Decomposing Loan Rate Dispersion in the Interbank Market*

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Abstract

This paper decomposes loan rate dispersion in the interbank market. Using transaction-level data, we document dispersion in uncollateralized overnight loan rates even during periods of low interest rates in Japan. Applying the AKM model, we quantify the contributions of borrower and lender heterogeneity to loan rate dispersion. Lender heterogeneity explains about three times more dispersion than borrower heterogeneity. The contribution of borrower heterogeneity declines over time. Positive assortative matching in borrowers' and lenders' average loan rates is observed. For term loans, borrower heterogeneity accounts for a larger share of loan rate dispersion than for overnight loans.

Keywords: interbank loans, loan rate dispersion, AKM model, over-the-counter market, bank heterogeneity

JEL Classification: E42, E52, E58, G21

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1 Introduction

The uncollateralized overnight loan market is an over-the-counter market where financial institutions lend reserves to one another. The average overnight loan rate serves as the operational target for monetary policy. Intraday dispersion in loan rates is a concern for the effectiveness of monetary policy transmission because some trades occur away from the target rate (Duffie and Krishnamurthy, 2016). Moreover, empirical evidence shows that dispersion in loan rates is related to macroeconomic variables, such as liquidity premium (Bianchi and Bigio, 2022) and bank lending rates for firms (Altavilla et al., 2019). However, dispersion in loan rates remains understudied.

This paper uses transaction-level data on overnight loans to study the dispersion of loan rates in the interbank market. Dispersion exists, even in Japan where the policy rate had remained close to zero. Since 2015, the intraday 90th-to-10th percentile gap has varied between 0.8 and 8.5 basis points. We aim to quantify the extent to which loan rate dispersion is driven by heterogeneity across financial institutions. To this end, we estimate a loan rate model with additive borrower and lender fixed effects, following Abowd, Kramarz, and Margolis (1999), henceforth referred to as AKM.

We first construct transaction-level data on uncollateralized overnight loans from Japanese payment records (BOJ-NET) following Furfine (1999). To the best of our knowledge, this paper is the first to construct transaction-level data on overnight loans in Japan. Moreover, a key advantage of BOJ-NET is that it distinguishes uncollateralized loans from repos by use of explicit repo flags, whereas the payment data in other countries often cannot fully separate repos from uncollateralized loans.[1]

We estimate a linear model with borrower, lender, and daily fixed effects following the AKM model to decompose loan rate variance into borrower, lender, time, covariance, and residual components. The premise is that the persistent characteristics of borrowers and lenders influence loan rates. Borrower characteristics may reflect counterparty risk or liquidity needs, while lender characteristics may stem from risk capacity or available funds. Other factors, such as bargaining power and transaction costs, may also affect loan rates. These characteristics are difficult to observe, which motivates fixed effects in the AKM model.

The interbank market is well suited for the application of the AKM framework. First, ten years of daily frequency data are available with about 140 transactions observed per day, providing a long time dimension and rich cross-sectional variation. Second, the number of fixed effects to be estimated is not large, with approximately 150 borrowers and 140 lenders. Finally, the market structure is well-connected. On average, each borrower trades with 20.9 lenders, and each lender

[1] This limitation is known in the U.S. federal funds market (Afonso and Lagos, 2012; Armantier and Copeland, 2015) and TARGET2 data (Arciero et al., 2016).

trades with 19.3 borrowers, ensuring separate identification of borrower and lender fixed effects. These features mitigate concerns about limited-mobility bias (Bonhomme et al., 2023).

Variance decomposition shows that lender heterogeneity contributes two to three times more to loan rate dispersion than borrower heterogeneity. When the interest on reserves is set to positive levels, lender heterogeneity explains 57% of the total variation, whereas borrower heterogeneity explains 14%. During periods when the policy rate is targeted at negative levels, lender heterogeneity explains 13%, while borrower heterogeneity accounts for 6% of loan rate variation.

The literature's emphasis on borrowers' counterparty risk could make the smaller contribution of borrower heterogeneity seem unexpected (Afonso, Kovner, and Schoar, 2011). Two factors contribute to this finding. First, excess aggregate reserves reduce banks' liquidity demands in Japan. With excess aggregate reserves amounting to 90% of GDP, few institutions rely on the interbank market for liquidity. This leads to a uniformly low level of liquidity demand among borrowers. Second and more importantly, the marginal return on reserves does not diminish. This makes borrowing rates competitive. Borrowers aim to earn arbitrage profits by borrowing at rates lower than the interest on reserves and depositing those funds in reserve accounts to earn the interest on reserves. Since the central bank pays the same interest rate regardless of the level of reserves, all borrowers competitively bid for higher borrowing rates. This competition reduces arbitrage profits and borrower heterogeneity.

We also investigate the sorting of borrowers and lenders in the interbank market, measured as the correlation between borrower and lender fixed effects. A positive correlation implies that participants frequently trade with counterparts who have similar average loan rates. During the period of negative interest rates, we find positive assortative matching, indicated by a correlation of 0.31. Notably, after the policy rate was set at positive levels, matching became random, with the correlation dropping to -0.03. The observed positive sorting amplifies loan rate dispersion, as borrowers with high loan rates tend to trade with lenders who also offer high loan rates, thereby driving up loan rates. A counterfactual exercise that randomly assigns trading partners reveals that positive sorting increases loan rate dispersion by 10% compared to a random matching counterfactual.

Examination of the time-series properties of the variance decomposition yields two key findings. First, borrower heterogeneity exhibits a clear downward trend: by 2024, the variance of borrower fixed effects dropped to just 10% of its value in 2017. Two factors caused this decline: (i) borrowers who previously paid higher rates moved closer to the average, while those who traded at lower rates experienced little change, and (ii) the intensive margin, in which borrowers who previously borrowed at higher rates now borrow at average rates, plays a more significant role, whereas the extensive margin, defined as the increase in the proportion of borrowers borrowing at average rates, has a smaller impact.

A second finding of the time-series properties is that the variance of loan-rate residuals has remained stable over the past ten years. These residuals capture deviations from the average borrower–lender components and can serve as an indicator of the functioning of the interbank market (Bianchi and Bigio, 2022). Despite anecdotal concerns that Japan's prolonged periods of low interest rates may have impaired the market's functioning, the stable variance of residuals provides little evidence of increased pricing deviations from the model.

During the COVID-19 crisis, borrower heterogeneity contributed twice as much to loan rate dispersion as in normal periods. We calculate the difference between the standard deviation of model-fitted values and counterfactual loan rates with borrower heterogeneity shut down. We find that 0.6 basis points of loan rate dispersion are attributable to borrower heterogeneity during the COVID-19 crisis, compared to 0.3 basis points during normal periods.

The final section examines the variance decomposition of term loans with maturities longer than one day. We find that borrower heterogeneity accounts for 30 to 40 percent of the variation in loan rates with maturities of one month or longer, exceeding the variation observed for overnight loans. Furthermore, borrower heterogeneity contributes to a greater share of the variation as loan maturities increase from less than one month to three months.

Related literature While the AKM model has been applied to various markets,[2] its application to the interbank market remains relatively unexplored. The AKM model contributes to the literature on the interbank loan market in the following ways.

First, this paper contributes to the literature on loan rate determination in interbank markets. On the lender side, factors such as liquidity hoarding (Allen, Carletti, and Gale, 2009; Acharya and Skeie, 2011; Acharya and Merrouche, 2013) and available funds (Afonso and Lagos, 2015b) can influence loan rates. On the borrower side, counterparty risk is a key determinant of funding costs (Furfine, 2001; Afonso, Kovner, and Schoar, 2011; Angelini, Nobili, and Picillo, 2011; Heider, Hoerova, and Holthausen, 2015). Additionally, reserve scarcity and search frictions (Afonso and Lagos, 2015b), intermediary activity by large banks (Lagos and Navarro, 2023), and market share (Ashcraft and Duffie, 2007) can also shape pricing.

This paper addresses three gaps. First, the contribution of unobserved characteristics to loan rate dispersion remains underexplored, as existing studies focus on observable factors. We address this gap by incorporating fixed effects in the AKM model. Second, the overall quantification of borrower and lender characteristics remains underexplored. In a result that may be unexpected, lender heterogeneity contributes more to loan rate dispersion than borrower heterogeneity in Japan. Third, existing studies provide limited evidence on how much of the loan rate variation *cannot* be explained by participant characteristics.

[2]Examples include labor markets (Abowd, Kramarz, and Margolis, 1999; Card, Heining, and Kline, 2013) and production networks (Bernard et al., 2022) among many others.

Second, this paper contributes to the literature on networks and relationships in interbank markets. Existing research shows that participants trade with specific counterparties more often than would be expected under random matching (Cocco, Gomes, and Martins, 2009). Studies have examined how participants select their counterparties (Afonso, Kovner, and Schoar, 2013) and how these relationships influence loan rates (Brauning and Fecht, 2017). Although banks frequently trade with specific counterparties, it remains unclear whether these relationships generate sorting, that is, a correlation between the average loan rates of borrowers and lenders. The AKM model addresses this gap by estimating borrowers' and lenders' average loan rates and calculating their correlation. Our results suggest that both positive assortative and random matching can occur. Whereas a related study Bittner, Jamilov, and Saidi (2025) identified assortative matching as based on size, our study focused on assortative matching based on average loan rates.

Third, this paper contributes to the literature on interbank market behavior during crises (Furfine, 2002; Afonso, Kovner, and Schoar, 2011; Brunetti, Di Filippo, and Harris, 2011; Garcia-de Andoain et al., 2016). Our methodology identifies borrowers' average loan rates based on unobserved characteristics and proposes a simple counterfactual exercise to quantify the loan rate dispersion caused by borrower heterogeneity. We show that the contribution of borrower heterogeneity to loan rate dispersion doubled during the COVID-19 crisis relative to normal times.

Layout The paper is organized as follows. Section 2 introduces the institutional background. Section 3 describes the datasets. Section 4 provides descriptive statistics on loan rate dispersion. Section 5 presents the main empirical results. Sections 6 and 7 analyze sorting and term loans, respectively. Section 8 concludes.

2 Institutional background

Payment of reserves The market for uncollateralized overnight loans consists of transactions without collateral involving reserve balances at the Bank of Japan (BOJ). Participants in the overnight loan market include commercial banks, trust banks, credit unions, securities companies, money market brokers, branches of foreign banks, and mutual funds. The market for overnight loans is an over-the-counter market. Participants contact one another directly to negotiate loan terms. Loans are settled through the Bank of Japan Financial Network System (BOJ-NET), a network operated by the BOJ to facilitate online reserve transfers.

Two main reasons motivate banks to trade overnight loans. First, financial institutions use overnight loans to address shortages in their reserve positions. Second, some participants see overnight loans as an investment opportunity. Since most financial institutions in Japan maintain abundant reserves, the first motive is less significant, causing the second to predominate. The mechanism through which it generates profits is explained below.

Reserve requirements The reserve requirement system obliges deposit-taking financial institutions to hold a minimum level of reserves, which are referred to as *required reserves*. The cumulative reserves over each reserve maintenance period (which lasts from the 16th of one month to the 15th of the next) must exceed the required reserves. Non-deposit-taking institutions, such as securities firms, hold reserve accounts but are not subject to this requirement.

Large excess holdings of reserves far above the required levels characterize Japanese monetary policy operations. In 2025, the ratio of aggregate reserves to GDP is 95%. Appendix F provides more details on the large reserve holdings of individual financial institutions. As a result, open market operations that change the aggregate supply of reserves have little effect on the overnight rate.

Interest on Reserves and Discount Window Rate The interest on reserves (IOR) and the discount window rate (DWR) are adjusted to guide the average overnight loan rate to the target level, known as the floor system. IOR refers to the interest rate the BOJ pays to financial institutions on their reserve balances. DWR is the interest rate charged by the central bank on short-term loans provided directly to financial institutions. The framework in which banks earn positive IOR and can borrow at the DWR was in effect prior to February 17, 2016, and following March 19, 2024, through the present.

The trading motive for overnight loans arises from the operational differences between institutions eligible for IOR, such as commercial banks and securities companies, and institutions not eligible for IOR, mainly mutual funds. IOR-eligible institutions act as borrowers and non-eligible institutions as lenders. The trading motivations of non-IOR-eligible institutions as lenders are as follows. Mutual funds that invest in risky assets, such as indexed funds, must hold cash to meet redemptions and make distributions to investors. The exact amount of cash required to meet redemptions and distributions is highly unpredictable because demand depends on their asset prices, which are difficult to predict. Therefore, they tend to hold excess cash after completing redemptions. Importantly, mutual funds' idle cash yields 0%, as they do not have reserve accounts at the BOJ and are IOR ineligible. To earn interest on this idle cash, mutual funds lend their cash as uncollateralized overnight loans that yield more than 0%.

The trading motive of IOR-eligible institutions acting as overnight borrowers is arbitrage profit. They borrow funds at rates below the IOR and then deposit them in reserve accounts that pay the IOR, thereby earning profits equaling the spread between the IOR and the overnight borrowing rate.

Mutual funds' volume and share of lending are substantial. The share of lending by mutual funds in total lending reaches 90% during the period of positive interest on reserves, as described in Appendix E.

Negative Interest on Reserves Between February 17, 2016, and March 19, 2024, the BOJ implemented a Negative Interest on Reserves (NIOR) policy, introducing a negative IOR and a three-tiered system governing the interest paid on reserves. Financial institutions earned three different rates on portions of their reserves: a rate of -0.1% applied to the top tier, 0% to the middle tier, and 0.1% to the bottom tier. The total interest paid to bank i during maintenance period t, given cumulative reserves $x_{i,t}$, is

$$\text{Interest Paid}_{i,t} = \begin{cases} 0.1\% \times x_{i,t}, & \text{if} \quad x_{i,t} \leq x^*_{i,t}, \\ 0.1\% \times x^*_{i,t} + 0\% \times (x_{i,t} - x^*_{i,t}), & \text{if} \quad x^*_{i,t} \leq x_{i,t} < x^{**}_{i,t}, \\ 0.1\% \times x^*_{i,t} + 0\% \times (x^{**}_{i,t} - x^*_{i,t}) - 0.1\% \times (x_{i,t} - x^{**}_{i,t}), & \text{if} \quad x^{**}_{i,t} \leq x_{i,t}, \end{cases}$$

where $x^*_{i,t}$ and $x^{**}_{i,t}$ are policy variables set by the BOJ. These vary depending on the financial institution and the maintenance period. The BOJ aimed to push the uncollateralized overnight rate below zero by generating trade motives based on each participant's marginal profit from reserves.

The trading motive generated by this system is as follows. Lenders' marginal return on reserves is -0.1%. By lending at a rate above this, they avoid the losses associated with holding reserves that earn -0.1%. Borrowers have marginal returns of 0% or 0.1%. Borrowing at a rate below these levels generates profits. For example, assume a transaction with an overnight loan rate of -0.05%. A lender avoids losses by reducing reserves that would cost -0.1%, and instead lends at -0.05%. A borrower would earn a profit of 0.05% if its marginal return on reserves is 0% or of 0.15% if its marginal return on reserves is 0.1%. In practice, observed loan rates are almost always within the range of -0.1% to 0%.[3]

Figure 1 shows the average uncollateralized overnight loan rate, IOR, and DWR, expressed as percentages. Before the introduction of NIOR, the IOR was 0.1% and the DWR was 0.3%. Under NIOR, banks faced the three IOR tiers: -0.1%, 0%, and 0.1%, with the average overnight rate generally falling between -0.1% and 0%. After NIOR was lifted, the BOJ raised both the IOR and the DWR. When IOR is positive, the overnight rate remains below IOR because trades mainly

[3] Loans from mutual funds with idle cash to IOR-eligible institutions continued even under the NIOR regime. Mutual funds were charged -0.1%. To avoid this charge, they lent surplus cash in the interbank market at rates higher than -0.1%. Under both the positive IOR and negative IOR regimes, institutional arrangements made overnight lending more attractive for mutual funds than holding idle cash.

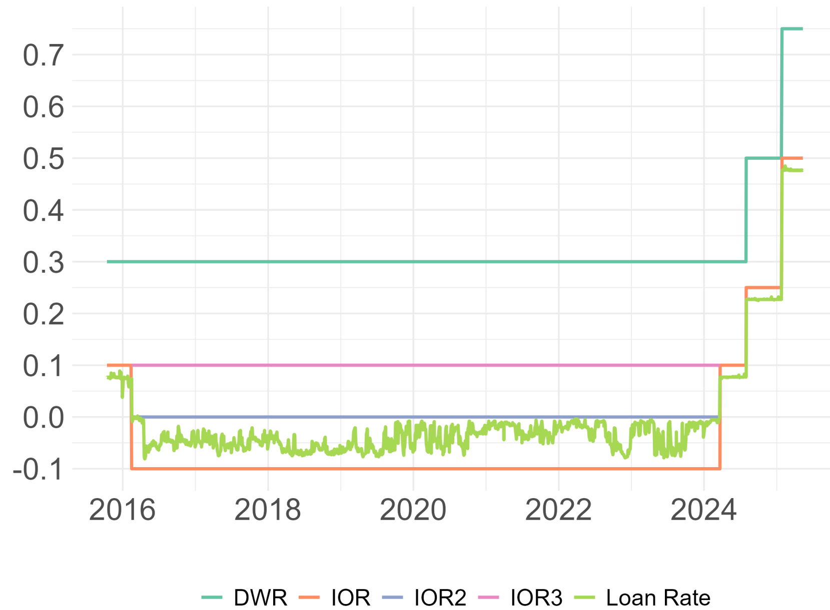


Figure 1: Average overnight loan rate, interest on reserves, and discount window rate.

Notes: This figure plots the time series of the average uncollateralized overnight loan rate (Loan Rate), the interest on reserves (IOR, IOR2, and IOR3), and the discount window rate (DWR), expressed as percentages. During the period of negative interest rates, reserves were subject to three different rates, and all three rates are plotted.

occur between IOR-eligible institutions and non-eligible institutions.

We define three policy regimes: "Pre-NIOR" (–February 16, 2016), "NIOR" (February 17, 2016–March 19, 2024), and "Post-NIOR" (March 20, 2024–).

