{j,t}$, leading to a greater lending-stage net worth choice, $n_{j,t+1}$. The bank leverage ratio, defined as assets over net worth, is declining with bank size. Small banks also face higher deposit rates, ${r^b}_{j,t}$. Their liquidity risk premia are high because, as we will see below, they are much more likely to suffer losses during the trading stage. Finally, the marginal propensity to lend declines with bank size, suggesting that the lending elasticity is higher for smaller banks.

Figure 5: Model Policy Functions



Notes: Bank-level choices of assets $l_{j,t}$, lending-stage net worth $n_{j,t+1}$, leverage $\frac{l_{j,t}}{n_{j,t}}$, retail deposit rate $r^b_{j,t}$, liquidity premium $(r^b_{j,t} - r^s_t)$, and marginal propensity to lend $\left(\frac{\partial l_{j,t}}{\partial n_{j,t}}\right)$ as a function of beginning-of-period net worth.

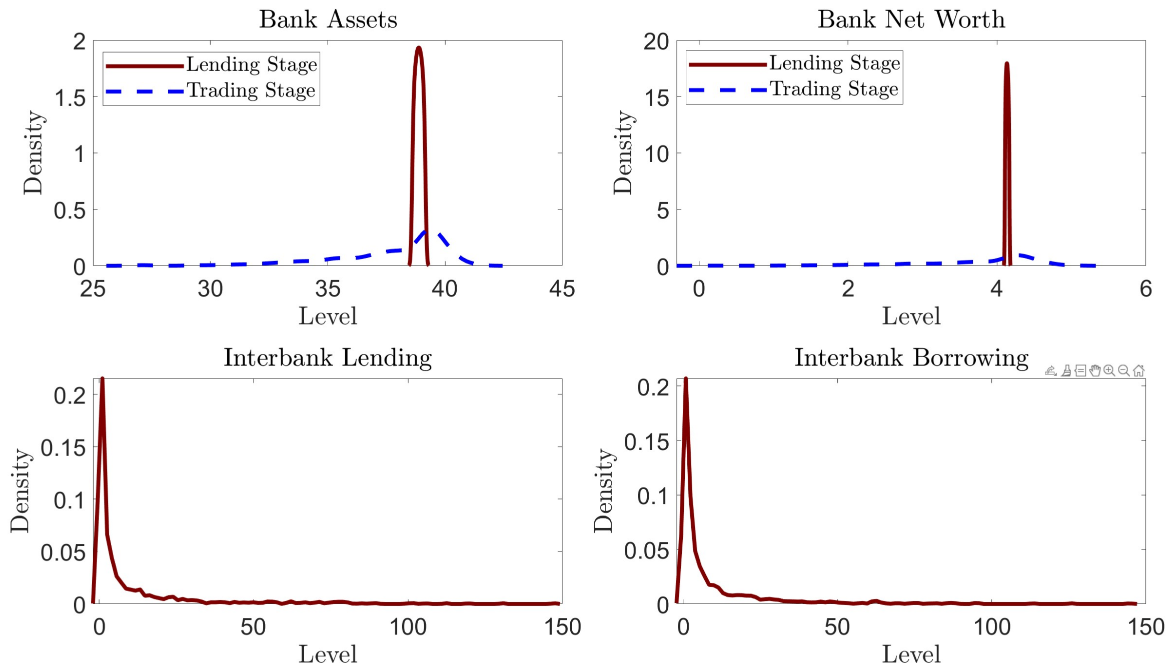
This observation is in line with the empirical evidence on the heterogeneous patterns of the bank lending channel (Kashyap and Stein, 1995, 2000).

5.3 Stationary Distributions

We continue the presentation of quantitative results by showing select stationary distributions of the banking sector and the interbank market. Figure 6 plots the densities of bank assets and net worth in the top two panels. In particular, for each variable we plot both lending-stage and trading-stage distributions. Notice how the cross-section of bank size is much more dispersed and noticeably left-skewed following the trading stage. Idiosyncratic deposit withdrawal shocks generate much ex-post heterogeneity in end-of-period net worth and assets. Moreover, this heterogeneity is fairly asymmetric as there is a small fraction of banks who approach zero net worth, i.e., illiquidity-induced insolvency. These banks are the least efficient franchises that also drew a large negative ξ_j.

In addition to the above, the two lower panels of Figure 6 plot stationary distributions of interbank lending and borrowing. These correspond to the object q^a_j for the two sides

Figure 6: Stationary Distributions



Notes: Stationary distributions of bank assets l_j, lending-stage ($n_{j,t+1}$) and trading-stage net worth ($\hat{n}_{j,t+1}$), and interbank trading q_j^a from the stationary general equilibrium of the model.

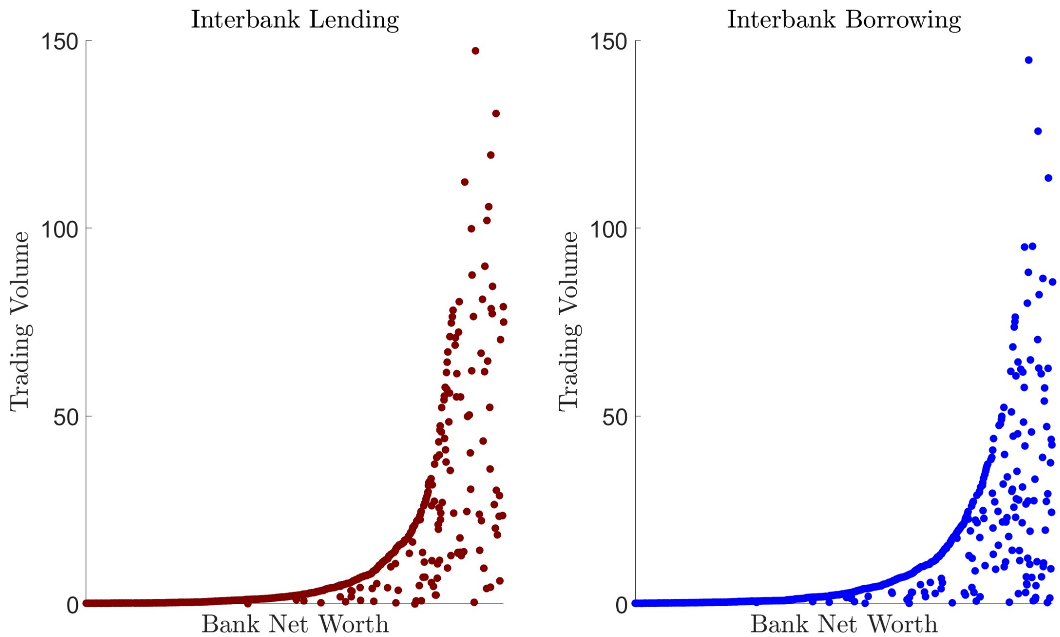
of the market from Section 3.5. These densities are right-skewed, implying that a small fraction of intermediaries engages in a large amount of trading. As we will see below, these are the ex-ante most efficient and largest banks who get to solve the liquidity management problem before anyone else.

5.4 Size-Based Trading

We next turn to the model counterpart of a key empirical relationship from Figure 2: there is a strong positive correlation between bank balance sheet size and both interbank lending and borrowing volumes. In Figure 7, we present the same objects based on the stationary equilibrium of our model. There is a clear positive association between bank size and the volume of both lending and borrowing. Here, we proxy size with bank net worth but the exact same relationships hold if we replace the horizontal axes with assets or deposits.

This observation reveals the following. Conditional on receiving a positive deposit shock $\xi_{j,t}$, lenders that have more beginning-of-period net worth engage in more intense interbank trading. Similarly, the borrowers—banks that draw a negative deposit

Figure 7: Bank Size and the Interbank Market



Notes: Model scatterplots of bank net worth on the x-axes and total interbank lending and borrowing volumes on the y-axes of the left and right panels, respectively.

withdrawal shock—borrow more from other banks in the interbank market if they are large. The ability of our model to match the empirical moment of Figure 2 constitutes an important validation test of the mechanism.

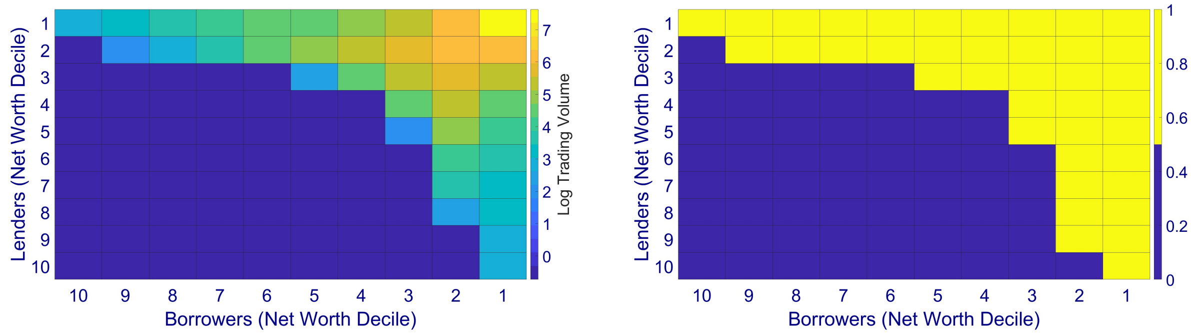
5.5 Assortative Matching in the Interbank Market

A key empirical finding of the paper is the presence of positive-assortative matching in the German interbank market: large banks not only trade more on average, but they also lend to and borrow from other large banks (Figure 3). We now construct a matrix-like figure that closely resembles the empirical counterpart. Figure 8 plots borrowers and lenders (both ranked by the begining-of-period net worth decile) on the horizontal and vertical axes, respectively. Recall that we have 1,500 active banks in the model, so each decile stands for roughly 75 individual banks. Panel (a) shows bank-to-bank interbank (log) exposure volumes, which represents the intensive margin in the market. Panel (b), instead, plots binary indicators with unity standing for at least one existing connection, which gauges the extensive margin.

