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

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Abstract

We develop a quantitative macroeconomic framework with heterogeneous financial intermediaries and active liquidity management. In the model, banks manage uninsured, idiosyncratic deposit withdrawal risk through an iterative over-the-counter interbank market with endogenous intensive and extensive margins and equilibrium 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 assortative matching in the data, thereby confirming the model's key mechanism. We show that assortative matching can inefficiently lead to reduced trading volumes and a broader region of inaction in the interbank market, a smaller and riskier banking sector, and a macroeconomy characterized by lower aggregate output. Using our empirically validated framework, we explore secular trends in interbank trading, the roles of liquidity and interest rate corridor policies, and the impact of deposit market power.

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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.

In our general equilibrium model, heterogeneous financial intermediaries face uninsured idiosyncratic deposit withdrawal risk and a binding minimum reserve requirement rule. Banks 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. 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.

There are two critical features of our framework. First, the model generates *assortative matching* in the interbank market: big banks tend to lend to and borrow from other big banks. This theoretical prediction is strongly supported by our micro data. Second, there is *equilibrium rationing out* of the small and less efficient banks. Our solution approach gives precedence to large and efficient intermediaries based on a "first come, first serve" basis: small, inefficient banks get to solve the liquidity management problem last, and by the time their turn arrives there may be no suitable counterparties left. Those who are left out must turn to the lender of last resort, borrow at a penalty rate, and face the stigma.

The solution algorithm for the interbank market is another contribution of our paper. It builds on the popular approach of settling the entry problem with heterogeneous firms and sectors (Atkeson and Burstein, 2008). In our framework, banks are ex-ante heterogeneous in monitoring efficiency (Stiglitz and Weiss, 1981), which in equilibrium yields a positive association between efficiency and size (net worth). Uninsured idiosyncratic deposit withdrawal shocks generate banks with deficit and excess reserves. When the interbank market opens, we assume that banks make portfolio choice decisions in order, which is determined by their efficiency-size profile. Suppose that the speed of arrival of trading opportunities correlates with bank franchise size. Thus, the largest and most efficient borrower with a deficit in reserves trades first. The borrower goes down the pecking order of lenders according to their own efficiency level.

There are variable and fixed costs of match formation. Importantly, variable costs are *match-specific*, making sorting and assortative matching more likely to occur in equilibrium. The borrower takes the decision of whether and how much to borrow from each lender depending on the outside option: the discount window of the central bank. Because this facility comes with a penalty, the borrower would generally prefer to borrow through the interbank market. However, costly match formation can yield inefficient outcomes for both sides. In the end, there could be rationing of *both* borrowers and lenders: a number of unlucky borrowers could be too far down in the pecking order. Those would be forced to borrow at the penalty rate. In the meantime, any rationed-out lenders would turn to their second-best option: the deposit facility of the central bank, which lends at a discount relative to the interbank market.

Besides assortative matching in the interbank market, the model predicts 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. As the discount window rate rises, the outside option for borrowers becomes less attractive, which causes an expansion in interbank trading along both 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 production and consumption.

We empirically validate these predictions and model mechanisms. To this end, 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 empirical evidence in favor of both assortative matching and rationing out in the German interbank market. Second, there is a positive correlation between interbank trading volume and bank balance sheet size. Third, following identified contractionary shocks to the European Central Bank's (ECB) monetary policy rate, German banks *increase* the amount of lending and the number of connections in the interbank market. Fourth and finally, we identify significant heterogeneous effects that suggest that assortative matching strengthens following positive monetary policy shocks, in line with our model. Thus, our empirical analysis strongly supports the model's main mechanisms along the cross-sectional and aggregate dimensions.

We then use our 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, 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 less than 1,500 as of 2020. We use our framework to show that this predicted change will likely have a positive effect on the financial sector and the real economy through a double dividend in the form of enhanced efficiency and financial stability.

Third, we study the effect of liquidity policies by simulating transitory changes in the minimum reserve requirement ratio. The model predicts that tighter reserve requirements improve financial stability by lowering the leverage ratio with mild and positive macroeconomic effects. Fourth and finally, we depart from the assumption of perfect banking competition and introduce bank market power in the deposit market. In this manner, we find that deposit market power—in combination with bank heterogeneity and an active interbank market—comes with considerable positive but ambiguous normative implications for equilibrium allocations in the financial sector and the real economy.

Related Literature Our paper relates to several distinct strands of the literature. First, a burgeoning new literature studies macroeconomic implications of heterogeneity in the financial sector (e.g., Corbae and D'Erasmo, 2021; Elenev et al., 2021; Begenau and Landvoigt, 2022; Coimbra and Rey, 2023; Bellifemine et al., 2024). In particular, our framework is most closely related to Jamilov and Monacelli (2024) and introduces a frictional interbank market. Our model can nest the canonical Gertler and Kiyotaki (2010) and 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; Allen et al., 2020; Anderson et al., 2020; Bianchi and Bigio, 2022). Our contribution to this literature is the introduction of persistent, ex-ante bank heterogeneity that produces a distribution of bank characteristics in equilibrium. Our quantitative and empirical emphasis on assortative matching is related to the literature on search and sorting (Chade et al., 2017; Wright et al., 2021).

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, 2020; Nuno and Thomas, 2017; Begenau et al., 2021; Bigio and Sannikov, 2023; Amador and Bianchi, 2024; Faccini et al., 2024). Our imperfect-competition extension builds on the canonical deposits channel of monetary policy (Drechsler et al., 2017, 2021, 2023).

Finally, we contribute to the applied literature that studies monetary policy transmission in the euro area. Some important studies include, among others, Maddaloni and Peydro (2011), Giannone et al. (2012), Ciccarelli et al. (2013), 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 endogenous 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 A1 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' 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 1 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 and match with our quantitative model.

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

[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

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

is defined as total assets. 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 *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 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 2, 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 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 lense of a sequential, "first come, first serve" matching algorithm. While the notion that banks systematically sort into borrowers of preferred profiles and build persistent relationships is ubiquitous (Degryse and Cayseele, 2000; Chodorow-Reich, 2014; Chang et al., 2023), we document a particular

[4]The patterns of size-based trading and assortative matching are highly robust over time and to various sub-periods (see Figure A1). In addition, this result is robust to the exclusion of building societies and development banks (see Figure A2).

form of sorting—assortative matching by size—in the context of interbank transactions for the largest euro-area economy.

Finally, in Figure 4 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. Quantitatively, the correlation between the two rates is over 99%.

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 5. The shocks are identified with the high-frequency approach of Jarocinski and Karadi (2020), building on Gurkaynak et al. (2005), Gertler and Karadi (2015), and Nakamura and Steinsson (2018).

Our empirical specification is a Jordà (2005)-style local projection, which we run on our full quarterly sample over 2002-2019. 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 the lagged dependent variable.

[5]Results without lender and borrower control variables are shown in Figure A3.

We are furthermore 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, which are identified as long as monetary policy is exogenously assigned.

Figure 6 presents the results in two stages. Panels (a) and (b) show dynamic estimates of $\hat{\beta}_h$ (in (1)) 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.

Panels (c) and (d) of Figure 6 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 connections in general. Larger banks also tend to lend more to other large banks, i.e., there is evidence of 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

[6] Results are robust to the exclusion of building societies and development banks (Figure A4).

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 Active 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 sets the interest rate corridor policy that all agents in the economy will take as given. The net interest rates on the lending facility, r_t^l, and reserves, r_t^s, constitute the corridor ceiling and floor, respectively. The interest rates satisfy the following restriction due to the absence of arbitrage: $r_t^l \geq r_t^s$. The rate at which banks will trade in the interbank market, r_t^i, is a weighted average of r_t^l and r_t^s, 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 pay out gross returns $R^b_{j,t}$. The sequence of household balance sheet constraints is:

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

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:

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

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

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

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:

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

where the pair $\{\nu_1, \nu_2\}$ captures non-interest expenses.

In particular, $\nu_2 > 1$ will achieve scale variance through convexity of these expenditures. Scale variance makes bank size matter—an important ingredient of our theory. 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, as is common in the literature, we assume that all non-interest expenses are rebated back to the household in the form of lump-sum payments, that banks are risk-neutral, cannot operate with negative net worth, and exit with an exogenous probability $1 - \sigma$. The latter also captures a fixed dividend payout rule because, upon exit, all accumulated bank earnings are transferred to the household.

3.5 Interbank Market

Uninsured Idiosyncratic Deposit Withdrawal Risk Banks face uninsured idiosyncratic deposit withdrawal shocks, $\xi_{j,t}$. 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 either deposit the same amount at another bank or to save it in a different financial vehicle. $\xi_{j,t}$ 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 may want to lend to 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.

Iterative Settlement Algorithm After deposit withdrawal shocks $\xi_{j,t}$ are realized, banks must settle any reserve shortages by the end of the period. To this end, we allow for an over-the-counter settlement market, which is similar to Afonso and Lagos (2015) and Bianchi and Bigio (2022) with one crucial difference: because banks are ex-ante heterogeneous in our model, clearing the interbank market requires additional assumptions.

We propose an iterative algorithm in the spirit of 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. In equilibrium, κ_j heterogeneity in combination with scale variance leads to a monotonic positive correlation between the lending-stage net worth choice $n_{j,t+1}$ and (the inverse of) κ_j. Thus, the largest and most efficient banks will get to "choose" first. 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*.