3 Data

The main dataset consists of transaction-level records covering all transfers of reserves made through BOJ-NET. A transaction occurs when a financial institution submits an electronic request to debit its reserve account by a specified amount and credit another financial institution's account. The reasons underlying transactions vary, with uncollateralized overnight loans representing a subset of BOJ-NET transactions. To identify overnight loans, we apply an algorithm based on Furfine (1999), which is widely adopted in the literature.[4] The procedure is described in Appendix D. To the best of our knowledge, this study is the first to construct transaction-level data on uncollateral-

[4]Since Furfine (1999) extracted federal funds transactions in the U.S. from Fedwire, many have employed it to extract transaction-level data on overnight loans from the payment data of various countries based on the Furfine algorithm. Examples include the U.K. (Millard and Polenghi, 2004) and the EU (Arciero et al., 2016).

ized overnight loans from payment data in Japan.[5]

The Furfine algorithm alone cannot distinguish uncollateralized loans from repos (Afonso and Lagos, 2012; Arciero et al., 2016). However, the BOJ-NET dataset includes transaction flags, which allow overnight repos to be distinguished from uncollateralized overnight loans. Specifically, BOJ-NET identifies transactions involving the simultaneous exchange of bonds and reserves using a Delivery Versus Payment (DVP) flag, which is used exclusively for repos or bond purchases. As uncollateralized loans do not involve an exchange of bonds, they are not assigned a DVP flag. Thus, after applying the Furfine algorithm, we then excluded all DVP-flagged transactions, leaving only uncollateralized overnight loans. For brevity, we hereafter refer to uncollateralized overnight loans as "overnight loans".

The loan rate is calculated as $(\text{repayment amount} - \text{principal})/\text{principal} \times 365$ and is represented in basis points.[6] Financial institutions are identified by the Unified Financial Institution Code. Our sample spans from October 13, 2015, to April 28, 2025.

Sample selection is as follows. First, we exclude borrowers who trade with only one lender and lenders who trade with only one borrower throughout the sample period. This procedure mitigates concerns about limited mobility bias, which occurs when participants interact with a small number of counterparties, and resulting in the exclusion of 1.5% of our initial sample. Second, we drop borrower–lender pairs that trade only once during the sample period.[7] This procedure eliminates an additional 0.8% of the total sample. Finally, we restrict the sample to the largest connected network, as borrower and lender fixed effects can only be identified within that network (Abowd, Creecy, and Kramarz, 2002). This step accounts for an additional reduction of less than 0.1% of our sample. These sample selection criteria are further discussed in Appendix A.

Summary statistics Table 1 reports the summary statistics for our data. The interbank market provides a suitable environment for applying the AKM model. Over a sample period of nearly ten years, we observe on average 140 trades per day, yielding a long time dimension. The number of fixed effects is relatively small, with 306 banks during the NIOR period and 108 banks after the NIOR period. Market participants trade with many counterparties, which facilitates the separation

[5]The only related study is Imakubo and Soejima (2010). Unlike the approach of Furfine (1999), their method identifies overnight loans by classifying all transactions of 100 million yen or more, where the amounts are exact multiples of 100 million yen, as overnight loans. Importantly, unlike the Furfine algorithm, their method does not verify whether a corresponding repayment occurred on the following business day. The Furfine algorithm offers a more precise method, as it identifies loans by detecting matching reverse transactions with interest paid on the next business day.

[6]Repayment is made on the following business day. If settlement takes place on a Friday or the day preceding a national holiday, payment does not occur on the next calendar day. In such cases, the loan rate is calculated as: $\text{Loan Rate} = \frac{\text{repayment amount}-\text{principal}}{\text{principal}} \times \frac{365}{\text{number of calendar days between settlement and repayment}}$.

[7]This procedure addressed concerns regarding potential misidentification of non-overnight transactions by the Furfine algorithm.

of lender and borrower fixed effects. These features further mitigate concerns about limited mobility bias, which occurs when participants interact with only a few counterparties, making it difficult to distinguish between lender and borrower fixed effects (Abowd et al., 2004).

Panel A presents daily trading activity and loan rate statistics. The average loan rate minus the IOR is -2.92 basis points before NIOR, -3.96 basis points during NIOR, and -2.23 basis points after NIOR. In this paper, during the NIOR period, the spread, defined as the loan rate minus the IOR, is calculated as the loan rate minus the second-lowest IOR, which equals zero; therefore, it coincides with the loan rate during that period. The corresponding standard deviations are 1.34, 2.52, and 0.65 basis points for the three respective regimes. The overnight loan market is deep. In 2025, the total annual trading volume was approximately twice Japan's annual GDP.

Panel B reports bank-related statistics that highlight the number of parameters estimated for borrower and lender fixed effects. In total, 159 banks borrow and 147 banks lend at least once during the NIOR period. After NIOR, 62 banks borrow and 46 banks lend. Panel C shows counterparty statistics, including the number of distinct counterparties with which the participants traded. To identify borrower and lender fixed effects, their trading network must be sufficiently connected; both should trade with multiple counterparties. During the NIOR regime, the median number of counterparties per borrower is 14, and the median number of counterparties per lender is 14, indicating that our borrower—lender trading network was sufficiently connected. Panel D presents summary statistics on trading pairs.

4 Empirical premises for the AKM model

Loan rate determination in an over-the-counter (OTC) setting highlights three empirical facts that serve as the basis for applying the AKM model to the data: (i) loan rates exhibit dispersion, (ii) average loan rates display systematic differences across borrowers and lenders, and (iii) both borrowers and lenders contribute additively to the loan rate.

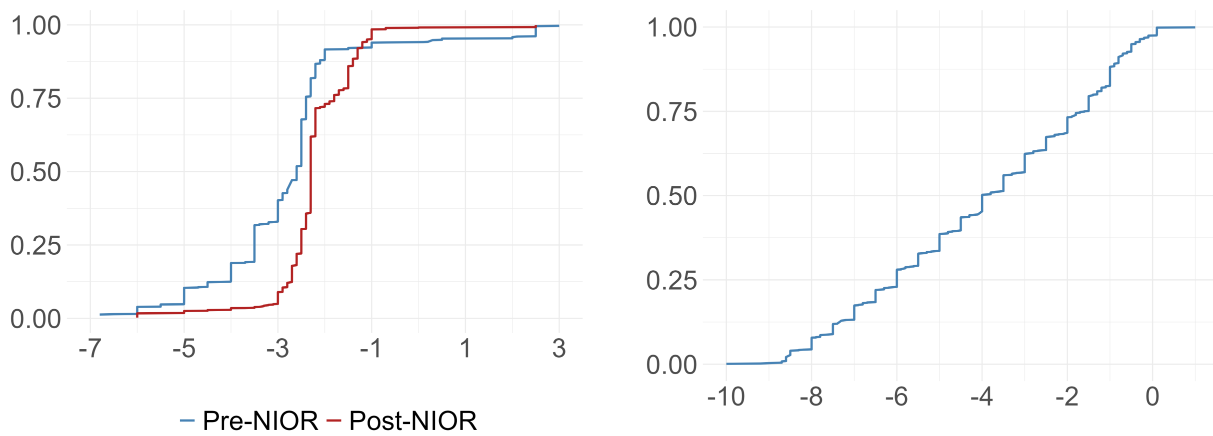
4.1 Overall loan rate dispersion

Figure 2(a) presents the cumulative distribution function (CDF) of the spread, defined as the loan rate minus IOR, for the periods before and after NIOR. The horizontal axis is expressed in basis points. In both regimes, clear loan rate dispersion is evident. Most trades occur at loan rates below IOR, as shown by negative spreads. Primary lenders are IOR-ineligible institutions, and they are willing to lend at rates lower than IOR. Borrowers, who are mainly financial institutions holding IOR-eligible reserves, aim to make a profit by borrowing funds at rates below the IOR and

Table 1: Summary statistics

Regime	Pre NIOR	NIOR	Post NIOR
Date Range	2015/10/13–2016/02/16	2016/02/17–2024/03/19	2024/03/20–2025/04/28
Panel A: Loan rate and loan size			
Total number of trades	11877	276660	35433
Average number of trades per day	150	141	132
Mean of loan rate - IOR	-2.92	-3.96	-2.23
Std. dev. of loan rate - IOR	1.34	2.52	0.65
Mean of trade size per transaction	37	79	78
Std. dev. of trade size per transaction	44	108	113
Panel B: Borrower and lender statistics			
Total number of borrowers	44	159	62
Total number of lenders	63	147	46
Mean number of borrowers per day	23	25	16
Mean number of lenders per day	22	44	22
Panel C: Counterparty statistics			
Mean number of lenders per borrower	7.7	19.3	5.7
Median number of lenders per borrower	4	14	4
25th pct.	2	5	2
75th pct.	12	28	8
Mean number of borrowers per lender	6.1	20.9	7.2
Median number of borrowers per lender	4	14	3
25th pct.	2	5	2
75th pct.	10	32	14
Panel D: Pair statistics			
Total number of pairs	340	3072	354
Mean number of transactions per pair	34.9	90.1	100.1
Median number of transactions per pair	10	7	29

Notes: Samples include overnight loans settled through BOJ-NET. The loans are identified using the Furfine algorithm. The loan rate minus IOR in Panel A is expressed in basis points, while the trade size is presented in billion yen. Participants are identified using the Unified Financial Institution Code.



(a) Positive IOR. (b) NIOR

Figure 2: Cumulative distribution function of loan rates minus the IOR

Notes: Panel (a) uses data from before and after the NIOR period. Panel (b) uses data from the NIOR period. In Panel (b), the IOR is set to zero. The horizontal axis is expressed in basis points.

depositing them into reserve accounts.

Figure 2(b) shows the CDF of the spread during the NIOR period, where the spread is equal to the loan rate. Under the NIOR regime, spreads range between -10 and 0 basis points. The marginal return on reserves during this period depends on a bank's reserve holdings and can be -10, 0, or 10 basis points. The second-highest IOR serves as a ceiling for loan rates, while the lowest IOR acts as a floor. Lenders with a marginal return on reserves equal to -10 basis points reduced their balances by lending at rates above -10 basis points, earning the spread as profit. Borrowers with a marginal return of 0 basis points profited by borrowing at rates below 0 basis points.

Figure 3 shows the time series of intraday loan rate dispersion. It displays the standard deviation and the 90th-to-10th percentile range, with both smoothed using a centered 10-day moving average. The vertical axis is expressed in basis points. The red vertical dotted lines indicate the introduction and removal of NIOR. The 90th-to-10th percentile range highlights the increase in dispersion during the NIOR period, peaking at 8.5 basis points in 2016. The gap dropped to 1.5 basis points after NIOR was lifted. Given that the average overnight loan rate was near zero, this level of dispersion is economically meaningful.

Two key points regarding the figure's time-series properties are noteworthy. First, the dispersion during the NIOR was higher than that observed during the positive interest rate regime. This is partly due to operational reasons: during the NIOR period, financial institutions with a marginal value of reserves at -10 basis points lent to those with a marginal value of reserves at 0 basis points. This 10 basis point gap creates greater potential for price dispersion under NIOR. Another reason for the higher dispersion during the NIOR period is the increased participation of financial

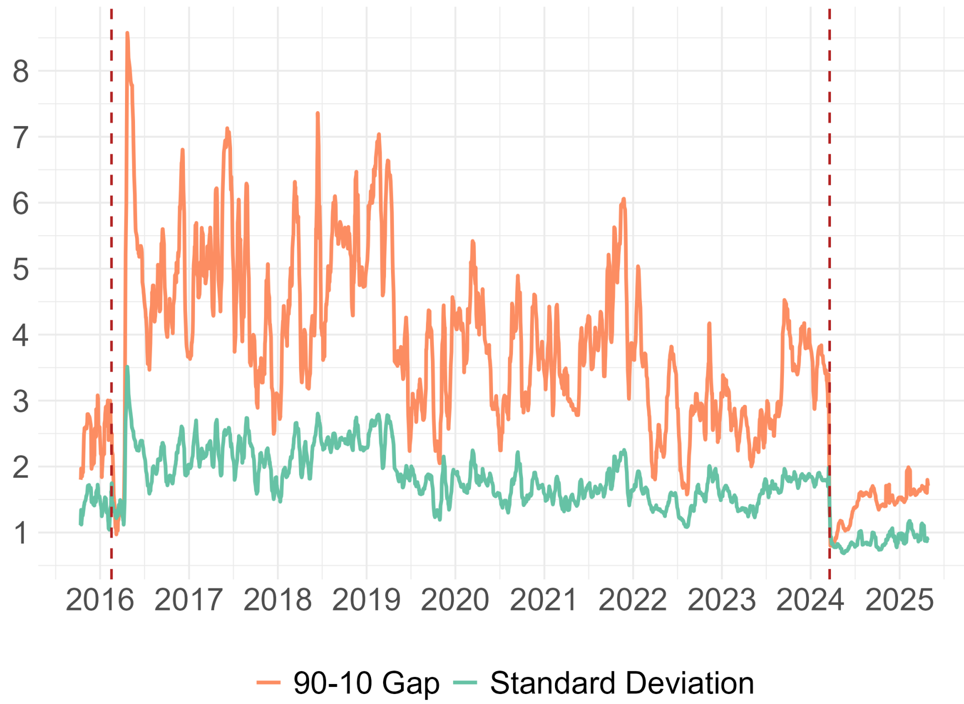


Figure 3: Intraday loan rate dispersion

Notes: This figure plots the time series of the intraday standard deviation of loan rates (represented in basis points) and the intraday gap between the 90th and 10th percentiles, after applying a centered 10-day moving average. Two red dotted lines represent the introduction and removal of the negative interest rate policy.

institutions in the interbank market, as shown in Panel B of Table 1. A higher number of participating institutions introduces greater heterogeneity, and the heterogeneous characteristics of these instirutions contribute to the more dispersed prices observed during the NIOR period.

The second key time-series property is the significant time-series fluctuations in intraday price dispersion, particularly in the 90th-to-10th percentile range. These large and high-frequency oscillations can represent non-systematic components that the model cannot explain. In contrast to this interpretation, the AKM model shows that the persistent characteristics of borrowers and lenders account for 70% to 80% of the total variation in loan rates.

4.2 Between-participants variation

Since fixed effects capture time-invariant differences in loan rates, the AKM model assumes that persistent heterogeneity influences overnight loan rates. This subsection highlights the systematic differences in average loan rates across borrowers and lenders. To measure these differences, we conduct a simple variance decomposition to separate the between-lender and between-borrower

Table 2: Between-lender and between-borrower decomposition of loan rate variation

Regime	Pre NIOR	NIOR	Post NIOR
Overall standard deviation	1.34	2.52	0.65
Between-lender share	40%	25%	57%
Between-borrower share	31%	20%	24%

Notes: The table presents the standard deviation of loan rates (in basis points) and the share of the total loan rate variation explained by the between-lender and between-borrower components.

components.

Let r_j^l denote the loan rate minus the IOR for transaction j by lender l, with n_l the number of transactions involving lender l and $N = \sum_{l=1}^{L} n_l$ total transactions. Define the lender-specific mean $\bar{r}^l = \frac{1}{n_l} \sum_{j=1}^{n_l} r_j^l$ and the overall mean $\bar{r} = \frac{1}{N} \sum_{l=1}^{L} n_l \bar{r}^l$. The between-lender variation is then given by $\frac{1}{N} \sum_{l=1}^{L} n_l \left(\bar{r}^l - \bar{r}\right)^2$, with the between-borrower variation defined analogously.

Table 2 reports the share of between-lender and between-borrower variation relative to the overall loan rate variation under each regime. The between-lender component accounts for 40%, 25%, and 57% of total variation across the respective regimes, while the between-borrower component accounts for 31%, 20%, and 24%. These results indicate systematic heterogeneity across both lenders and borrowers. Notably, the between-lender variation is larger than the between-borrower variation across all regimes, suggesting that lender heterogeneity may contribute more significantly to the total variation than borrower heterogeneity.

4.3 Additive structure and further premises

The AKM model assumes that prices equal the sum of fixed effects of two agents. Applied to the interbank market, loan rates are the sum of borrower and lender fixed effects. Under this assumption, lenders matched with high-rate borrowers transact at higher rates, and borrowers matched with high-rate lenders do the same. Figure 4 illustrates average loan rates across combinations of borrower and lender groups. Borrowers are ranked by their average loan rates and grouped into four categories, ranging from low to high, with lenders grouped similarly. Each transaction is assigned to one of the borrower–lender type cells in a four-by-four grid. For each cell, we compute the mean loan rate net of the IOR and visualize the resulting values as a heatmap. This procedure is repeated separately for each policy regime, and all values are expressed in basis points.

The heatmaps reveal patterns consistent with an additive borrower–lender structure. For a fixed borrower group, average loan rates increase with higher lender groups. Similarly, within a given lender group, higher borrower groups correspond to higher loan rates. The two dimensions vary independently in most cells across the three policy regimes. These patterns suggest that borrower and lender influences on loan rates are separable and additive, providing support for the AKM model.

Additional empirical premises are discussed in the Appendix. The AKM model assumes that loan rates reflect persistent heterogeneity across participants. Appendix B.1 demonstrates that the average loan rates at which each participant trades in the current month or quarter are highly correlated with those in the following month or quarter, indicating the existence of persistent characteristics influencing loan rates.

One potential concern in applying the AKM model to network-based data is the issue of a non-bipartite network, often referred to as the "reflection problem" (Bernard et al., 2022). In cases where financial institutions act as both lenders and borrowers, the trading network becomes non-bipartite, causing the estimated lender and borrower fixed effects to reflect equilibrium outcomes rather than the participants' characteristics. The identification strategy in the AKM model relies on the network being bipartite, and we find that the interbank network in Japan is highly bipartite. This is discussed in more detail in Appendix B.2.