Two important observations are noteworthy from this graph. First, the model quantitatively generates positive-assortative matching (PAM) by size. The north-east

Figure 8: Assortative Matching in the Model

(a) Intensive Margin (Continuous Volume) **(b)** Extensive Margin (Binary Indicator)



Notes: Equilibrium interbank market as produced by the baseline iterative matching algorithm. Borrowers are ranked by net worth decile and are on the x-axes. Lenders are ranked by net worth decile and are on the y-axes. Panel (a) presents (log) volume of transactions. Warmer shades correspond to greater volumes. Panel (b) shows the binary indicator which takes the value of unity if at least one match takes place and zero otherwise.

sloped pattern of match formation shows that large lenders establish connections with and lend to large borrowers. This is an essential ingredient of our theory, which is strongly present in the German administrative data as shown previously. Second, the extensive margin is very active in our model. Smaller borrowers and lenders do not engage in any interbank trading at all, as evidenced by a large mass of zeros in the right panel of the figure. This suggests that a non-trivial number of banks are *rationed out*, either due to prohibitively high marginal (φ_1) or fixed transaction costs ($\underline{q}$). Those borrowers are forced to borrow from the lender of last resort at a penalty rate, which feeds into a lower level of end-of-period net worth. At the same time, lenders are forced to park excess reserves at the deposit facility and earn a lower return. Thus, both borrowers and lenders would prefer to trade more in the interbank market, and gains from trade are possible but prevented by the cost frictions.

In comparison, the matching pattern of the constrained-efficient allocation looks markedly different. Figure A.1 in the Appendix presents matching matrices from the global joint surplus-maximizing algorithm. First, it is immediately clear that trade links are active in *all* deciles of the distribution, as seen from the right panel. In other words, there is no extensive margin. Second, the planner's preferred trade volumes are considerably smaller, as can be seen on the left panel. The planner does not face the iterative, rank-based trading friction and solves the global matching problem in a single step. In addition, it is able to better optimize conditional on the convex variable cost, which makes large trade quantities prohibitively costly. Finally, it is obvious that the constrained-efficient market does not resemble the German data in Figure 3: the data is much more concentrated and features clear PAM patterns along both the intensive and extensive margins.

Overall, the banking sector and the interbank market in our model are consistent with the data along several dimensions. First, we are able to generate realistic stationary distributions of bank size and interbank trading. Second, there is an empirically-consistent positive correlation between bank balance sheet size and both interbank lending and borrowing. Third and finally, there is PAM based on balance sheet size in the interbank market, as in the data.

6 Applications and Policy Experiments

In this section, we conduct several structural and policy counterfactuals on our calibrated model. First, we study equilibrium allocations in the benchmark model and in various special cases. Second, we use the model to understand the observed secular decline in German interbank trading. Third, examine the impact of the ongoing trending decline in the number of credit institutions. Fourth, we study monetary policy transmission by estimating responses to surprise changes in the interest rate corridor. Finally, we introduce imperfect competition into the deposit market that allows banks to charge mark-downs over the retail deposit rate.

6.1 Interbank Markets and Equilibrium Allocations

We begin the quantitative inspection of our model with the analysis of equilibrium allocations in the stationary steady state. Recall that this corresponds to the situation where all aggregate quantities are time-invariant, all agents optimize, and all markets clear. Table 3 reports key financial and macroeconomic aggregates in the baseline economy and in four illustrative special cases. We consider the following four cases: global surplus-maximizing matching (constrained-efficient allocation), random matching with replacement, frictionless interbank market (which is achieved by setting $\varphi_1 = 0$ and $\underline{q} = 0$), and no interbank trading (which is achieved by setting φ_1 to a very larger number).

The first column of Table 3 considers our baseline iterative matching algorithm that yields positive-assortative matching. We first report the interbank trading volume as a fraction of total bank assets. In the model, this value is 12.6%, very close to our target of 13%. The second row shows the share of interbank market assets that are accounted for by large banks, defined as the top 10% in terms of steady-state net worth. That share is greater than 55%, implying a considerable degree of concentration in the market. The third row reports our main extensive margin metric, the region of action, which is exactly

Table 3: Interbank Markets and Equilibrium Allocations

	(1) Baseline	(2) Constrained Efficiency	(3) Random Matching	(4) Frictionless Trading	(5) No Trading
		Interbank Market (IB)			
IB Assets / Total Bank Assets	0.126	0.530	0.001	0.594	0.000
Large Banks IB Assets Ratio	0.556	0.000	0.479	0.204	0.000
IB Market Extensive Margin	0.107	0.013	0.000	1.000	0.000
		Banking Sector and Aggregate Economy			
Total Bank Assets	37.772	38.233	37.700	38.304	37.463
Total Bank Net Worth	3.731	4.007	3.685	4.050	3.370
Total Assets / Total Net Worth	10.124	9.542	10.231	9.457	11.115
Average Tobin's Q	1.070	0.895	1.088	0.884	1.224
Average Retail Deposit Rate	1.847	1.828	1.850	1.827	1.865
Interbank Market Rate	2.780	2.780	2.780	2.780	2.780
Average Liquidity Premium	0.012	0.004	0.014	0.003	0.021
Aggregate Output	3.696	3.713	3.694	3.715	3.685

Notes: Equilibrium values in the steady state. Column (1) is the baseline with the iterative algorithm and positive-assortative (PAM) matching. Column (2) is the constrained-efficient benchmark with the global joint surplus-maximizing matching. Column (3) is random matching with replacement. Column (4) is the frictionless interbank market (first-best allocation). Column (5) is the case with no interbank trading.

endogenously equal to 10%. The next three rows report total bank assets, net worth, and the leverage ratio. The latter, as in the data, is 10. The average bank's Tobin's Q, which corresponds to the ratio of the franchise value to net worth, is greater than unity, which is consistent with the presence of the collateral constraint. Finally, the next four variables are the average retail deposit rate, the interbank market rate, the liquidity premium, and aggregate output. The interbank market rate is equal to 2.78% p.a., our empirically motivated target. The retail deposit rate is inclusive of the endogenous liquidity premium.

We now study the second column of Table 3, which presents the constrained-efficient allocation that is produced by the global surplus-maximizing algorithm. The constrained-efficient economy is characterized by (i) a much more active interbank market, (ii) a larger and safer (as proxied by the leverage ratio) banking sector, (iii) lower liquidity premia and retail deposit rates, and (iv) aggregate output that is greater by 46 basis points, which is a significant amount for a relatively low-growth developed economy such as Germany. Thus, we have shown quantitatively that the iterative matching algorithm is inefficient relative to the second-based allocation.[11]

[11] Our preferred efficiency metric is aggregate output, Y, and not consumption, because of aggregate non-interest expenses. These expenses can be either deducted from output under the assumption of them being resource-unit losses, or rebated back to the household in the form of income for financial services. As the size of the banking industry is greater in the constrained-efficient allocation, so are the non-interest costs.

Next, the third column of Table 3 considers a random matching algorithm with replacement. In this situation, borrowers are still ranked based on the efficiency metric κ_j. In the first round, the most efficient borrower can be matched with any single lender, after which the borrower decides whether to engage in a trade and how much to borrow. Afterwards, the lender is returned back to the pool and the second-best borrower is randomly matched with a single lender, and so on. Random matching is inefficient, more so than the baseline model and marginally better than when there is no interbank market at all (last column). Thus, while the iterative matching algorithm is inefficient relative to the constrained-efficient allocation, it is more desirable than some other simple alternatives such as random matching schemes.

Finally, the last two columns of Table 3 present two extreme benchmarks: the frictionless interbank market and an economy with no interbank market at all. These represent, respectively, the ceiling and the floor of the equilibrium allocations. The frictionless benchmark is first-best, with the most active interbank market, the largest and safest banking industry, the lowest liquidity premium and market rate, and the most aggregate output produced. In contrast, shutting down the interbank market achieves the worst possible allocation out of the five considered. Intuitively, in this case, idiosyncratic deposit withdrawal risk is not hedged at all, leading to a significant net worth fluctuation problem and a reduction of overall economic activity. As such, this observation is consistent with the broader evidence that bank illiquidity problems by themselves can associate with deteriorating macroeconomic conditions, separately from insolvency considerations (Jamilov et al., 2024).

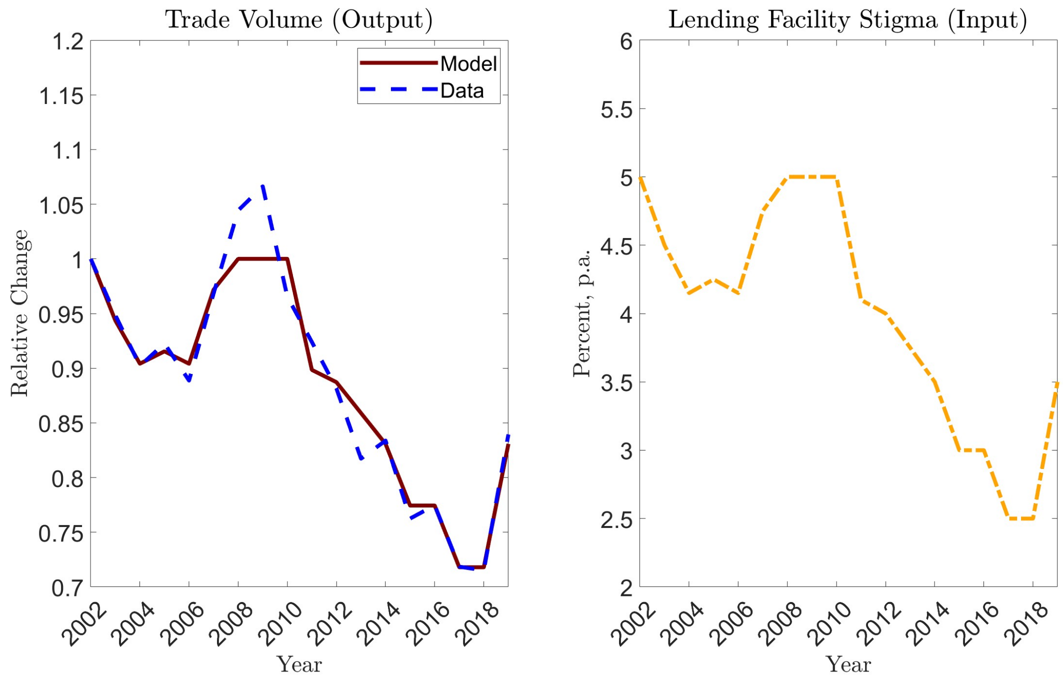
In summary, this section has examined the role of interbank market structures and their corresponding equilibrium outcomes. In a descending order of efficiency—measured by aggregate output—we rank the frictionless market (first-best) as the most efficient, followed by the surplus-maximizing algorithm (constrained efficiency), iterative positive-assortative matching (baseline), random matching, and, finally, the complete shutdown of the interbank market.

6.2 The Secular Decline in Interbank Lending

The basic stylized fact of the German interbank market—as showcased in Figure 1a—is that the total volume of transactions has declined steadily over the past 20 years. We now use our quantitative framework and attempt to explain this secular trend with a persistent change in a key parameter: the stigma that is associated with discount window

Thus, the arbitrary assumption of how to expense these costs can impact how net consumption changes from one allocation to another.

