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**Abstract**

This paper decomposes loan rate dispersion in the interbank loan market. Using transaction-level data, we documented dispersion in uncollateralized overnight loan rates even during periods of low interest rates in Japan. Applying the AKM model, we quantified the contributions of borrower and lender heterogeneity to loan rate dispersion. Lender heterogeneity accounted for approximately three times more dispersion than borrower heterogeneity. The contribution of borrower heterogeneity exhibited a downward trend over time. Positive assortative matching along borrowers' and lenders' average loan rates was observed. For term loans, borrower heterogeneity accounted for a larger share of loan rate dispersion than did 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 in which financial institutions lend reserves to one another. The average overnight loan rate serves as the target for monetary policy operations. Intraday dispersion in loan rates is a concern in terms of the effectiveness of monetary policy transmission because some trades occur away from the target rate (Duffie and Krishnamurthy, 2016). Moreover, as empirical evidence shows, dispersion in loan rates is related to such macroeconomic variables, as liquidity premium (Bianchi and Bigio, 2022) and lending rates for firm loans (Altavilla et al., 2019). However, dispersion in loan rates remains understudied.

This paper used transaction-level data on overnight loans to study the dispersion of loan rates in the interbank market. Dispersion exists and fluctuates, 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 aimed to quantify the extent to which loan rate dispersion is driven by heterogeneity across financial institutions. To this end, we estimated a loan rate model with additive borrower and lender fixed effects, following Abowd, Kramarz, and Margolis (1999), henceforth referred to as AKM.

Following Furfine (1999), we first constructed transaction-level data on uncollateralized overnight loans from Japanese payment records (BOJ-NET). To the best of our knowledge, this is the first study 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 of variance. The premise is that the persistent characteristics of borrowers and lenders influence loan rates. Borrowers' characteristics may reflect counterparty risk or liquidity needs, while lenders' 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 to the AKM framework for several reasons. First, the data are available at a daily frequency for nearly ten years, providing a long time dimension and rich cross-sectional variation with about 140 transactions observed per day. Second, the number of fixed effects to be estimated is moderate, with approximately 150 borrowers and 140 lenders. Finally, the

[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).

market structure is well-connected. On average, each borrower trades with 20.9 lenders, and each lender 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).

A variance decomposition exercise 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 the variation.

The smaller contribution of borrower heterogeneity might be unexpected because borrowers' counterparty risk is often emphasized in the literature (Afonso, Kovner, and Schoar, 2011). The smaller contribution can be attributed to two factors. 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 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, this matching became random, with the correlation dropping to $-0.03$. The observed positive sorting amplified 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.

When examining the time-series properties of the variance decomposition, two key findings emerge. First, borrower heterogeneity shows a clear downward trend: by 2024, the variance of borrower fixed effects dropped to just 10% of its value in 2017. This decline is primarily driven by two factors: (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 time-series finding is that the variance of residuals has remained stable over the past ten years. 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 functioning of the interbank market, the stable variance of residuals provides little evidence of increased pricing deviations from the model.

When analyzing crisis episodes, we find that borrower heterogeneity contributes twice as much to loan rate dispersion during the COVID-19 crisis 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 in 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 for maturities of one month or longer, which is higher than that 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 addresses gaps in the literature on the interbank market.

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) 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) 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 using 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 het-

[2]Examples include labor markets (Abowd, Kramarz, and Margolis, 1999; Card, Heining, and Kline, 2013), health care markets (Finkelstein, Gentzkow, and Williams, 2016), and production networks (Bernard et al., 2022).

erogeneity 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.

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; Hatzopoulos et al., 2015). Studies have examined how participants select their counterparties (Afonso, Kovner, and Schoar, 2013) and how these relationships influence loan rates (Temizsoy, Iori, and Montes-Rojas, 2015; 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. A related study is Bittner, Jamilov, and Saidi (2025), which identifies size-based assortative matching, while our study focuses on assortative matching based on average loan rates.

Third, this paper contributes to the literature on interbank markets 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 example of 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.

There are two main reasons for trading 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. In Japan, however, most financial institutions maintain abundant reserves, which makes the first motive less significant, while the second motive becomes more prominent. The mechanism for generating profits is explained below.

**Reserve requirements** The reserve requirement system obliges deposit-taking financial institutions to hold a minimum level of reserves, referred to as required reserves. The cumulative reserves over each reserve maintenance period (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.

Japanese monetary policy operations are characterized by large excess holdings of reserves far above the required levels. 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 paid by the BOJ 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, applies before February 17, 2016, and after March 19, 2024.

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. Trades are conducted with IOR-eligible institutions acting 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, need to 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 do not have reserve accounts at the BOJ and are not eligible to receive IOR, so their idle cash yields 0%. To invest this idle cash, mutual funds lend their cash as uncollateralized overnight loans that yield more than 0%.

The trading motive of IOR-eligible institutions as borrowers is arbitrage profit. These borrowers are financial institutions that receive the IOR. They borrow funds at rates below the IOR and deposit them in reserve accounts that yield the IOR, thereby earning profits equal to the spread between the IOR and the overnight borrowing rate.

The volume and share of lending by mutual funds 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 for 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 variable set by the BOJ. They vary depending on the financial institution and the maintenance period. The marginal return on an additional yen of reserves is 0.1% in the bottom tier, 0% in the middle tier, and -0.1% in the top tier.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 are institutions for which the marginal return on reserves is $-0.1\%$. By lending at a rate above $-0.1\%$, they avoid the losses associated with holding reserves that earn $-0.1\%$. Borrowers are institutions with marginal returns of 0% or 0.1%. Borrowing at a rate below these levels generates profits. For example, suppose there exists 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 earns a profit of 0.05% if its marginal return on reserves is 0%, or 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 uncollateralized overnight loan rate (volume-weighted), IOR, and DWR,

[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 $-0.1\%$. In both the positive IOR and negative IOR regimes, institutional arrangements made overnight lending more attractive for mutual funds than holding idle cash.

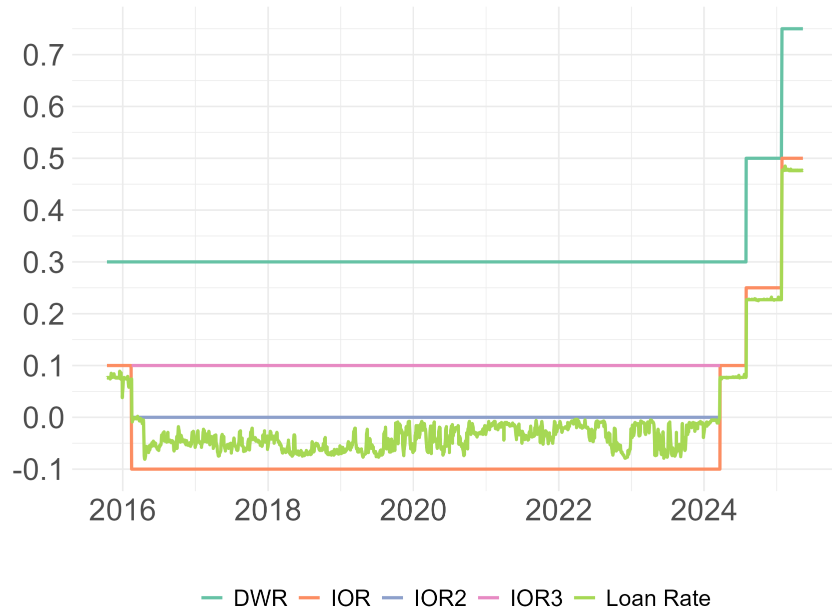



Figure 1: Average uncollateralized overnight loan rate, interest on reserves, and discount window rate.

*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.

expressed in percent. Before the introduction of NIOR, the IOR was $0.1\%$ and the DWR was $0.3\%$. Under NIOR, banks faced 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 stays below IOR because trades 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. These transactions may occur for various reasons, and uncollateralized overnight loans represent 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 uncollateralized overnight loans using payment data in Japan.[5]

The Furfine algorithm alone cannot distinguish uncollateralized loans from repos (Afonso and Lagos, 2012; Arciero et al., 2016). An advantage of the BOJ-NET dataset is that it includes transaction flags, which allow us to differentiate overnight repos from uncollateralized overnight loans. Specifically, BOJ-NET assigns a Delivery Versus Payment (DVP) flag to transactions involving the simultaneous exchange of bonds and reserves, and this flag is used exclusively for repos or bond purchases. In contrast, uncollateralized loans are not associated with this flag because they do not involve the exchange of bonds. After applying the Furfine algorithm, we exclude all DVP-flagged transactions, leaving only uncollateralized overnight loans in our sample. 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.