5 AKM decompositions

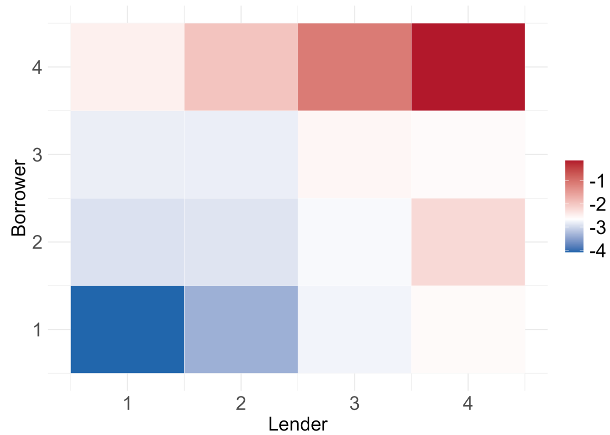
5.1 Main analysis

We estimate the following model:

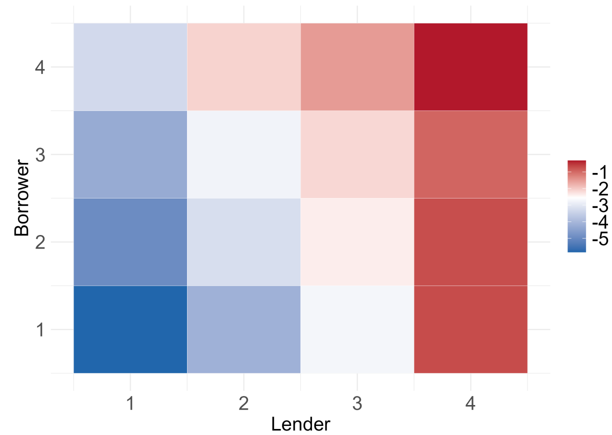
$$r_{i,l,b,t} = \alpha_l + \beta_b + \theta_t + \varepsilon_{i,l,b,t}, \tag{1}$$

where $r_{i,l,b,t}$ is the loan rate minus IOR of transaction i between lender l and borrower b, conducted on day t. Here, α_l denotes the lender l fixed effect, β_b represents the borrower b fixed effect, and θ_t is the daily time fixed effect. The borrower and lender fixed effects capture persistent characteristics that affect loan rates, including time-invariant counterparty risk, bargaining power, transaction costs, and available funds. For example, borrowers with relatively high counterparty risk face higher loan rates and are fitted with a higher β_b. The daily fixed effect absorbs macroeconomic conditions, such as the average overnight loan rate and aggregate demand for securing reserves through overnight loans. We classify transactions into three regimes, pool all observations within each regime, and then estimate the model for each of the three regimes.

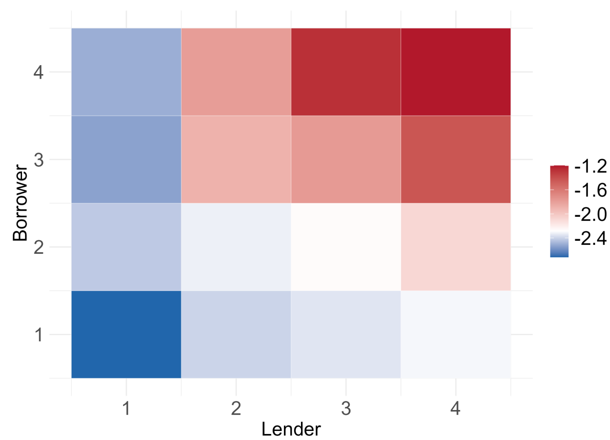
Our baseline specification excludes observable characteristics of borrowers and lenders. We prefer models without observable characteristics as the baseline because estimated fixed effects are interpreted as participants' average loan rates, and the interpretation of coefficients is more



(a) Pre NIOR.



(b) NIOR.



(c) Post NIOR.

Figure 4: Mean loan rates across borrower–lender quartiles

Notes: This figure illustrates the average loan rates across combinations of borrower and lender groups. Borrowers are ranked by their average loan rates and grouped into four categories, ranging from low to high, with lenders grouped in a similar manner. Each transaction is thus assigned to one of the sixteen borrower–lender type cells in a four-by-four grid. For each cell, we compute the mean loan rate net of the IOR and visualize the resulting values as a heatmap in basis points. The three panels use samples from before NIOR, during NIOR, and after NIOR.

straightforward. We conduct two analyses concerning the observable characteristics of the financial institutions. First, we incorporate observable characteristics and estimate the model in Appendix B.3. Second, we estimate the model without observable characteristics and then examine the relationship between the estimated fixed effects and the observable characteristics in Section 5.1.1.[8]

[8]This approach follows that of Alvarez et al. (2018) who regresses the estimated fixed effects on balance sheet information, as is commonly done in the labor economics literature.

Another consideration is time-varying parameters. The baseline specification assumes persistent characteristics of banks. In practice, some characteristics are persistent whereas others vary with time. The baseline quantifies how much of the variation in loan rates can be attributed to persistent characteristics. In fact, fixed characteristics captured important aspects of loan rates; for instance, participants' average loan rates were found to be highly correlated over time, as shown in Appendix B.1. However, we provide two additional analyses to account for the time-varying characteristics. First, we estimate the model in (1) using a one-year rolling window and present the results in Section 5.2. Within a one-year horizon, bank characteristics are likely to remain highly stable, making the assumptions of the model in (1) more likely to hold. Second, we estimate an alternative model that allows for time-varying parameters, as described in Appendix A.1.

We quantify the contribution of each component on the right-hand side of (1) to explain the variation in loan rates. We compute the share of the total variance in loan rates attributable to each component using the following expressions:

$$\frac{\mathrm{Var}(\alpha_l)}{\mathrm{Var}(r_{i,l,b,t})}, \quad \frac{\mathrm{Var}(\beta_b)}{\mathrm{Var}(r_{i,l,b,t})}, \quad \frac{\mathrm{Var}(\theta_t)}{\mathrm{Var}(r_{i,l,b,t})}, \quad \frac{2\mathrm{Cov}(\alpha_l,\beta_b)}{\mathrm{Var}(r_{i,l,b,t})}, \quad \frac{2\mathrm{Cov}(\alpha_l+\beta_b,\theta_t)}{\mathrm{Var}(r_{i,l,b,t})}, \quad \frac{\mathrm{Var}(\varepsilon_{i,l,b,t})}{\mathrm{Var}(r_{i,l,b,t})}.$$

These components sum to one.

Table 3 presents the decomposition results. The standard deviations of the loan rates are 1.34, 2.52, and 0.65 basis points for the pre-NIOR, NIOR, and post-NIOR regimes, respectively. The high total variation during the NIOR regime reflects the time-series variation of average loan rates, as shown in Figure 1. The time fixed effects account for 58% of the variation during the NIOR regime. Since the time-series variation in average loan rates is smaller during the pre- and post-NIOR regimes, time fixed effects account for 11% and 3% of the variation, respectively.

The fixed characteristics of borrowers account for 16%, 6%, and 14% of the total variation in the respective regimes. Afonso, Kovner, and Schoar (2011) found that borrower counterparty risk was a key factor during the crisis period. Our findings suggest that persistent borrower characteristics play a smaller role on average.

Lender fixed effects account for a larger share of loan rate variation than borrower fixed effects in all regimes: 36%, 13%, and 57% of the total variation, respectively. The contribution of lender fixed effects is 2.2, 2.2, and 4.1 times larger than that of the borrower fixed effects in the respective regimes.

The relatively smaller contribution of borrower heterogeneity reflects the borrower's homogeneous liquidity demand and the highly competitive arbitrage conditions. Two primary factors typically drive borrower trading: the need to secure reserves due to scarcity (i.e., liquidity demand) and the pursuit of arbitrage profits. Regarding the first trading motive, most financial institutions in

Table 3: Variance decomposition of loan rates

Sample Period	Pre NIOR	NIOR	Post NIOR
Panel A			
Borrow	16%	6%	14%
Lend	36%	13%	57%
Time	11%	58%	3%
2Cov(Borrow,Lend)	1%	6%	-1%
2Cov(Borrow+Lend,Time)	0%	-1%	-1%
Residual	36%	18%	28%
Std. dev. of loan rate	1.34	2.52	0.65
Panel B			
Pair	15%	4%	17%
Residual	21%	14%	11%
Panel C			
Cor(Borrow, Lend)	-0.07	0.31	-0.03

Notes: The results are from OLS estimation of equation (1) and (2). Variance decomposition in Panel A is given by $\text{Var}(r_{i,l,b,t}) = \text{Var}(\alpha_l) + \text{Var}(\beta_b) + \text{Var}(\theta_t) + 2\text{Cov}(\alpha_l, \beta_b) + 2\text{Cov}(\alpha_l + \beta_b, \theta_t) + \text{Var}(\varepsilon_{i,l,b,t})$. In Panel B, we show $\frac{\text{Var}(\varepsilon_{i,l,b,t})}{\text{Var}(r_{i,l,b,t})}$ from (2) in "Residual", and $\frac{\text{Var}(\varepsilon_{i,l,b,t})}{\text{Var}(r_{i,l,b,t})}$ from (1) minus $\frac{\text{Var}(\varepsilon_{i,l,b,t})}{\text{Var}(r_{i,l,b,t})}$ from (2) in "Pair". Panel C shows $\text{Cor}(\alpha_l, \beta_b)$.

Japan maintain abundant reserves, with only a very small fraction relying on the interbank market for immediate liquidity.[9] Use of the discount window facility, often considered an indicator of unmet liquidity demand, is at an extremely low level (Bank of Japan, 2025).[10] Few borrowers trade loans to secure liquidity, resulting in relatively smaller heterogeneity in liquidity demand.

The second motive for trading is to earn arbitrage profits by borrowing funds at rates below the IOR and depositing them into reserve accounts that yield the IOR. A unique feature of the interbank market plays a key role here: the linear relationship between the reserve amount and its return. Regardless of the reserve level, the central bank pays interest equal to the product of the reserve amount and the IOR. In other words, the marginal return on reserves is always equal to IOR and is not diminishing. Because of this linearity, banks aggressively borrow in the interbank market. This competitive arbitrage reduces the heterogeneity of borrowers. If one bank borrows at a low rate to generate higher arbitrage profits, other banks aggressively respond by increasing their

[9] Data on the reserves held by financial institutions is provided in Appendix F. The appendix shows that over 99% of financial institutions participating in the interbank market maintain reserves exceeding 1.5 times their required levels, 97% hold more than 3 times their required reserves, and 93% hold more than 10 times their required reserves.

[10] Afonso, Kovner, and Schoar (2011) uses the discount window facility as a proxy for unmet liquidity demand. The fact that financial institutions in Japan rarely use the discount window rate can also be confirmed from the cumulative distribution function of overnight loan rates. Figure 2 shows that the upper percentiles of overnight loan rates remain close to the IOR, indicated as zero in the figure. The discount window rate is 20 basis points higher than the IOR. Borrowers who require liquidity can secure it without resorting to the use of the discount window rate.

own bids, erasing any competitive advantage. Note that if the return on reserves were concave, borrowers would not be able to sustain competition, as higher levels of reserves would lead to diminishing returns.[11]

The large heterogeneity among lenders highlights the variation in trade sizes, namely the yen loan amounts per transaction. We calculate the mean trade size for each lender and report the 10th, 50th, and 90th percentiles of the mean trade size across lenders, which are 8 billion, 17 billion, and 105 billion yen, respectively. Borrower trade profits, defined as trade size $\times$ (IOR $-$ loan rate), also vary substantially across lenders: the 90th-percentile lender generates 13.1 times the profit of the 10th-percentile lender. If borrowers compare trades across different lenders and choose the most profitable trade, different lenders should provide comparable trade profits. For lenders with smaller trade sizes resulting in smaller trade profits for borrowers, the loan rates must be lower to ensure competitive profits for borrowers. This heterogeneity in trade size gives rise to loan rate variation across lenders. A formal analysis using a model of loan rate determination along with empirical support for this argument is presented in Appendix C.

The shares 36%, 18%, and 28% of the total dispersion in loan rates remain unexplained by borrower, lender, and time fixed effects across the respective regimes. Several factors could influence the residual variation. First, it could stem from time-varying bank characteristics, such as credit risk or funding needs. To assess the impact of these time-varying characteristics, we analyze lender-by-time and borrower-by-time fixed effects in Appendix A.

Another important source of residual variation is search frictions in the OTC market. As suggested by the search-and-matching model of the interbank market (Afonso and Lagos, 2015a,b), search frictions create loan rate dispersion even when participants are ex-ante homogeneous.[12] Due to the random nature of matching between participants, their marginal value of reserves becomes differentiated, resulting in loan rate dispersion among ex-ante homogeneous participants.The AKM model provides insights into the extent to which search frictions contribute to loan rate dispersion by decomposing the variation into components explained by participant characteristics and unexplained residuals, the latter of which is partially driven by search frictions. While not all residual variation is attributable to search frictions, the AKM model contributes to the literature on OTC markets in the interbank context.

Next, we consider the following questions: How prevalent are relationships between lenders and borrowers? More specifically, to what extent can relationships explain the residuals in the

[11] For example, consider the standard setup where banks lend to firms. Since the marginal product of a firm's output is diminishing, banks would not lend very large amounts of funds to firms. There exists a certain level of lending to firms where the marginal return on lending equals the banks' funding costs. However, in the interbank market, the marginal return on lending to the central bank is always equal to the IOR. As a result, banks are incentivized to aggressively collect funds and deposit them in reserve accounts.

[12] Afonso and Lagos (2015a) present a model of the interbank market with search frictions and derive an analytical solution for loan rates. They shows that intraday loan rate dispersion exists even when banks are ex-ante homogeneous.

additive model? To address these questions, we test the inclusion of pair fixed effects:

$$r_{i,l,b,t} = \eta_{l,b} + \theta_t + \varepsilon_{i,l,b,t}, \tag{2}$$

where $\eta_{l,b}$ represents a borrower–lender pair fixed effect, and θ_t is the daily time fixed effect. We aim to isolate the relationship component beyond the additive structure of borrower and lender characteristics. The procedure is as follows. After estimating (2), we compute the residual variance and compare it to that from (1). The residual variance in (2) is weakly smaller than that in (1) because the pair fixed effect, $\eta_{l,b}$, nests the sum of the borrower and lender fixed effects, $\alpha_l + \beta_b$. The decline in the residual variance from the additive model to the pair model is attributed to the contribution of the pair-specific effect.[13]

To better understand this approach, consider the following example: suppose lender x and borrower y both engage in transactions at higher loan rates when not trading with one another. However, when x and y trade with one another, the observed loan rate is consistently lower. In this case, α_x and β_y in (1) are estimated to be higher because x and y have higher average loan rates. The loan rate $r_{x,y}$ is captured as a residual in (1) due to the low $r_{x,y}$ and the high values of α_x and β_y. In (2), this loan rate is attributable to the low $\eta_{x,y}$ rather than being treated as a residual.

Panel B shows the additional variation that can be explained by the pair fixed effect in (2). The unexplained variation in Panel A equals the sum of the unexplained variation in Panel B and the share in the "Pair" row. For the three regimes, the additional variation explained by including the pair fixed effect comprises 15%, 4%, and 17% of the total variation. Although any persistent, pair-specific relationship component has pricing power in our setting, its share depends on the regime. Even after controlling for pair fixed effects, the residual variation remains at 21%, 14%, and 11% of the total loan rate variation.

5.1.1 Estimated fixed effects and balance sheet characteristics

We examine the relationship between estimated fixed effects and participants' balance sheet characteristics.[14] Specifically, we conduct cross-sectional regressions of the estimated borrower and lender fixed effects on their respective balance sheet characteristics. The regressions include standard balance sheet variables: assets, leverage, the deposit-to-liability ratio, the non-performing loan (NPL) rate, return on assets (ROA), the wholesale funding ratio, and the liquid assets ratio.

[13] This approach follows the literature on match-specific effects of firms and workers in wage determination, as in Woodcock (2008).

[14] This approach is analogous to the method commonly used in labor economics for wage determination, where firm and worker fixed effects are regressed on observed characteristics, such as firm value added per worker (Alvarez et al., 2018).

Balance sheet data are sourced from the *Zenkoku Ginkou Kyoukai*, covering city banks, regional banks, second-tier regional banks, and a subset of trust banks and online banks. The balance sheets of foreign banks, credit unions, a subset of trust banks, and mutual funds are not included. All balance sheet information corresponds to the average between 2016 and 2024.

Table 4 presents the results of the cross-sectional regression of borrower fixed effects on balance sheet variables, while Table 5 shows the results for lender fixed effects. We estimated separate regressions for the NIOR and post-NIOR periods. Lenders in the post-NIOR period consist primarily of mutual funds, which lack available balance sheet information, and results for lenders during this period are not reported.

Overall, observable balance sheet characteristics account for a relatively small fraction of the variation in the estimated fixed effects. For borrowers, the R^2 is 0.30 in the specification including all variables during the NIOR period and 0.17 in the specification with all variables during the post-NIOR period. For lenders, the R^2 is 0.09 in the specification with all variables during the NIOR period.

Although the results vary across specifications and regimes, a notable pattern is that borrowers with higher non-performing loan ratios tend to have higher fixed effects during the NIOR period. The coefficient is positive and statistically significant.[15] A 1% increase in the share of non-performing loans to total loans corresponds to a 0.59 basis point rise in the average interbank loan rate. This result is intuitive: banks with higher NPL ratios are likely perceived as riskier and, consequently, tend to borrow at higher overnight loan rates. This statistically significant relationship is absent in the post-NIOR period. We attribute this to reduced participation of banks in the post-NIOR regime, as banks with higher NPL ratios appear less likely to participate in the market.

Additional analysis We provide additional analyses to address potential concerns and gain further insights. First, robustness checks for the main AKM decomposition are presented in Appendix A. Second, while observable characteristics were not included in the baseline analysis, Appendix B.3 demonstrates that the main results remain robust when these characteristics are incorporated. Third, additional insights into the nature of the deviations from the model are obtained by examining the average estimated residuals for different groups of lenders and borrowers. Violations of the separability assumptions could lead to large mean residuals for certain types of

[15] We report t-statistics for regressions using borrower and lender fixed effects estimated in the first-stage AKM model. These statistics should be interpreted with caution, as the estimated fixed effects are generated regressors and the second-stage inference ignores first-stage estimation error. While bootstrap methods are commonly used in two-step settings, they are generally infeasible in AKM-type models because identification relies on the connectedness of the network, which resampling can disrupt. As a result, constructing standard errors that fully account for first-stage uncertainty is difficult in practice, and the reported t-statistics should be viewed as descriptive rather than definitive. Despite these concerns, the estimation error is arguably small when the sample size is large and the number of fixed effects is small.