Figure 9: The Secular Decline in Interbank Trading



Notes: Panel (a) shows the empirical target moment and the matched model path for total interbank trading volume. Panel (b) shows the path of the lending facility stigma that is consistent with the model-implied path of the trading volume that matches the data.

borrowing.

The stigma is well-documented, particularly in the case of the United States (Ennis and Weinberg, 2013; Armantier et al., 2015, 2024). However, there is plenty of anecdotal evidence to suggest that over the past decade stigma in the euro area may have been declining (Lee and Sarkar, 2018). First, the ECB usually does not report individual bank-level borrowings under the lending facility. The additional layer of privacy alleviates any fears on behalf of the banks that their borrowings can be known by the market. Second, collateral and counterparty policies are identical for the lending facility and standard open market operations. Third, the marginal lending facility of the ECB is not thought of as a "last-resort" or "backup" source of funds. The use of the ECB's lending facilities is often considered to be routine with little to no signaled information regarding illiquidity or any other vulnerability.

All of the above considerations motivate the following experiment. First, we compute the measured change in total interbank trading relative to 2002 over the 2003-2019 period. Next, for each year we reverse-engineer the stigma that delivers the same relative change in interbank trading in the model. Figure 9 plots the result of this exercise. Panel (a) shows the trend in the data and the simulated trend in the model. Panel (b) presents the path of the stigma, in terms of percent per year, that is required to generate the model-implied decline in trading that matches the data.

We find that a roughly twofold decline in the stigma is sufficient to explain the 30% relative decline in interbank trading. As lending-facility stigma falls, the outside option becomes more attractive and more borrowers prefer to turn to the discount window. The interbank market shrinks along both the intensive and extensive margins. Since match formation in the interbank market is costly, this additional efficiency gain also results in a larger and less risky banking sector, lower liquidity premia, and greater aggregate production (not shown).

6.3 Monetary Policy Transmission

In this section, we estimate responses to unexpected, mean-reverting "MIT" shocks to the interest-rate corridor. Following the insights from Boppart et al. (2018) and Auclert et al. (2021), our shooting method first computes the path of policy functions backwards (by conjecturing that the economy returns to the steady state by the terminal period) and then computes the distribution and the interbank-market decisions forward.

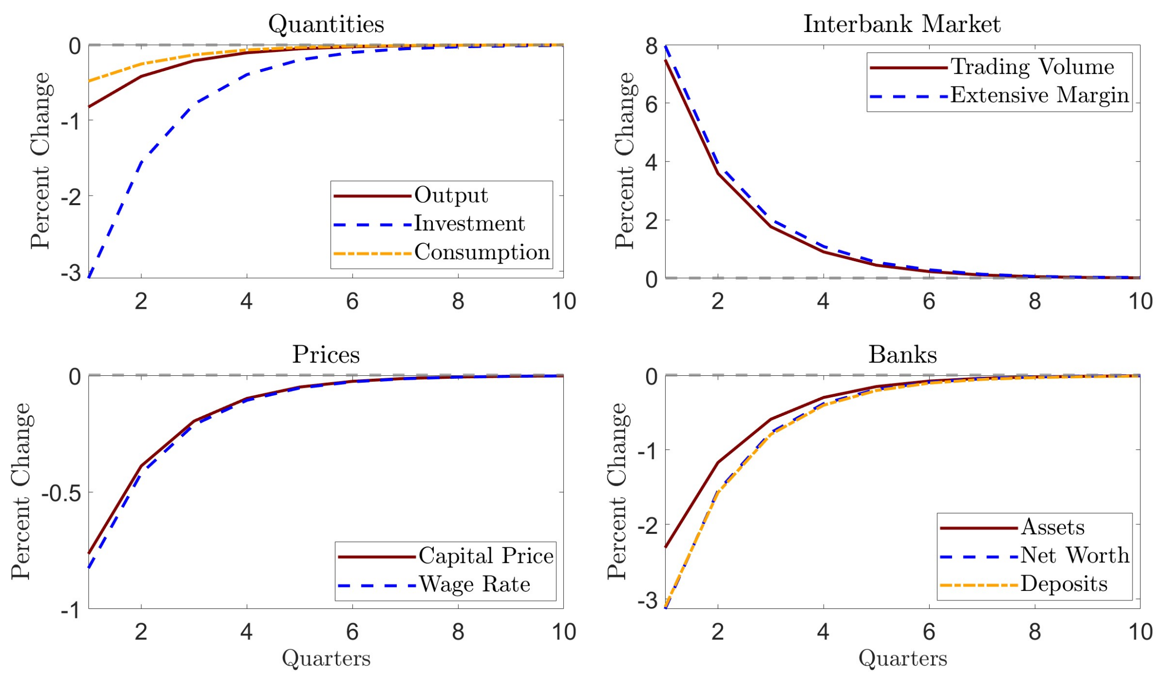
Throughout the section, the shock constitutes a 1% p.a. increase in the deposit facility rate, r^s, and a 1% p.a. widening of the interest rate corridor, $r^l - r^s$. This experiment compares the different shapes of the ECB interest rate corridor over the past years: the high-interest, high-spread environment of 2000-2009 and the low-interest, low-spread environment of 2010-2019. Following the shock, the interest rate and the spread revert back at the rate of 0.5.

6.3.1 Baseline Model

Figure 10 presents impulse responses for the baseline model. First, we observe that, following the monetary contraction, total lending and the number of connections—i.e., both the intensive and the extensive margins—in the interbank market *increase*. The rise of interbank-market activities following monetary contractions is in line with our empirical results from Figure 4 and is due to the following effect. Since the interest rate corridor has widened, the rise of the discount window rate, r^l_t, makes the outside option from the perspective of borrowers in the interbank market less attractive. Thus, the volume of trade and the action region both rise.

Second, we see that all bank-level aggregates—total assets, deposits, and equity (net worth)— shrink, and the economy contracts as aggregate output falls. This is driven by the pass-through from r^s_t to the retail deposit rate, r^b_t, via the liquidity risk channel. Both

Figure 10: Impulse Response to a Contractionary Monetary Shock



Notes: Model impulse responses to a contractionary monetary policy shock, defined as a simultaneous 1% p.a. increase in the interest on reserves and a 1% p.a. widening of the interest rate corridor spread. The shock hits the economy in period 0 and reverts back to the steady-state level with the autocorrelation rate of 0.5.

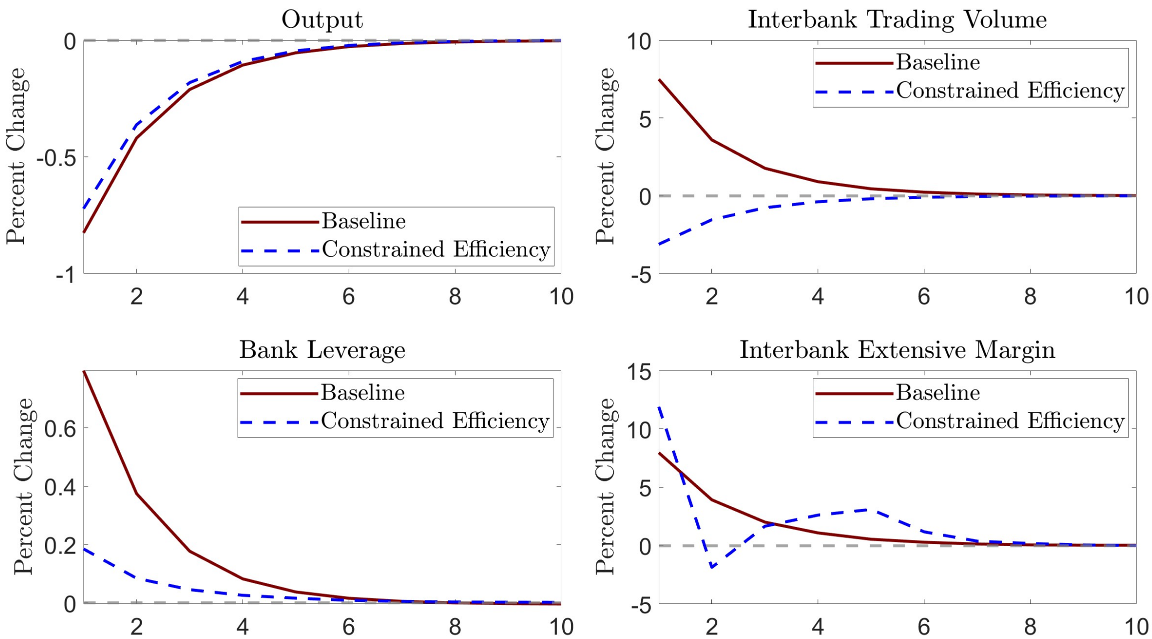
the risk-free and the liquidity premium components of r_t^b rise due to tighter borrowing conditions. Higher costs of external financing inhibit bank balance sheet growth, which reduces loan supply, capital formation, and final good production. Weaker demand for financial intermediation also pushes down the price of capital, lowers the wage rate, and raises the average bank's Tobin's Q (not shown). All in all, model impulse responses are broadly consistent with the empirical results from local projections using our German micro-data as well as standard evidence from the empirical bank lending channel literature.

6.3.2 Constrained-Efficient and Frictionless Benchmarks

In order to quantify the impact of specific interbank-market structures on monetary policy transmission, we now compute impulse responses for the constrained-efficient and frictionless benchmarks. That is, the monetary policy shock now unexpectedly hits these two economies in their respective steady states.

We begin with the constrained-efficient case. Figure 11 compares the responses to the same monetary impulse as before. Relative to the second-best benchmark, we observe that

Figure 11: Interbank Markets and Monetary Policy



Notes: Model impulse responses to a contractionary monetary policy shock, defined as a simultaneous 1% p.a. increase in the interest on reserves and a 1% p.a. widening of the interest rate corridor spread. Straight (dashed) lines correspond to the baseline economy with iterative and positive-assortative matching (global joint surplus-maximizing matching). The shock hits the economy in period 0 and reverts back to the steady-state level with the autocorrelation rate of 0.5.

the assortative-matching baseline amplifies the effects of monetary policy: the response of aggregate output is more negative both on impact and along the transition path. As shown in Figure A.3 in the Appendix, which presents cumulative responses, the output differential two years after the shock amounts to approximately 25 basis points.

Importantly, Figure 11 also reveals that—while the response of the extensive margin is broadly similar across the two cases—the behavior of interbank trading volume differs markedly between the baseline and the constrained-efficient economies. Only the baseline is consistent with the data; the constrained-efficient case incorrectly predicts that a monetary contraction leads to a *reduction* in interbank-market activity. Thus, our baseline iterative algorithm quantitatively outperforms the constrained-efficient counterfactual in aligning with this empirical evidence.