Denote with x_l and x_b the integer ranks of lenders and borrowers, respectively. Each borrower's objective is to minimize total borrowing costs associated with establishing a single match. Each match incurs convex variable costs that are parameterized by the pair $\{\varphi_1, \varphi_2\}$. This is akin to portfolio settlement frictions (Bianchi and Bigio, 2023). These costs are *match-specific* and scale not only with the volume of the transaction but also with the ranks x_l and x_b. The total variable cost for a transaction of volume q between borrower b and lender l is as follows:

$$VC_{bl} = x_b \times x_l \times \varphi_1 q_{bl}^{\varphi_2}. \tag{15}$$

As a result, variable costs will be low if high-ranked borrowers and lenders are matched together. This friction will deliver an active intensive margin and positive assortative matching in equilibrium. Parameters $\{\varphi_1, \varphi_2\}$ will be made empirically consistent with our German data. The second cost of an interbank connection is a minimum trade threshold $\underline{q}$. It applies to every individual transaction. The threshold parameter is used to establish a region of inaction (extensive margin) in the market.

In sum, the objective of each borrower b is to choose how much to borrow from each lender l by minimizing the total cost of borrowing subject to the outside option—the discount window of the central bank:

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

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 $\underline{q}$.

Interbank Market Rate Determination The interbank market rate, r_t^i, is determined as a weighted average between the interest rate 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 the quantitative portion of the paper, 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 $q^a_{j,t}$ and $q^b_{j,t}$ the amount of reserves allocated to the interbank market and central bank, respectively, and with $\hat{x}$ denoting *end-of-period* variables. Thus, the evolution of net worth, $\hat{n}_{j,t+1}$, is as follows:

$$\hat{n}_{j,t+1} = \begin{cases} n_{j,t+1} - r^i_t q^a_{j,t} - r^l_t q^b_{j,t}, & \text{if} \quad \xi_{j,t} < 0 \\ n_{j,t+1} + r^i_t q^a_{j,t} + r^s_t q^b_{j,t}, & \text{if} \quad \xi_{j,t} \geq 0. \end{cases} \tag{18}$$

Because of frictional interbank trading activities, end-of-period aggregate net worth could be lower, everything else equal, than in the frictionless benchmark. And since net worth is a state 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 insolvency if $\hat{n}_{j,t+1}$ falls below zero. This risk is priced into the retail deposit contract in the form of a liquidity premium. Conditional on illiquidity-induced insolvency, the household recovers nothing. The solution to the household's problem determines the risky retail deposit rate:

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

where $p_{j,t}$ is given by $p_{j,t} = prob_t\Big(\hat{n}_{j,t+1} < 0\Big)$ 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.

3.6 General Equilibrium

A steady-state competitive equilibrium is characterized by a stationary distribution of bank net worth and permanent types Γ, a vector of exogenous government policies $\{R^s, R^l\}$, endogenous aggregate prices $\{R^i, Q, R^k, W\}$, bank-level policies and value functions $\{V_j, l_j, b_j, n_j, s_j, q^a_j, q^b_j\}$, and endogenous bank-level premia and prices $\{p_j, R^b_j\}$ such that (i) bank policies and the value function solve the banks' optimization problem; (ii) households and firms optimize; (iii) Γ is consistent with bank-level policies; (iv) markets for deposits, interbank trading, capital, and goods clear.

3.7 Recursive Bank Lending Problem

To define the banks' lending-stage dynamic problem, we temporarily adopt recursive notation. At the beginning of each lending stage, the aggregate state variable includes only the distribution of banks, Γ. The idiosyncratic 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:

$$V(n,\kappa;\Gamma) = \max_{\{l,b,s,n'\}\geq 0} \left\{ \beta\mathbb{E}\Big[(1-\sigma)n' + \sigma V'(n,\kappa;\Gamma'|\Gamma)\Big]\right\} \tag{20}$$

subject to:

$$\begin{aligned} & n' = R^{k'}(\Gamma'|\Gamma)l + R^s s - \Big(1+\kappa r^{b'}(n,\kappa;\Gamma'|\Gamma)\Big)b - \nu_1 l^{\nu_2} \\ & b + n = l + s \\ & \lambda l \leq V(n,\kappa;\Gamma) \\ & s \geq \omega b. \end{aligned}$$

Policy Functions Because banks are risk-neutral, they will always lever up until the leverage constraint is binding. In addition, we assume that the reserve requirement constraint holds with equality. The policy function for bank-level lending can be shown to take on the following form:

$$l(n,\kappa;\Gamma) = \frac{\mathbb{E}\Big\{\tilde{\Lambda}\Big(\frac{(1+\kappa r^{b'}(n,\kappa;\Gamma'|\Gamma)) - R^s\omega}{1-\omega}n - \nu_1 l^{\nu_2}\Big)\Big\}}{\lambda - \mathbb{E}\Big\{\tilde{\Lambda}\Big(R^{k'}(\Gamma'|\Gamma) - \frac{(1+\kappa r^{b'}(n,\kappa;\Gamma'|\Gamma)) - R^s\omega}{1-\omega}\Big)\Big\}}, \tag{21}$$

where $\tilde{\Lambda} \equiv \Lambda(1-\sigma+\sigma V')$ 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 (2024), we can now characterize the marginal propensity to lend (MPL), an object that 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:

$$\frac{\partial l(n,\kappa;\Gamma)}{\partial n} \equiv MPL(n,\kappa;\Gamma) = \frac{\mathbb{E}\Big\{\tilde{\Lambda}\Big(\frac{(1+\kappa r^{b'}(n,\kappa;\Gamma'|\Gamma))-R^s\omega}{1-\omega}\Big)\Big\}}{\lambda - \mathbb{E}\Big\{\tilde{\Lambda}\Big(R^{k'}(\Gamma'|\Gamma) - \frac{(1+\kappa r^{b'}(n,\kappa;\Gamma'|\Gamma))-R^s\omega}{1-\omega}\Big)\Big\} + \nu_1\nu_2 l(n,\kappa;\Gamma)^{\nu_2-1}}. \quad (22)$$

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.

3.8 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 interbank market 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 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 Gertler et al. (2020) or Amador and Bianchi (2024). 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.

4 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 and sorting relationships that are in line with our micro data.

4.1 Calibration

Table 3 reports our model parameterization strategy along with the sources and targets for each parameter. We discuss our calibration approach block by block, beginning with the basic macro parameters. Concavity of the production function, α, is set to 0.36. We assign to the elasticity of intertemporal substitution, ψ, unit value. The discount factor, β, is set to 0.99547 in order to target the risk-free component of the retail deposit rate of 1.82% p.a. This value is equal to the average deposit facility rate over 2003-2008, a period that we refer to as the "normal" years before the onset of the low-for-long period. 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 approximate the continuum of banks in our economy with $\mathcal{N} = 1,500$. This number corresponds to the number of operational credit institutions in Germany as of 2020, as can be seen from Figure 1.

We now move to the interbank market. The bargaining power parameter, η, is calibrated internally in order to hit the average interbank rate over 2003-2008 of about 2.78%, a value that corresponds to measured ECB data. 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 11, 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 remaining block that we must parameterize involves the government's policy choices. The reserve requirement ratio is set to 1.65%. The interest rate on reserves is set to 1.82% per year. Finally, the lending facility rate is set conditional on two assumptions. First, the average measured rate over the normal years was about 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 5, we study the role of the stigma in equilibrium allocations.

4.2 Policy Functions

We begin to analyze our calibrated model with the presentation of select policy functions in Figure 7. 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. This observation is in line with the empirical evidence on the heterogeneous patterns of the bank lending channel (Kashyap and Stein, 1995, 2000).

4.3 Stationary Distributions

We continue the presentation of quantitative results by showing select stationary distributions of the banking sector and the interbank market. Figure 8 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 8 plot stationary distributions of interbank lending and borrowing. These correspond to the object q^a_j 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. In standard models, none of the aforementioned distributions exist due to scale invariance and linearity of the bank lending problem with respect to net worth.

4.4 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 9, 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 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.

4.5 Assortative Matching in the Interbank Market

A key empirical finding of the paper is the presence of assortative matching in the 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 10 plots borrowers and lenders (both ranked by the 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 generates equilibrium *assortative matching* by size. The north-east 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 bottom 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.

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 assortative matching in the interbank market along the balance sheet size dimension, both in the model and the data.

5 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 model responses to surprise changes in the interest rate corridor and reserve requirement policies. Finally, we introduce imperfect competition into the deposit market that allows banks to charge markdowns over the retail deposit rate.

5.1 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 4 reports key financial and macroeconomic aggregates in the baseline economy and in four illustrative special cases. Panel A summarizes parameter values, and Panel B presents the corresponding equilibrium values.

The first column of Table 4 (and Table 5) presents the benchmark economy. We first report the interbank trading volume as a fraction of total bank assets. In the model, this value is 12.5%, 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 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 11. 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 deposit rate is inclusive of the endogenous liquidity premium.

We now study the second column of Table 4, which presents an important special case of our model with no interbank match costs, i.e., when φ_1 is set to zero. Comparing this economy with the baseline identifies the impact of interbank market frictions on steady-state outcomes. We make three general observations. First, relative to the benchmark, the frictionless economy features a much more active interbank market along the intensive margin. Total volume is greater by a factor of 4.7 but the region of action is substantially lower. The latter implies efficiency gains as variable match formation costs are avoided. Second, in the frictionless economy the financial sector is larger and *less risky*. The frictional interbank market baseline prevents financial intermediaries from managing uninsured deposit withdrawal risk. Third, liquidity premia fall by 1.2 basis points, relieving external financing pressure for the banks. Finally, total output is up by around 40 basis points in lifetime units. In sum, we conclude that interbank market frictions associated with size-based trading and sorting lead to inefficiencies and negative aggregate financial and real-economy implications.

The third column of Table 4 considers a scenario where we shut down the interbank market by setting φ_1 to a large number. As interbank trading is now prohibitively costly, the lender of last resort becomes the only viable source of emergency liquidity. Removing the instrument of managing idiosyncratic fluctuations makes banks more prone to deposit withdrawals. Greater liquidity risk ascends to the bank franchise level as well, as the banking sector shrinks in size, while the average leverage ratio and Tobin's Q increase. Tighter liquidity conditions also get priced into higher retail deposit rates due to elevated premia, which puts further pressure on bank balance sheet growth. As a result, aggregate output drops by some additional 11 basis points relative to the benchmark economy.