Table 4: Cross-sectional regression of borrower fixed effects on balance sheet information

	NIOR	NIOR	NIOR	Post-NIOR	Post-NIOR	Post-NIOR
	(1)	(2)	(3)	(4)	(5)	(6)
Assets	-0.217^{***}		-0.093	-0.065		-0.057
	(0.075)		(0.091)	(0.051)		(0.094)
NPL		82.103^{***}	59.126^{**}		-4.096	-10.086
		(18.619)	(23.877)		(17.147)	(18.597)
Leverage			5.740			6.396
			(4.159)			(4.264)
Deposit/Liability			-0.531			-0.566^{*}
			(0.523)			(0.322)
ROA			24.119			88.329
			(49.701)			(57.774)
Wholesale funding			-2.365			-1.431
			(1.451)			(1.759)
Liquid assets			-0.537			-0.278
			(0.765)			(0.490)
Observations	103	103	103	45	45	45
R^2	0.149	0.205	0.308	0.051	0.001	0.176

Notes: Variable definitions are as follows. "Assets" is the log of assets. "Leverage" is the liability-to-asset ratio. "Deposit/Liability" is the deposit-to-liability ratio. "NPL" is non-performing loan ratio, defined as the sum of bankrupt and restructured claims divided by total loans. "ROA" is the net-income-to-asset ratio. "Wholesale funding" is the wholesale funding ratio, where wholesale funding is the sum of negotiable certificates of deposit, call money, commercial paper, borrowings, and corporate bonds, treating missing values as zero; the wholesale funding ratio is wholesale funding divided by total liabilities. "Liquid assets" is the liquid assets ratio, where liquid assets are the sum of cash, call loans, reverse repos, securities lending margins, Japanese government bonds, and regional government bonds, treating missing values as zero; the liquid asset ratio is liquid assets divided by total assets. Heteroskedasticity-robust standard errors are reported. * p<0.1; ** p<0.05; *** p<0.01.

matches. This issue is discussed in detail in Appendix B.4. Finally, a simple model of loan rate determination is presented in Appendix C.

5.2 Trends in variance decomposition

We investigate the time-series properties of the variance decomposition. Specifically, we partition the sample along the time dimension and estimate the model (1) separately for each period. The model is estimated using rolling one-year windows, shifting the window forward by two months.[16]

[16] Since the NIOR data begins on 2016/02/17, the first estimation window covers the period from 2016/02/17 to 2017/02/16. The next window spans from 2016/04/17 to 2017/04/16. If the remaining sample period is shorter than

Table 5: Cross-sectional regression of lender fixed effects on balance sheet information

	NIOR	NIOR	NIOR
	(1)	(2)	(3)
Assets	-0.307^{**}		-0.276
	(0.132)		(0.210)
NPL		91.779^{**}	70.946
		(45.452)	(62.591)
Leverage			8.520
			(14.556)
Deposit/Liability			1.117
			(1.643)
ROA			115.107
			(172.041)
Wholesale funding			1.081
			(5.048)
Liquid assets			1.784
			(2.369)
Observations	92	92	92
R^2	0.058	0.044	0.091

Notes: Variable definitions are as follows. "Assets" is the log of assets. "Leverage" is the liability-to-asset ratio. "Deposit/Liability" is the deposit-to-liability ratio. "NPL" is non-performing loan ratio, defined as the sum of bankrupt and restructured claims divided by total loans. "ROA" is the net-income-to-asset ratio. "Wholesale funding" is the wholesale funding ratio, where wholesale funding is the sum of negotiable certificates of deposit, call money, commercial paper, borrowings, and corporate bonds, treating missing values as zero; the wholesale funding ratio is wholesale funding divided by total liabilities. "Liquid assets" is the liquid assets ratio, where liquid assets are the sum of cash, call loans, reverse repos, securities lending margins, Japanese government bonds, and regional government bonds, treating missing values as zero; the liquid asset ratio is liquid assets divided by total assets. Heteroskedasticity-robust standard errors are reported. * p<0.1; ** p<0.05; *** p<0.01.

Figure 5 presents the time series of Var(α_l), Var(β_b), and Var($\varepsilon_{i,l,b,t}$). The red dashed line marks the end of NIOR.

The variance of the lender fixed effects is larger than that of the borrower fixed effects throughout the sample period, consistent with Table 3. Moreover, the lender fixed effect shows an increase in 2018 and 2023, whereas the other components exhibit only minor changes during these periods.

When NIOR was lifted, the variance of lender fixed effects decreased significantly. This finding is consistent with the fact that, during the NIOR period, a variety of institutions, such as city banks, regional banks, and mutual funds, participated as lenders. However, after NIOR, lenders were

three months, we terminate the NIOR estimation on 2023/12/15. For the positive IOR regime, we followed the same procedure, starting on 2024/03/19, and again using one-year rolling windows with two-month increments.

predominantly mutual funds (Bank of Japan, 2024).[17] The changed composition of lender type aligned with the decrease in lender fixed effects variance.

The residual term remained stable over time during the NIOR period but declined when NIOR was lifted in 2024. The residuals of loan rates in (1) capture the variation left unexplained by the sum of the borrower, lender, and aggregate components. These residuals serve as one of the indicators of OTC market functioning.[18] The evidence shows no significant change in OTC market functioning during the NIOR period, as the unexplained dispersion in loan rates remained stable with no indication of abnormal pricing behavior. In Japan, monetary policy has remained accommodative for an extended period, keeping rates near zero. Although concerns have been raised that prolonged easing may impair interbank market functioning (Shirakawa, 2008), we find no significant changes in residuals.

The borrower fixed effect variance decreased significantly, from approximately 0.75 in 2016 to about 0.07 in 2024. By 2024, loan rates had become nearly uniform across borrowers, in contrast to the earlier years of the sample period, when loan rates varied depending on the borrower.

To understand the decline in borrower fixed effect contributions, we decompose the total change into changes in borrower share and fixed effects. By definition, $\mathrm{Var}(\beta_b) \equiv \sum_b w_b(\beta_b - \overline{\beta})^2$, where w_b represents the share of transactions borrowed by borrower b. The time-series change in $\mathrm{Var}(\beta_b)$ can be decomposed into changes in borrower shares (w_b) and changes in fixed effects (β_b). To distinguish, we calculate two counterfactual variances: one that holds the share of transactions fixed at an earlier period while allowing the fixed effects to vary, and another that holds the borrower fixed effects fixed at their earlier period values while allowing the transaction shares to vary.[19]

Figure 6(a) presents the results. The variance of borrower fixed effects, calculated by holding borrower shares constant and allowing the fixed effects to vary over time, exhibits a clear downward trend. In contrast, the variance calculated by holding the borrower fixed effects constant at their earlier period values, while allowing borrower shares to vary over time, remains relatively stable. Intuitively, the decline in the variance of borrower fixed effects could be attributed to either (i) banks that were initially close to the average trading more actively over time, or (ii) banks that

[17] Figure E.1 in Appendix E shows that the share of money market funds as lenders rose from 60% to 90% after the lifting of NIOR.

[18] The approach of measuring the functioning of the interbank market through loan rate dispersion is adopted in Altavilla et al. (2019) and Bianchi and Bigio (2022). Our approach differs from theirs with respect to decomposition: while the literature computes the intraday dispersion of loan rates, this paper filters out the heterogeneity in borrowers and lenders from the overall loan rate dispersion and interprets the residuals as a measure of the interbank market's functioning.

[19] We begin by constructing borrower shares and estimating borrower fixed effects using transactions from the first half of the NIOR period. Then, borrower fixed effects are re-estimated using rolling one-year windows, advanced by two months at a time, over the entire sample period. Using these, we create two counterfactual time series by combining (i) shares from the earlier period with contemporaneous fixed effects and (ii) fixed effects from the earlier period with contemporaneous shares.

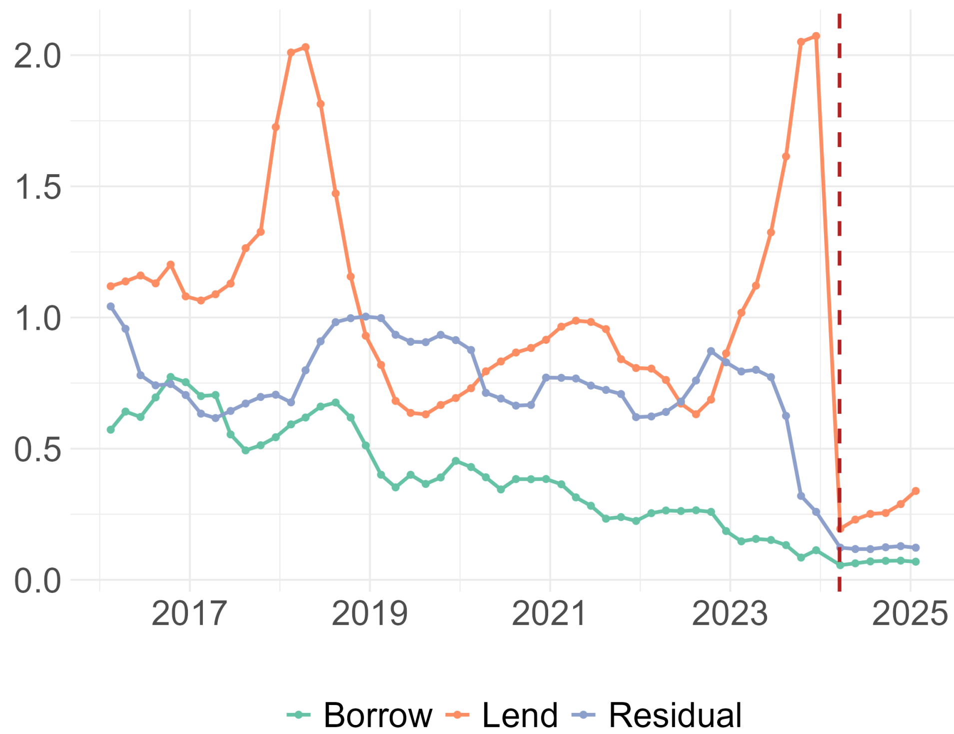
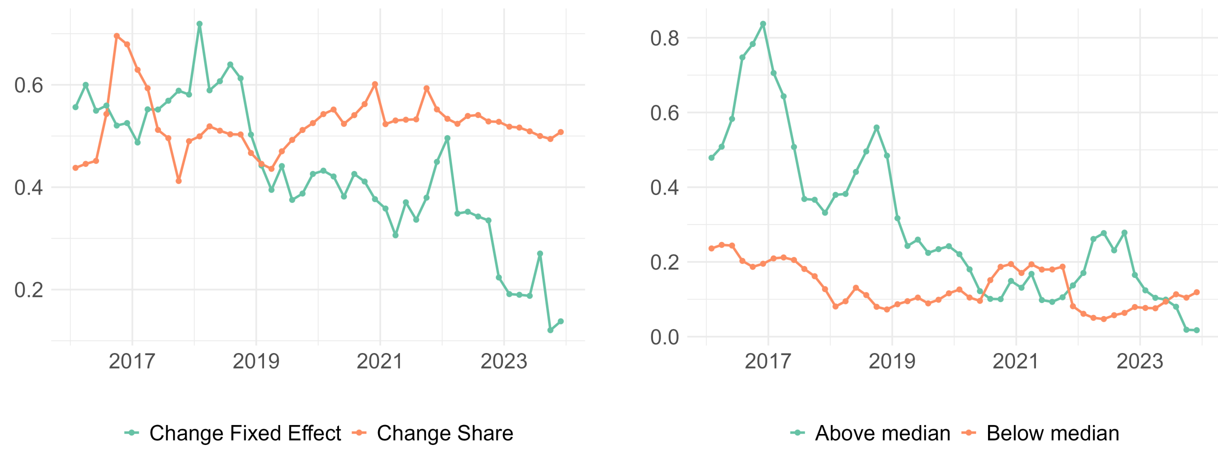


Figure 5: Variance decomposition of loan rates over time

Notes: This figure reports time-series estimates of the variance decomposition using one-year rolling windows with two-month increments. The orange line plots $\text{Var}(\alpha_l)$. The green line plots $\text{Var}(\beta_b)$. The blue line plots $\text{Var}(\varepsilon_{i,l,b,t})$. The red dashed line indicates the date when the NIOR policy was lifted.

were higher than the average converging toward the average level. The evidence indicates that the latter mechanism provides a better explanation for the observed downward trend.

Another investigation focuses on whether the upper or lower tails of the borrower fixed effect distribution exhibit a decline in dispersion. We plot the variance of the borrower fixed effect, β_b, conditional on whether it lies below or above its median; that is, $\text{Var}\big(\beta_{b(i)} \mid \beta_{b(i)} > \text{Median}\big(\beta_{b(i)}\big)\big)$ and $\text{Var}\big(\beta_{b(i)} \mid \beta_{b(i)} \leq \text{Median}\big(\beta_{b(i)}\big)\big)$. Figure 6(b) demonstrates that the dispersion within the upper tail contracts substantially over time, whereas the dispersion in the lower tail remains relatively stable. This finding suggests that the reduction in borrower fixed-effect variance is primarily driven by changes in the upper tail of the distribution. More intuitively, banks that historically borrowed at relatively low rates stay at a similar level, while those that previously borrowed at higher rates borrow at rates much closer to the average.



(a) Decomposition of shares and fixed effects.

(b) Change in the distribution of fixed effects.

Figure 6: Decomposition of the variance of borrower fixed effects

Notes: Panel (a) shows the decomposition of the variance of borrower fixed effects into two counterfactual series: the green line, calculated by holding borrower shares constant and allowing fixed effects to vary, and the red line, calculated by holding fixed effects constant and allowing shares to vary. Panel (b) displays the variance of borrower fixed effects calculated separately for those above and below the median at each point in time. Borrower shares and fixed effects are estimated using rolling one-year windows, advanced in two-month increments.

5.3 Crisis episode and counterfactual

Overnight loan markets are an immediate source of liquidity. During periods of financial stress, a greater number of banks may participate in the interbank market to secure liquidity, which increases participant heterogeneity. For example, as found by Furfine (2002) and Afonso, Kovner, and Schoar (2011) in the U.S. interbank market, banks considered to have high counterparty risk may experience significant stress during crises and trade more aggressively to obtain liquidity.

This subsection quantifies the role of participant heterogeneity in shaping rate dispersion during crises. We conduct a simple counterfactual exercise. First, we compute the model's fitted values in (1):

$$\hat{r}_i \equiv \hat{\alpha}_{l(i)} + \hat{\beta}_{b(i)} + \hat{\theta}_{t(i)}. \tag{3}$$

To evaluate the contributions of borrower and lender heterogeneity to dispersion, we substitute their sample means for their respective fixed effects:

$$r_i^L \equiv \overline{\alpha} + \hat{\beta}_{b(i)} + \hat{\theta}_{t(i)}, \qquad r_i^B \equiv \hat{\alpha}_{l(i)} + \overline{\beta} + \hat{\theta}_{t(i)},$$

where $\overline{\alpha}$ and $\overline{\beta}$ represent the sample means of the lender and borrower fixed effects. For each day

t, we compare the dispersion of the fitted rates and the counterfactual rates:

$$\Delta_t^L \equiv \text{sd}_t(\hat{r}_i) - \text{sd}_t(r_i^L), \qquad \Delta_t^B \equiv \text{sd}_t(\hat{r}_i) - \text{sd}_t(r_i^B).$$

These differences summarize, on a day-to-day basis, the extent to which lender and borrower heterogeneity contribute to the variation in loan rates. Figure 7(a) illustrates the intraday counterfactual contributions of lender (Δ_t^L) and borrower (Δ_t^B) heterogeneity. The values are computed using a 20-day moving average.

A sharp rise in borrowers' contribution to loan rate dispersion emerges during the COVID-19 crisis, as evidenced by the spike in early 2020. The Δ_t^B peaks at 0.6 basis points, compared to roughly 0.3 basis points afterward, indicating a 100% increase in the contribution of borrower heterogeneity. Notably, lender fixed-effect dispersion does not increase during the crisis, consistent with Afonso, Kovner, and Schoar (2011), who found no significant change in lender behavior. Another notable feature is that total loan rate dispersion remains relatively modest during this period (Figure 3).