Interestingly, we also observe that the response of bank leverage—measured as the ratio of total assets to total net worth—increases by more than four times in the baseline compared to the constrained-efficient case. Thus, the baseline economy is riskier not only in the stationary steady state but also along the transition paths following exogenous monetary shocks. While measurable financial stability concepts such as costly insolvency are absent in our framework, in many macro-banking models, leverage is an almost perfect predictor of the probability and/or cost of bank default (Bellifemine et al., 2024). Thus, it is fair to conclude that the impact of monetary policy on financial fragility is stronger if the interbank market operates under the less efficient, positive-assortative matching regime.

To summarize, in this section we have studied the monetary transmission mechanism in our macro-financial model with bank heterogeneity and liquidity management. Our framework passes an important validation test by producing impulse responses that are broadly in line with our German data and the empirical banking literature. Moreover, we have analyzed how different forms of interbank trading impact the conduct of monetary policy. Relative to the constrained-efficient benchmark, our baseline economy with positive-assortative matching (i) strengthens the impact of monetary shocks on aggregate demand, (ii) produces the correct response of interbank-market trading, and (iii) has a potentially stronger effect on financial fragility.

6.4 Model Extensions and Sensitivity Analysis

6.4.1 The Secular Decline in the Number of Credit Institutions

The number of credit institutions in Germany has been declining steadily over the past few decades. This pattern is part of a broader, worldwide trend of rising concentration and falling number of institutions in the conventional banking sector (Corbae and D'Erasmo, 2020, 2021). The number of German banks has fallen from around 2,000 in 2005 to less than 1,500 in 2020. If this trend continues, then a back-of-the-envelope forecast suggests that this number will reach 1,000 by 2035.

We now use our quantitative framework to estimate the macroeconomic impact of this forecast. Having now set the number of banks $\mathcal{N}$ in our model to 1,000, we re-compute the stationary steady state. Column (2) of Table 4 reports new equilibrium values. First, we observe that the interbank market is projected to expand along both intensive and extensive margins. Intuitively, as the shock structure remains unchanged, idiosyncratic deposit withdrawal risk is less likely to wash out in the aggregate in smaller samples. As a result, demand for insurance against these shocks goes up. Second, even though the number of institutions is down by approximately 33%, the size of the banking sector in terms of total credit and equity is actually larger. In addition, banks' leverage ratios, Tobin's Q ratios, and liquidity premia are all marginally lower—implying greater financial stability. The effect on aggregate output is positive but small.

The above exercise addresses one of the most central questions in macro-banking: what is the optimal number of financial intermediaries? Our simple experiment suggests

Table 4: Model Extensions and Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)
	Baseline model	Low number of banks (2035 forecast)	Deposit market power	Low bargaining power of borrowers	Low deposit withdrawal volatility
			Panel A: Parameter Settings		
σ_ξ	1.83	1.83	1.83	1.83	0.01
η	0.86	0.86	0.86	0.11	0.86
χ	0.00	0.00	2.60	0.00	0.00
$\mathcal{N}$	1500	1000	1500	1500	1500
			Panel B: Equilibrium Values		
IB Assets / Total Bank Assets	0.126	0.182	0.125	0.039	0.001
Large Banks IB Assets Ratio	0.556	0.432	0.556	0.811	0.618
IB Market Extensive Margin	0.107	0.220	0.109	0.033	0.001
Total Bank Assets	37.772	37.790	38.831	37.725	38.396
Total Bank Net Worth	3.731	3.741	3.868	3.701	4.103
Total Assets / Total Net Worth	10.124	10.103	10.039	10.192	9.359
Average Tobin's Q	1.070	1.046	1.075	1.085	0.857
Average Retail Deposit Rate	1.847	1.844	1.198	1.850	1.820
Interbank Market Rate	2.780	2.780	2.780	7.736	2.780
Average Liquidity Premium	0.012	0.011	0.012	0.014	0.000
Aggregate Output	3.696	3.697	3.733	3.695	3.718

Notes: Parameter settings (Panel A) and equilibrium values (Panel B) in the steady state. Column (1) is the baseline with the iterative algorithm and positive-assortative (PAM) matching. Column (2) is for a lower number of active banks as forecasted for 2035. Column (3) is imperfect competition in the retail deposit market. Column (4) is low bargaining power of borrowers in the interbank market. Column (5) is low volatility of idiosyncratic deposit withdrawal shocks.

that the consolidation trend yields dual dividends in the form of efficiency and financial stability. However, our framework abstracts from credit market power and any normative considerations. Assuming that markups in the bank asset market scale with size, a lower number of credit institutions may potentially put upward pressure on the average markup as banks consolidate. Thus, the net impact on welfare is not clear.

6.4.2 Introducing Deposit Market Power

A salient feature in many banking markets is the presence of a spread between the retail deposit rate and the policy rate of the central bank. An important series of contributions by Drechsler et al. (2017, 2021, 2025) along with Egan et al. (2017) and Wang et al. (2022) have put forth the so-called "deposits channel" of monetary policy, which relies on bank market power in the deposit market. Quantitative studies such as Jamilov and Monacelli (2025) have since introduced deposit market power (DMP) and heterogeneous deposit markdowns into macro-banking frameworks and found that the deposits channel impacts business-cycle fluctuations. In the context of our paper, we are interested in studying the impact of an imperfect deposit-market competition extension on the benchmark model with frictional interbank trading.

In the case of our German data, the spread between retail deposit rates and the refinancing rate is very stark. Figure B.2 plots the policy rate corridor together with the interest rate on household deposits. Notice how the spread is large on average and generally procylical—banks actively trade off the benefit of a larger spread during times of monetary contractions against the cost of a deposit withdrawal and an ensuing lending decline. The pass-through from changes in the policy rate to deposit rates is low. Note a particularly low pass-through episode during the 2022-2023 contractionary phase.

To generate an equilibrium deposit spread, we proceed with a monopolistic competition extension of the baseline model. We now assume that households derive utility from deposit holdings, because they provide special liquidity services. Banks fully internalize these preferences and charge a mark-down over the competitive retail deposit rate. The size of the mark-down is proportional to the extent of preferences for liquidity, governed by the parameter $\chi > 0$. We calibrate χ in order to match the observed average deposit spread of around 0.62% p.a. Appendix A.3 provides further theoretical details.

Column (3) of Table 4 reports equilibrium values from the imperfect-competition steady state. First, observe that the average retail deposit rate, as expected, is significantly lower. Second, financial aggregates (assets and net worth) are greater on average. This outcome is the result of the monopolistic competition extension: banks pay a lower interest rate to depositors, which reduces the cost of liabilities and leads to more lending as well as a greater appetite for risk-taking. The latter can be seen from our derivations of the marginal propensity to lend in (22) and the positive association between the lending elasticity and the net interest margin. A greater stock of capital, as a result, raises aggregate output. Finally, while the *level* of interbank trading is higher in the imperfect-competition economy, the *ratio* over total assets is quantitatively unchanged. This ratio is driven by other model fundamentals such as the magnitude of stochastic deposit withdrawal risk. In addition, the extensive margin remains unchanged.

To conclude, DMP significantly affects bank balance sheets, leading to leverage-driven growth of the banking sector and a 1 percentage-point increase in aggregate demand. However, our model does not predict that DMP interacts with the interbank market in a quantitatively significant way.

6.4.3 Sensitivity Analysis

We conclude the quantitative analysis of the paper with two final exercises. First, we increase the bargaining power of lenders in the interbank market to test the quantitative role of η. Second, we reduce by tenfold the volatility of the idiosyncratic deposit withdrawal process, σ_ξ.

Column (4) of Table 4 presents equilibrium allocations from a steady state of the model with η set to 0.11. The bargaining power of interbank-market borrowers is substantially reduced, which increases the interbank offer rate, r^i, for any given interest rate corridor $\{r^s, r^l\}$. This, as a result, aggravates the capacity to borrow reserves as r^i gets very close to the ceiling, r^l. Relative to the baseline, both the intensive and the extensive margins of the interbank market drop considerably. Hence, since the liquidity problem is more severe, average bank net worth falls, leading to less lending to firms and weaker aggregate demand.

Finally, column (5) of Table 4 showcases a scenario where we dramatically reduce the volatility of stochastic deposit withdrawal shocks, σ_ξ, to 0.01. The near-absence of idiosyncratic risk removes the need for the interbank market as the volume of trade essentially shrinks to zero, as does the region of action. As the economy is much less fundamentally volatile, the financial sector is characterized by banks that are larger and less levered. The liquidity premium disappears and aggregate output goes up by as much as 59 basis points.

7 Conclusion

This paper presents a tractable, general equilibrium framework for monetary policy analysis with bank heterogeneity and liquidity management. We supplement our quantitative theory with detailed empirical work that leverages administrative bank-to-bank linked data from Germany. Our quantitative predictions are validated in the data.

The interbank market features equilibrium *positive-assortative matching* (PAM) among the largest banks and *rationing out* of the smallest banks. The interplay between the frictional interbank market and ex-ante bank heterogeneity generates non-trivial macroeconomic implications. In particular, we find that size-based trading and PAM can be inefficient: they lead to less interbank market activity, a smaller and riskier banking sector, and lower aggregate demand. Furthermore, contractionary monetary policy is shown to expand interbank trading along both the intensive and extensive margins, while the real economy contracts. This conditional pattern is also borne out in the data.

Our results point to the state of the interbank market impacting monetary policy transmission. Relative to the constrained-efficient benchmark, PAM—which matches well the German data—amplifies the effects of non-systematic monetary shocks on aggregate demand and bank leverage, potentially signifying trade-offs between macroeconomic and financial stabilization for the central bank.

Future studies can expand on our work by focusing more on unconventional monetary policy and bank-to-firm linkages, which we currently abstract from.

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Online Appendix for
“Assortative Matching, Interbank Markets, and Monetary Policy”

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August 2025

Contents

A Model Appendix

A.1 Iterative Trading Algorithm

This appendix shows that the iterative interbank trading algorithm leads to an equilibrium matching that is positive-assortative: borrower 1 matches with lender 1, borrower 2 matches with lender 2, and so on. Moreover, the matching is stable (Gale and Shapley, 1962).

Let borrowers $\mathcal{B} = \{1, \ldots, N\}$ and lenders $\mathcal{L} = \{1, \ldots, N\}$ be indexed by their integer rank. Types are indexed such that lower rank implies higher efficiency (low κ_j): borrower 1 is the best borrower, lender 1 the best lender. Borrowers solve the portfolio problem, in the order of their own and lenders' efficiency. There is a minimum quantity threshold $\underline{q}$ for any potential trade. For any proposed bilateral volume $q \geq \underline{q}$, the variable monitoring cost is $VC_{bl}(q) = b \times l \times \varphi_1 q_{bl}^{\varphi_2}$ with $\varphi_1 > 0,\ \varphi_2 > 1$. The cost can be split arbitrarily according to a pre-specified fixed rule. No side-payments are allowed and surplus (utility) from trades is non-transferable as in Smith (2006).