The 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 entire sample period. This procedure addresses concerns about limited mobility bias and results in the exclusion of 1.5% of the total 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 the total sample. These sample selection criteria are further discussed in

[4]Since Furfine (1999) extracted federal funds transactions in the U.S. from Fedwire, a large body of literature has developed transaction-level data on overnight loans extracted from payment data in various countries based on the Furfine algorithm. Examples include the U.K. (Millard and Polenghi, 2004) and the EU (Arciero et al., 2016).

[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. Their method does not verify whether a corresponding repayment occurs 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, which is not necessarily the next calendar day. For example, this occurs when settlement takes place on a Friday or when the following day is a national holiday. 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 addresses concerns regarding the potential misidentification of non-overnight transactions as overnight loans by the Furfine algorithm. Overnight loans are typically conducted through established credit lines, meaning that borrowers and lenders trade only within these credit lines and do not randomly choose trading partners. If a borrower–lender pair trades only once during the sample period spanning more than 10 years, it is less likely to represent an overnight loan. Even in cases where such trades are indeed overnight loans, they likely contain fewer systematic components that the model can accurately capture. As such, these transactions are excluded from the analysis.

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. We observe 140 trades per day over the 10-year sample period, resulting in 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 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 is 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 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 reports statistics on counterparties, indicating the number of distinct counterparties participants trade with. To separately identify borrower and lender fixed effects, the trading network must be sufficiently connected. Banks typically trade with multiple counterparties. For instance, during the NIOR regime, the median number of counterparties per borrower is 14, and the median number of counterparties per lender is 14. Panel D presents summary statistics on trading pairs.

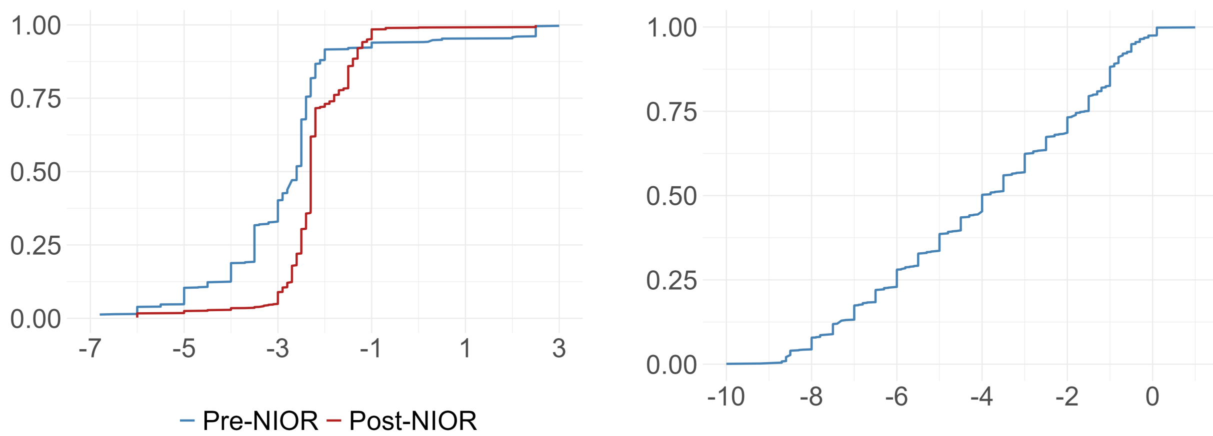
# 4 Empirical premises for the AKM model

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) there is dispersion in loan rates, (ii) there are systematic differences in average loan rates across borrowers and lenders, and (iii) both borrowers and lenders contribute additively to the loan rate.

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:* This figure plots the cumulative distribution function of overnight loan rates minus the IOR. 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.

## 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, there is a clear loan rate dispersion. Most trades occur at loan rates below IOR, as shown by negative spreads. Primary lenders are institutions ineligible for IOR, 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 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 depended on a bank's reserve holdings and can be -10, 0, or 10 basis points. The second-highest IOR served as a ceiling for loan rates, while the lowest IOR acted 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 range between the 90th and 10th percentiles, with both measures 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 gap between the 90th and 10th percentiles 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. Considering that the average overnight loan rate was near zero, this level of dispersion is economically meaningful.

There are two key points to note regarding the time-series properties. 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 institutions in the interbank market, as shown in Panel B of Table 1. A higher number of participating institutions naturally introduces greater heterogeneity, and these heterogeneous characteristics contribute to the more dispersed prices observed during the NIOR period.

The second key time-series property is that significant time-series fluctuations are observed in intraday price dispersion, particularly in the gap between the 90th and 10th percentiles. These large and high-frequency oscillations might suggest that such fluctuations 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 components.

Let $r_j^l$ denote the loan rate minus the IOR for transaction $j$ by lender $l$, with $N = \sum_{l=1}^{L} n_l$ 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 the between-lender and between-borrower variation relative to the overall loan rate variation for 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.

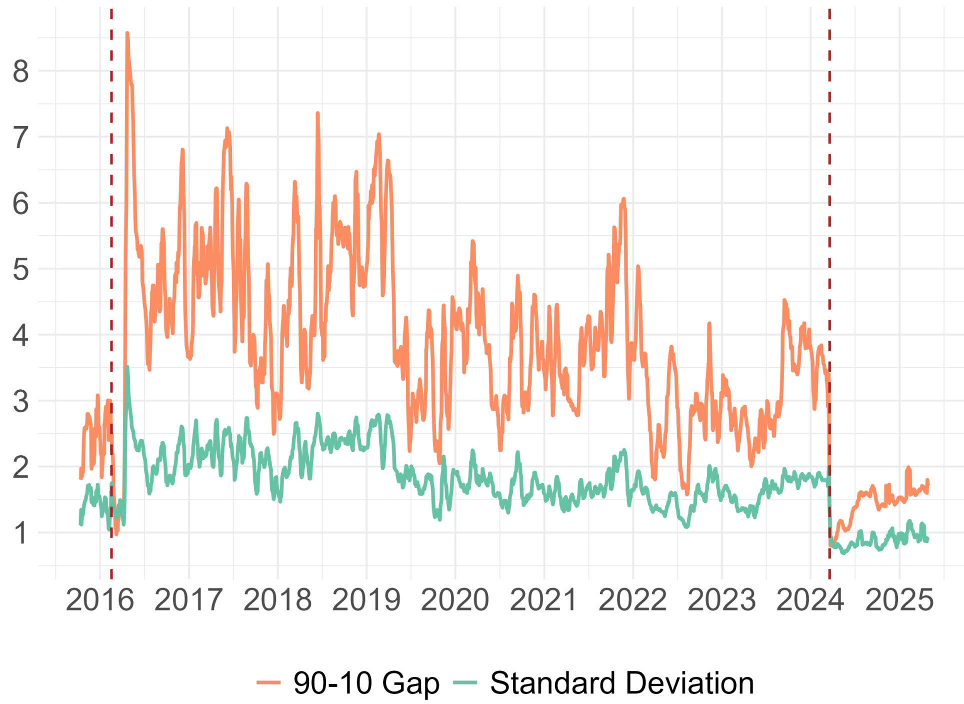



Figure 3: Intraday loan rate dispersion

*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.

## 4.3 Additive structure and further premises

The AKM model assumes that 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.

Table 2: Decomposition of loan rate variation by between-lender and between-borrower

| 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 proportions of the total loan rate variation explained by the between-lender and between-borrower components.

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.

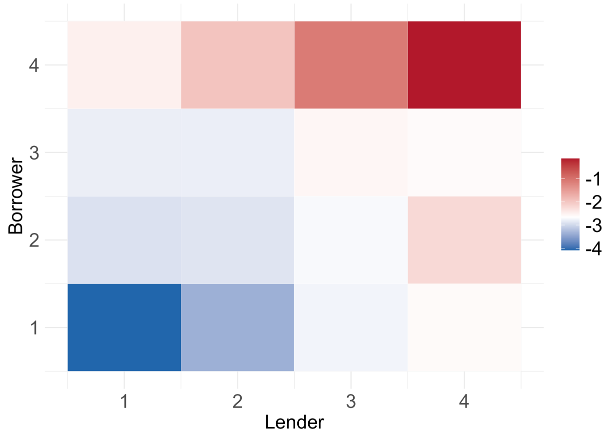
# 5 AKM decompositions

## 5.1 Main analysis

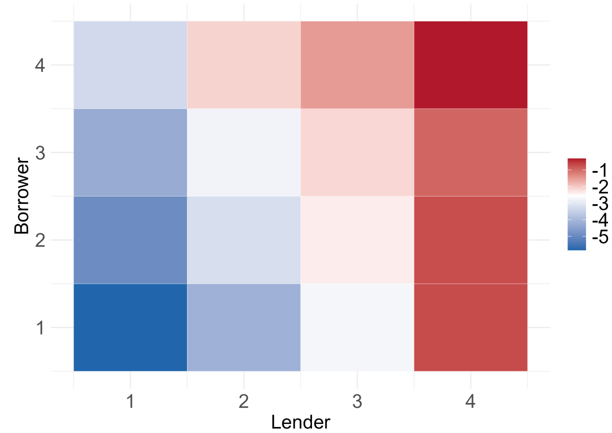
We estimate the following model:

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

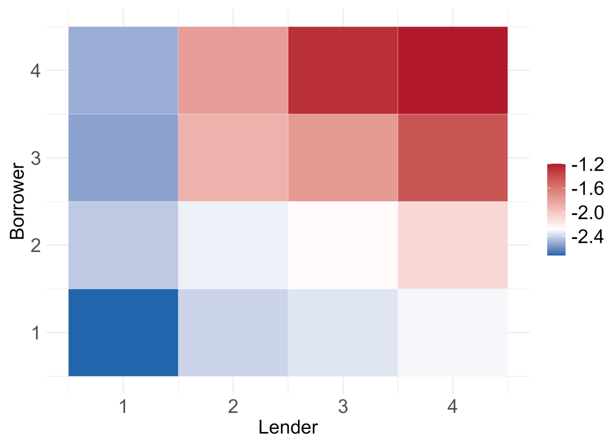
where $r_{i,l,b,t}$ is the loan rate minus IOR of transaction $i$, with lender $l$, borrower $b$, and day $t$. Here, $\alpha_l$ denotes the lender $l$ fixed effect, $\beta_b$ represents the borrower $b$ fixed effect, and $\theta_t$ is the daily time fixed effect. The borrower and lender fixed effects capture the relevant characteristics that are persistent and affect loan rates, including time-invariant counterparty risk, bargaining power, transaction costs, and available funds. For example, borrowers with higher counterparty risk will face higher loan rates and will have higher $\beta_b$. The daily fixed effect absorbs macroeconomic




(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.

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

Another consideration is time-varying parameters. The baseline specification assumes persistent characteristics of banks. In practice, some characteristics are persistent while others are time-varying. The baseline quantifies how much of the variation in loan rates can be attributed to persistent characteristics. In fact, fixed characteristics capture important aspects of loan rates: participants' average loan rates are highly correlated over time, as shown in Appendix B.1. However, we provide two 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. Over 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 explaining the variation in loan rates. We compute the share of the total variance in loan rates attributable to each component using the following expressions:

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

The components sum to one.

Table 3 presents the decomposition results. The standard deviation of loan rates is 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% during the NIOR regime. Since there is a smaller time-series variation in average loan rates during the pre- and post-NIOR regimes, time fixed effects account for 11% and 3%, 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. In contrast, our findings suggest that persistent borrower characteristics play a smaller role outside the crisis period.

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 times as large as that of borrower fixed effects in the respective regimes.

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

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 $\mathrm{Var}(r_{i,l,b,t}) = \mathrm{Var}(\alpha_l) + \mathrm{Var}(\beta_b) + \mathrm{Var}(\theta_t) + 2\mathrm{Cov}(\alpha_l, \beta_b) + 2\mathrm{Cov}(\alpha_l + \beta_b, \theta_t) + \mathrm{Var}(\varepsilon_{i,l,b,t})$. In Panel B, we show $\frac{\mathrm{Var}(\varepsilon_{i,l,b,t})}{\mathrm{Var}(r_{i,l,b,t})}$ from (2) in "Residual", and $\frac{\mathrm{Var}(\varepsilon_{i,l,b,t})}{\mathrm{Var}(r_{i,l,b,t})}$ from (1) minus $\frac{\mathrm{Var}(\varepsilon_{i,l,b,t})}{\mathrm{Var}(r_{i,l,b,t})}$ from (2) in "Pair". Panel C shows $\mathrm{Cor}(\alpha_l, \beta_b)$.

The relatively smaller contribution of borrower heterogeneity reflects their homogeneous liquidity demand and the highly competitive arbitrage conditions. Borrowers' trading motives are primarily driven by two factors: 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 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

[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 IOR, which is 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.

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 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. This implies that 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. The residual variation may be influenced by several factors. 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 unex-

[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 an intraday loan rate dispersion exists even when banks are ex-ante homogeneous.

plained 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? More specifically, to what extent can relationships explain the residuals in the 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 the borrower–lender pair fixed effect, and $\theta_t$ 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 they are not trading with each other. However, when $x$ and $y$ trade with one another, the observed loan rate is consistently lower. In this case, $\alpha_x$ and $\beta_y$ 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 $\alpha_x$ and $\beta_y$. In (2), this loan rate is attributed to the low $\eta_{x,y}$ rather than being treated as a residual. We aim to quantify how common such examples are in the data.

Panel B shows the additional variation that can be explained by considering the pair fixed effect in (2). The unexplained variation in Panel A is equal to the sum of the unexplained variation in Panel B and the share in the "Pair" row. The additional variation explained by including the pair fixed effect is 15%, 4%, and 17% of the total variation. Any persistent, pair-specific relationship component has pricing power in our setting, but 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.

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

### 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. 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. Separate regressions are estimated for the NIOR and post-NIOR periods. For lenders in the post-NIOR period, the sample primarily consists of mutual funds, which lack available balance sheet information. Consequently, results for lenders during the post-NIOR 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.

[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 a firm's value added per worker (Alvarez et al., 2018).

[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.

A common question is why a risk premium exists even for overnight borrowing between financial institutions with low default risk. The key is that lenders evaluate borrowers relative to one another. For example, if both a global bank and a local Japanese bank offer the same borrowing rate, lenders are unlikely to view them as equivalent and will, at least weakly, prefer to lend to a global bank. Offering identical rates would therefore not constitute an equilibrium, even at an overnight maturity. To attract sufficient funds, the local bank must typically borrow at a higher rate to clear 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 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 regression model (1) separately for each period. The model is estimated using rolling one-year windows, shifting the window forward by two months.[16] Figure 5 presents the time series of $\mathrm{Var}(\alpha_l)$, $\mathrm{Var}(\beta_b)$, and $\mathrm{Var}(\varepsilon_{i,l,b,t})$. The red dashed line marks the time when NIOR was lifted.

The variance of the lender fixed effect 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. The increased variation in lender effects contributes to greater loan rate dispersion.

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

[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, and this procedure continues. If the remaining sample period is shorter than three months, we terminate the NIOR estimation on 2023/12/15. Subsequently, we restart the same procedure for the positive IOR regime beginning on 2024/03/19, again using one-year rolling windows with two-month increments. In our estimations, $r_{i,l,b,t}$ is represented in basis points.

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. Heteroskedastic robust standard errors are reported. $^{*}$ $p<0.1$; $^{**}$ $p<0.05$; $^{***}$ $p<0.01$.

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. Heteroskedastic robust standard errors are reported. $^{*}$ $p<0.1$; $^{**}$ $p<0.05$; $^{***}$ $p<0.01$.

predominantly mutual funds (Bank of Japan, 2024).[17] The change in the composition of observed lender types aligns with the decline in the variance of lender fixed effects.

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 without any 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 variance of the borrower fixed effect 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 ($\beta_b$). 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 in terms of 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.