We compute the counterfactual contributions of borrowers with high and low estimated fixed effects:

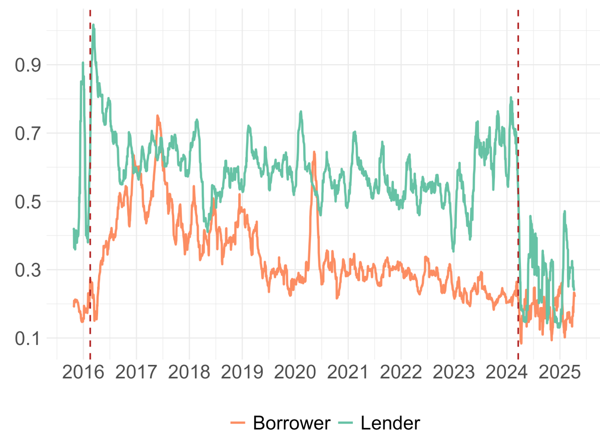
$$\Delta_t^{B,H} \equiv \text{sd}_t(\hat{r}_{i,l,b,t}) - \text{sd}_t\left(r_{i,l,b,t}^{b,H}\right), \quad \Delta_t^{B,L} \equiv \text{sd}_t(\hat{r}_{i,l,b,t}) - \text{sd}_t\left(r_{i,l,b,t}^{b,L}\right),$$

$$r_{i,l,b,t}^{b,H} \equiv \begin{cases} \hat{\alpha}_{l(i)} + \overline{\beta} + \hat{\theta}_{t(i)}, & \text{if } \hat{\beta}_{b(i)} > \text{median}_i\left(\hat{\beta}_{b(i)}\right), \\ \hat{r}_{i,l,b,t}, & \text{if } \hat{\beta}_{b(i)} \leq \text{median}_i\left(\hat{\beta}_{b(i)}\right), \end{cases}$$

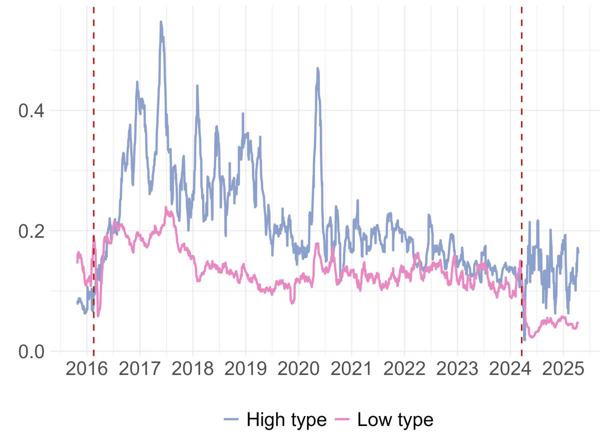
$$r_{i,l,b,t}^{b,L} \equiv \begin{cases} \hat{\alpha}_{l(i)} + \overline{\beta} + \hat{\theta}_{t(i)}, & \text{if } \hat{\beta}_{b(i)} \leq \text{median}_i\left(\hat{\beta}_{b(i)}\right), \\ \hat{r}_{i,l,b,t}, & \text{if } \hat{\beta}_{b(i)} > \text{median}_i\left(\hat{\beta}_{b(i)}\right). \end{cases}$$

If high-type borrowers contributed more significantly to loan rate dispersion during the COVID-19 crisis, $\Delta_t^{B,H}$, which captures the effect of shutting down high-type heterogeneity, should exhibit a spike. Figure 7(b) displays $\Delta_t^{B,H}$ (High type) and $\Delta_t^{B,L}$ (Low type). The figure reveals a spike in $\Delta_t^{B,H}$ during the COVID-19 period, whereas $\Delta_t^{B,L}$ remains stable. The contribution of high-type borrowers increases to approximately 0.4 basis points at the onset of the crisis, compared to around 0.2 basis points afterward. In contrast, the contribution from low-type borrowers ($\Delta_t^{B,L}$) remains stable at nearly 0.1 basis points both during and outside the crisis.

This pattern suggests that borrowers with high fixed effects became more active during the COVID-19 episode, while borrowers with low fixed effects displayed minimal changes. Compared



(a) Difference in fitted and counterfactual dispersion



(b) High- vs. low-fixed-effects borrower contributions

Figure 7: Dispersion driven by borrower and lender heterogeneity

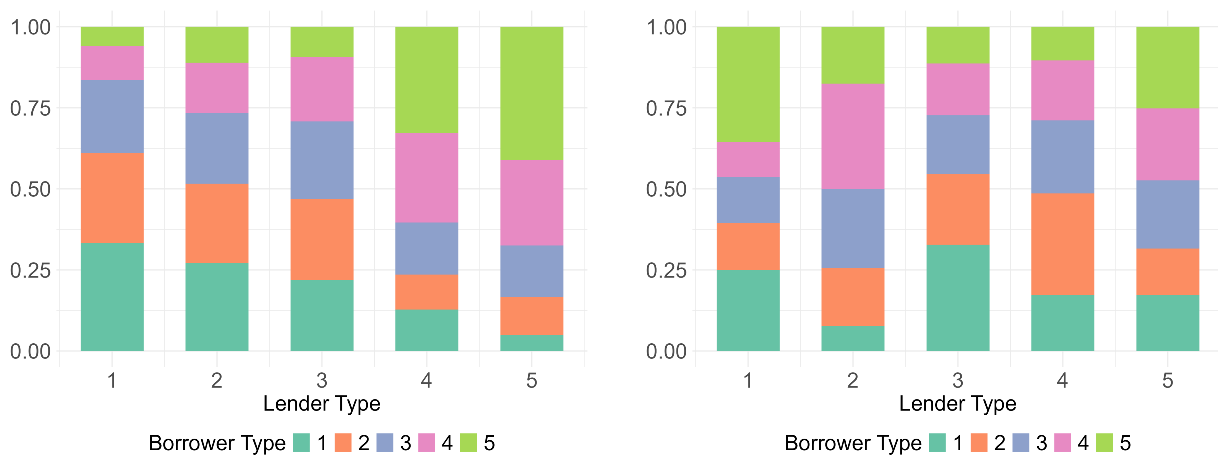
Notes: Panel (a) shows the contributions of lender and borrower heterogeneity to loan rate dispersion, calculated as the differences between fitted rates and counterfactual rates with fixed effects replaced by the sample means. These daily estimates are smoothed using a 20-day moving average. Panel (b) presents counterfactual contributions of borrowers with high and low fixed effects, defined relative to the median of the borrower fixed-effect distribution. Both panels use fixed effects estimated from the AKM decomposition of loan rates.

to the existing literature (Furfine, 2002; Afonso, Kovner, and Schoar, 2011), our methodology identifies borrower types based on unobserved characteristics through the AKM model, whereas prior studies rely on observed characteristics, such as assets and non-performing loans.

6 Sorting

Sorting is defined as the correlation between the estimated two-way fixed effects. In labor economics, for example, positive sorting refers to the positive correlation between firm and worker fixed effects and captures whether high-productivity firms are matched with high-productivity workers (Bonhomme, Lamadon, and Manresa, 2019). Sorting has been extensively studied in various markets,[20] but it has received less attention in interbank markets. Theoretical models of interbank matching typically assume random matching (Afonso and Lagos, 2015b). On the empirical side, the literature emphasizes relational trading patterns (Cocco, Gomes, and Martins, 2009; Brauning and Fecht, 2017), i.e., participants frequently trade with specific counterparties. However, it remains empirically unclear whether these relationships create a correlation between the average loan rates of borrowers and lenders.

[20] Examples include the labor market (Bonhomme, Lamadon, and Manresa, 2019) and the marriage market (Becker, 1973).



(a) NIOR (b) Post NIOR

Figure 8: Conditional distribution of borrower fixed effects across lender fixed effects

Notes: This figure plots the share of matched borrower fixed effects conditional on lender fixed effects. Both borrower and lender fixed effects are divided into five groups, ranging from low to high. For each lender group, we calculate the share of borrower groups within the matched pairs. Samples for NIOR are presented in Panel (a), and post-NIOR samples are presented in Panel (b).

Panel C in Table 3 presents the correlation between borrower and lender fixed effects. During the NIOR regime, the correlation is 0.31, implying that lenders offering higher (lower) loan rates trade frequently with borrowers who also face higher (lower) rates. In contrast, under pre-NIOR and post-NIOR, the correlations are closer to zero, as indicated by -0.07 and -0.03, respectively.

Sorting becomes visually evident when we plot the share of matched borrower fixed effects conditional on lender fixed effects. Both borrower and lender fixed effects are divided into five groups, ranging from low to high. For each lender group, we calculate the share of borrower groups within the matched pairs. Figure 8(a) illustrates the results using data from the NIOR regime, showing that matching is clearly positively assortative. Figure 8(b) presents the results for the post-NIOR regime, where matching appears to be nearly random.

Sorting is important from an operational perspective because it increases loan rate dispersion. When borrowers and lenders with similar rates frequently pair, loan rates become more varied because loan rates are modeled with an additive structure of borrower and lender fixed effects. For example, if borrowers with higher fixed effects trade with lenders with higher fixed effects, the resulting loan rate becomes even higher. To measure the impact of sorting on loan rate dispersion, we compare the variance of the model-fitted loan rates (Equation (3)) with that of a counterfactual scenario where borrowers and lenders are randomly assigned. Under the counterfactual, for each day t, we generate a random permutation of borrowers and reassign them to lenders while maintaining (i) the set of participating borrowers and lenders and (ii) the number of transactions per

Table 6: Reallocation exercise

Sample Period	Pre-NIOR	Entire NIOR	First half of NIOR	Post-NIOR
Variance of model-fitted loan rates	1.14	5.26	4.50	0.30
Variance of reallocated loan rates	1.12	4.92	3.95	0.30
Reallocated-to-fitted variance (%)	98.2%	93.5%	87.8%	100%

Notes: The table shows how sorting relates to loan rate dispersion by comparing the variance of model-fitted loan rates to a counterfactual scenario. Each day, borrowers are randomly reassigned to lenders, keeping market participants and transaction counts unchanged. Counterfactual variances are averaged over 10,000 random permutations. Results are shown for the NIOR, early NIOR, pre-NIOR, and post-NIOR periods.

participant. We repeat the random reassignment 10,000 times and compute the average variance of the counterfactual loan rates. The results in Table 6 show that, during the NIOR regime, the counterfactual variance is 93.5% of the model-fitted variance. We also show results using the sample from the early NIOR period, when sorting is stronger, and the counterfactual variance is 87.8% of the data. For the pre- and post-NIOR periods, the counterfactual variances are 98.2% and 100%, respectively.

6.1 Potential mechanism of sorting

Why does the interbank market exhibit positive assortative matching in one regime and near-random matching in another? Our paper does not provide a complete explanation for the formation of sorting. We intentionally limit our model to the AKM model, which does not provide the mechanisms underlying sorting. Nevertheless, we highlight several possible explanations below.

Two key characteristics driving sorting in average loan rates emerge. First, matching is also sorted along participant shares, a pattern evident in both the NIOR and post-NIOR regimes. Second, borrowers and lenders with larger shares generally have lower average loan rates. This pattern indicates that sorting by share leads to sorting by average loan rates during the NIOR regime. However, in the post-NIOR regime, this correlation between share and average loan rates disappears, breaking the connection between sorting by share and sorting by average loan rates.

Sorting across participants' shares Empirically, high-share participants were observed to trade with each other more frequently than random matching would predict. To conceptualize sorting across shares within the framework of random matching, we introduce a simple model of matching between borrowers and lenders, both of which are heterogeneous in terms of their shares. Consider a market comprising L lenders and B borrowers who participate in N bilateral transactions. Each lender i engages in n_i transactions, and its corresponding market share $s_i = \frac{n_i}{N} \in (0,1)$. Similarly, each borrower j participates in m_j transactions, with a market share $t_j = \frac{m_j}{N} \in (0,1)$.

In random matching, each lender and each borrower in a transaction are drawn randomly according to their transaction shares. Lender i is chosen with probability s_i, and borrower j with probability t_j, so the pair (s_i, t_j) occurs with probability $s_i t_j$. Because the two sides are selected independently, the lender's and borrower's transaction shares in any given trade are uncorrelated at the transaction level. This is formally written as follows:

Proposition 1. *Under random matching, the transaction-level lender and borrower shares are uncorrelated:*

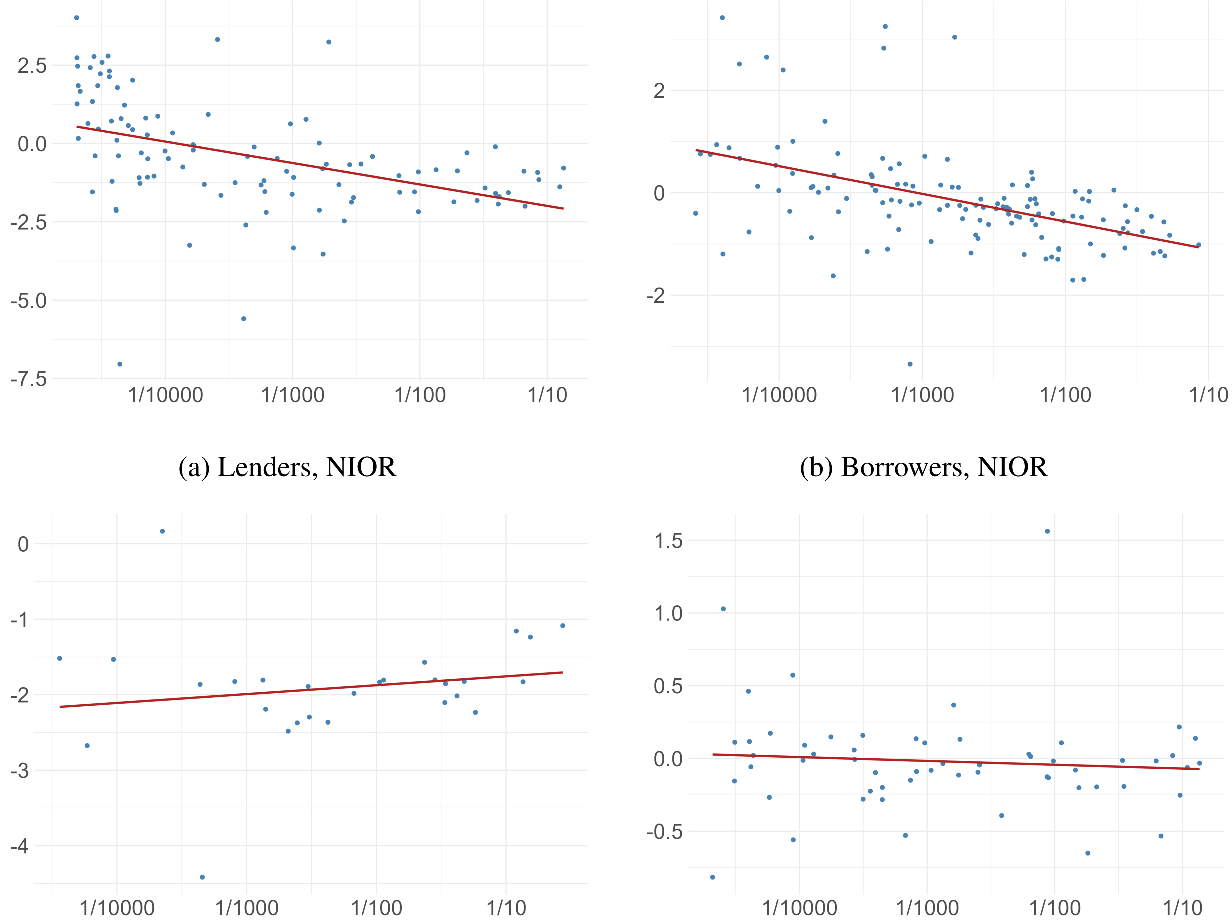
$$\mathrm{Corr}(s_i, t_j) = 0.$$

Proof. Proof is provided in Appendix G.1. □

The hypothesis that the correlation between borrowers' and lenders' shares equals zero is rejected empirically. The empirical counterpart of this matching correlation is strictly positive. During the NIOR period, the correlation is estimated as $\mathrm{Corr}(s_i, t_j) = 0.24$, whereas in the post-NIOR period, it is $\mathrm{Corr}(s_i, t_j) = 0.27$. To formally test whether these correlations could result from random matching, we conduct a permutation test in which borrower identities are randomly reassigned across transactions while keeping lender identities and the distributions of transaction shares fixed. This procedure generates the null distribution implied by random matching. In both regimes, the observed correlations lie above the simulated correlations, resulting in p-values below 0.01%.[21] Consequently, we reject the null hypothesis of random matching, providing evidence that matching in the interbank market is positively sorted along transaction shares. Furthermore, if we consider a theoretical model where matching is sorted by share, it can be shown that the correlation between borrower and lender shares, $\mathrm{Corr}(s_i, t_j)$, is necessarily positive. A detailed description of the model and proof of this proposition are provided in Appendix G.2.

Share and average loan rates During the NIOR period, the correlation between the trade volume share (the ratio of each participant's trading volume to the aggregate trading volume) and the participant's fixed effect is strongly negative for both borrowers and lenders. Figures 9(a) and (b) display the estimated fixed effects on the vertical axis and the share of trade volume on the horizontal axis. Each dot represents a participant, and a fitted line is included to visualize the relationship. For both lenders and borrowers, the correlation is negative: -0.53 for borrowers and -0.52 for lenders. Figures 9(c) and (d) present the corresponding plots for the post-NIOR sample. In this

[21] We conduct the following procedure 10,000 times: borrower identities are randomly reassigned across transactions, while keeping lender identities and the distributions of transaction shares fixed. Then, we compute $\mathrm{Corr}(s_i, t_j)$ using the counterfactual data. The p-value is calculated as the proportion of counterfactual exercises that result in a correlation higher than the observed correlation in the data, divided by 10,000.



(a) Lenders, NIOR

(b) Borrowers, NIOR

(c) Lenders, Post-NIOR

(d) Borrowers, Post-NIOR

Figure 9: Share and fixed effects

Notes: Panels (a) and (b) show the relationship between participants' fixed effects and trade volume shares during the NIOR period, with shares on the horizontal axis and fixed effects on the vertical axis. Each point represents a participant, and a fitted line illustrates the trend. Panels (c) and (d) display similar plots for the post-NIOR period, using the same estimation method based on participant-level transaction data.

period, the previously observed negative correlation between the share of trade and fixed effects is no longer evident.

Two pieces of evidence support the strong share-average loan rate correlation during NIOR, which disappears post-NIOR. The interbank market sorted participants by shares, and why this correlation exists constitute importants questions remaining for future research.

7 Term Loans

This section analyzes loans with maturities of more than one business day, referred to as term loans. Specifically, we examine term loans with maturities of one, two, or three weeks, as well as one, two, or three months.[22] Summary statistics are provided in Table D.1, which indicate that the network of term loans is also well-connected.

7.1 Loan rate dispersion of overnight and term loans

The analysis of term loans is motivated by the observation that loan rate distributions and trading motives differ between overnight and term loans. Figure 10 shows the cumulative distribution function of loan rate minus the IOR for the NIOR and post-NIOR regimes across various maturities, with the vertical axis expressed in basis points. A term premium is evident and increases with maturity.

A significant proportion of term loans trade above the IOR, which is represented as zero in the figure, whereas overnight loans are almost exclusively priced below the IOR. Trade in the term loan market is driven more by liquidity demand than by arbitrage opportunities. If arbitrage by IOR-eligible financial institutions were the primary motive, loan rates would necessarily fall below the IOR. However, many term loans exhibit rates above the IOR. Financial institutions assign greater value to securing liquidity over a longer horizon.[23]

As loan maturity increases, borrower heterogeneity may become a more important factor in determining loan rates. Overnight loans are generally viewed as low-risk by most financial institutions. In contrast, three-month loans may be regarded as riskier, with others still considered relatively safe, depending on the borrower institution. In the term loan market, borrower heterogeneity thus has a greater impact on loan rate dispersion than does the overnight market.