If the costs are paid by the borrower, then the borrower's pay-off is $\max_{q \geq \underline{q}} \Big[(R^l - R^i)q - VC_{bl}(q)\Big]$ and the lender's pay-off is $(R^i - R^s)q$. If the costs are paid by the lender, then the borrower's pay-off is $(R^l - R^i)q$ and the lender's pay-off is $\max_{q \geq \underline{q}} \Big[(R^i - R^s)q - VC_{bl}(q)\Big]$. Finally, if costs are split symmetrically, then the lender's pay-off is $\max_{q \geq \underline{q}} \Big[(R^i - R^s)q - \frac{1}{2}VC_{bl}(q)\Big]$ and the borrower's pay-off is $\max_{q \geq \underline{q}} \Big[(R^l - R^i)q - \frac{1}{2}VC_{bl}(q)\Big]$.

The pay-off of the choosing agent, regardless of how the matching costs are split, is super-modular in efficiency κ_j—types are strategic complements as in the classic model of Becker (1973). Ranks b and l are negatively-ordered integers—such that lower values are better—and the objective is to minimize match-specific cost. Thus, the iterative mechanism favors positive-assortative matching (PAM) that assigns low-b borrowers to low-l lenders.

Formally, the agent that solves the portfolio problem and chooses q faces a strictly concave objective function. The interior optimum is:

$$q_{bl}^{*} = \left(\frac{S}{\alpha^i \varphi_1 \varphi_2\, bl} \right)^{\frac{1}{\varphi_2 - 1}}, \tag{A.1}$$

where S in the numerator is the relevant interest rate spread and $0 < \alpha^i \leq 1$ is the cost share borne by the choosing agent. The optimal quantity q_{bl}^{*} is strictly decreasing in both b and l. Hence, regardless of how the monitoring costs are split, the preference for both the lender and the borrower is $1 \succ 2 \succ \cdots \succ N$.

Now, a *matching* μ is a bijection $\mu : \mathcal{B} \rightarrow \mathcal{L}$. Following Gale and Shapley (1962), μ

is *stable* if there is no blocking pair (b, l) that can deviate and both trade at least $\underline{q}$ while making each party strictly better off than under μ.

Below is the proof of Proposition 1.

Proof. (i) $\mu^\star$ is stable. Borrower b is matched with lender b. Any alternative lender $m > b$ is worse for borrower b, and any alternative borrower $k > b$ is worse for lender b, because both sides have the strict common priority over ranks. Hence, no pair wishes to deviate, even if allowed to trade $\underline{q}$.

(ii) Any non-assortative matching is blocked. Suppose $\tilde{\mu} \neq \mu^\star$. Then, $\exists k > b$ such that $\tilde{\mu}(b) = l > \tilde{\mu}(k) = m$. Both borrower b and lender m strictly prefer each other to their present partners. Since $l > m$, borrower b strictly prefers m to l; and since $k > b$, lender m strictly prefers b to k. Thus, the pair (b, m) would drop their old links and trade at least $\underline{q}$ with each other. Hence, (b, m) blocks $\tilde{\mu}$, contradicting stability. Therefore $\mu^\star$ is the sole stable matching. □

If the minimum-trade rule is disposed of, ordinal preferences are not impacted, and the proof still goes through with PAM as the unique stable matching outcome: if q is freely chosen, (b, m) can deviate at $q^*_{bm} > 0$. Similarly, the result survives any cost split rule. Equation A.1 simply rescales the optimal quantity of trade but leaves the ranking of partners unchanged. Thus, the iterative trading algorithm always converges to a PAM equilibrium, regardless of who pays the monitoring cost.

A.2 Global Joint Surplus-Maximizing Allocation

This appendix provides more theoretical details on the interbank trading algorithm that maximizes joint surplus. Unlike the iterative trading approach, global maximization establishes bank-to-bank linkages and volumes of trade simultaneously. Thus, trades do not occur in rounds and the ordering based on κ_j is not relevant.

As before, let lenders $\mathcal{L} = \{1, \ldots, N\}$ each hold excess reserves $\Delta_l^+ > 0$; borrowers $\mathcal{B} = \{1, \ldots, N\}$ each face a liquidity gap $\Delta_b^- > 0$. All trades take place conditional on the pre-determined interest rate R^i and the central bank's facility rates (R^s, R^l), such that $R^l \geq R^i \geq R^s$. Assume that match-specific costs $VC_{bl}(q) = \varphi_1 \, b \, l \, q^{\varphi_2}$, $\varphi_1 > 0$, $\varphi_2 \geq 1$ are fully borne by the borrower. A link is either closed ($q_{bl} = 0$) or trades at least a fixed amount $\underline{q} \geq 0$. The pay-off of the borrower is $(R^l - R^i)q - VC_{bl}(q)$ and the pay-off of the lender is $(R^i - R^s)q$. Utilities are non-transferable.

The planner's program, as in the main text, is as follows:

$$
\begin{aligned}
\max_{q,z} \quad & \sum_{b,l} \Big[(R^l - R^s)\, q_{bl} - \varphi_1 \, bl \, q_{bl}^{\varphi_2} \Big] \\
\text{s.t.} \quad & \sum_{b} q_{bl} \leq \Delta_l^+, \quad \sum_{l} q_{bl} \leq \Delta_b^-, \\
& \underline{q}\, z_{bl} \leq q_{bl} \leq \bar{q}_{bl}\, z_{bl}, \qquad \bar{q}_{bl} := \min\{\Delta_l^+, \Delta_b^-\}, \\
& z_{bl} \in \{0, 1\}.
\end{aligned}
$$

The objective is concave for every $\varphi_2 \geq 1$ and a mixed-integer optimum exists. As in the main text, an allocation (q, z) is pairwise-stable if for every borrower-lender pair (b, l) the following holds: (a) If $z_{bl} = 1$ (the link is already active): no $\delta \in (0, \bar{q}_{bl} - q_{bl}]$ makes both agents strictly better off; (b) If $z_{bl} = 0$ (the link is inactive): no $\delta \in [\underline{q}, \bar{q}_{bl}]$ makes both agents strictly better off.

Below is the proof of Proposition 2.

Proof. Let $\lambda_l, \mu_b, \xi_{bl} \geq 0$ be Karush-Kuhn-Tucker multipliers. For any active link with $q_{bl}^\star > 0$,

$$
(R^l - R^s) - \varphi_1 \varphi_2 \, b \, l \, (q_{bl}^\star)^{\varphi_2 - 1} = \lambda_l + \mu_b + \xi_{bl} \ \geq 0.
$$

Active link. At the optimum, the borrower's marginal gain at $q_{bl}^\star$ is:

$$
\begin{aligned}
(R^l - R^i) - \varphi_1 \varphi_2 \, bl \, (q_{bl}^\star)^{\varphi_2 - 1} &= \\
(R^l - R^i) - \Big(R^l - R^s - \lambda_l - \mu_b - \xi_{bl} \Big) &= \\
-(R^i - R^s) + (\lambda_l + \mu_b + \xi_{bl}) &\ \leq 0.
\end{aligned}
$$

The last weak inequality follows from the fact that a bilateral increase $\delta > 0$ is feasible only if the lender has capacity left, i.e. $\lambda_l = 0$, the borrower still needs liquidity, i.e. $\mu_b = 0$, and the pair is below the upper bound, i.e. ξ_{bl}. Under these conditions, the marginal gain reduces to simply $-(R^i - R^s) \leq 0$. Lender's marginal gain is $+(R^i - R^s) \geq 0$. Hence, any extra trade weakly benefits the lender but weakly hurts the borrower; the pair will not deviate as both agents are not strictly better off. Alternatively, if any of the $(\lambda_l, \mu_b, \xi_{bl})$ is positive, at least one capacity constraint is binding, and no positive δ is feasible, which means no blocking-pairing is possible.

Shut link. At $q_{bl} = 0$, complementary slackness on ξ_{bl} implies $\varphi_1\varphi_2\, bl\, \underline{q}^{\varphi_2 - 1} \geq R^l - R^s$. Therefore, the borrower's net gain from the first feasible quantity $\underline{q}$ is $(R^l - R^i) - \varphi_1\varphi_2\, bl\, \underline{q}^{\varphi_2 - 1} \leq (R^l - R^i) - (R^l - R^s) = -(R^i - R^s) \leq 0$. Thus, the borrower sees no profitable deviation.

Lender pays cost. The result does not change if the matching cost is borne fully by the lender. In this case, the pay-offs are $(R^l - R^i)q$ and $(R^i - R^s)q - VC_{bl}(q)$ for the borrower and the lender, respectively. When links are active, the lender blocks every deviation because the lender's marginal benefit is $-(R^l - R^i) \leq 0$ even if the benefit for the borrower is $+(R^l - R^i) \geq 0$. When links are inactive, similarly, the lender sees no profitable deviation since its marginal benefit is $-(R^l - R^i) \leq 0$.

Symmetric cost split. Suppose now that the cost is split 50-50 (symmetrically). In the case of active links, the marginal benefit of the borrower at the optimum is $\frac{1}{2}(R^l - R^i - (R^i - R^s))$, again imposing zeros on all KKT multipliers. The marginal benefit of the lender, in turn, is $-\frac{1}{2}(R^l - R^i - (R^i - R^s))$. Suppose that $R^l - R^i \neq R^i - R^s$. This is the quantitatively relevant case, given the stigma of the lending facility. Then, one marginal pay-off is strictly negative and the other is strictly positive. Extra trade does not make both agents better off. Alternatively, suppose $R^l - R^i = R^i - R^s$. In this knife-edge case, the two banks are indifferent but not strictly better off; a deviation still does not block the allocation. In the case of inactive links, the marginal benefits are $\leq \frac{1}{2}(R^l - R^i - (R^i - R^s))$ and $\leq \frac{1}{2}(R^i - R^s - (R^l - R^i))$, with strict inequality if $R^l - R^i \neq R^i - R^s$. Thus, either at least one marginal pay-off is negative or the pair is indifferent and a deviation is not strictly profitable.

No bilateral deviation benefits both parties, regardless of whether the link is active or inactive, and regardless of who pays the matching cost. The allocation is pairwise-stable. □

To conclude, regardless of whether the monitoring cost is paid by the borrower, the lender, or shared evenly, any feasible extra trade makes at least one party strictly worse off (or leaves both indifferent). Hence, the global joint surplus-maximizing allocation lies in the exchange core and is pairwise-stable in every cost-sharing scenario.