The fourth column of Table 4 reports results from a special case of our model with no minimum interbank trading requirements ($\underline{q} = 0$). We see a substantial increase in interbank market activities as volume increases by 50%. We also observe a considerable, 56 percentage-point increase in the region of action. A more efficient interbank market translates into a larger banking sector that is also less fragile. As a result, aggregate production is slightly higher. Quantitatively, the macroeconomic impact of removing the minimum trade threshold $\underline{q}$, which heuristically represents a form of "fixed costs," is smaller than in the case of removing variable match costs.

The last column of Table 4 considers an environment with large bargaining power of interbank market lenders. The interbank market rate is greater by approximately 5 percentage points and is close to the ceiling that is imposed by the lending facility rate plus the stigma. Costly liquidity leads to an interbank market that is much more shallow and concentrated. The banking sector shrinks as leverage and Tobin's Q rise. The retail deposit rate goes up as the liquidity premium rises due to higher illiquidity-induced insolvency risk. Finally, the negative effect on total output is roughly of the same magnitude as that resulting from shutting down the interbank market completely.

Finally, column 2 of Table 5 showcases a scenario where we dramatically reduce the volatility of stochastic deposit withdrawal shocks, σ_ξ. The 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 banking sector is characterized by banks that are larger and less levered. The liquidity premium disappears and aggregate output goes up by as much as 46 basis points.[7]

5.2 The Secular Decline in Interbank Lending

The basic stylized fact of the German interbank market—as showcased in Figure 1—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 borrowing.

The stigma is well documented, particularly in the case of the United States (Ennis and Weinberg, 2013; Armantier et al., 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

[7]We also consider a situation where ex-ante heterogeneity in bank cost efficiency is much more pronounced and σ_κ is increased by 0.1. Column 3 of Table 5 shows that the financial and macroeconomic impacts of this change are minimal.

other vulnerability.

All of the above considerations motivate the following experiment. First, we compute the measured change in total interbank trading relative to 2003 over the 2004-2019 period. Next, for each year we reverse-engineer the stigma that delivers the same relative change in interbank trading in the model. Figure 11 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. 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, no liquidity premia, and greater aggregate production (not shown).

5.3 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 4 of Table 5 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 negligible.

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 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.

5.4 Impulse Response to Monetary and Liquidity Policy Shocks

5.4.1 Monetary Policy

In this section, we conduct two conditional tests in the model. We compute the state of the economy in every period following an unexpected "MIT" shock that shifts the economy to a new equilibrium on impact with a slow transition to the initial steady state over time.

We begin by studying the effects of unexpected changes in the non-systematic component of monetary policy. We consider a one-time mean-reverting exogenous change to two objects. First, we consider a positive shock to R^s_t that amounts to 0.82% p.a. Second, we consider a symmetric positive shock to the corridor spread that amounts to 1.14% p.a. These correspond to 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. Thus, our experiment involves studying the effect of a simultaneous exogenous hike of the interest rate on reserves and widening of the interest rate corridor.

Figure 12 presents the transition functions. The monetary shock hits at quarter 3, before which the economy is at the baseline steady state. Following the shock, the interest rate and the spread revert back, with an autocorrelation rate of 0.85.

We now discuss several observations. First, total lending and the number of connections—i.e., both the intensive and the extensive margins—in the interbank market *go up*. Moreover, total response is driven by the large banks (defined as those in the top decile of the net worth distribution) whose trading volume increases significantly. This corresponds to the positive and significant sign of the heterogeneous effect for the intensive margin in our local projections exercise (Figure 6). The rise of interbank market activities following monetary contractions is in line with our empirical analysis 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 go up.

Second, bank assets and 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. The risk-free component of R_t^b is always constant. The liquidity premium part of R_t^b, on the other hand, rises due to tighter borrowing conditions. Higher costs of external franchise 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 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.

5.4.2 Reserve Requirement

We now consider exogenous, transitory changes in liquidity policies. Our instrument of interest is the reserve requirement ratio ω_t, which is now time-varying. We assume that before the shock occurs, the economy is in the benchmark steady state with $\omega_t = 1.62\%$ p.a. Then, ω_t is increased unexpectedly by 10 percentage points and brought back to the steady state with an autocorrelation coefficient of 0.85.

Figure 13 presents the results. First, a transitory increase in ω_t is generally contractionary for the interbank market but expansionary at the real-economy level. The banking sector now has a larger buffer stock of reserves and can withstand the same idiosyncratic fluctuations more resiliently. As a result, demand for insurance subsides as the volume of trade and the region of action in the interbank market go down for the same level of the interest rate corridor.

Second, due to a greater stock of reserves in the banking sector, the economy is endogenously less fragile. Banks accumulate more net worth and issue more credit to non-financial firms. Bank leverage falls considerably, as does the retail deposit rate due to lower liquidity premia. The macroeconomy expands by a few basis points. Thus, higher reserve requirements achieve greater financial resiliency and at no immediate cost to credit supply or aggregate production.

5.5 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, 2023), 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 (2024) have since introduced deposit market power 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 14 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 the following extension. We now assume that households derive utility from deposit holdings because they provide special liquidity services. The period utility function now takes on the following form:

$$U(C_t, B_t) = \begin{cases} \frac{1}{1-\psi} C_t^{1-\psi} + \chi B_t & , \psi \neq 1 \\ \ln C_t + \chi B_t & , \psi = 1, \end{cases} \tag{23}$$

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:

$$B_t = \int_0^1 b_{j,t}. \tag{24}$$

The deposit rate is now priced according to a Lerner-type equation that sets a *markdown* over the risk-free rate:

$$R_{t+1}^b = \left(1 - \frac{U_B\left(C_t, B_t\right)}{U_C\left(C_t, B_t\right)}\right) R_{t+1}. \tag{25}$$

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

The household budget constraint is now:

$$C_t + \int_0^1 b_{j,t} + M_t \leq R_t M_{t-1} + W_t + \int_0^1 R_t^b b_{j,t-1} + \mathrm{Div}_t + T_t, \tag{26}$$

where M_t are mutual fund holdings and R_t is the real risk-free interest rate on them. The difference between mutual funds and bank deposits as a form of saving lies in the former not possessing liquidity-in-utility features.

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 markdown over the risk-free rate. We calibrate χ in order to match the measured average deposit spread of 0.62% p.a.

Column 5 of Table 5 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.

To conclude, deposit market power interacts significantly with bank balance sheets, leading to leverage-driven growth in the banking sector and an over 80 basis-point macroeconomic expansion. However, a natural side effect of this extension is the lower return on savings for the households, which yields ambiguous implications for welfare.

6 Conclusion

This paper presents a tractable, general equilibrium framework for monetary and liquidity policy analysis with bank heterogeneity and active liquidity management. We supplement our quantitative theory with detailed empirical work that leverages administrative bank-to-bank linked data from Germany. The interbank market is at the center stage of our analysis. In equilibrium, the interbank market in the model features *assortative matching* among the largest banks and *rationing out* of the smallest banks. This prediction is strongly validated in the data. 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 assortative matching can be inefficient: they lead to less interbank market activity, a smaller and riskier banking sector, and less aggregate production. Furthermore, contractionary monetary policy is shown to expand interbank market trading along both the intensive and extensive margins, while the real economy contracts. This conditional pattern is also borne out in the data. Future studies can expand on our work by focusing more on unconventional monetary policy and bank-to-firm linkages in the model as well as in the data.

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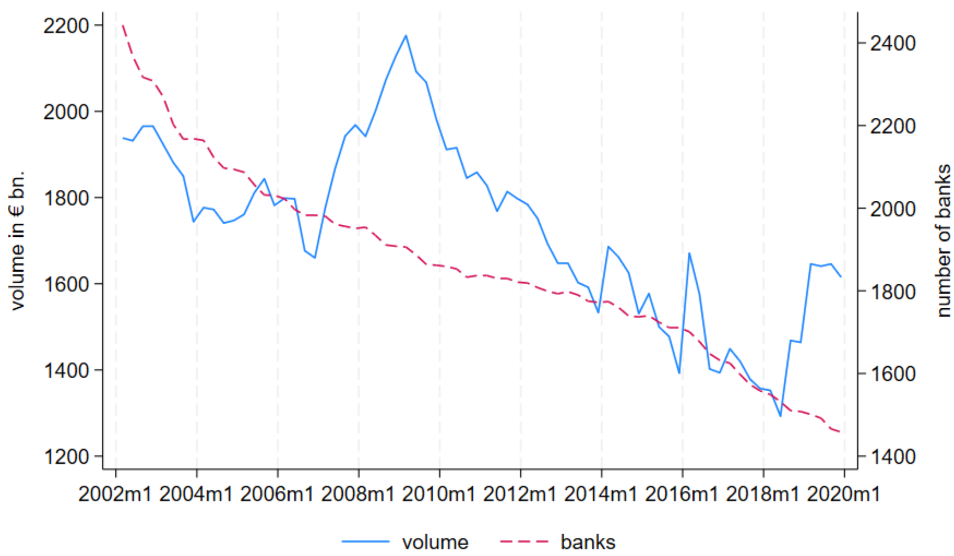
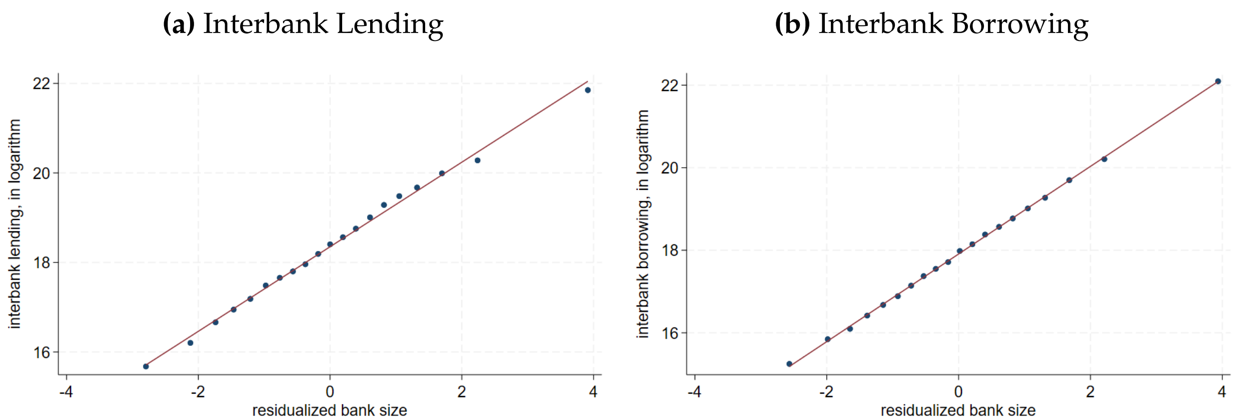
Figures

Figure 1: German Interbank Market over Time



Notes: 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.