7.2 Variance decomposition

We estimate the following model:

$$r_{i,l,b,t} = \alpha_l + \beta_b + \theta_t + \delta_{\text{term(i)}} + \varepsilon_{i,l,b,t}, \tag{4}$$

[22] The algorithm to extract term loans is described in Appendix D.2.

[23] This analysis is supported by the report on term loans, which notes that securities firms utilize term loans to comply with Liquidity Coverage Ratio regulations (Bank of Japan, 2024).

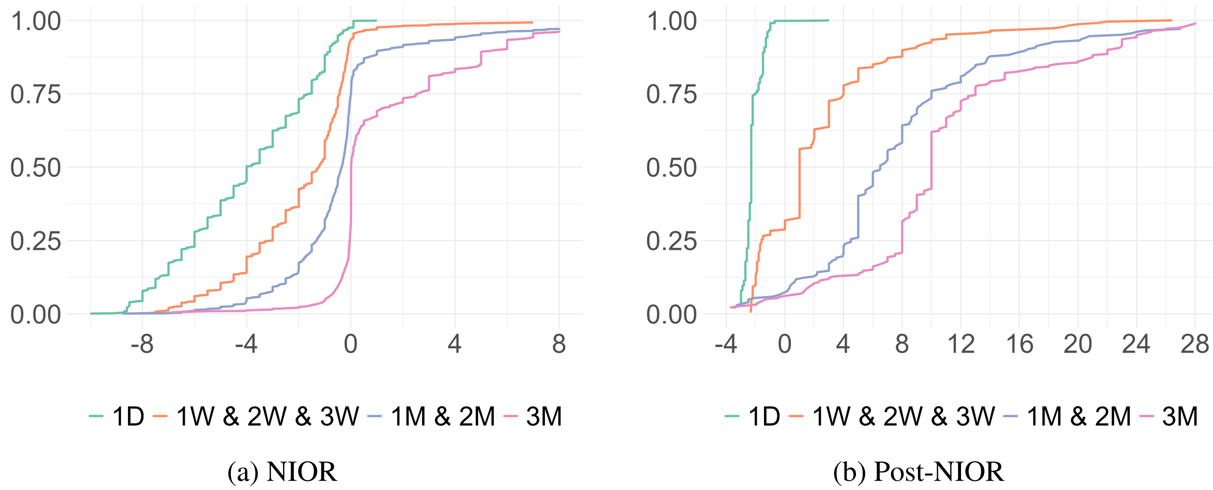


Figure 10: Cumulative distribution function of loan rate minus IOR for overnight and term loans

Notes: This figure plots the cumulative distribution function of loan rates minus IOR in basis points for different maturities. The label "1D" refers to overnight loans; "1W & 2W & 3W" pools loans with one-, two-, and three-week maturities; "1M & 2M" pools one- and two-month loans; and "3M" corresponds to three-month loans. Panel (a) uses the sample data from the NIOR period, whereas Panel (b) uses the sample data from after the NIOR period.

where $r_{i,l,b,t}$ is the loan rate for transaction i between lender l and borrower b with maturity term(i) at time t. The term α_l denotes lender fixed effects, β_b borrower fixed effects, and θ_t monthly maintenance-period fixed effects, defined over intervals running from the sixteenth day of a given month to the fifteenth day of the following month. For each specification, $\delta_{\text{term(i)}}$ denotes a set of maturity fixed effects, where each distinct maturity bucket is assigned its own fixed effect. We fitted three separate regressions with loan transaction data pooled over: (i) all maturities, (ii) maturities of one, two, and three weeks, and (iii) maturities of one, two, and three months. Due to the smaller sample size of term loans, we report the results for additive models.

Table 7 presents the variance decomposition. The total variation in loan rates is larger for term loans than for overnight loans. The standard deviation of term loan rates is 3.03 and 7.17 basis points in the respective regimes. For overnight loans, the standard deviation is 2.52 basis points during the NIOR period and 0.65 basis points during the post-NIOR period.

The primary result of this analysis concerns the change in the contribution of borrower fixed effects with respect to loan maturity. For overnight loans, borrower fixed effects account for only a small share of the total variation: 6% in the NIOR regime and 14% in the post-NIOR regime. In contrast, for term loans with maturities of one month or longer, borrower fixed effects explain a much larger share of the variation: 45% in the NIOR regime and 30% in the post-NIOR regime. This pattern aligns with the idea that counterparty risk becomes more significant as loan maturity increases. When we compare the variance decomposition across different maturities, the contribu-

Table 7: Variance decomposition of term loan rates

Regime and Maturity	NIOR	NIOR Week	NIOR Month	PIOR	PIOR Week	PIOR Month
Borrow	30%	16%	45%	15%	6%	30%
Lend	12%	18%	11%	6%	32%	11%
Time	7%	16%	2%	4%	16%	9%
Term	3%	1%	0%	7%	2%	1%
2Cov(Borrow,Lend)	8%	6%	5%	-1%	-2%	-11%
Other covariance	3%	5%	0%	10%	2%	-7%
Residual	37%	38%	37%	59%	44%	67%
Standard deviation of loan rate	3.03	2.47	3.30	7.17	4.98	6.89

Notes: Results from OLS estimation of equation (4) are reported. Column "NIOR" denotes the Negative Interest on Reserve regime and includes all term loans. Column "PIOR" denotes the period after NIOR was lifted and also includes all term loans. The "Week" column contains loans with maturities of one, two, or three weeks. The "Month" column contains loans with maturities of one, two, or three months. The other covariance term is defined as $2\left(\text{cov}(\alpha_l+\beta_b,\theta_t+\delta_{\text{term}})+\text{cov}(\theta_t,\delta_{\text{term}})\right)$.

tion of borrower heterogeneity increases with maturity.

8 Conclusion

This paper analyzes loan rate dispersion in the Japanese interbank loan market using transaction-level BOJ-NET data. An AKM model addresses a gap in the literature on interbank markets by capturing unobserved heterogeneity in financial institutions. An AKM decomposition shows that lender heterogeneity explains a larger share of the dispersion than borrower heterogeneity.

Future research could model how participants' characteristics, such as counterparty risk, appear as fixed effects in the AKM model. Over 70% of observed loan rate dispersion is explained by the additive model of borrower and lender fixed effects. While we present a simple loan rate determination model, developing a microfounded equilibrium model is a promising path. Another important avenue is to explain sorting through trading-partner selection. We show that central bank policy impacts sorting, with both positive and random patterns. A framework where participants endogenously select counterparties could clarify sorting variations.

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Appendix

A Robustness checks for the AKM decomposition

This section presents robustness checks for the main analysis of the AKM decomposition

A.1 Time-varying parameters

A concern for the baseline analysis is that some bank characteristics may change over time. In reality, some characteristics are persistent while others are time-varying. This paper quantifies how much of the variation in loan rates can be attributed to persistent characteristics. For instance, differences in counterparty risk between a global bank and a local bank in Japan may involve both persistent and temporary elements, but they are likely to be largely persistent. The model focuses on the persistent aspect, assuming that the global bank is persistently safer than the local bank.

Despite this research goal, we consider the time-varying characteristics of borrowers and lenders. Allowing for time-varying fixed effects enables us to capture changes in individual institutions' pricing behavior over time, reflecting factors such as evolving funding conditions and balance sheet constraints. Specifically, we include lender-by-time and borrower-by-time fixed effects and examine how the results differ from the case where lender and borrower fixed effects are assumed to be time-invariant. The following regression is estimated:

$$r_{i,l,b,t} = \alpha_l + \omega_{b,t} + \varepsilon_{i,l,b,t}, \tag{5}$$

$$r_{i,l,b,t} = \gamma_{l,t} + \beta_b + \varepsilon_{i,l,b,t}, \tag{6}$$

where $r_{i,l,b,t}$ represents the loan rate of transaction i, lender l, borrower b, and time t. Here, $\gamma_{l,t}$ denotes the lender-by-time fixed effect, and $\omega_{b,t}$ represents the borrower-by-time fixed effect. To prevent the introduction of an excessive number of parameters, we choose a longer time horizon, t, of one quarter.

Note that allowing both lender and borrower fixed effects to vary freely over time changes the identification of variance decomposition across different t. Following Amiti and Weinstein (2018), when the model is specified as

$$r_{i,l,b,t} = \alpha_{lt} + \beta_{bt} + \varepsilon_{i,l,b,t}, \tag{7}$$

Table A.1: Variance decomposition of loan rate with time-varying characteristics

Sample Period	NIOR	Post NIOR
Panel A: model (5)		
Borrower-Quarterly	49%	17%
Lender	12%	56%
2Cov(Borrower-Quarterly, Lender)	6%	-1%
Residual	33%	28%
Panel B: model (6)		
Borrower	3%	13%
Lender-Quarterly	59%	61%
2Cov(Borrower, Lender-Quarterly)	6%	-1%
Residual	32%	27%

Notes: Results from OLS estimation of equation (5) in Panel A and (6) in Panel B. Variance decomposition in Panel A is $\text{Var}(r_{i,l,b,t}) = \text{Var}(\alpha_l) + \text{Var}(\omega_{b,t}) + 2\text{Cov}(\alpha_l, \omega_{b,t}) + \text{Var}(\varepsilon_{i,l,b,t})$. Variance decomposition in Panel B is $\text{Var}(r_{i,l,b,t}) = \text{Var}(\gamma_{l,t}) + \text{Var}(\beta_b) + 2\text{Cov}(\gamma_{l,t}, \beta_b) + \text{Var}(\varepsilon_{i,l,b,t})$.

each observation links a borrower–time effect and a lender–time effect only within the same period. There is no restriction tying these effects across periods, implying that the borrower–lender graph is disconnected over time. As a result, the levels of lender and borrower fixed effects are identified only up to a period-specific normalization, and relative loan rate levels across time are not identified, even within the largest connected set. Consequently, while the model permits a meaningful decomposition of cross-sectional variation within each period, it does not support variance decompositions pooled over time, as such objects would be driven by arbitrary period-specific normalizations rather than meaningful heterogeneity. Therefore, we provide an analysis of (i) models that partially allow for time variation along one dimension, as in (5) and (6), and (ii) variance decompositions using a one-year time span, as shown in Section 5.2.

Table A.1 shows the results of model (5) and (6). Panel A estimates the model (5), and Panel B estimates the model (6). The model with time-varying characteristics also shows that lender heterogeneity is much larger than borrower heterogeneity, as confirmed in the baseline model. The exception is the model (5) during NIOR. It is reasonable to observe a larger borrower contribution in model (5) because the model allows time-varying parameters for borrowers, and the number of free parameters on the borrower side is larger than those on the lender side. Notably, during the post-NIOR period, the contribution of the lender is larger than that of the borrower even in the model (5).

Table A.2: Variance decomposition in full sample and leave-one-out

Sample Period Regime	Full sample NIOR	Leave-one-out NIOR	Full sample Post NIOR	Leave-one-out Post NIOR
Panel A				
Borrow	6%	6%	9%	9%
Lend	15%	15%	68%	68%
Time	53%	53%	2%	2%
2Cov(Borrow,Lend)	4%	4%	-0%	0%
2Cov(Borrow+Lend,Time)	-0%	-0%	1%	1%
Residual	22%	22%	20%	20%
Standard deviation	2.60	2.60	0.81	0.81
Panel B				
Pair	4%	4%	12%	13%
Residual	18%	18%	8%	7%
Panel C				
Cor(Borrow, Lend)	0.18	0.18	-0.00	0.00
Panel D				
Sample size	281909	281896	36736	36719

Notes: Results from OLS estimation of equation (1) and (2). "Full sample" implies no sample restrictions, and we then extract the largest connected set. "Leave-one-out" implies the leave-one-out sets in Kline, Saggio, and Sølvsten (2020).

A.2 Sample selection, limited mobility bias, and leave-one-out

We perform robustness checks using both the full sample and the leave-one-out set. In our baseline analysis, we apply sample selection criteria to exclude transactions as follows: (i) borrowers who trade with only one lender and lenders who trade with only one borrower throughout the entire sample period, and (ii) borrower–lender pairs that trade only once during the sample period. First, we do not impose any sample restrictions and include only the largest connected set. Second, we restricted the sample to the leave-one-out set for estimation (Kline, Saggio, and Sølvsten, 2020). Table A.2 presents the results. The main findings remain consistent across both the full sample and the leave-one-out set.

To observe the impact of the limited mobility bias, we restrict the sample to financial institutions that trade with more than N counterparties following Bonhomme et al. (2023). For this exercise, we consider three scenarios: $N = 0$ (indicating no restrictions on the number of counterparties), $N = 3$, and $N = 5$. Note that $N = 1$ represents the baseline case. As participants trade with a larger number of counterparties, the sample size decreases, but the concern for limited mobility bias becomes less significant. Table A.3 presents the results. Overall, the minimum number of

Table A.3: Variance decomposition and number of counterparties

Sample Period Regime	$N=0$ NIOR	$N=3$ NIOR	$N=5$ NIOR	$N=0$ PIOR	$N=3$ PIOR	$N=5$ PIOR
Panel A						
Borrow	6%	6%	5%	9%	10%	10%
Lend	15%	14%	13%	68%	65%	63%
Time	53%	58%	58%	2%	2%	2%
2Cov(Borrow,Lend)	4%	6%	5%	-0%	0%	-1%
2Cov(Borrow+Lend,Time)	-0%	-0%	-1%	1%	1%	1%
Residual	22%	16%	20%	20%	22%	25%
Standard deviation of loan rate	2.60	2.54	2.53	0.81	0.77	0.73
Panel B						
Pair	4%	5%	5%	12%	14%	16%
Residual	18%	11%	15%	8%	8%	9%
Panel C						
Cor(Bor Fix. Eff, Lend Fix. Eff)	0.18	0.32	0.32	-0.00	0.00	-0.01
PanelD						
Sample size	281909	276152	269208	36736	34789	32711

Notes: The results are obtained from the OLS estimation of equations (1) and (2). The analysis is restricted to samples consisting of participants who trade with N or more distinct counterparties.

counterparties does not strongly influence the outcomes. The only significant difference across the columns is the correlation between borrower and lender fixed effects in NIOR for $N=0$, where the correlation is underestimated compared to cases with higher numbers of counterparties.

A.3 Other robustness checks

We also implement a split of the NIOR sample into the first and second halves of the sample period. Since NIOR spans almost ten years, the characteristics captured by fixed effects might evolve over time rather than remain constant throughout the entire period. Thus, we split the sample period of the NIOR regime. The first and second columns in Table A.4 show the results. Overall, the quantitative magnitude is similar to the baseline analysis.

We also divide the sample by calendar year, from 2016 to 2024 in one-year spans, and estimate the model separately for each year. Next, we calculate the average of each decomposition across the years. The results are presented in the third column in Table A.4. This approach confirms that the time-fixed effect remains significant, and lender characteristics play a more substantial role in explaining variation than borrower characteristics.

A common concern in AKM-type analyses is incidental parameter bias. If this bias were severe, estimates would be highly sensitive to random sampling variation, and splitting the sample randomly would yield substantially different results, as estimation would be driven by noise rather than systematic variation. To assess the stability of the estimated parameters, we randomly split the sample and estimate equation (1) separately. Specifically, we divide the sample into two groups based on whether the day of the month is even or odd and then estimate the equation separately for each group. Since we have a long period of daily data, unlike firm-employer data, we can evaluate the stability of parameters by splitting along the time horizon. Table A.5 shows that the results of the variance decomposition are similar across the two groups, confirming that the limited mobility bias is not a significant concern.

We assess the sensitivity of our results to trade size by re-estimating the model with weighted least squares, using transaction volume or its logarithm as weights to give more influence to larger trades. We then perform a variance decomposition with variances and covariances weighted by trade size. Table A.6 reports the resulting variance decompositions. The main patterns remain robust when log-volume weights are used. In contrast, weighting by raw volume produces different results during the NIOR period. This difference reflects the highly skewed distribution of trade sizes: the trade at the 75th percentile is approximately ten times larger than that at the 25th percentile. Raw-volume weighting thus overemphasizes large trades, a problem avoided with log-volume weights.

Table A.4: Variance decomposition of loan rate with a split sample

Sample Period	First half of NIOR	Second half of NIOR	Annual average
Panel A			
Borrow	10%	4%	12%
Lend	19%	16%	20%
Time	41%	60%	45%
2Cov(Borrow,Lend)	11%	4%	7%
2Cov(Borrow+Lend,Time)	-0%	-0%	0%
Residual	19%	16%	16%
Panel B			
Pair	5%	3%	4%
Residual	14%	13%	12%
Panel C			
Cor(Bor Fix. Eff, Lend Fix. Eff)	0.40	0.24	0.22

Notes: Results from OLS estimation of equation (1) and (2). In the first and second column, the sample is divided into two subperiods of the NIOR period: one before its midpoint date and the other after it. In the third column, we divide the sample by calendar year, from 2016 to 2024, in one-year span and estimate the model separately for each year. Then, we calculate the average of each decomposition across the years.

Table A.5: Variance decomposition of loan rate using an even-odd day split

Sample Period	Even day in NIOR	Odd day in NIOR	Even day in Post NIOR	Odd day in Post NIOR
Panel A				
Borrow	6%	6%	14%	13%
Lend	13%	13%	55%	59%
Time	58%	58%	3%	2%
2Cov(Borrow,Lend)	5%	5%	-2%	-1%
2Cov(Borrow+Lend,Time)	-1%	-1%	-1%	-1%
Residual	19%	19%	31%	28%
Standard deviation of loan rate	2.52	2.53	0.64	0.66
Panel B				
Pair	4%	4%	18%	17%
Residual	15%	15%	13%	11%
Panel C				
Cor(Bor Fix. Eff, Lend Fix. Eff)	0.31	0.30	-0.03	-0.02

Notes: Results from OLS estimation of equation (1) and (2). We divide the sample into two groups based on whether the day of the month is even or odd and then estimate the equation separately for each group.