A.3 Details on the Deposit Market Power Extension

This appendix provides more theoretical details on the imperfect-competition extension in Section 6.4.2. The period utility function now takes on the following form:

$$U(C_t, B_t) = \begin{cases} \frac{1}{1-\psi} C_t^{1-\psi} + \chi B_t & , \psi \neq 1 \\ \ln C_t + \chi B_t & , \psi = 1, \end{cases} \tag{A.2}$$

where χ determines the extent of deposit market power of banks. This power is rooted in preferences: households desire deposits for their liquidity services and banks, fully internalizing this, pay a lower interest rate. We assume that deposit franchises are perfect substitutes:

$$B_t = \int_0^1 b_{j,t}. \tag{A.3}$$

Denote by $\tilde{R}^b_{j,t+1}$ the competitive retail deposit rate that is obtained in the baseline economy with perfect competition. The deposit rate is now priced according to a Lerner-type equation that sets a *mark-down* over the competitive rate:

$$R^b_{j,t+1} = \left(1 - \frac{U_B\left(C_t, B_t\right)}{U_C\left(C_t, B_t\right)}\right) \tilde{R}^b_{j,t+1}. \tag{A.4}$$

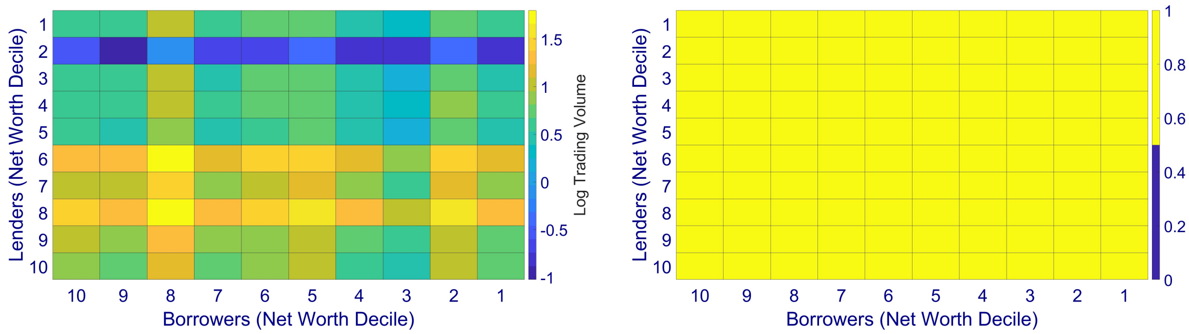
The object in brackets corresponds to the mark-down, which is positive whenever $\chi > 0$.

For as long as $\chi > 0$, positive marginal utility from deposit holdings leads to deposit market power of banks and a positive spread term, $\frac{U_B(C_t,B_t)}{U_C(C_t,B_t)}$, which yields a mark-down over the competitive rate. We calibrate χ in order to match the measured average deposit spread of 0.62% p.a.

A.4 Additional Quantitative Results

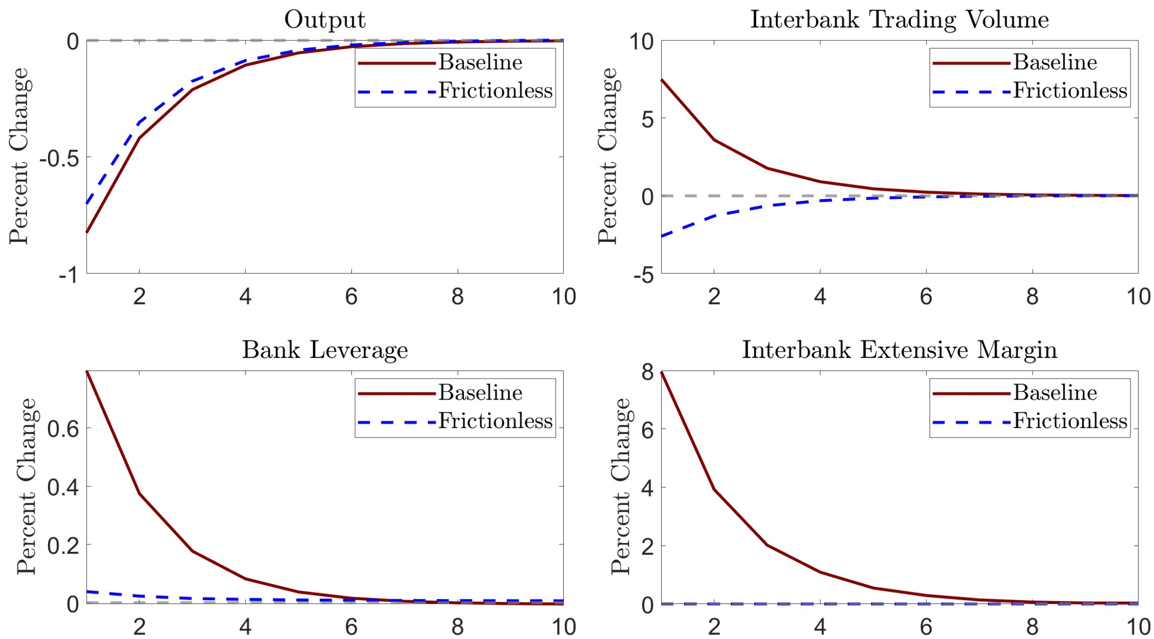
Figure A.1: Global Joint Surplus-Maximizing Matching

(a) Intensive Margin (Continuous Volume) **(b)** Extensive Margin (Binary Indicator)



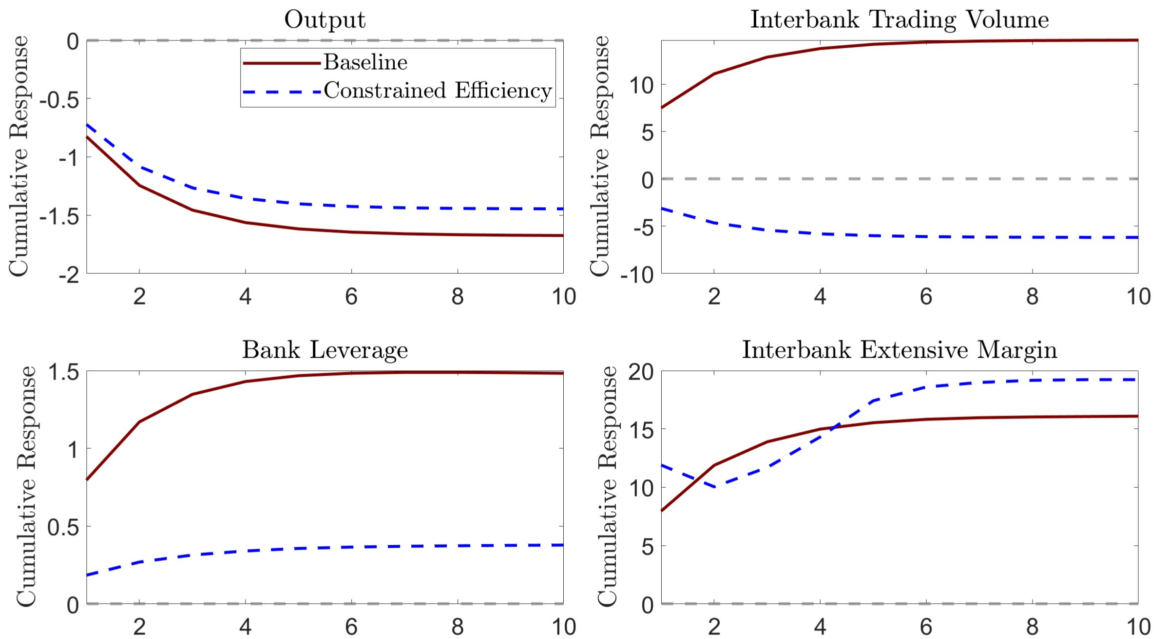
Notes: Bank-to-bank matching metrics in the model's interbank market based on the global surplus-maximizing algorithm. Borrowers that are ranked by net worth decile are on the horizontal axes. Lenders that are ranked by net worth decile are on the vertical axes. Panel (a) presents (log) volume of transactions. Warmer shades correspond to greater volumes. Panel (b) shows the binary indicator which takes the value of unity if at least one match takes place and zero otherwise.

Figure A.2: Frictionless Interbank Markets and Monetary Policy



Notes: Model impulse responses to a contractionary monetary policy shock, defined as a simultaneous 1% p.a. increase in the interest on reserves and a 1% p.a. widening of the interest rate corridor spread. Straight (dashed) lines correspond to the baseline economy with iterative and positive-assortative matching (frictionless interbank markets where $\varphi_1 = 0$ and $\underline{q} = 0$). The shock hits the economy in period 0 and reverts back to the steady-state level with the autocorrelation rate of 0.5.

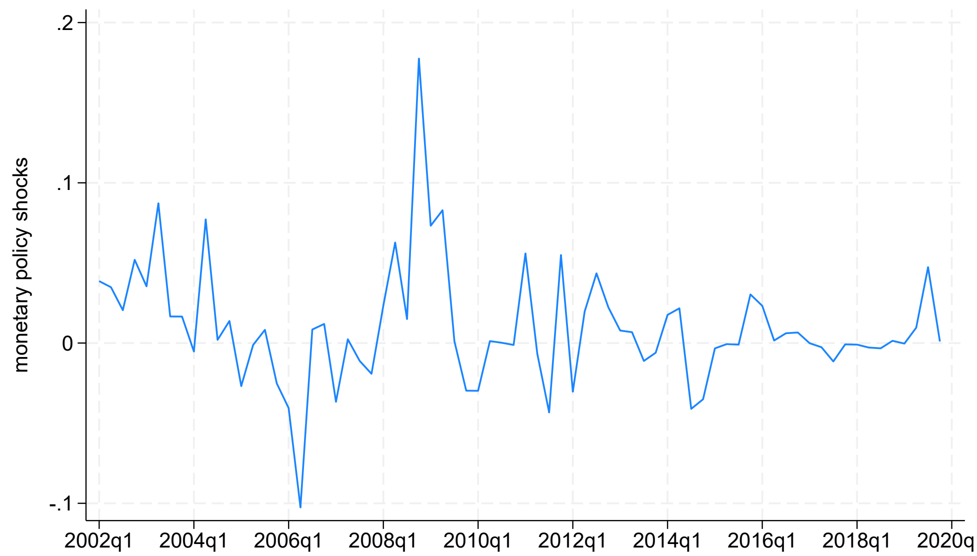
Figure A.3: Cumulative Responses to Monetary Policy and Constrained Efficiency



Notes: Cumulative model impulse responses to a contractionary monetary policy shock, defined as a simultaneous 1% p.a. increase in the interest on reserves and a 1% p.a. widening of the interest rate corridor spread. Straight (dashed) lines correspond to the baseline economy with iterative and positive-assortative matching (global surplus-maximizing matching). The shock hits the economy in period 0 and reverts back to the steady-state level with the autocorrelation rate of 0.5.