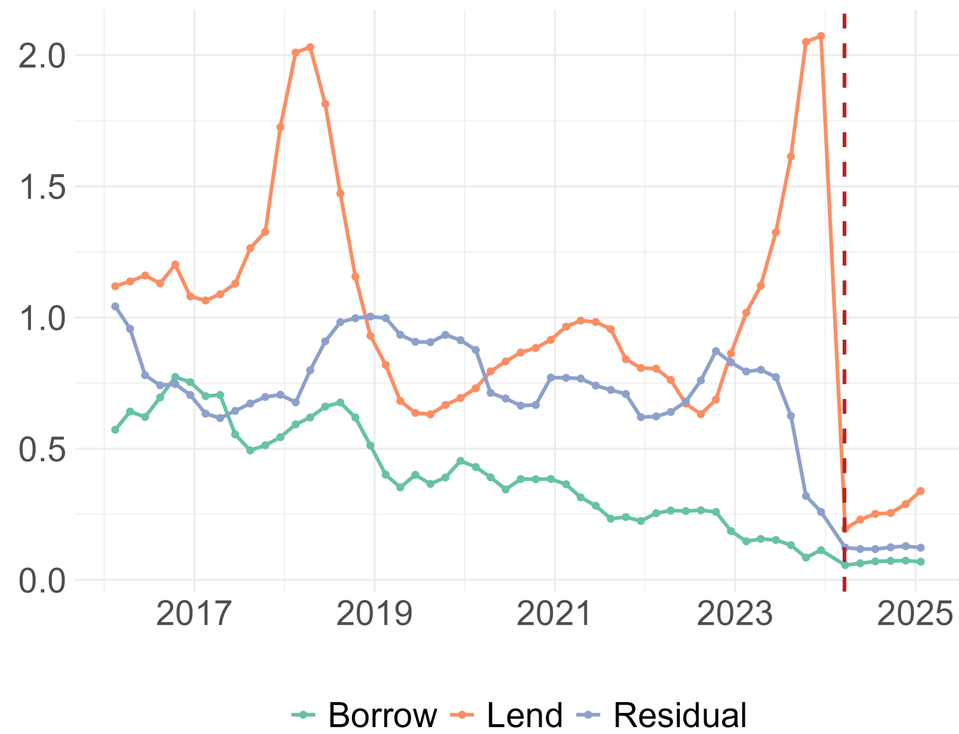
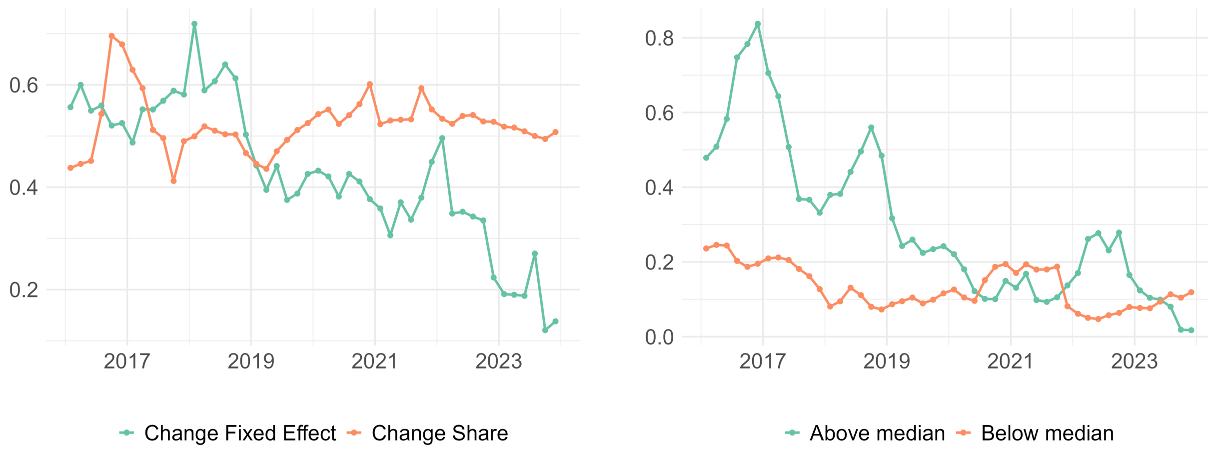



Figure 5: Variance decomposition of loan rates over time

*Notes:* This figure reports time-series estimates of the variance decomposition using one-year rolling windows with two-month increments. The red line plots $\mathrm{Var}(\alpha_l)$. The green line plots $\mathrm{Var}(\beta_b)$. The blue line plots $\mathrm{Var}(\varepsilon_{i,l,b,t})$. 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, $\beta_b$, conditional on whether it lies below or above its median; that is, $\mathrm{Var}\big(\beta_{b(i)} \mid \beta_{b(i)} > \mathrm{Median}\big(\beta_{b(i)}\big)\big)$ and $\mathrm{Var}\big(\beta_{b(i)} \mid \beta_{b(i)} \leq \mathrm{Median}\big(\beta_{b(i)}\big)\big)$. 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 stress, more 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 replace the fixed effects with their sample means:

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

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 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 ($\Delta_t^L$) and borrower ($\Delta_t^B$) 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 $\Delta_t^B$ reaches 0.6 basis points at its peak, 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:

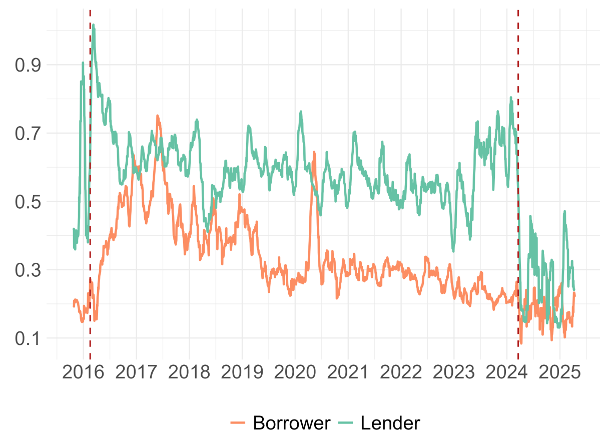
$$\Delta_t^{B,H} \equiv \text{sd}_t(\hat{r}_{i,l,b,t}) - \text{sd}_t\big(r_{i,l,b,t}^{b,H}\big), \quad \Delta_t^{B,L} \equiv \text{sd}_t(\hat{r}_{i,l,b,t}) - \text{sd}_t\big(r_{i,l,b,t}^{b,L}\big),$$

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

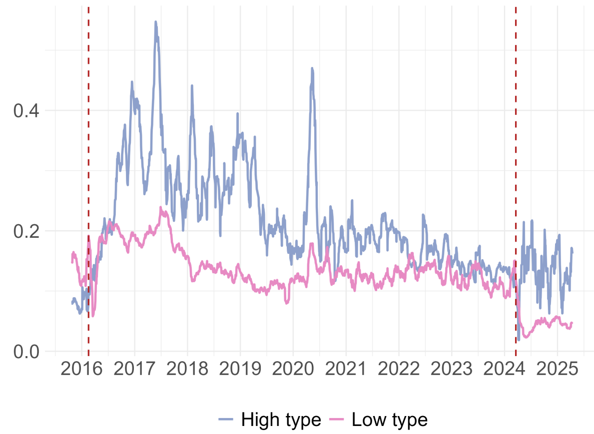
$$r_{i,l,b,t}^{b,L} \equiv \begin{cases} \hat{\alpha}_{l(i)} + \overline{\beta} + \hat{\theta}_{t(i)}, & \text{if } \hat{\beta}_{b(i)} \leq \text{median}_i\left(\hat{\beta}_{b(i)}\right), \\ \hat{r}_{i,l,b,t}, & \text{if } \hat{\beta}_{b(i)} > \text{median}_i\left(\hat{\beta}_{b(i)}\right). \end{cases}$$

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

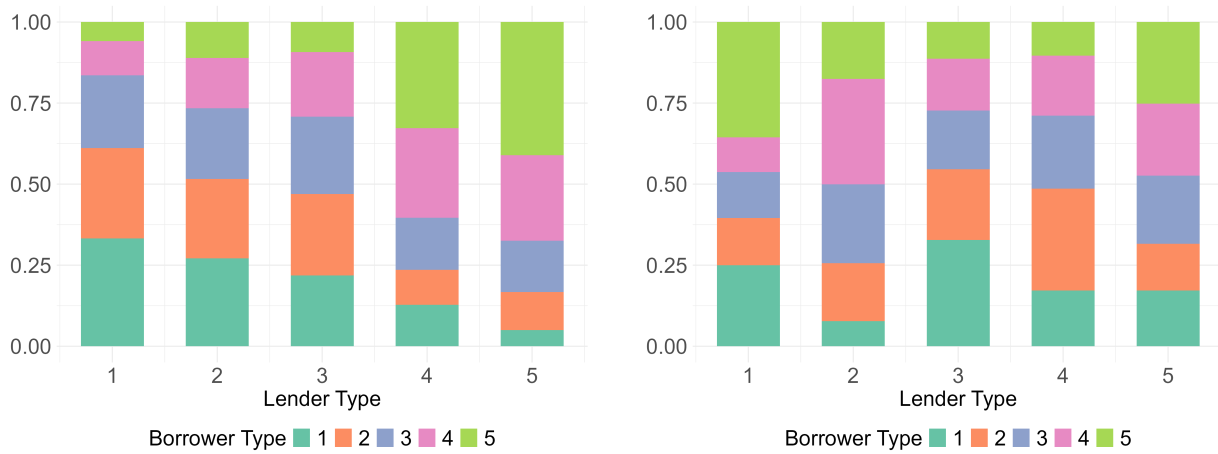
*Notes:* Panel (a) shows the contributions of lender and borrower heterogeneity to loan rate dispersion, calculated as the differences between fitted rates and counterfactual rates with fixed effects replaced by the sample means. These daily estimates are smoothed using a 20-day moving average. Panel (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 predominantly 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

[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).

average loan rates of borrowers and lenders.

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.

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 main-

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.

taining (i) the set of participating borrowers and lenders and (ii) the number of transactions per 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.