Table A.6: Variance decomposition of loan rate using trade-size weighted estimates

Sample Period Weight	NIOR Volume	NIOR Log of volume	PIOR Volume	PIOR Log of volume
Panel A				
Borrow	4%	6%	23%	14%
Lend	4%	12%	46%	56%
Time	75%	59%	9%	3%
2Cov(Borrow,Lend)	2%	5%	-4%	-2%
2Cov(Borrow+Lend,Time)	4%	-0%	-1%	-1%
Residual	11%	17%	28%	29%
Panel B				
Pair	9%	13%	12%	12%
Residual	2%	4%	16%	17%
Panel C				
Cor(Bor Fix. Eff, Lend Fix. Eff)	0.21	0.31	-0.07	-0.03

Notes: Results from estimation of equation (1) and (2) using weighted least squares. Each observation is weighted either by transaction volume or the logarithm of transaction volume.

B Additional analysis

B.1 Persistency of average loan rates and bank characteristics

To assess the appropriateness of estimating borrower and lender fixed effects, we examine the persistence of borrowing and lending rates across participants. Estimating fixed effects is meaningful only if the underlying participant characteristics are sufficiently persistent over time—that is, if high- or low-rate participants tend to remain so across periods. To quantify this persistence, we compute for each maintenance period t the Spearman rank correlation between the rankings of average loan rates in consecutive periods, defined as

$$\rho_t = \text{corr}_{\text{Spearman}}\left(\text{rank}(r_{l,t}), \text{rank}(r_{l,t+h})\right),$$

where $r_{l,t}$ denotes the average lending rate charged by lender l during period t, and $\text{rank}(r_{l,t})$ is the rank ranging from 0 to 1. The borrower-side measure is defined analogously. Each maintenance period corresponds to a monthly observation window that begins on the 16th of one month and ends on the 15th of the next month. After computing ρ_t for each maintenance period t, we take the average across t.

Table B.1 shows the correlation of borrower and lender rank for each regime. For the pre-NIOR regime, the time span is shorter, so we omit this analysis. We compute the rank correlation for 1 month, 1 quarter, and 2 quarter ahead. Both borrower and lender loan rate rank are persistent for example, during NIOR, 1 month ahead borrower rank is 0.70 and lender rank is 0.81. It suggests that the fixed effect model of borrower and lender would fit the loan rate determination.

B.2 The bipartite property of network

The non-bipartite property of the network is also a concern, as is known as the reflection problem (Bernard et al., 2022). Lagos and Navarro (2023) shows that in the U.S. federal fund market, fewer large banks engage in intermediating activity, borrowing and lending federal funds on the same day, making the network largely non-bipartite. In contrast, in Japan, fewer banks engage in intermediating activities, making the interbank network bipartite.

A measure of the bipartite property is the number of financial institutions that engage in both borrowing and lending activities. During the NIOR regime, on an average day, 25 institutions engage in borrowing, and 44 institutions engage in lending activities. On average, only 2.1 banks engage in both borrowing and lending activities on the same day. During the post-NIOR regime, on an average day, 16 institutions engage in borrowing, and 22 institutions engage in lending

Table B.1: Rank correlations of borrower and lender types across horizons

Regime	NIOR	Post NIOR
Borrower, 1 month ahead	0.70	0.84
Lender, 1 month ahead	0.81	0.94
Borrower, 1 quarter ahead	0.66	0.79
Lender, 1 quarter ahead	0.76	0.88
Borrower, 2 quarters ahead	0.62	0.75
Lender, 2 quarters ahead	0.75	0.86

activities. On average, only 1.0 institution engages in both borrowing and lending activities on the same day. This implies that the network is not perfectly bipartite but is close to the bipartite property, making the reflection problem less concerning.

The reallocation index, based on Afonso and Lagos (2015b), measures how much trading volume is used for reallocating funds between banks. It is defined as follows: Let O^p_{it} be the cumulative yen amount of loans purchased by bank i on day t, and O^s_{it} be the cumulative yen amount of loans sold by bank i on day t. The measure of excess funds reallocation is:

$$X_{it} = O^p_{it} + O^s_{it} - |O^p_{it} - O^s_{it}|, \quad \text{and} \quad X_t = \sum_i X_{it}.$$

This metric captures the volume of funds traded beyond what is needed for each bank's net balance change. For example, if all participants only lend or borrow, then $X_{it} = 0$ for all i, so $X_t = 0$. However, if participants engage in both lending and borrowing with the same volume ($O^p_{it} = O^s_{it}$), then $X_{it} = O^p_{it} + O^s_{it} = 2O^p_{it} > 0$.

The proportion of intermediated funds relative to the aggregate daily volume of traded funds is then computed as:

$$\iota_t = \frac{X_t}{\sum_i \left(O^s_{i,t} + O^p_{i,t}\right)}.$$

The time-series average of ι_t is 2.7% during the NIOR period and 1.8% during the post-NIOR period. In Japan, fewer than 3% of the trading volume is devoted to reallocation, where agents borrow and lend on the same day. This contrasts with the U.S. federal funds market, where about 40% of the volume is reallocated (Afonso and Lagos, 2012). Japan's highly bipartite network reduces the reflection problem.

B.3 Observable characteristics and loan rate variance decomposition

In the baseline analysis we omit observable characteristics for the AKM model. In this subsection, we explore (i) how much of the loan rate variation can be explained by observables, and (ii) how the estimation the in AKM model is affected by the inclusion of observable characteristics.

The choice of observables follows (Ashcraft, Duffie, and McAndrews, 2007). The first group captures aggregate liquidity, including the total daily number of transactions and the daily total yen volume of completed trades. The second group captures borrower and lender characteristics, including the share of trades for each and monthly average transaction volumes. These measures summarize each bank's typical interbank market activity. We also include the "banking types", a common categorization. [24]. We include a dummy variable for 30-minute time windows (e.g., 8:00-8:29 AM, 8:30-8:59 AM), overnight loan rate volatility (measured as intraday standard deviation, following Ashcraft, Duffie, and McAndrews (2007)), the daily log value of borrower reserves in yen, and the trade size per transaction (yen value per transaction). Since lender reserve holdings, mainly mutual funds, are unobservable, we only include borrower reserve values.

We compute how much of the total variation is explained by observables. Panel A in Table B.2 shows the decomposition exercise. When we compare the contribution of observables (41%, 27%, and 50% for the respective regimes), and unexplained residuals (59%, 73%, and 50%), we find that a larger share of total variation is still unexplained by the observable characteristics.

Panel B presents results from a model with borrower, lender, and time fixed effects, along with observable characteristics. Variables from Panel A that are not collinear with the fixed effects include trade size and 30-minute transaction time windows. We also include month-specific trade shares for borrowers and lenders. Reserve holdings are excluded due to the unavailability of lender reserve data for mutual funds, and including only borrower reserves would alter the relative contributions of borrower and lender heterogeneity. We estimate the following specification:

$$r_{i,l,b,t} = \omega X_i + \alpha_l + \beta_b + \theta_t + \varepsilon_{i,l,b,t}, \tag{8}$$

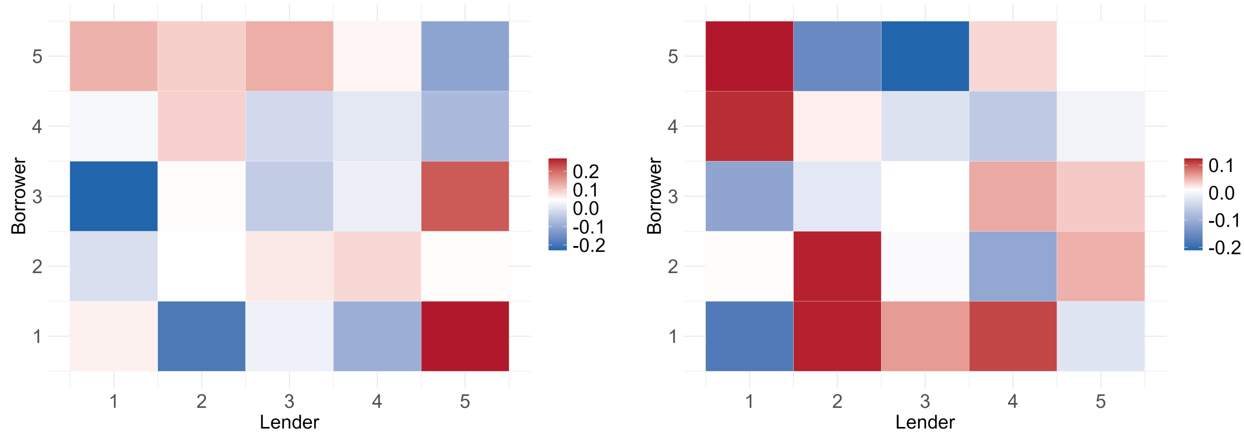
which extends the baseline model in (1) by incorporating trade size as an observable characteristic. Panel B of Table B.2 reports the variance decomposition.

[24] In Japan, banks are classified into frequently used categories according to their regulatory status, business scope, and institutional function. These classifications are deeply embedded in the Japanese financial system and are widely employed in official statistics, regulatory frameworks, and central bank reports. The definition is set by the Bank of Japan and the Financial Services Agency. The categories include city banks, regional banks, regional banks type two, trust banks, foreign banks, *Shinkin* banks, and other banks.

Table B.2: Variance decomposition of loan rates by observable characteristics

Sample Period	Pre NIOR	NIOR	Post NIOR
Panel A: Only observables			
Aggregate number of trades	22%	15%	4%
Aggregate trade volume	26%	2%	5%
Borrower monthly average trade volume	0%	1%	0%
Lender monthly average trade volume	1%	0%	17%
Borrower type	1%	3%	4%
Lender type	12%	6%	12%
Log of borrower reserves	10%	0%	6%
Trade size	1%	1%	4%
Intraday standard deviation of loan rate	0%	8%	0%
30-minute window	6%	1%	12%
Sum of observables	41%	27%	50%
Residual	59%	73%	50%
Panel B: AKM model with observables			
Trade size	2%	0%	1%
30-minute window	3%	1%	12%
Borrower-month trade share	2%	0%	0%
Lender-month trade share	1%	0%	2%
Borrower fixed effect	20%	6%	8%
Lender fixed effect	33%	14%	70%
Time fixed effect	11%	59%	3%
2Cov(Borrow,Lend)	2%	5%	-2%
2Cov(Borrow+Lend,Time)	0%	-0%	-1%
2Cov(X,Borrow+Lend+Time)	-7%	-2%	-17%
Residual	34%	17%	25%

Note: The table presents the variance decomposition of loan rate variation across three distinct sample periods: Pre-NIOR, NIOR, and Post-NIOR. Panel A deconstructs the total variation into portions attributed to observable characteristics and unexplained residuals. To represent aggregate liquidity conditions, the analysis includes the total daily number of transactions and the daily total yen trade volume. Borrower- and lender-specific characteristics, such as the average monthly transaction share by the "group" of banks, capture the activity levels of market participants. The term "group" refers to commonly used categories of banks, such as city bank, regional bank, securities company, and trust banks among others. Additionally, the analysis includes dummy variables for each 30-minute time window. "Trade size" represents the yen value of the trade size of individual transactions. In Panel B, the AKM model is extended to incorporate further variables, including trade size, 30-minute time windows, and the trade shares of borrowers and lenders. The monthly trade shares are calculated for each participant and provide further insights into their contributions during the respective periods.



(a) NIOR. (b) Post-NIOR.

Figure B.1: Mean residuals by borrower and lender types in additive model.

B.4 Match specific errors

This subsection explores the match-specific error for different groups of borrowers and lenders following the exercise in labor market and wage determination literature (Card, Heining, and Kline, 2013). To search for interactions, we divided the estimated borrower and lender effects into five groups, and computed the mean residuals in each 25 groups. Figure B.1 shows the mean residuals in each cell using the sample from NIOR and Post NIOR represented in basis points. If the model is systematically misspecified, there would be larger or smaller average residuals among the specific type (can be high or low type) of borrowers and lenders. There looks less clear systematic pattern of mean residuals for borrower and lender types.

C Model of loan rates determination in the interbank market

In this section, we describe a simple model of loan rate determination the in interbank market. The goal is to provide theoretical predictions that are consistent with empirical findings. The model is based on Afonso and Lagos (2015b).

Time is discrete and infinite, $t = 0, 1, 2 \cdots$. There exist two borrowers in the market, and they participate every period. The type of borrower is denoted as $b \in \{m, n\}$. Lenders constitute a unit mass and are categorized into two types: large lenders (L) with population p, and small lenders (S) with population $1 - p$. The type of lender is denoted as $l \in \{L, S\}$

In each period, borrowers are matched with lenders with a matching probability δ, following the framework of matching frictions in the interbank market as outlined by Afonso and Lagos (2015b). When $\delta = 1$, it implies that there are fewer borrowers compared to the number of lenders;

thus, borrowers can always find a lender when they search. Conversely, when $\delta = 0$, the market is characterized by many borrowers and relatively few lenders, making it unlikely for borrowers to successfully find a lender upon participation in the market.

Conditional on the meeting, borrowers meet type L lender with probability p and type S lender with probability $1-p$. Upon the meeting, borrowers and lenders bargain over loan size a and repayment R in Nash bargaining. Borrower's surplus for borrower type b is given by

$$(1+i)a - R + u^b(a) - \delta V^b,$$

where i is the interest on reserves set by the central bank, and $u^b(a)$ is the liquidity value of reserves, and δV^b is the continuation value of type b borrowers.Borrowers have two trading motives: arbitrage profits and liquidity demand. The first term $(1+i)a - R$ represents arbitrage profits, where $(1+i)a$ is the return from borrowing and depositing at the reserve account, and R is the loan cost. The second term, $u^b(a)$, captures the liquidity demand, representing additional trading motives beyond arbitrage profits. The continuation value is equal to the expected trade surplus:

$$V^b = p\theta\left((1+i)a^L - R + u^b(a^L) - \delta V^b\right) + (1-p)\theta\left((1+i)a^L - R + u^b(a^L) - \delta V^b\right).$$

Lender's surplus is given by

$$-(1+i^o)a + R,$$

where i^o is the opportunity cost of funds for lenders. In the context of the Japanese interbank market, lenders are mainly mutual funds that are not eligible for interest on reserve. The idle funds yield zero, so hereafter, $i^o = 0$. Lender's surplus is just given by repayment R. Note that lenders do not have an outside option. Since there exists a continuum of lenders, the probability of a lender trading in the next period is assumed to be generically zero. The gross loan rate is defined as $\frac{R}{a}$.

There is a constraint on loan size that ensures lenders cannot lend more than their available funds:

$$a \leq a^l,$$

where a^l denotes the available funds for a lender of type l, which are exogenous. It is assumed that large lenders own more available funds, $a^l \in \{a^S, a^L\}$, and $a^S < a^L$. The problem of bargaining between borrower type b and lender type l is given by

$$\underset{a^{l,b}, R^{l,b}}{\text{argmax}} \quad \left[(1+i)a^{l,b} - R^{l,b} + u^b(a^{l,b}) - \delta V^b\right]^\theta \left(R^{l,b}\right)^{1-\theta}, \quad \text{subject to} \quad a^{l,b} \leq a^l,$$

where θ is the bargaining power of borrower. We get the solution for gross loan rates between type (L,b) and (S,b):

$$\frac{R^{L,b}}{a^L} = (1-\theta)\left[\left(1-\frac{\delta}{1+\delta}p\theta\right)\left((1+i)+\frac{u^b(a^L)}{a^L}\right)-\frac{\delta}{1+\delta}(1-p)\theta\left((1+i)\frac{a^S}{a^L}+\frac{u^b(a^S)}{a^L}\right)\right]$$
$$\frac{R^{S,b}}{a^S} = (1-\theta)\left[\left(1-\frac{\delta}{1+\delta}p\theta\right)\left((1+i)+\frac{u^b(a^S)}{a^S}\right)-\frac{\delta}{1+\delta}(1-p)\theta\left((1+i)\frac{a^L}{a^S}+\frac{u^b(a^L)}{a^S}\right)\right] \tag{9}$$

Abundant reserves and competitive market First, we give the baseline case where there does not exist loan rate dispersion. This case is obtained where (i) banks have all abundant reserves, so the value of liquidity is zero ($u^b(a) = 0$) (ii) there exists a lot of borrowers, and the borrower side of interbank market is competitive so $\delta = 0$. In this case, for any combination of (l,b), the gross loan rate is determined by

$$\frac{R^{l,b}}{a^l} = (1-\theta)(1+i).$$

There exists no price dispersion. In the case where borrowers do not have an outside option, that is capture by $\delta = 0$, even though small and large lenders have different trade size, the gross loan rates are equalized.

Proposition 2. *In the case of* $u^b(a) = 0$ *and* $\delta = 0$*, the loan rate is unique and determined by*

$$\frac{R^{l,b}}{a^l} = (1-\theta)(1+i).$$

The gross loan rate is given by the product of the bargaining power of lender and interest on reserves. In the limiting case where lender has no bargaining power ($\theta = 1$), the repayment is zero, and the gross loan rate is equal to zero. In contrast, when borrower has no bargaining power ($\theta = 0$), lender can obtain the full of trade surplus, and the gross loan rate is equal to $1+i$.

A numerical example of mapping from data to model is as follows. In April 2024, BOJ sets the interest on reserve at 50 basis points, and average overnight loan rate is 47.7 basis points. Then $1-\theta$ is calibrated at $\frac{1+0.47/100}{1+0.5/100}$.

Abundant reserves and less competitive market The data show (i) price dispersion and (ii) that lender heterogeneity drives larger price dispersion than borrower heterogeneity, potentially due to trade size (a^l). We derive an analytical solution where loan rate dispersion exists across lenders, but not borrowers, and prove that larger trade sizes yield higher gross loan rates: $\frac{R^{L,b}}{a^L} > \frac{R^{S,b}}{a^S}$.

Assuming abundant reserves with zero liquidity value and a less competitive borrower side ($\delta > 0$). The gross loan rates are:

$$\frac{R^{L,b}}{a^L} = (1-\theta)\left[\left(1 - \frac{\delta}{1+\delta}p\theta\right)(1+i) - \frac{\delta}{1+\delta}(1-p)\theta(1+i)\frac{a^S}{a^L}\right],$$
$$\frac{R^{S,b}}{a^S} = (1-\theta)\left[\left(1 - \frac{\delta}{1+\delta}p\theta\right)(1+i) - \frac{\delta}{1+\delta}(1-p)\theta(1+i)\frac{a^L}{a^S}\right]. \tag{10}$$

Since $a^L > a^S$, and $\frac{R^{L,b}}{a^L} > \frac{R^{S,b}}{a^S}$, the gross loan rate when trading with large lenders is higher than that of small lenders.