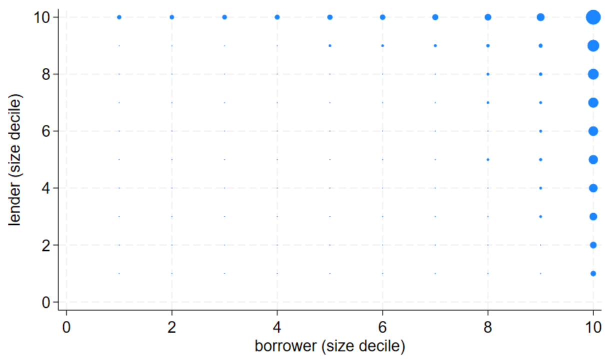
Figure 2: Interbank Exposures and Bank Size in the German Data



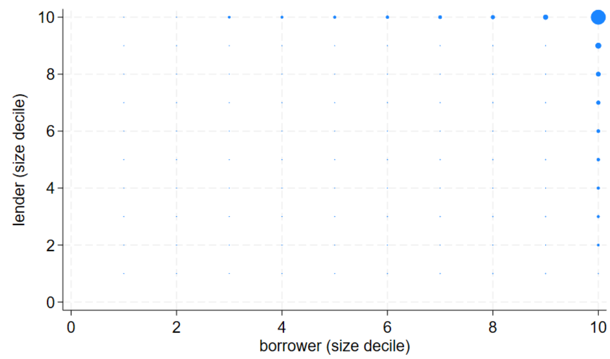
Notes: Binned scatterplots of (log) lending and (log) borrowing in the interbank market on the vertical axes of Panels (a) and (b), respectively, as well as residuals on the horizontal axes obtained from regressing (log) assets on year-quarter fixed effects. The quarterly sample is 2002:q1-2019:q4.

Figure 3: Assortative Matching in the German Interbank Market

(a) Weighted by Matches

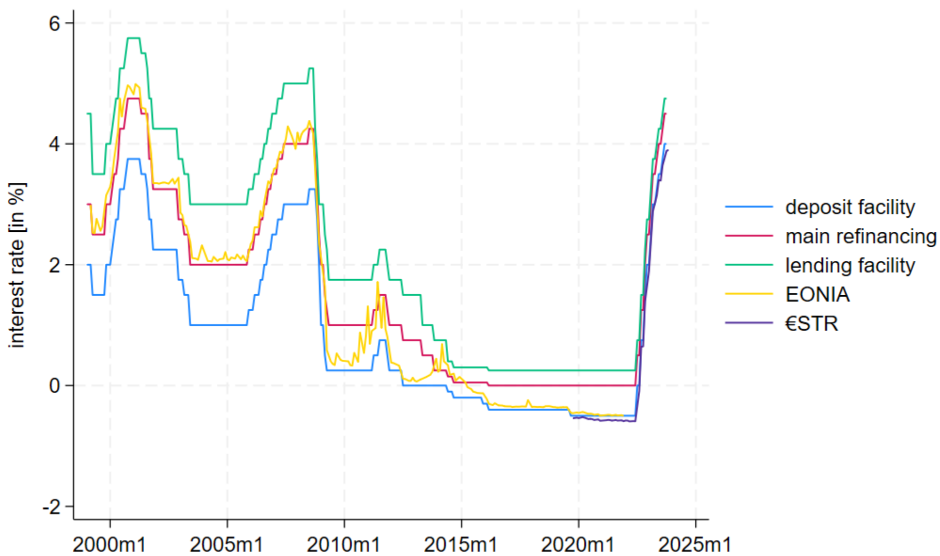


(b) Weighted by Volume



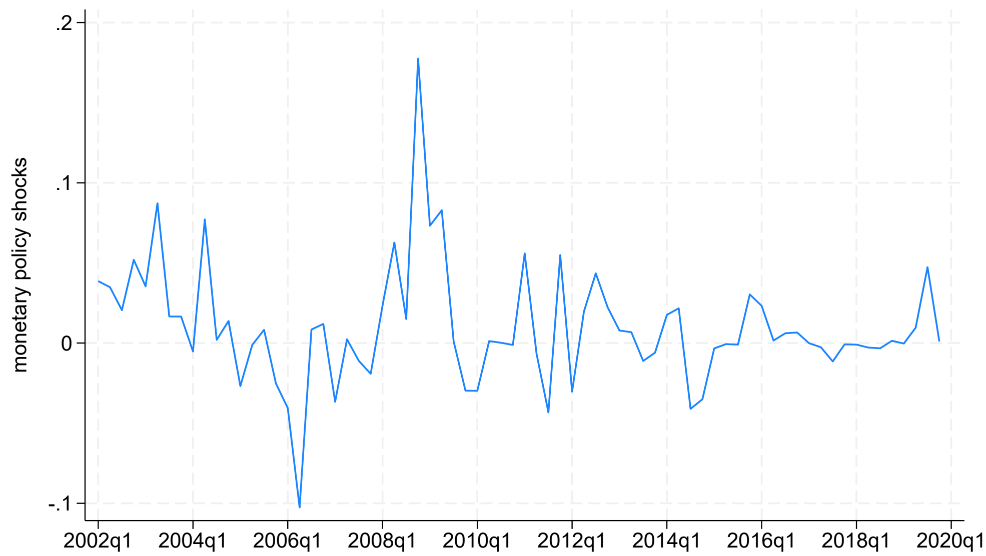
Notes: Bank-to-bank linkages in the German interbank market over 2002:q1-2019:q4. Size deciles of borrowers and size deciles of lenders are on the horizontal and vertical axes, respectively. The intensity of lender-borrower matches is represented by the size of circles. Panel (a) weights lender-borrower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

Figure 4: Interest Rates



Notes: Time series of the deposit facility, main refinancing, lending facility, interbank (EONIA) and the euro short-term interest rates. Source: ECB.

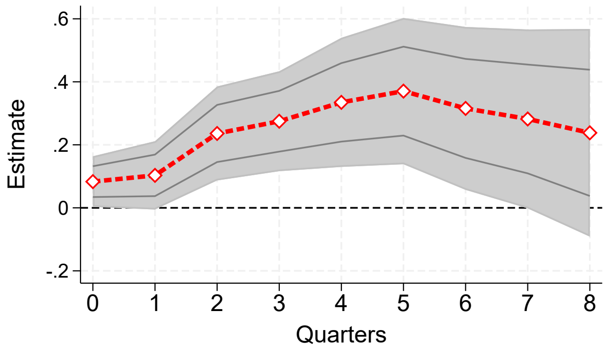
Figure 5: Monetary Policy Shocks



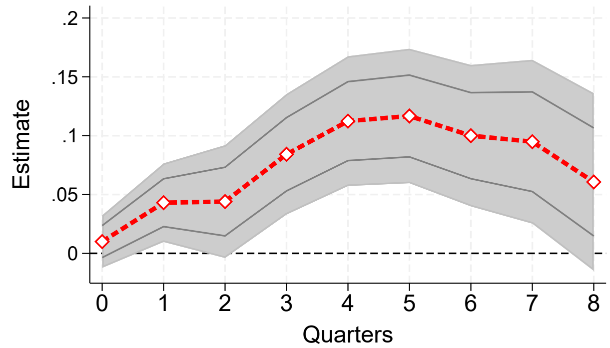
Notes: Monetary policy shock for the euro area, identified with the high-frequency identification approach. Source: Jarocinski and Karadi (2020).