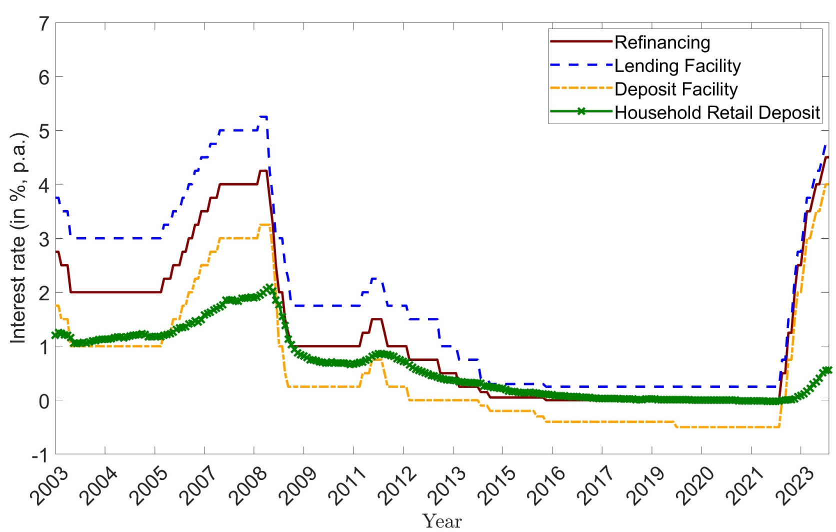
B Data Appendix

Figure B.1: Monetary Policy Shocks



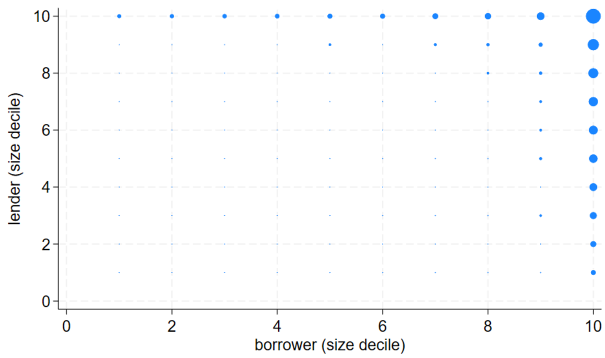
Notes: Monetary policy shock for the euro area, identified with the high-frequency identification approach. Source: Jarociński and Karadi (2020).

Figure B.2: Retail Deposit and Policy Rates

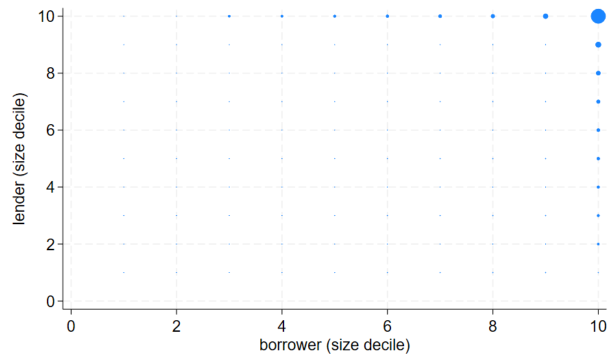


Notes: Time-series of the deposit facility, main refinancing, lending facility, and household retail deposit rates. Source: ECB.

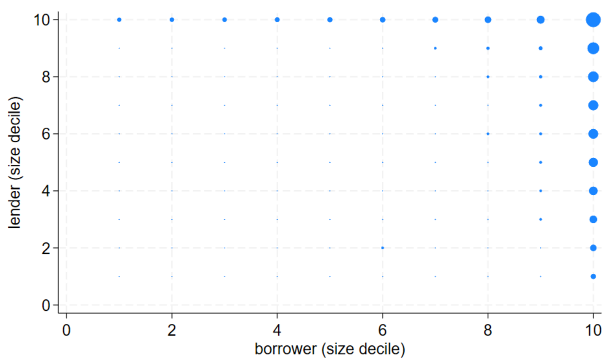
Figure B.3: Assortative Matching in the German Interbank Market—Different Subperiods



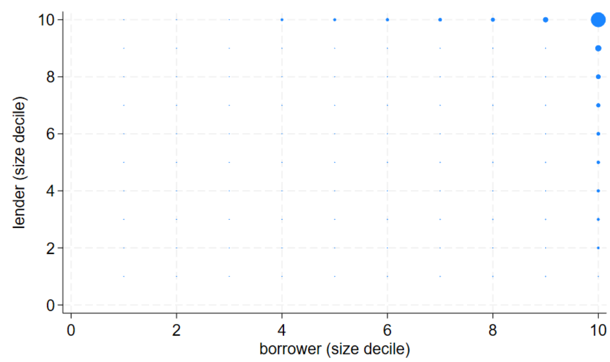
(a) Weighted by Matches, 2002-2006



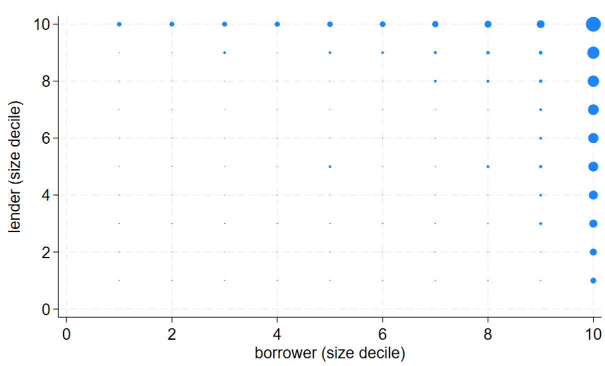
(b) Weighted by Volume, 2002-2006



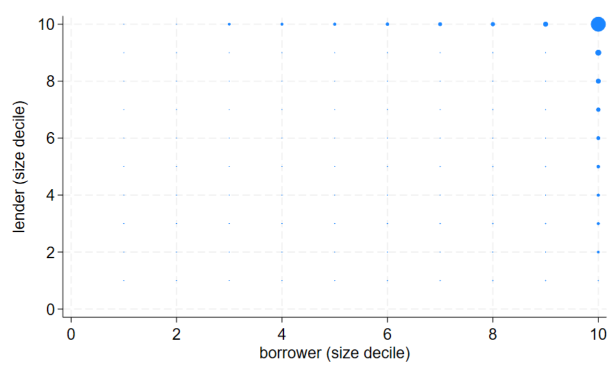
(c) Weighted by Matches, 2007-2009



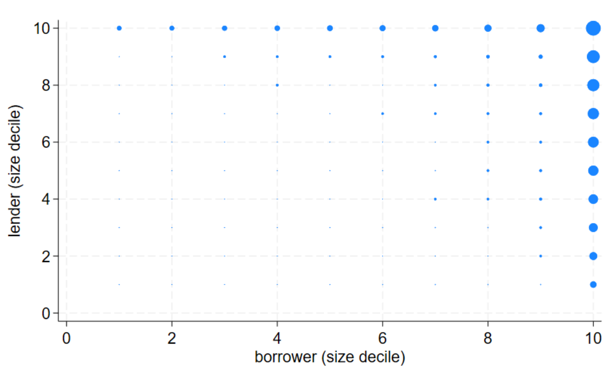
(d) Weighted by Volume, 2007-2009



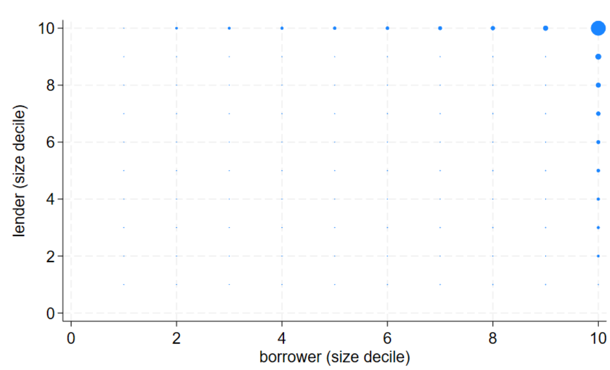
(e) Weighted by Matches, 2010-2014



(f) Weighted by Volume, 2010-2014



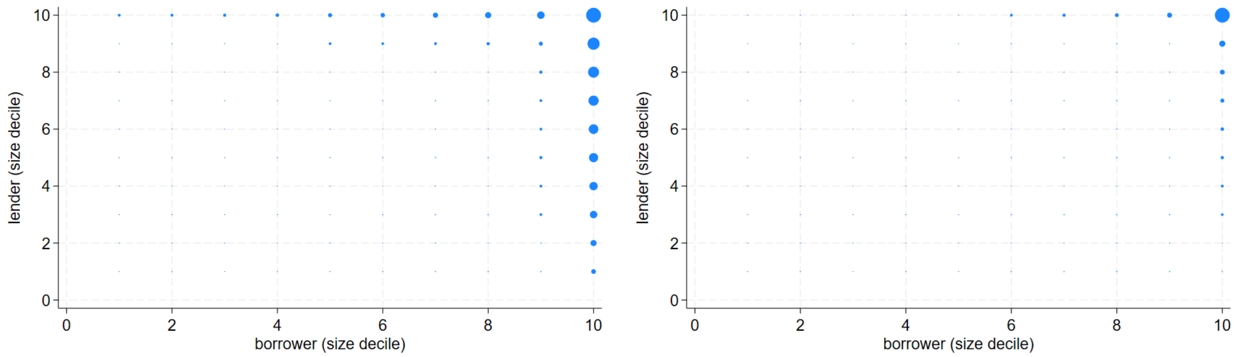
(g) Weighted by Matches, 2015-2019



(h) Weighted by Volume, 2015-2019

Notes: Bank-to-bank linkages in the German interbank market for different periods between 2002 and 2019: before the global financial crisis (2002-2006), during the global financial crisis (2007-2009), post global financial crisis (2010-2014), and during quantitative easing (2015-2019). Size deciles of borrowers and size deciles of lenders are on the horizontal and vertical axes, respectively The intensity of lender-borrower matches is represented by the size of circles. Panel (a) weights lender-borrower interactions by the number of matches, and Panel (b) weights lender-borrower interactions by the volume of transactions.