The loan rate dispersion from lender heterogeneity arises from the borrower's outside option (δV^b). Although borrowers face the same outside option with both large and small lenders, trade profits are higher for large lenders ($(1+i)a^L > (1+i)a^S$). Borrowers' trade surplus is adjusted via repayment, with smaller lenders offering lower repayments to provide more surplus. This results in lower loan rates for smaller lenders. This is summarized as follows:

Proposition 3. *Suppose reserves are abundant so that their liquidity value is zero, while borrowers are less competitive* ($\delta > 0$). *The gross loan rate is increasing in trade size, that is,*

$$\frac{R^{L,b}}{a^L} > \frac{R^{S,b}}{a^S}.$$

Proof. From the analytical solution of loan rate (10). □

There exists price dispersion across different lenders, but price dispersion across borrowers does not exist because both arbitrage profits $(1+i)a$ are homogeneous across borrowers, and liquidity value is shut down.

Scarce reserves and less competitive market When aggregate reserves are not abundant, some institutions place a positive value on holding reserves, implying a utility from reserve holdings, $u^b(a) > 0$. If there is heterogeneity in the valuation of reserves, heterogeneity also arises along the borrower dimension. In this case, the loan rates for borrowers b and b' differ even when they trade with the same lender whenever $u^b(a) \neq u^{b'}(a)$ from equations (9).

Empirical support for Proposition 3 We empirically support Proposition 3 by running a cross-sectional regression of the lender's fixed effect ($\hat{\alpha}_l$) from (1) on the median trade size, defined as the median yen value of loan sizes per lender. The model is estimated separately for the NIOR and post-NIOR periods, using mutual funds with zero cash yields when not invested. Table C.1 shows

Table C.1: Cross-sectional regression of mutual funds' fixed effects on median trade size

	NIOR	Post-NIOR
	(1)	(2)
Log(Median Trade Size in Yen)	0.005***	0.003***
	(0.002)	(0.001)
Observations	26	22
R^2	0.162	0.260

Note: Heteroskedastic robust standard errors are reported. * p<0.1; ** p<0.05; *** p<0.01.

a statistically significant positive relationship between the log of median trade size and the lender's fixed effect, supporting the proposition that larger trade sizes lead to higher loan rates.

The omission of trade size in regression (1) may raise concerns about biased estimates. Table B.2 includes trade size in (1), showing that it explains 1% of the total variation. This suggests that within-lender changes in trade size have little impact on loan rate determination, while differences in median trade size across lenders strongly affect it. Since these differences are persistent, they are captured by the lender's fixed effect in (1). Note that there is a negative correlation between share and α_l in Figure 9 while Table C.1 shows a positive correlation between median trade size and α_l. A difference is that Figure 9 shows all financial institutions and Table C.1 uses only mutual funds.

D Furfine algorithm adapted for BOJ-NET

D.1 Overnight

This section outlines the algorithm used to extract uncollateralized overnight loans from BOJ-NET, following the approach of Furfine (1999). We adapt the original algorithm to the BOJ-NET setting. BOJ-NET provides several additional flags that help exclude transactions involving reserves that are not overnight loans. This adaptation reduces the risk of misidentifying non-overnight loan transactions as overnight loans.

The algorithm is as follows. First, we exclude transactions that we know are not overnight loans. Specifically, (i) Only transactions conducted through the Real-Time Gross Settlement

(RTGS) Account are included. Transactions made via the Regular Account are excluded.[25] (ii) exclude transactions where the flag is not associated with uncollateralized overnight loans.[26] In summary, we can exclude transactions that involve payments for major commercial activities between a bank's clients. Additionally, we can exclude repos. (iii) include transactions equal to or greater than 100 million yen, and that are exact multiples of 100 million yen, the remainder is zero. This is based on market convention. Second, overnight loans are identified as transactions between a pair of counterparties i and j that involve a BOJ-NET transfer from i to j, which can be matched with a return transfer from j to i on the following business day. The return amount should be close to the original transfer, with the difference plausibly representing interest. This difference between the two payments is interpreted as the interest earned on the loan.[27] Third, the set of potential overnight loans is refined further by limiting the range of plausible loan rates. During the sample period of Positive Interest Regime, interest on reserves is 0.1%, 0.25%, or 0.5%. The corresponding band of interest rates is (0,0.2%], (0,0.35%], and (0,0.6%]. While the upper bound may seem low, increasing it does not change the results, and it is sufficiently high compared to the maximum rate published by the BOJ. Furthermore, as shown in Figure 2, which displays the CDF of overnight loan rates, this upper bound is also confirmed to be adequately high. In the Negative Interest Regime, the range is -0.2% to 0.1%. Fourth, if multiple repayments could match one outgoing payment, the median rate is identified as the rate on the loan.

D.2 Term Loans

For term loans, our analysis focuses on maturities of one week, two weeks, three weeks, one month, two months, and three months, as these represent the most commonly used benchmarks in the market. Loans with other maturities (e.g., four days or ten days) are not frequently traded in markets. We describe the algorithm employed to extract term loans, which follows the approach

[25]BOJ-NET offers two types of accounts: the Regular Account and the RTGS Account. By market convention, overnight loans are settled through the RTGS Account.

[26]We use two types of flags: a mandatory flag and a voluntary flag. All transactions are marked with the mandatory flag, though its information is limited. The voluntary flag provides more detail, but not all transactions have it. The mandatory flag corresponds to the *Gyoumu Shori Kubun Mei* ("Operation Type Name"), where "Market Trades" identifies overnight loans from market conventions. We exclude transactions not flagged as "Market Trades". The voluntary flag, corresponding to *Bikoumei* ("Note Label"), offers detailed information, such as identifying uncollateralized overnight loans, correspondent account transfers, and foreign exchange settlements. While not all overnight loans are labeled as such, we exclude transactions where the Note Label indicates a different type. In summary, we retain transactions flagged as overnight loans in the Note Label or those with an empty Note Label and the mandatory flag "Market Trades".

[27]For example, when the loan rate on a principal of 100 million yen is 1%, the repayment amount is 100 million yen plus 2,739 yen, calculated as $100{,}000{,}000 \times \frac{1}{365 \times 100}$. If the borrowing day is Friday, the repayment day falls on the following Monday, resulting in a three-day interest period. In this case, the repayment amount is 100 million yen plus 8,217 yen, calculated as $100{,}000{,}000 \times \frac{3}{365 \times 100}$.

of Kuo et al. (2013) in identifying such transactions from Fedwire in the United States. The basic logic is the same as for overnight loans, but there are several important differences.

The algorithm consists of two categories. First, for one-week, two-week, and three-week maturities, the contractual maturity is set to 7, 14, and 21 calendar days, respectively, ensuring repayment on a business day. For one, two, and three-month maturities, two conventions are applied. Under the fixed-day convention, maturities are set to 28, 56, and 84 calendar days, ensuring repayment on a business day. Second, under the calendar-day-matching convention, the maturity date falls on the same day of the next month, or within one day. If the target date falls on a weekend, repayment is made on the nearest business day. For example, a one-month loan settled on January 10 is repaid on February 10, and a three-month loan on April 10. If the target date falls on a weekend, repayment occurs on the nearest business day (e.g., February 9 or 11 if February 10 is a weekend).

The second modification sets an interest rate band. We apply different filters for the positive interest on reserve regime and the negative interest on reserve regime:

- Positive interest on reserve regime: We retain trades whose implied interest rates lie between $x-10$ and $x+30$ basis points, where x denotes IOR.
- Negative interest on reserve regime: We retain trades whose implied interest rates fall between -15 and 25 basis points.

These bands are sufficiently wide to ensure that only a negligible number of term loans fall outside the admissible range.

Table D.1 presents summary statistics for term loans. The data are well suited for identifying borrower and lender fixed effects: the sample size is sufficiently large relative to the number of fixed effects, and lenders trade with multiple borrowers while borrowers trade with multiple lenders. The pre-NIOR regime is excluded because it spans four months, and the number of loans traded is insufficient.

E Mutual funds

The volume and share of lending by mutual funds are substantial. Figure E.1 (a) presents the time-series of trading volumes for overnight loans extended by mutual funds. In 2015, the daily volume of such loans was approximately 7 trillion yen, which increased to 23 trillion yen by 2025. Figure E.1 (b) shows the share of mutual funds in total overnight lending, calculated as the ratio of lending by mutual funds to total lending. This share reaches 90% in 2025, indicating that mutual funds have become the dominant lenders in the overnight loan market. In this figure, we use the entire sample of overnight loans, and we do not implement any sample selection.

Table D.1: Summary statistics for term loans

Maturity	NIOR	NIOR Week	NIOR Month	Post-NIOR	Post-NIOR Week	Post-NIOR Month
Panel A: Loan statistics						
Total number of trades	30319	18024	12295	700	227	473
Mean of loan rate - IOR in bps	-0.93	-1.82	0.39	7.40	2.53	9.74
Std. dev. of loan rate - IOR in bps	3.03	2.47	3.30	7.17	4.98	6.89
Panel B: Bank statistics						
Total number of borrowers	127	124	126	17	12	15
Total number of lenders	120	118	119	16	12	16
Panel C: Counterparty statistics						
Mean number of lenders per borrower	19.8	18.3	15.4	5.9	3.7	5.7
Median number of lenders per borrower	16	14	12	4	2	5
Mean number of borrower per lender	20.9	19.2	16.3	6.3	3.7	5.4
Median number of borrower per lender	16	14	11	5	2	5
Panel D: Pair statistics						
Total number of pair	2513	2271	1935	101	44	86

Notes: Column "NIOR" denotes the Negative Interest on Reserve regime and includes all term loans. Column "PIOR" denotes the Positive Interest on Reserve regime and also includes all term loans. The "Week" column contains loans with maturities of one to three weeks. The "Month" column contains loans with maturities of one to three months.

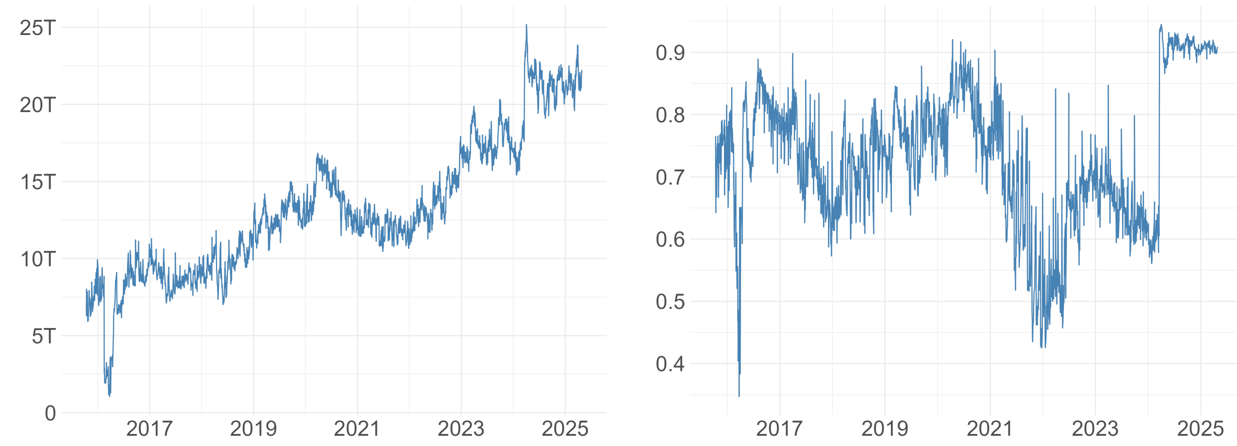
F Data on financial institutions' reserves

Japanese monetary policy has long been characterized by a substantial volume of aggregate reserves. Figure F.1 illustrates the ratio of aggregate reserves to nominal GDP over the sample period. In 2015, this ratio stood at 33%, rising sharply to 100% by 2022. From 2022 to 2025, reserve levels have remained around 95% of GDP.

Although aggregate reserves have grown substantially, the required reserves that banks must hold have not increased at the same pace. The ratio of total required reserves across banks to GDP was 1.6% in 2016 and 2.3% in 2025. This indicates that banks are maintaining a significant volume of excess reserves, defined as the difference between total reserves and required reserves.

Due to a significant increase in reserves and a moderate change in required reserves, banks hold abundant reserves. Table F.1 shows the reserve-to-required-reserve ratios for 2015 and 2024, based on banks that traded at least once in the overnight loan market. For each bank and maintenance period, we calculate the ratio of cumulative reserves to required reserves on the final day and determine the proportion of banks in each range.

In 2024, only 0.8% of institutions have a reserves-to-required-reserves ratio between 1 and



(a) Lending volume by mutual funds (b) Lending share of mutual funds

Figure E.1: Lending by mutual funds

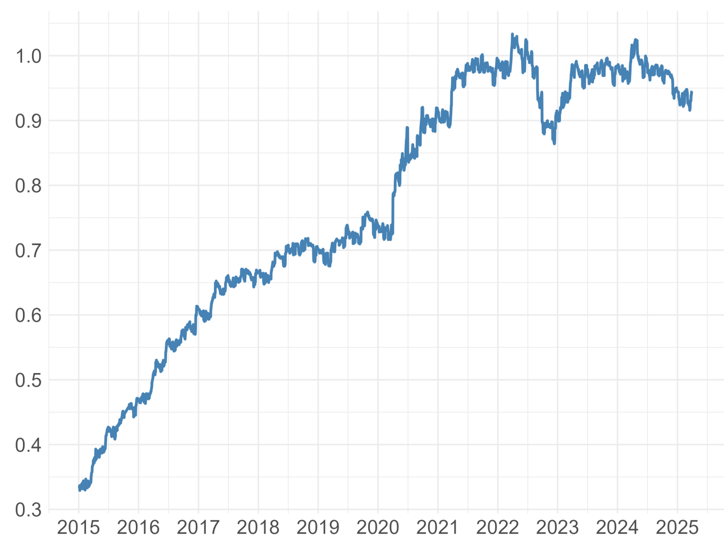


Figure F.1: Aggregate Reserve to GDP Ratio.

1.5, while over 90% hold reserves exceeding ten times the required amount. This suggests that Japanese financial institutions maintain abundant reserves, using interbank reserve trading primarily for liquidity management or other trading motives, rather than to meet reserve requirements.

Table F.1: Distribution of Reserve to Required Reserves in 2015 and 2024

Reserve / Required Reserve	Share in 2015	Share in 2024
1–1.5	1.7%	0.8%
1.5–3	5%	1.6%
3–10	16.2%	5.8%
10–50	40.6%	55.6%
50–	36.5%	36.0%

G Proof

G.1 Proof of proposition 1

Proof. Let (X,Y) denote the pair of market shares associated with a randomly chosen transaction, where $X = s_i$ if lender i is selected and $Y = t_j$ if borrower j is selected. Under random matching, the probability that transaction (i, j) occurs is $\Pr(X = s_i, Y = t_j) = s_i t_j$. The expectations of X and Y are

$$\mathbb{E}[X] = \sum_{i=1}^{L} s_i^2, \qquad \mathbb{E}[Y] = \sum_{j=1}^{B} t_j^2.$$

The expectation of the product XY is

$$\mathbb{E}[XY] = \sum_{i=1}^{L} \sum_{j=1}^{B} (s_i t_j) \cdot (s_i t_j) = \sum_{i=1}^{L} s_i^2 \sum_{j=1}^{B} t_j^2 = \mathbb{E}[X]\,\mathbb{E}[Y].$$

Therefore, the covariance between X and Y and its correlation is zero. □

G.2 Proposition and proof of assortative matching.

This subsection presents a simple example of positive assortative matching, showing that the correlation between borrower and lender shares is weakly positive. Following Section 6, we index lenders and borrowers such that $s_1 \geq s_2 \geq \cdots \geq s_L$ and $t_1 \geq t_2 \geq \cdots \geq t_B$. Under random matching, lender i is chosen with probability s_i and borrower j with probability t_j, making the pair (s_i, t_j) occur with probability $s_i t_j$. Positive assortative matching reallocates probability toward similarly ranked pairs, so high-share lenders match more with high-share borrowers and low-share lenders with low-share borrowers.

Proposition 4. *Let $\pi_{ij}^{(0)} = s_i t_j$ denote the random matching probabilities. A matching pattern π_{ij} is called* positive assortative *if it can be constructed from $\pi_{ij}^{(0)}$ through a finite sequence of the* *following 2×2 transfers: for some $i < k$ and $j < \ell$, choose $\delta > 0$ such that $\delta \leq \min\{\pi_{i\ell}, \pi_{kj}\}$, and update*

$$\pi_{ij} = \pi_{ij}^{(0)} + \delta,\ \pi_{k\ell} = \pi_{k\ell}^{(0)} + \delta,\ \pi_{i\ell} = \pi_{i\ell}^{(0)} - \delta,\ \pi_{kj} = \pi_{kj}^{(0)} - \delta.$$

leaving all other entries unchanged. Then, any positive assortative matching satisfies

$$\mathrm{Corr}(s_i, t_j) \geq 0.$$

Proof. Let π_{ij} denote the probability that a randomly selected transaction is between lender i and borrower j. A positive assortative deviation preserves $\mathbb{E}[X]$ and $\mathbb{E}[Y]$. Let $X = s_i$ and $Y = t_j$ in a transaction of type (i, j). The effect of a single transfer on $\mathbb{E}[XY]$ is

$$\Delta\mathbb{E}[XY] = \delta\left(s_i t_j + s_k t_\ell - s_i t_\ell - s_k t_j\right) = (s_i - s_k)(t_j - t_\ell) \geq 0.$$

The last inequality is from $s_i \geq s_k$ and $t_j \geq t_\ell$. Since $\mathbb{E}[X]$ and $\mathbb{E}[Y]$ do not change, it follows that

$$\Delta\mathrm{Cov}(X, Y) = \Delta\mathbb{E}[XY] \geq 0,$$

The correlation inherits the same inequality. □