Figure 6: Local Projections

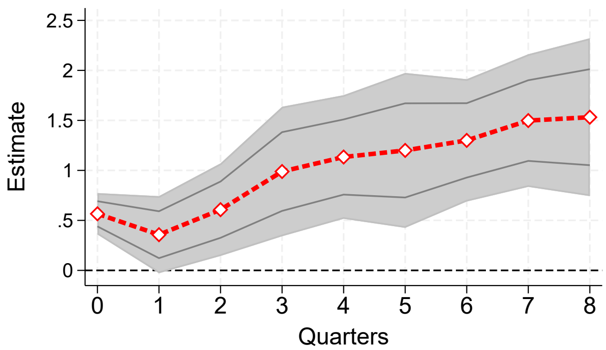
(a) Average Effect: Intensive Margin



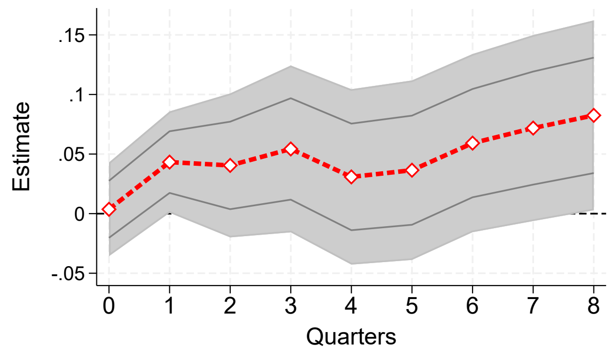
(b) Average Effect: Extensive Margin



(c) Heterogeneous Effect: Intensive Margin

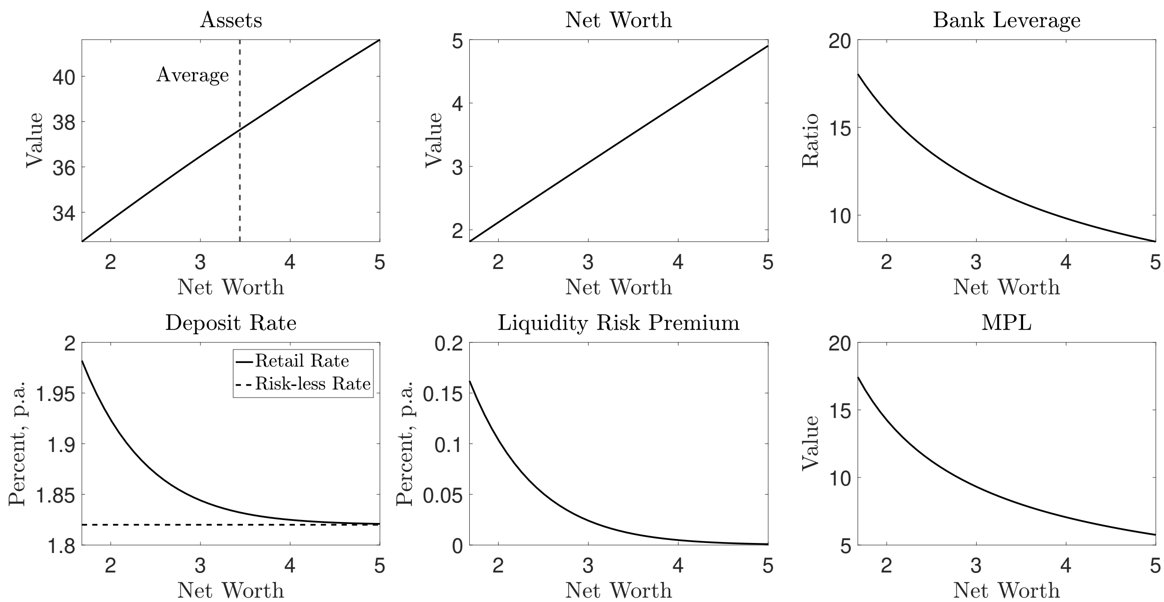


(d) Heterogeneous Effect: Extensive Margin



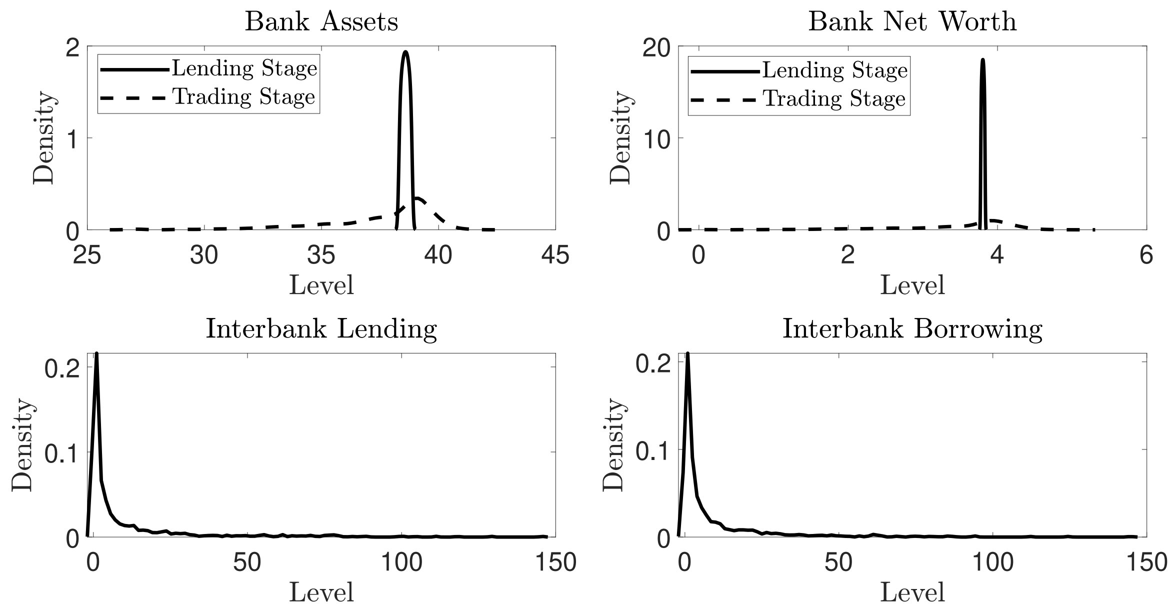
Notes: Local projections with respect to identified monetary policy shocks (shown in Figure 5). The quarterly sample is 2002:q1-2019:q4. Panels (a) and (b) show $\hat{\beta}_h$ for $h \in [0, 8]$, varying the dependent variable to reflect either the intensive or extensive margin of interbank connections 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.

Figure 7: Select Model Policy Functions



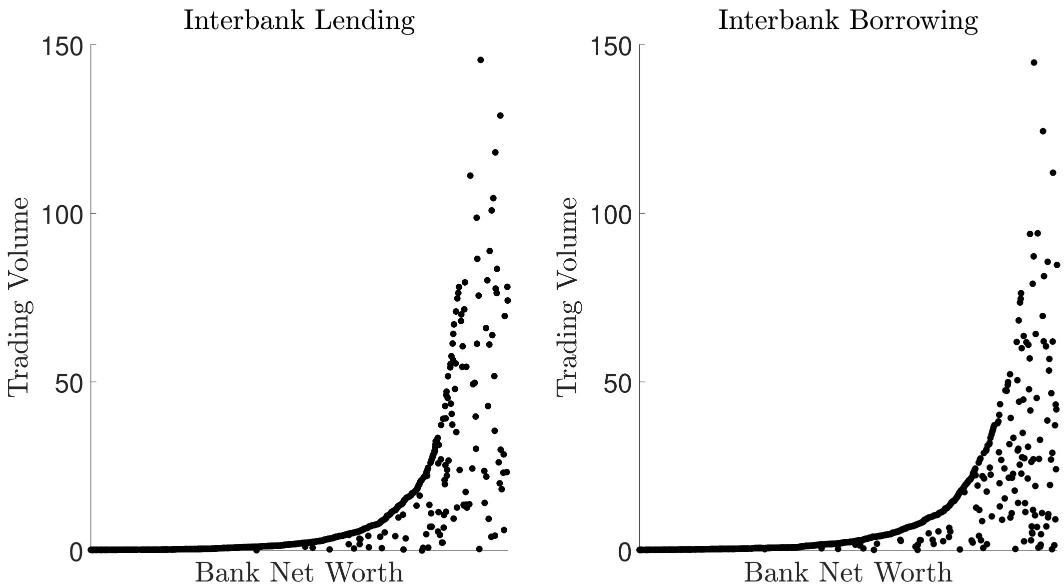
Notes: Bank-level choices of assets $l_{j,t}$, net worth $n_{j,t+1}$, leverage $\frac{l_{j,t}}{n_{j,t}}$, retail deposit rate $r^b_{j,t}$, liquidity premium $(r^b_{j,t+1} - \frac{1}{\Lambda_{t+1}})$, and marginal propensity to lend $\left(\frac{\partial l_{j,t}}{\partial n_{j,t}}\right)$ as a function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

Figure 8: Select Stationary Distributions in the Model



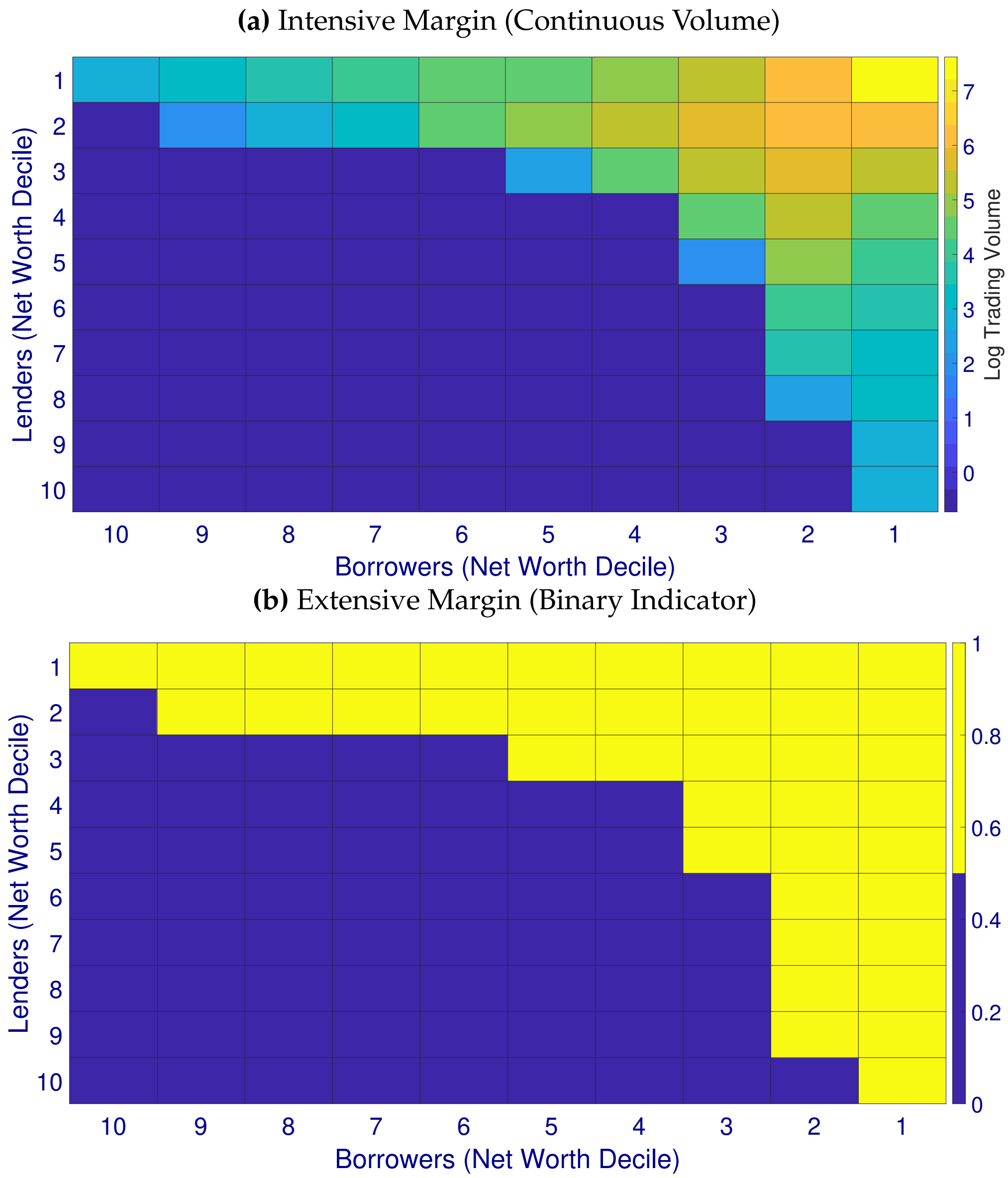
Notes: Stationary distributions of banks assets l_j, net worth n_j, and interbank trading q_j^a from the stationary general equilibrium of the model.