Figure B.4: Assortative Matching in the German Interbank Market—Robustness Bank Sample

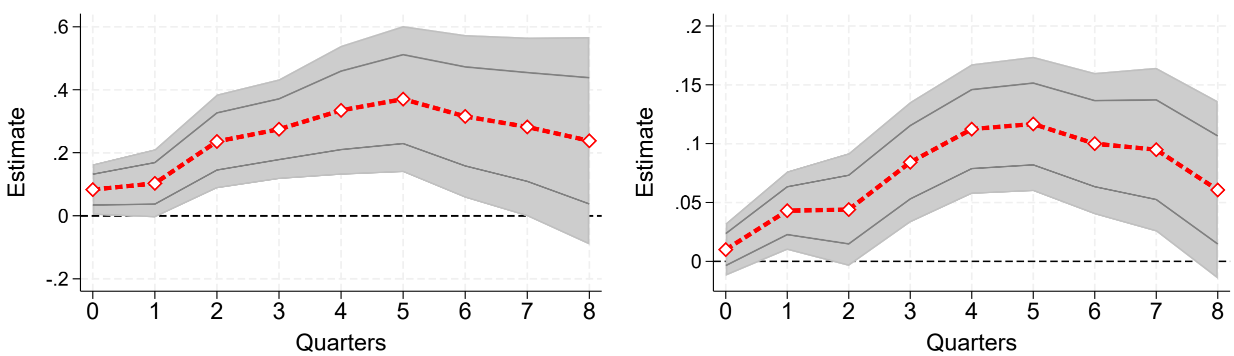


(a) Weighted by Matches

(b) Weighted by Volume

Notes: Bank-to-bank linkages in the German interbank market between 2002 and 2019, excluding building societies and development banks. Size deciles of borrowers and size deciles of lenders are on the horizontal and vertical axes, respectively. The intensity of lender-borrower matches is represented by the size of circles. Panel (a) weights lender-borrower interactions by the number of matches, and Panel (b) weights lender-borrower interactions by the volume of transactions.

Figure B.5: Local Projections—Robustness without Bank Controls

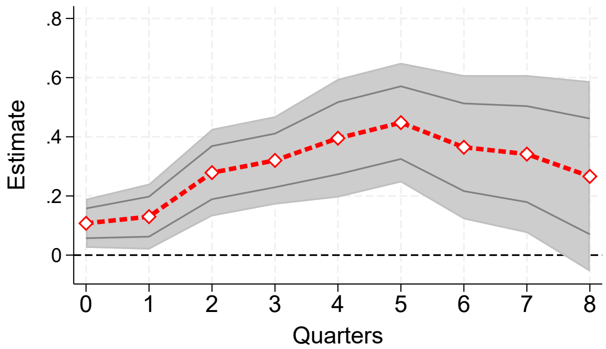


(a) Average Effect: Intensive Margin

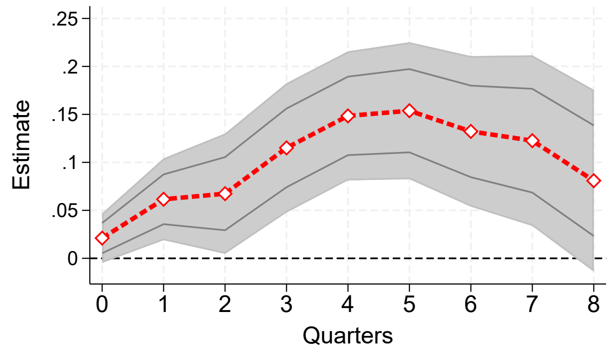
(b) Average Effect: Extensive Margin

Notes: Local projections with respect to identified monetary policy shocks (shown in Figure B.1). The quarterly sample is 2002:q1-2019:q4. Panels (a) and (b) show $\hat{\beta}_h$ for $h \in [0, 8]$, varying the dependent variable to reflect either the intensive or extensive margin of interbank connections in specification (1), but without the additional bank-level controls (lagged size, leverage, and liquidity). Gray lines and shaded areas correspond to 68% and 90% confidence intervals, respectively. Standard errors are three-way clustered at the year-quarter, lender, and borrower levels.

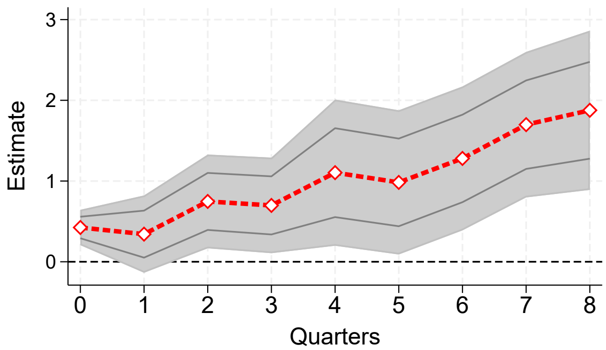
Figure B.6: Local Projections—Robustness Bank Sample



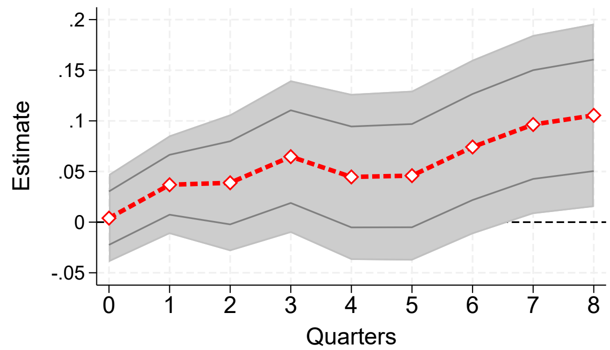
(a) Average Effect: Intensive Margin



(b) Average Effect: Extensive Margin



(c) Heterogeneous Effect: Intensive Margin



(d) Heterogeneous Effect: Extensive Margin

Notes: Local projections with respect to identified monetary policy shocks (shown in Figure B.1). The quarterly sample is 2002:q1-2019:q4, and excludes building societies and development banks. Panels (a) and (b) show $\hat{\beta}_h$ for $h \in [0, 8]$, varying the dependent variable to reflect either the intensive or extensive margin of interbank connections in specification (1). For the same dependent variables, Panels (c) and (d) show $\hat{\phi}_h$, i.e., the coefficient on the triple interaction term in specification (2). Gray lines and shaded areas correspond to 68% and 90% confidence intervals, respectively. Standard errors are three-way clustered at the year-quarter, lender, and borrower levels.

Table B.1: Lender-Borrower Matrix

		borrower							
		commercial	state	savings	corporative	mortgage	building societies	development	=
lender	commercial banks	0.10	0.03	0.00	0.00	0.09	0.01	0.02	0.26
	state banks	0.06	0.05	0.08	0.00	0.03	0.00	0.02	0.25
	savings banks	0.01	0.10	0.00	0.00	0.03	0.00	0.01	0.14
	corporative banks	0.01	0.01	0.00	0.00	0.02	0.00	0.05	0.09
	mortgage banks	0.02	0.03	0.00	0.00	0.00	0.00	0.01	0.06
	building societies	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.03
	development banks	0.02	0.02	0.02	0.05	0.05	0.00	0.02	0.18
	=	0.23	0.24	0.11	0.05	0.22	0.02	0,13	

Notes: Interbank market lending and borrowing share by bank type (commercial, state savings, corporative, mortgage, and development banks as well as building societies). Lenders are shown in rows and borrowers in columns, i.e., lending from savings banks to state banks represent 10% of total interbank lending, whereas borrowing of savings banks from state banks represent 8% of total interbank borrowing. Aggregate values are based on the full sample between 2002:q1-2019:q4.

Table B.2: Lender-Borrower Matching in the German Interbank Market

	$Match_{bct}$		$Match^{weighted}_{bct}$	
$Entity_{bt}$:	Top lender	Top borrower	Top lender	Top borrower
	(1)	(2)	(3)	(4)
$Entity_{bt} \times 2^{nd}$ decile $counterparty_{ct}$	0.001*	0.012***	0.014**	0.088***
	(0.001)	(0.002)	(0.007)	(0.017)
$Entity_{bt} \times 3^{rd}$ decile $counterparty_{ct}$	0.002*	0.024***	0.026**	0.188***
	(0.001)	(0.004)	(0.012)	(0.031)
$Entity_{bt} \times 4^{th}$ decile $counterparty_{ct}$	0.004**	0.037***	0.043***	0.283***
	(0.002)	(0.006)	(0.016)	(0.045)
$Entity_{bt} \times 5^{th}$ decile $counterparty_{ct}$	0.006***	0.048***	0.061***	0.380***
	(0.002)	(0.007)	(0.017)	(0.058)
$Entity_{bt} \times 6^{th}$ decile $counterparty_{ct}$	0.008***	0.056***	0.079***	0.453***
	(0.002)	(0.008)	(0.021)	(0.069)
$Entity_{bt} \times 7^{th}$ decile $counterparty_{ct}$	0.013***	0.064***	0.117***	0.537***
	(0.004)	(0.010)	(0.030)	(0.083)
$Entity_{bt} \times 8^{th}$ decile $counterparty_{ct}$	0.019***	0.077***	0.168***	0.670***
	(0.005)	(0.012)	(0.046)	(0.106)
$Entity_{bt} \times 9^{th}$ decile $counterparty_{ct}$	0.032***	0.095***	0.273***	0.857***
	(0.007)	(0.014)	(0.066)	(0.132)
$Entity_{bt} \times 10^{th}$ decile $counterparty_{ct}$	0.120***	0.156***	1.210***	1.508***
	(0.014)	(0.017)	(0.141)	(0.171)
N	58,767,439	58,767,439	58,767,439	58,767,439
R^2	0.326	0.333	0.323	0.330
Lender-Year FE	✓	✓	✓	✓
Borrower-Year FE	✓	✓	✓	✓
SE Cluster	Lender and Borrower			

Notes: The sample is a filled panel for all possible combinations at the bank-counterparty-year level *bct* from 2002 to 2019. $Entity_{bt}$ is an indicator variable for a lender *b* in the top decile ("Top lender" in columns 1 and 3) or borrower *b* in the top decile ("Top borrower" in columns 2 and 4). $Counterparty_{ct}$ refers to borrowers in columns 1 and 3, and to lenders in columns 2 and 4. We generate separate indicator variables for counterparties according to their position in the size distribution in year t, with the bottom decile being the omitted category. The dependent variable in columns 1 and 2, $Match_{bct}$, equals 1 in case of a relationship between lender and borrower in a given year t, and 0 otherwise. The dependent variable in columns 3 and 4, $Match^{weighted}_{bct}$, is defined as $Match_{bct} \times \ln(Volume)_{bct}$, where $Volume_{bct}$ is the exposure between lender and borrower in a given year t. Standard errors (in parentheses) are double-clustered at the lender and borrower level.

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