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, the 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 are observed to trade with each other more frequently than the levels predicted by random matching models. 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 is defined as $s_i = \frac{n_i}{N} \in (0,1)$. Similarly, each borrower $j$ participates in $m_j$ transactions, with a market share defined as $t_j = \frac{m_j}{N} \in (0,1)$.

Random matching is defined as a process in which each transaction is formed by independently drawing a lender and a borrower 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:*

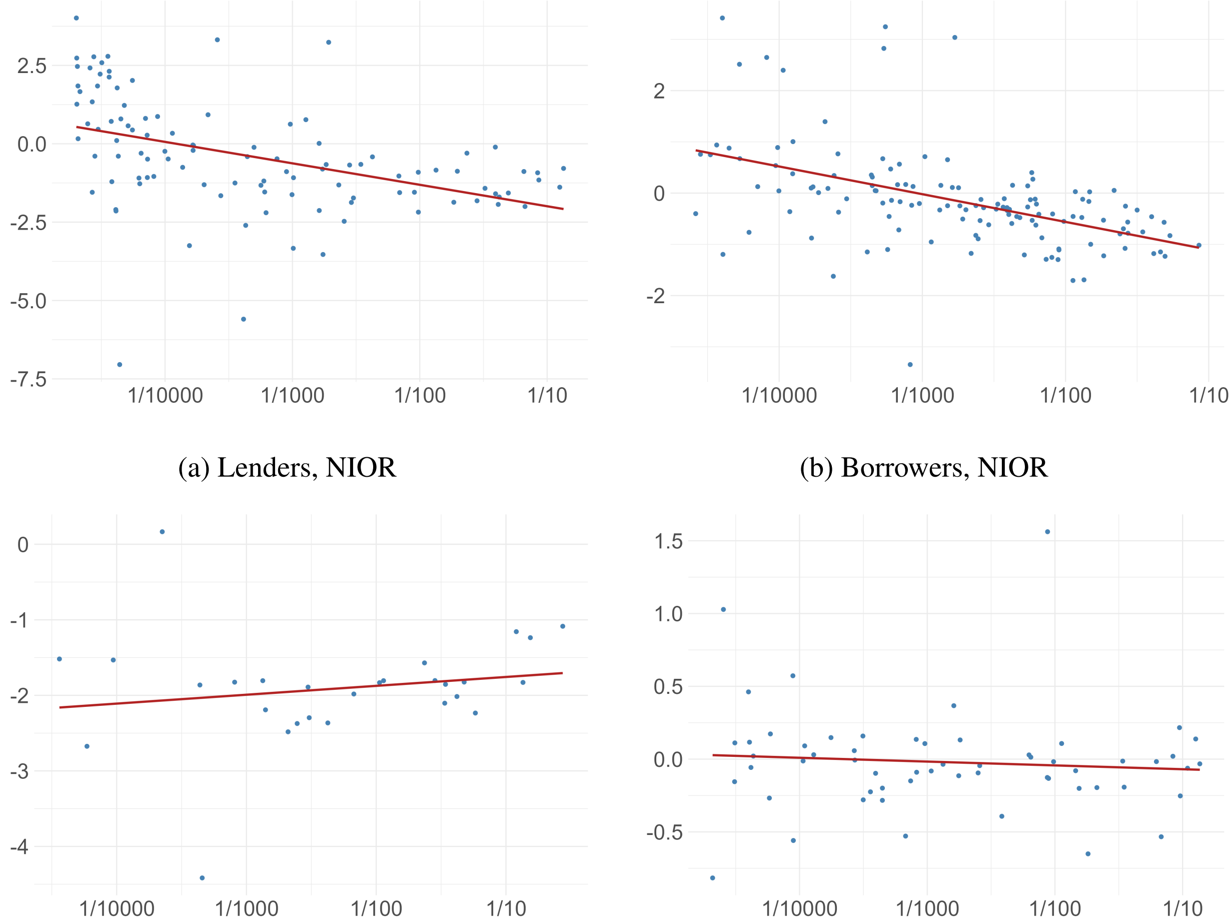
$$\mathrm{Corr}(s_i, t_j) = 0.$$

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

The hypothesis that the correlation between borrowers' and lenders' shares is 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** When we compute the correlation between the share of trade (defined as the ratio of each participant's trading volume to the aggregate trading volume) and the participant's fixed effect, we find a strong negative correlation during the NIOR period for both borrowers and lenders. Figure 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

[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.

fitted line is included to visualize the relationship. For both lenders and borrowers, the negative correlation is evident: participants with larger shares of trade tend to have lower fixed effects. Specifically, the correlation is -0.53 for borrowers and -0.52 for lenders. This pattern, however, is not observed during the post-NIOR period. Figures 9(c) and (d) present the corresponding plots for the post-NIOR sample. In this period, the previously observed negative correlation between the share of trade and fixed effects is no longer evident.

We present two pieces of evidence. First, participants are sorted by their shares in both the NIOR and post-NIOR periods. Second, the correlation between shares and loan rates is observed only during the NIOR period and disappears in the post-NIOR period. Together, these findings partially explain the strong correlation in average loan rates during the NIOR period and the weaker correlation thereafter. An important question remains: why does the interbank market sort participants by their shares, and why are shares correlated with participants' average loan rates? We view these as important questions 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

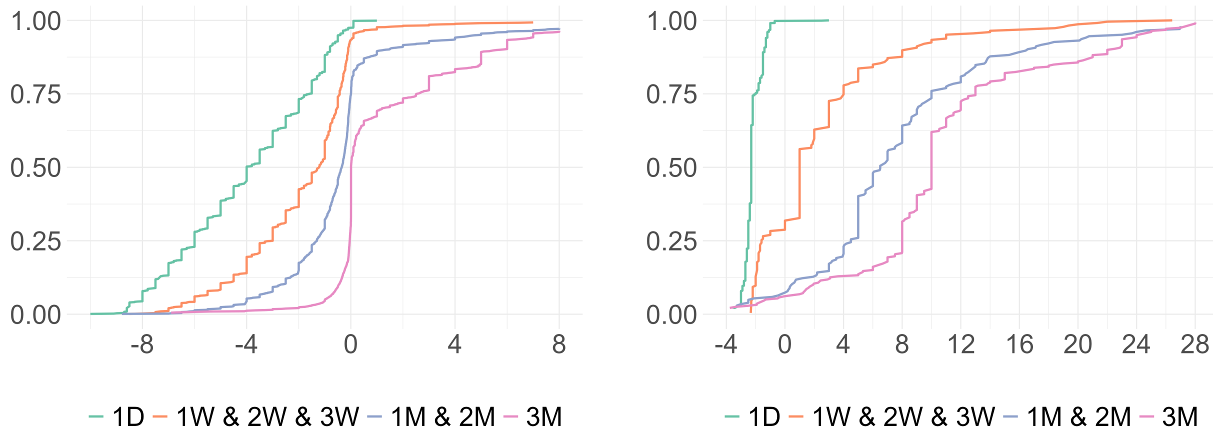
The analysis of term loans is motivated by the observation that loan rate distributions and trading motives differ between overnight and term loans. Figure 10 illustrates the cumulative distribution function of the loan rate minus the IOR for the NIOR and post-NIOR regimes across various maturities, 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. Trading 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 place greater value on securing liquidity over a longer horizon.[23]

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

[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).




(a) NIOR (b) Post-NIOR

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 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. The horizontal axis is represented in basis points.

## 7.2 Variance decomposition

We estimate the following regression:

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

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 $\alpha_l$ denotes lender fixed effects, $\beta_b$ borrower fixed effects, and $\theta_t$ 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 estimate the model in three separate pooled regressions: (i) pooling all maturities, (ii) pooling loans with maturities of one, two, and three weeks, and (iii) pooling loans with 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.

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 $2\left(\mathrm{cov}(\alpha_l+\beta_b,\theta_t+\delta_{\mathrm{term}})+\mathrm{cov}(\theta_t,\delta_{\mathrm{term}})\right)$.

The main result concerns how the contribution of borrower fixed effects changes with 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 contribution of borrower heterogeneity increases with maturity. This result remains robust when the model is estimated for more detailed maturity categories. We estimate the model in (4) separately for each maturity and compute each component's contribution. The results confirm that borrower fixed effects play a greater role as maturity increases, as shown in Figure B.2.

# 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. An important avenue is explaining 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<br>Regime | Full sample<br>NIOR | Leave-one-out<br>NIOR | Full sample<br>Post NIOR | Leave-one-out<br>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<br>Regime | $N=0$<br>NIOR | $N=3$<br>NIOR | $N=5$<br>NIOR | $N=0$<br>PIOR | $N=3$<br>PIOR | $N=5$<br>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 NIOR regime. Table A.4 shows 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 Table A.5. 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.6 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.