Figure 9: Bank Size and the Interbank Market in the Model



Notes: Model scatterplots of bank size (net worth) on the horizontal axis and total interbank lending and borrowing volumes on the vertical axes of the left and right panels, respectively.

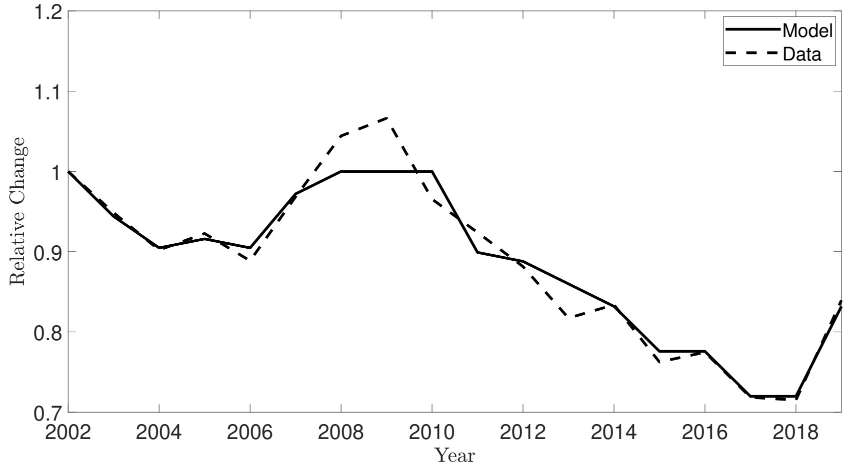
Figure 10: Assortative Matching in the Model



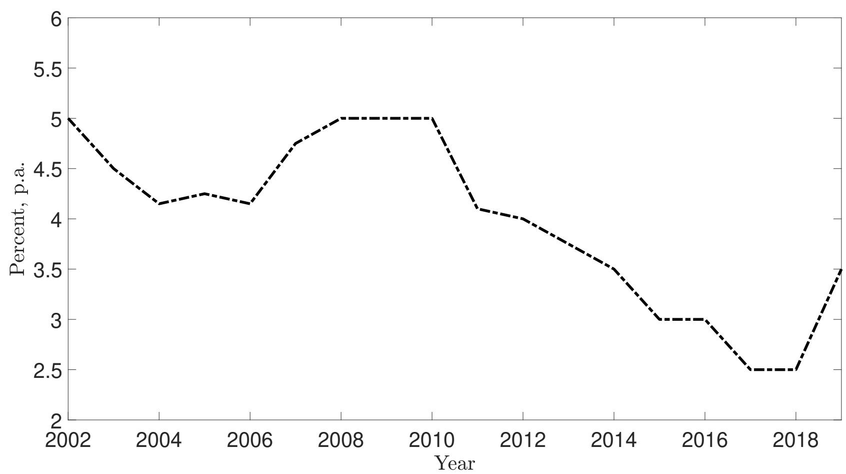
Notes: Bank-to-bank matching metrics in the model's interbank market. Borrowers that are ranked by net worth decile are on the horizontal axes. Lenders that are ranked by net worth decile are on the vertical axes. Panel (a) presents (log) volume of transactions. Warmer shades correspond to greater volumes.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

Figure 11: The Secular Decline in Interbank Trading

(a) Trading Volume (Output)

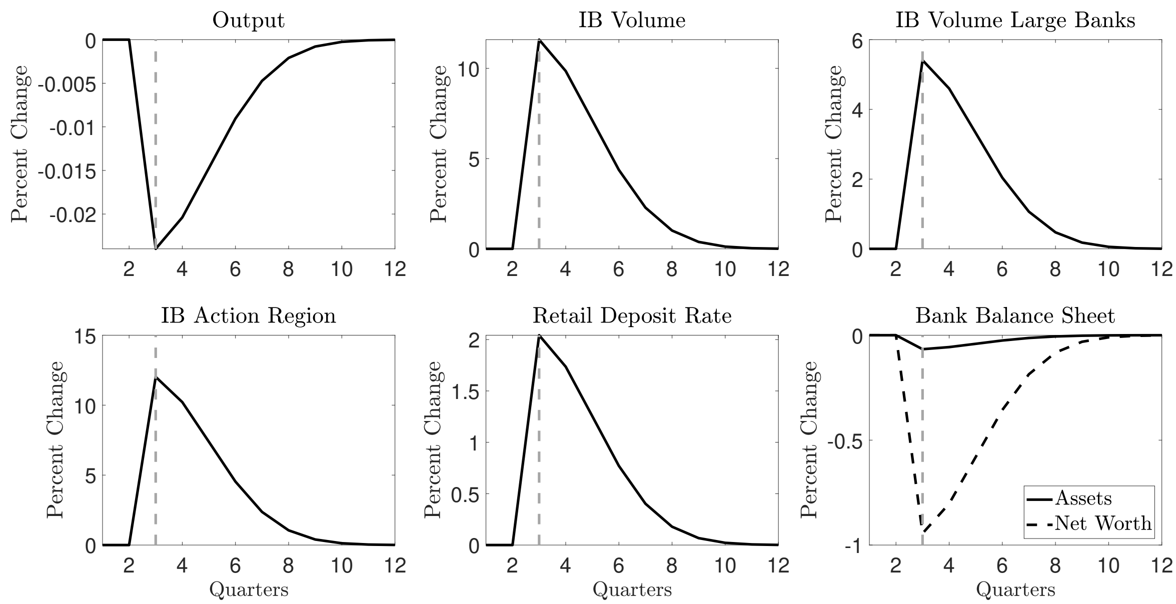


(b) Lending Facility Stigma (Input)



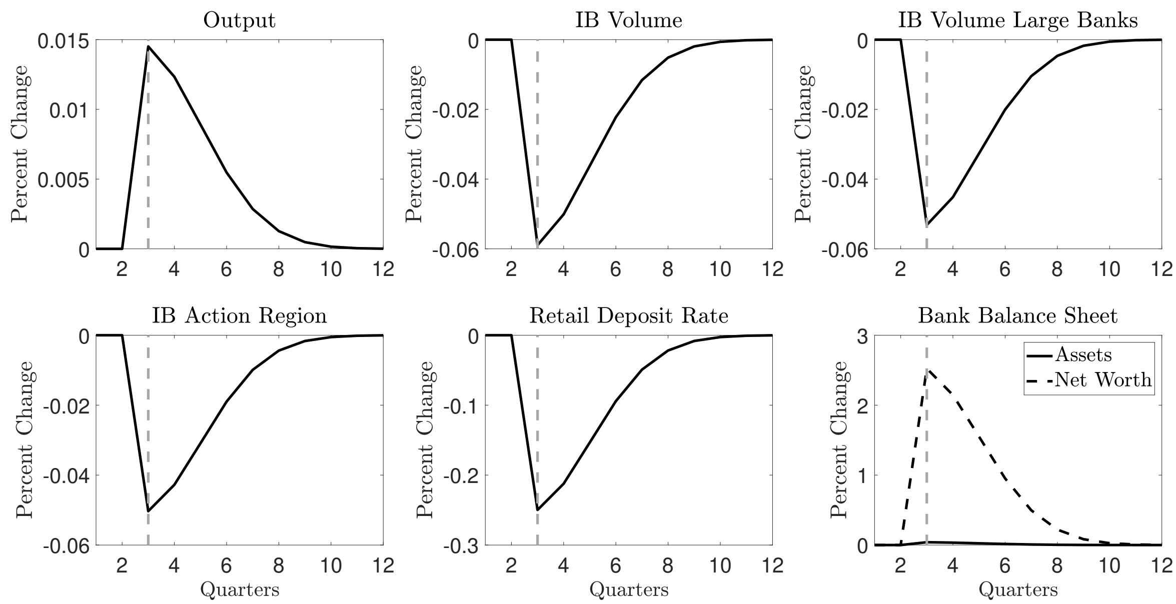
Notes: Trend-matching exercise in the model. Panel (a) shows the empirical target moment and the matched path from the model. Panel (b) shows the path of the lending facility stigma that is consistent with the model-implied path of interbank-market trading volume that matches the data.

Figure 12: Impulse Response to a Contractionary Monetary Shock



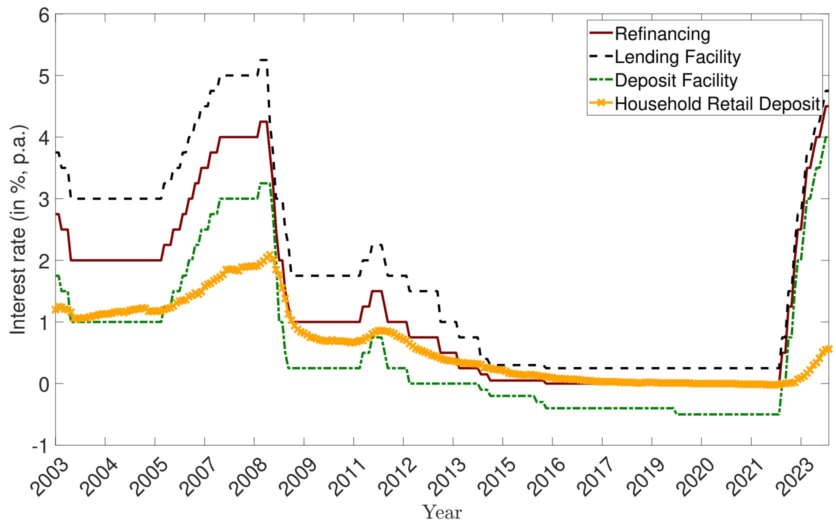
Notes: Model impulse responses with respect to a contractionary monetary policy shock, defined as a simultaneous 0.82% p.a. increase in the interest on reserves and a 1.14% p.a. widening of the interest rate corridor spread. The shock hits the economy in period 3 and reverts back to the steady-state level with the autocorrelation rate of 0.85.

Figure 13: Impulse Response to Higher Reserve Requirements



Notes: Model impulse responses with respect to a contractionary liquidity policy shock, defined as a 10 percentage point increase in the minimum reserves requirement ratio starting from the steady state. The shock hits the economy in period 3 and reverts back to the steady-state level with the autocorrelation rate of 0.85.

Figure 14: Retail Deposit and Policy Rates



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

Tables

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.

Table 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$_{bt}$ $\times$ 2nd decile counterparty$_{ct}$	0.001*	0.012***	0.014**	0.088***
	(0.001)	(0.002)	(0.007)	(0.017)
Entity$_{bt}$ $\times$ 3rd decile counterparty$_{ct}$	0.002*	0.024***	0.026**	0.188***
	(0.001)	(0.004)	(0.012)	(0.031)
Entity$_{bt}$ $\times$ 4th decile counterparty$_{ct}$	0.004**	0.037***	0.043***	0.283***
	(0.002)	(0.006)	(0.016)	(0.045)
Entity$_{bt}$ $\times$ 5th decile counterparty$_{ct}$	0.006***	0.048***	0.061***	0.380***
	(0.002)	(0.007)	(0.017)	(0.058)
Entity$_{bt}$ $\times$ 6th decile counterparty$_{ct}$	0.008***	0.056***	0.079***	0.453***
	(0.002)	(0.008)	(0.021)	(0.069)
Entity$_{bt}$ $\times$ 7th decile counterparty$_{ct}$	0.013***	0.064***	0.117***	0.537***
	(0.004)	(0.010)	(0.030)	(0.083)
Entity$_{bt}$ $\times$ 8th decile counterparty$_{ct}$	0.019***	0.077***	0.168***	0.670***
	(0.005)	(0.012)	(0.046)	(0.106)
Entity$_{bt}$ $\times$ 9th decile counterparty$_{ct}$	0.032***	0.095***	0.273***	0.857***
	(0.007)	(0.014)	(0.066)	(0.132)
Entity$_{bt}$ $\times$ 10th 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.

Table 3: Model Parameterization

Parameter	Value	Description	Target/Source
		Macro	
α	0.36	Capital share	Standard
ψ	1	Risk Aversion	Standard
β	0.99547	Discount factor	Risk-less deposit rate $R^b = 1.82\%$
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 = 11
		Policy and Interest Rates	
ω	1.62%	Reserve requirement ratio	ECB data
R^s	1.82%	Interest rate on reserves	ECB data
R^l	8.78%	Lending facility rate	Stigma = 5% (Bianchi and Bigio, 2022)

Table 4: Model Analysis

	Benchmark model	No interbank match cost	No interbank market	No minimum trade threshold	Low bargining power
Panel A: Parameter Settings					
φ_1	4.5E-6	0	100	4.5E-6	4.5E-6
$\underline{q}$	0.032	0.032	0.032	0	0.032
η	0.862	0.862	0.862	0.862	0.15
Panel B: Equilibrium Values					
Interbank Assets / Total Assets	0.125	0.589	0.000	0.189	0.039
Large Banks IB Assets / Total IB Assets	0.555	0.204	0.000	0.366	0.812
Interbank Market Extensive Margin	0.106	0.003	0.000	0.666	0.033
Total Bank Assets	37.568	37.975	37.463	37.624	37.490
Total Bank Net Worth	3.439	3.720	3.370	3.484	3.389
Leverage Ratio (Assets / Net Worth)	10.923	10.209	11.115	10.798	11.062
Average Bank Tobin's Q Ratio	1.187	0.950	1.224	1.154	1.219
Average Retail Deposit Rate	1.859	1.832	1.865	1.855	1.865
Interbank Market Rate	2.78	2.78	2.78	2.78	7.736
Average Liquidity Premium	0.018	0.006	0.021	0.016	0.021
Aggregate Output	3.689	3.704	3.685	3.691	3.686

Notes: Key financial and economic aggregates from the benchmark steady state and select special cases.

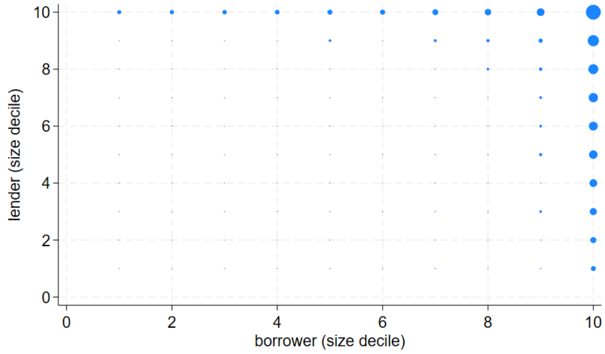
Table 5: Model Extensions and Sensitivity Analysis

	Benchmark model	Low withdrawal volatility	High heterogeneity dispersion	Low number of banks (2035 forecast)	Deposit market power
		Panel A: Parameter Settings			
σ_ξ	1.83	0.01	1.83	1.83	1.83
σ_κ	0.01	0.01	0.11	0.01	0.01
χ	0.00	0.00	0.00	0.00	2.60
$\mathcal{N}$	1500	1500	1500	1000	1500
		Panel B: Equilibrium Values			
Interbank Assets / Total Assets	0.125	0.001	0.130	0.182	0.124
Large Banks IB Assets / Total IB Assets	0.555	0.619	0.558	0.432	0.556
Interbank Market Extensive Margin	0.106	0.001	0.109	0.219	0.108
Total Bank Assets	37.568	38.056	37.556	37.604	38.459
Total Bank Net Worth	3.439	3.542	3.442	3.467	3.402
Leverage Ratio (Assets / Net Worth)	10.923	10.743	10.911	10.847	11.304
Average Bank Tobin's Q Ratio	1.187	0.969	1.175	1.131	1.251
Average Retail Deposit Rate	1.859	1.820	1.858	1.854	1.195
Interbank Market Rate	2.78	2.78	2.78	2.78	2.78
Average Liquidity Premium	0.018	0.000	0.017	0.016	0.021
Aggregate Output	3.689	3.706	3.689	3.690	3.720

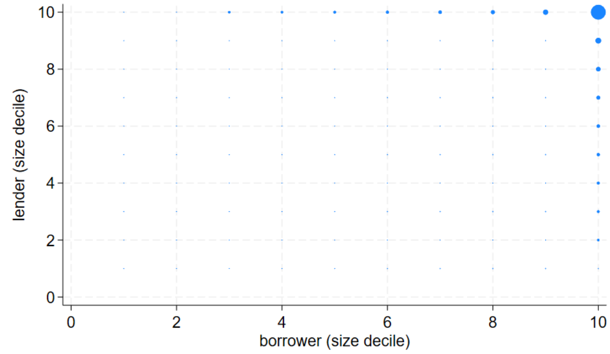
Notes: Key financial and economic aggregates from various model extensions.