In addition, we assess the sensitivity of our results to the relative importance of large versus small trade-size transactions by re-estimating the model using weighted least squares. Each observation is weighted by either transaction volume or its logarithm, thereby assigning greater influence to trades that account for a larger share of market activity. We then conduct a variance decomposition using weighted variances and weighted covariances, with weights based on transaction volume or its logarithm. Table A.7 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. As a result, raw-volume weighting places disproportionate emphasis on very large trades, an issue that does not arise under log-volume weighting.

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

| Sample Period | First half of NIOR | Second half of NIOR |
|---|---|---|
| Panel A | | |
| Borrow | 10% | 4% |
| Lend | 19% | 16% |
| Time | 41% | 60% |
| 2Cov(Borrow,Lend) | 11% | 4% |
| 2Cov(Borrow+Lend,Time) | -0% | -0% |
| Residual | 19% | 16% |
| Standard deviation of loan rate | 2.39 | 2.33 |
| Panel B | | |
| Pair | 5% | 3% |
| Residual | 14% | 13% |
| Panel C | | |
| Cor(Bor Fix. Eff, Lend Fix. Eff) | 0.40 | 0.24 |

*Notes:* Results from OLS estimation of equation (1) and (2). The sample is divided into two subperiods of the NIOR period: one before its midpoint date and the other after it.

Table A.5: Variance decomposition of loan rate based on annual estimation

| Sample Period | NIOR |
|---|---|
| Panel A | |
| Borrow | 12% |
| Lend | 20% |
| Time | 45% |
| 2Cov(Borrow,Lend) | 7% |
| 2Cov(Borrow+Lend,Time) | 0% |
| Residual | 16% |
| Panel B | |
| Pair | 4% |
| Residual | 12% |
| Panel C | |
| Cor(Bor Fix. Eff, Lend Fix. Eff) | 0.22 |

*Notes:* Results from OLS estimation of equation (1) and (2). We divide the sample by calendar year, from 2016 to 2024, in one-year span and estimate the model separately for each year. Next, we calculate the average of each decomposition across the years.

Table A.6: 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.7: Variance decomposition of loan rate using trade-size weighted estimates

| Sample Period<br>Weight | NIOR<br>Volume | NIOR<br>Log of volume | PIOR<br>Volume | PIOR<br>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

$$\rho_t = \mathrm{corr}_{\mathrm{Spearman}}\big(\mathrm{rank}(r_{l,t}), \mathrm{rank}(r_{l,t+h})\big),$$

where $r_{l,t}$ denotes the average lending rate charged by lender $l$ during period $t$, and $\mathrm{rank}(r_{l,t})$ 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 $\rho_t$ 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.

Another measure related to the bipartite property is the reallocation index based on Afonso and Lagos (2015b). The measure captures how much of trading volume is for reallocating funds; a bank borrows from one bank and then lends funds to another bank. The reallocation index is constructed as follows: Let $O_{it}^{p}$ denote the cumulative yen amount of loans purchased by bank $i$ on day $t$, and let $O_{it}^{s}$ denote the cumulative yen amount of loans sold by bank $i$ on day $t$. Define the measure of excess funds reallocation as:

$$X_{it} = O_{it}^{p} + O_{it}^{s} - \left| O_{it}^{p} - O_{it}^{s} \right|, \quad \text{and} \quad X_t = \sum_i X_{it}.$$

This metric captures the volume of funds traded in excess of what would be required to accommodate each bank's net change in balance. For example, if all participants engage exclusively in either lending or borrowing, then $X_{it} = 0$ for all $i$, and consequently $X_t = 0$. On the other hand, if participants engage in both lending and borrowing with the same volume ($O_{it}^{p} = O_{it}^{s}$), then $X_{it} = O_{it}^{p} + O_{it}^{s} = 2O_{it}^{p} > 0$.

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

$$\iota_t = \frac{X_t}{\sum_i \left( O_{i,t}^{s} + O_{i,t}^{p} \right)}.$$

In the case where all participants engage in both lending and borrowing with the same volume, $\iota_t = 1$. The time-series average of $\iota_t$ $\left(\equiv \frac{1}{T} \sum_t \iota_t\right)$ is 2.7% during the NIOR period and 1.8% during the post-NIOR period. In Japan, fewer than 3% of the total trading volume is devoted to reallocation activity, where a single agent borrows and lends funds on the same day. This stands in stark contrast to the federal funds market in the U.S., where approximately 40% of the total trading volume is devoted to reallocation activity (Afonso and Lagos, 2012). However, in Japan, the network is highly bipartite, and thus the reflection problem is less of a concern.

## B.3 Observable characteristics and loan rate variance decomposition

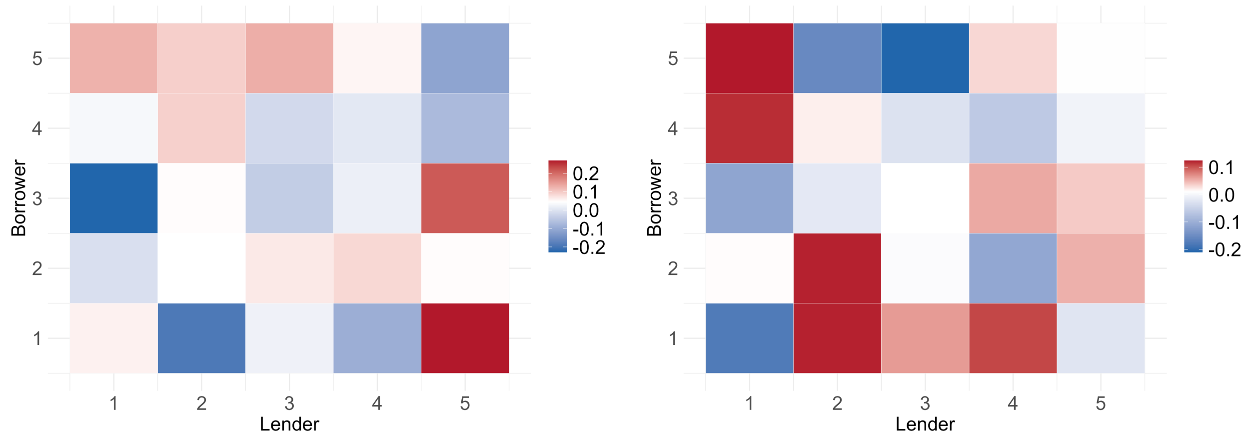
In the baseline analysis we omit observable characteristics for the AKM model. In this subsection, we explore (i) how much of the loan rate variation can be explained by observables, and (ii) how the estimation the in AKM model is affected by the inclusion of observable characteristics.

The choice of observables is based on (Ashcraft, Duffie, and McAndrews, 2007). The first group of observables captures aggregate liquidity conditions. We include the total daily number of transactions, and the daily total yen volume of all completed trades. The second group of observables captures the characteristics of borrowers and lenders. We include the share of trades for borrowers and lenders; monthly transaction volumes are summed for each participants and then averaged across months. These measures summarize each bank's typical level of activity in the interbank market. We also include the "group" of banks, commonly used category of banks[24]. We also include a dummy variable representing 30-minute time windows (e.g., 8:00 AM-8:29 AM, 8:30 AM-8:59 AM, and so on), the volatility of overnight loan rates (measured as the intraday standard deviation of overnight loan rates. Ashcraft, Duffie, and McAndrews (2007) uses volatility measure as the determinant of overnight loan rates), the daily log value of reserves in yen for borrowers, and the trade size per transaction, which is defined as the yen value of each transaction. Regarding the lender's daily reserve holdings, the primary lenders in the market are mutual funds, and their firm-level cash holdings are not observable. Therefore, we include only the borrower's reserve value.

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 reports the results from estimating a model with borrower, lender, and time fixed effects, along with observable characteristics. The variables included in Panel A that are not collinear with time fixed effects, borrower fixed effects, or lender fixed effects are trade size and transaction time, which spans 30-minute time windows. Additionally, we include the trade shares for borrower and lender month-specific participants: for each month, we calculate each participant's trade share for both borrowers and lenders. We exclude the borrower's reserve holdings because lender reserve

[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.




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

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

holdings for mutual funds are not available. Including only the borrower's reserve holdings would change 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.