Appendix

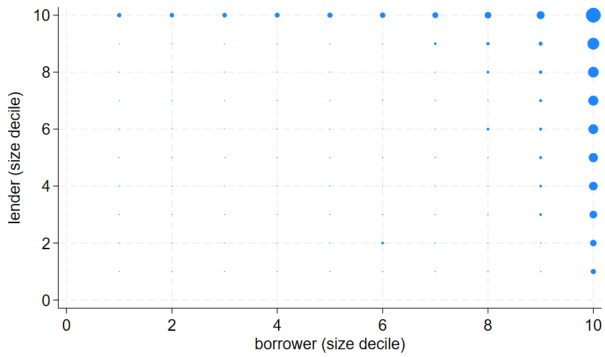
Figure A1: Assortative Matching in the German Interbank Market—Different Subperiods



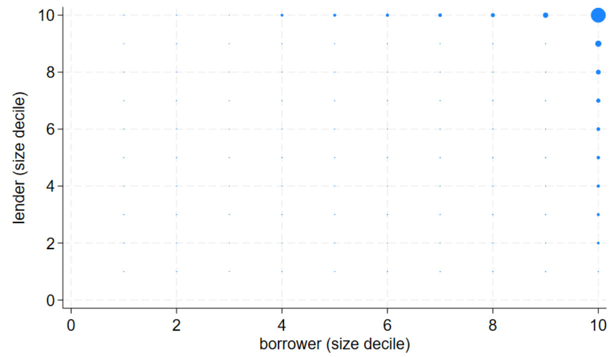
(a) Weighted by Matches, 2002-2006



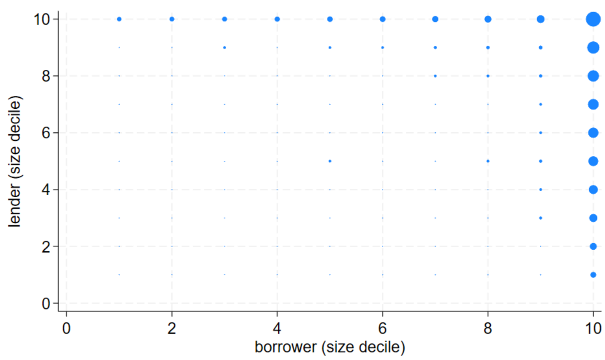
(b) Weighted by Volume, 2002-2006



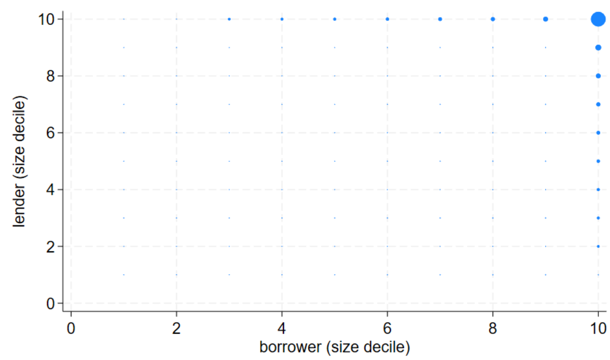
(c) Weighted by Matches, 2007-2009



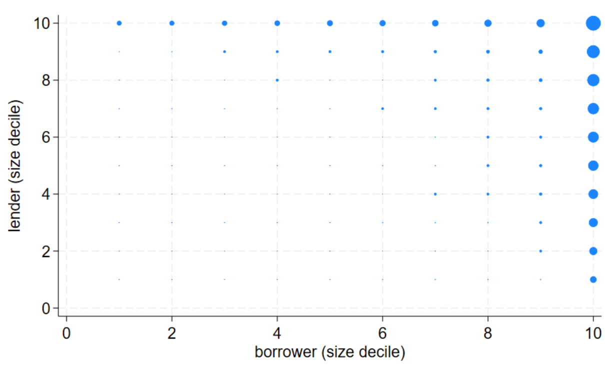
(d) Weighted by Volume, 2007-2009



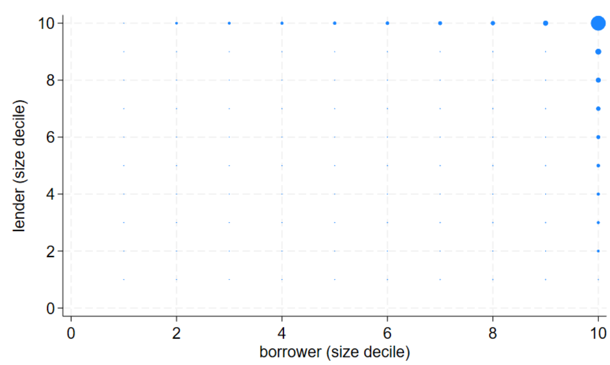
(e) Weighted by Matches, 2010-2014



(f) Weighted by Volume, 2010-2014



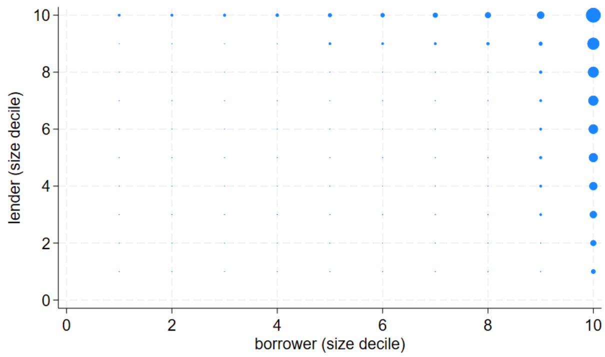
(g) Weighted by Matches, 2015-2019



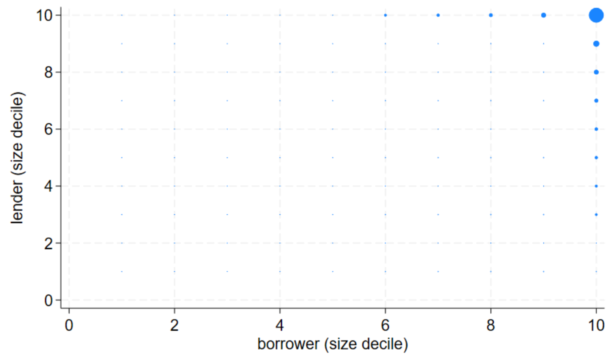
(h) Weighted by Volume, 2015-2019

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 A2: Assortative Matching in the German Interbank Market—Robustness Bank Sample



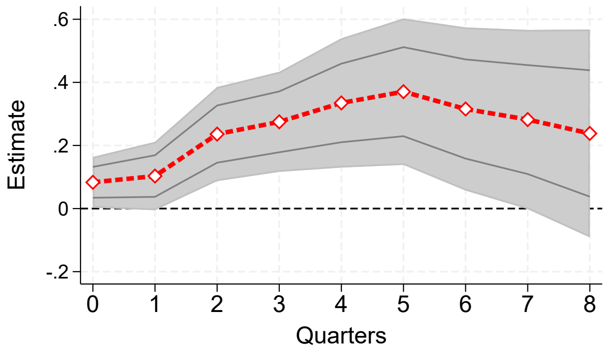
(a) Weighted by Matches



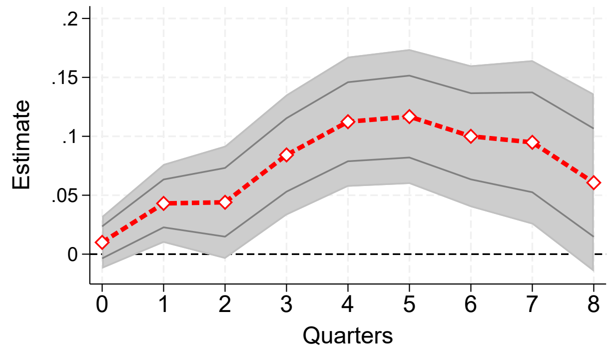
(b) Weighted by Volume

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 A3: Local Projections—Robustness without Bank Controls



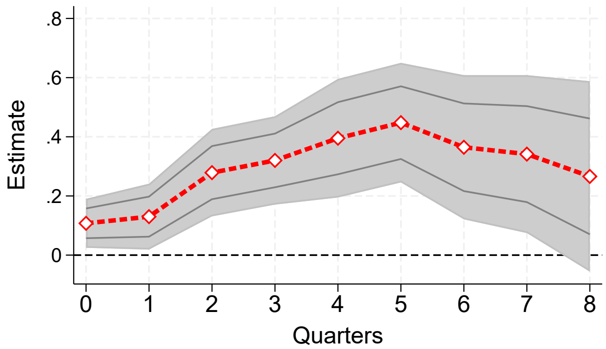
(a) Average Effect: Intensive Margin



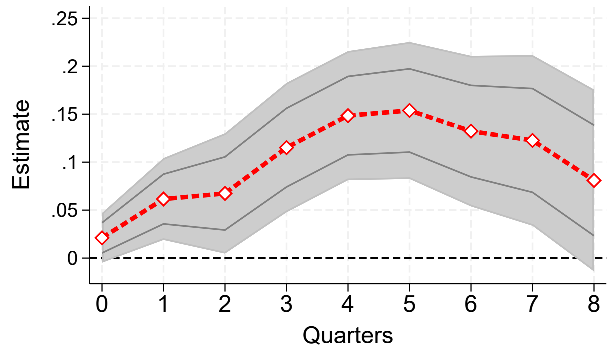
(b) Average Effect: Extensive Margin

Notes: Local projections with respect to identified monetary policy shocks (shown in Figure 5). 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.

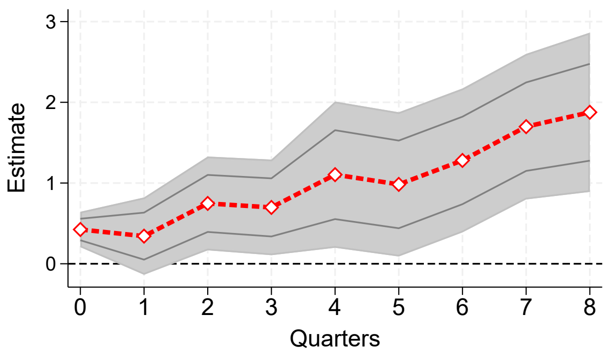
Figure A4: Local Projections—Robustness Bank Sample



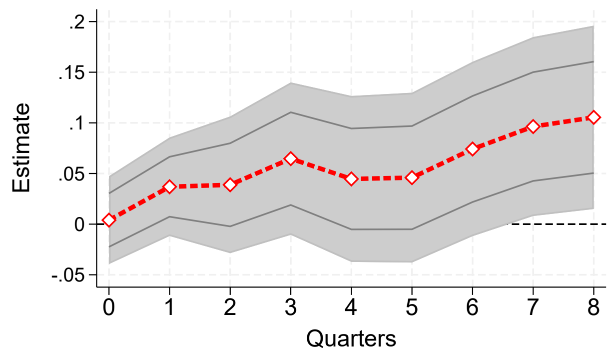
(a) Average Effect: Intensive Margin



(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 5). 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 A1: 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.