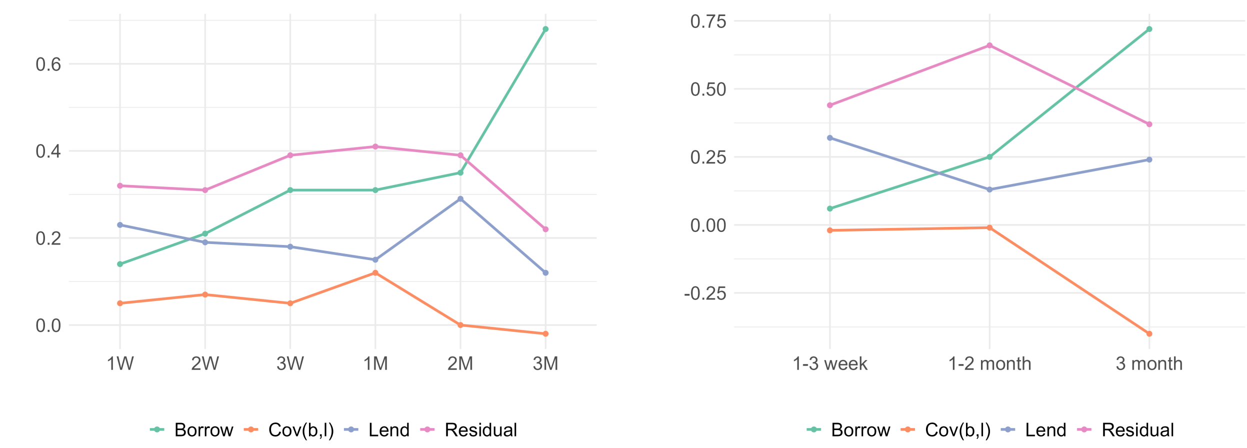
## B.4 Match specific errors

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.

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.2: Variance decomposition by maturity across monetary policy regimes.

### B.5 Robustness and additional analysis for term loans

In Figure B.2, we estimate the model in (4) separately for six maturity groups: one week, two weeks, three weeks, one month, two months, and three months. For each group, we compute the following variance components:

$$\frac{\text{var}(\alpha_l)}{\text{var}(r_{i,l,b,t})}, \qquad \frac{\text{var}(\beta_b)}{\text{var}(r_{i,l,b,t})}, \qquad \frac{\text{var}(\varepsilon_{i,l,b,t})}{\text{var}(r_{i,l,b,t})}, \qquad \frac{2\,\text{cov}(\alpha_l, \beta_b)}{\text{var}(r_{i,l,b,t})}.$$

Panel (a) presents the results for the NIOR regime, while Panel (b) provides the results for the post-NIOR period. Since the sample size is smaller in the post-NIOR regime, maturities are grouped into broader categories. The findings display a clear pattern: the share of borrower fixed effects increases as the loan maturity lengthens.

## 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 $\delta$, 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 $\delta V^b$ is the continuation value of type $b$ borrowers. In general, borrowers have two trading motives; arbitrage profits and liquidity demand. The first and second term $((1+i)a - R)$ represent arbitrage profits, and the second term $\left(u^b(a)\right)$ represents liquidity demand. The first term, $(1+i)a$, represents the return of loans as an investment vehicle; borrowers borrow by $b$ and deposit it at reserve account. Then, the central bank pays interest at $i$, so the total profits ralized tomorrow are $(1+i)a - R$. The third term is additional trading motive beyond securing arbitrage profits, that is captured as $u^b(a)$.

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

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

subject to

$$a^{l,b} \leq a^l,$$

where $\theta$ is the bargaining power of borrower. Since higher $a^l$ improves the trade surplus, $a = a^l$. The problem can be written as

$$\underset{R^{l,b}}{\operatorname{argmax}} \quad \left((1+i)a^l - R^{l,b} + u^b(a^l) - \delta V^b\right)^\theta \left(R^{l,b}\right)^{1-\theta}.$$

The first order condition gives

$$R^{l,b} = (1-\theta)\left((1+i)a^l + u^b(a^l) - \delta V^b\right).$$

We get the solution for repayment between type $(l,b)$:

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

**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** In the data, (i) there exists price dispersion (ii) the lender heterogeneity creates a larger price dispersion than borrowers. Moreorver, the lender heterogeneity potentially comes from the trade size ($a^l$).

Next, we obtain the analytical solution so that there eixsts loan rate dispersion across lenders, but no dispersion across borrowers. Also, we prove that the gross loan rate for larger trade size is higher than that for smaller trade size $\frac{R^{L,b}}{a^L} > \frac{R^{S,b}}{a^S}$.

We keep considering the case where reserves are abundant, so their liquidity value is zero. However, borrower side is less competitive, and $\delta > 0$ holds. In this case, gross loan rate is given by

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

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 created by lender heterogeneity is generated by the outside option for borrower ($\delta V^b$). When borrowers meet large lenders and small lenders, they face the same outside options, but the profits generated by trade are larger for large lenders ($(1+i)a^L > (1+i)a^S$). Trade surplus for borrower is adjusted through repayment, and the smaller lenders have to provide lower repayment to provide borrowers more trade surplus. This leads to a lower loan rate when lenders are smaller. 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 (9). □

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 $u^b(a) \neq u^{b'}(a)$:

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

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

**Empirical support for Proposition 3** We provide empirical support for Proposition 3. Specifically, we run a cross-sectional regression of the estimated lender's fixed effect ($\hat{\alpha}_l$) in (1) on the lender's median trade size. A lender's median trade size is defined as the median yen value of loan sizes observed for each lender. We estimate the model separately for the NIOR and post-NIOR periods. The sample is restricted to the mutual funds considered in this section, whose cash yields are zero when not invested; that situation is considered in the previous model. Table C.1 shows that the log of median trade size is positively and significantly related to the lender's fixed effects. This finding supports the previous proposition, which states that larger trade sizes lead to higher loan rates.

This analysis may raise a concern that the omission of trade size in regression (1) could lead to biased estimates. Table B.2 includes trade size in (1) and finds that trade size accounts for 1% of the total variation. This implies that changes in trade size *within* lenders hardly explain loan rate determination. However, differences in median trade size *across* lenders strongly affect loan rate determination. Since differences in trade size *across* lenders are highly persistent, they can be captured by the lender's fixed effect in (1).

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.

Note that there is a negative correlation between share and $\alpha_l$ in Figure 9 while Table C.1 shows a positive correlation between median trade size and $\alpha_l$. 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

[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. The primary distinction between these accounts lies in their settlement mechanics and timing. The Regular Account operates within the BOJ's conventional payment system, where transactions are typically settled through a netting process and not in real time. In contrast, the RTGS Account supports real-time, gross settlement of payments, meaning each transaction is settled individually and immediately, without the need for netting.

[26] We utilize two types of flags in the dataset: a mandatory flag and a voluntary flag. All transactions are marked with the mandatory flag, although the information it provides is limited. In contrast, the voluntary flag offers more

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%]. This upper bound, the interest on reserves plus 0.1%, might seem low; however, we confirm that increasing the upper bound does not affect the results. Additionally, this upper bound is sufficiently high, considering the maximum overnight loan rate officially published by 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 rate regime, the maximum is 0.1% and the minimum is -0.2%.[28] Fourth, if multiple repayments could match one outgoing payment, the median rate is identified as the rate on the

detailed information, but not all transactions include it. The mandatory flag corresponds to the "Operation Type Name" (*Gyoumu Shori Kubun Mei*). By market convention, overnight loans are identified by the label "Market Trades" in this field. We exclude all transactions that are not flagged as "Market Trades". Other operation types include: (i) Yen-Denominated Foreign Exchange Settlement, (Cross-border transactions where payments are made and received in Japanese yen) (ii) Large-Value bank funds transfer, such as payments for major commercial transactions between firms, and (iii) Delivery-versus-Payment Settlement for Corporate Bonds and Related Securities. Those types of transactions are excluded from our samples. It is also important to note that transactions labeled as "Market Trades" may include both uncollateralized overnight loans and other types of transactions. The voluntary flag we used as the second source of information corresponds to the "Note Label" (*Bikoumei*). While many lack this label, this flag provides detailed transaction information. For example, this Note Label shows that transactions are uncollateralized overnight loans, correspondent account transfer (settling payments by moving funds through accounts that one bank holds with another bank), foreign exchange settlement (payment flows arising from FX trades where the yen is settled domestically in Japan and the corresponding foreign currency is settled abroad), Negotiable Certificate of Deposit, including many other types of labels. While not all uncollateralized overnight loans are labeled as uncollateralized overnight loans in this voluntary flag, we can confidently exclude transactions where the Note Label indicates a type other than overnight loan. In summary, we retain transactions that are either explicitly flagged as overnight loans in the Note Label or have an empty Note Label with a mandatory flag of "Market Trades". All other transactions are excluded.

[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 $100{,}000{,}000 \times \frac{1}{365\times100}$. 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 $100{,}000{,}000 \times \frac{3}{365\times100}$.

[28] We also confirm that this band is wide enough that almost no transactions appear near the upper bound and the lower bound. During the NIOR regime, the loan rate with exactly 0% is excluded. The reason is as follows. In BOJ-NET that records all transfers of reserve, for example, Bank A sends a transfer to Bank B for one billion yen and Bank B send Bank A for one billion yen on the same day repeatedly. If we include 0% loan rate, those transactions are identified as overnight loans. However, those often include non-overnight loans, especially when Bank A and Bank B are larger banks with many transactions each other. For this reason, 0% loan rate is excluded.

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 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.

1. For maturities of one week, two weeks, and three weeks, the contractual maturity is defined as exactly 7, 14, and 21 calendar days, respectively. This rule ensures that when the settlement date is a business day, the corresponding repayment date also falls on a business day. For maturities of one month, two months, and three months, the data exhibit two distinct conventions. Under the fixed-day convention, maturities are set to 28, 56, and 84 calendar days, respectively; this guarantees a business-day repayment date even though the repayment day of the month may differ from the settlement day (for example, a one-month loan settled on January 1 is repaid on January 29). Under the calendar-day-matching convention, the maturity date is scheduled on the same calendar day in the subsequent month, or within one calendar day of that date. For example, a one-month loan settled on January 10 is repaid on February 10, and a three-month loan is repaid on April 10. When the target date falls on a weekend, repayment typically occurs one business day before or after (e.g., February 9 or February 11 when February 10 is a weekend).

2. 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.

3. We additionally exclude transactions as follows. This procedure comes from the difficulty when the loan rate is very close to zero. To understand, suppose Bank A lends to Bank B

an overnight loan of 1 billion yen at -5 basis points every day during NIOR. The repayment amount is

$$1000000000 \times \left(1 + \frac{-0.05}{365 \times 100}\right) \approx 999998630.$$

If such trades occur every day, a transaction from A to B for 1 billion yen on, for example, September 1 and a transaction from B to A for 999,998,630 on September 8 can be misidentified as a one-week loan with loan rate at $\frac{-0.05}{7}\%$ even though each trade was actually an overnight loan.

This misidentification does not occur when the IOR is well above zero, for example 25 bps, because the implied loan rate in that case is far from zero and is inconsistent with an overnight rate of 25 bps. For example, the repayment of 1 billion yen for overnight loan is

$$1000000000 \times \left(1 + \frac{0.25}{365 \times 100}\right) \approx 1000006849,$$

whereas the repayment of 1 billion yen for 1 week loan with 25 bps of loan rate is

$$1000000000 \times \left(1 + \frac{0.25 \times 7}{365 \times 100}\right) \approx 1000047945.$$

The two are sufficiently different and less likely to be misidentified as the same loan.

However, when the loan rate is close to zero during NIOR and the initial interest-rate band ($-10$ to $+20$ bps) includes zero, these spurious one-week loans with loan rate very close to zero (in the above example $-0.05/7\%$ ) appear in the data.

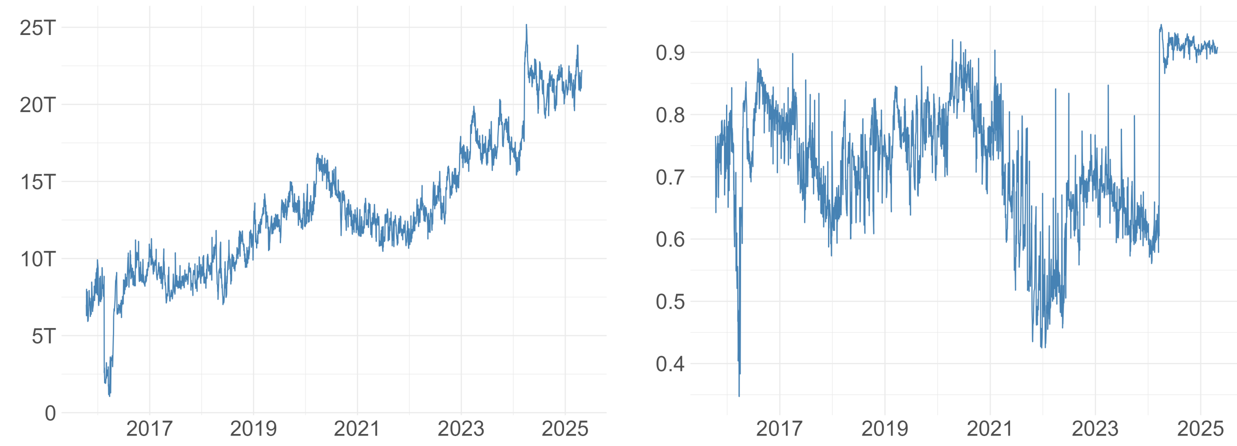
To address this concern, if we identify a transaction of payment for both overnight and terms, we exclude term transactions and regard this payment as an overnight loan. This restriction comes from the fact that overnight loans are much more common (80% of transactions are overnight), and they are repetitive (bank A lends to bank B frequently and repeatedly for overnight loans, but term loans are much less frequent and not repetitive.)

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.

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 |
| 25th percentile of loan rate - IOR in bps | -2.27 | -3.00 | -0.80 | 1.80 | -1.55 | 5.50 |
| 75th pct. | -0.07 | -0.43 | 0.20 | 10.00 | 4.00 | 12.00 |
| 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 |
| 25th pct. | 9 | 7 | 6 | 5 | 3 | 4 |
| 75th pct. | 29 | 28 | 21 | 7 | 5 | 8 |
| 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 |
| 25th pct. | 7 | 6 | 6 | 6 | 3 | 4 |
| 75th pct. | 28 | 27 | 22 | 7 | 4 | 6 |
| 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.




(a) Lending volume by mutual funds

(b) Lending share of mutual funds

Figure E.1: Lending by mutual funds

# 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.

# F Micro 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.

As a result of the significant increase in reserves, coupled with a moderate change in required reserves, banks hold abundant reserves. Table F.1 shows the reserve-to-required-reserve ratios

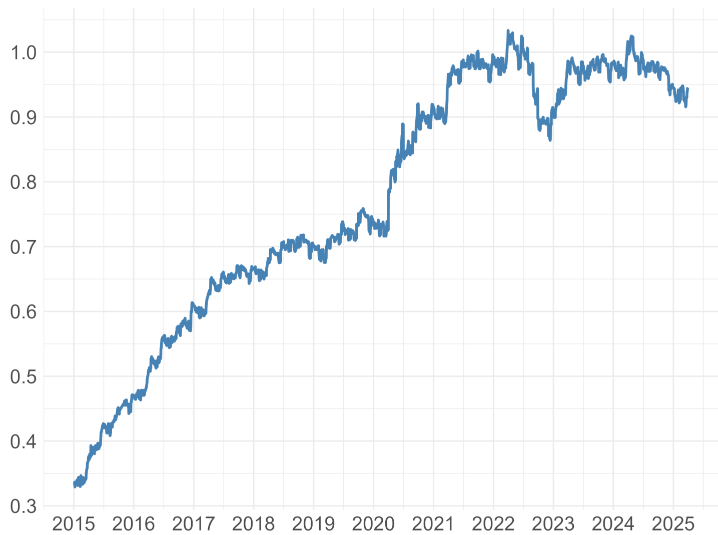



Figure F.1: Aggregate Reserve to GDP Ratio.

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% |

at the bank level for 2015 and 2024. We restrict sample banks such that they traded at least once in overnight loan market. For each bank and maintenance period, we calculate the ratio of actual cumulative reserves to required reserves on the final day of maintenance period. Then, we determine the proportion of banks falling within the ranges shown in Table F.1.

Only a small number of financial institutions hold reserves close to the level of their required reserves. In 2024, the share of institutions with a reserves-to-required-reserves ratio between 1 and 1.5 is 0.8%. More than 90% of institutions hold reserves exceeding ten times their required reserves. This indicates that Japanese financial institutions generally maintain abundant reserves. When they engage in interbank reserve trading, their objective is therefore not to meet required reserves, but rather to manage liquidity or pursue other trading motives.

# 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.

In this subsection, we present the simplest example of positive assortative matching and show that the correlation between borrower and lender shares is strictly positive. The setting follows Section 6. Without loss of generality, index lenders and borrowers so 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 $t_j$, so the pair $(s_i, t_j)$ occurs with probability $s_i t_j$. A simple form of positive assortative matching reallocates probability mass through $2 \times 2$ transfers toward similarly ranked pairs, so that high-share lenders match more frequently with high-share borrowers and low-share lenders more frequently with low-share borrowers.

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

$$\pi_{ij} \leftarrow \pi_{ij} + \delta,\ \pi_{k\ell} \leftarrow \pi_{k\ell} + \delta,\ \pi_{i\ell} \leftarrow \pi_{i\ell} - \delta,\ \pi_{kj} \leftarrow \pi_{kj} - \delta.$$

*leaving all other entries unchanged.*

*Then, any positive assortative matching satisfies*

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

*Proof.* Let $\pi_{ij}$ 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

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

Finally, the correlation inherits the same inequality. □