Distance and Loan Pricing Revisited: A Structural Estimation Approach*

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This version: January 31, 2026
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Abstract

In this paper, we examine how firms' borrowing costs are affected by geographic distance from bank branches. We develop a model where firms endogenously choose their lenders by considering loan rates determined à la Bertrand competition among banks, and estimate the structural parameters using a dataset that combines firm- and bank-level microdata from Japan. The estimation results indicate that distance affects loan pricing by influencing both banks' and borrowers' costs, and that a simple reduced-form approach may yield biased estimates due to firms' endogenous lender choice. Counterfactual simulations indicate that the impact of bank consolidation depends on regional competitive conditions.

Keywords: Banking; Loan pricing; Spatial price discrimination.
JEL Classification Codes: G21, L13, L14, D43.

*We thank Yusuke Imani, Yoshiaki Ogura, Manju Puri, Iichiro Uesugi, and participants at the Econometric Society World Congress 2025, the Japan Society of Monetary Economics Conference 2025, SWET 2025, the TDB-CAREE conference, and a workshop at RIETI. Katagiri and Wakamori gratefully acknowledge financial support from the JSPS KAKENHI Grant Numbers 21H00704 and 22H00837.

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1 Introduction

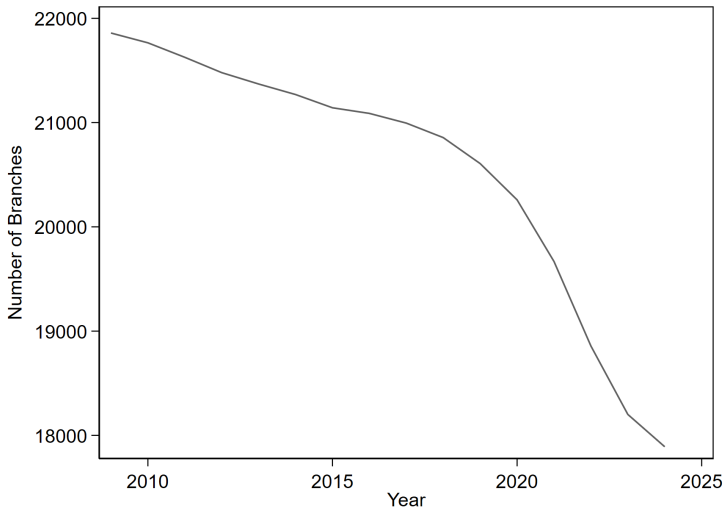
Accessibility to banks has been declining in many countries due to bank branch closures.[1] For example, as shown in Figure 1, more than 20 percent of bank branches have closed in Japan over 15 years. This trend is driven by bank consolidation in response to, for example, low profitability and the digitization of financial services. Though these changes may represent banks' optimal responses to evolving financial conditions, they raise policy concerns about declining competition in the banking sector. In particular, reduced access to banks can increase borrowing costs for small businesses, as loan rates tend to rise with the distance between firms and competing banks (e.g., Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). Given the ongoing decline in bank accessibility due to branch closures, a key question for financial authorities is the extent to which the longer distances increase borrowing costs for businesses.

This paper examines how geographic distance between borrowers and lenders affects loan rates by adopting a structural estimation approach. Specifically, we develop a model in which firms optimally select a bank branch to borrow (hereafter, the "lender"), and equilibrium interest rates are determined through an English auction under Bertrand competition among banks (Allen et al., 2019). As explained below, we assume that distance influences interest rates by potentially affecting both lenders' and borrowers' costs, consistent with prior empirical and theoretical studies. We then estimate the model parameters via maximum likelihood using a unique dataset that combines firm-level microdata with a financial institution directory in Japan. Finally, we use the estimated model to conduct a counterfactual simulation to assess how bank branch closures affect businesses' borrowing costs.

Previous theoretical and empirical literature argues that greater distance between firms and bank branches may affect loan rates by increasing both lenders' and borrowers' costs. On the lender side, prior studies emphasize that longer distances raise banks' monitoring costs, as banks may find it more difficult to obtain private information about more distant firms (e.g., Agarwal and Hauswald, 2010; Granja et al., 2022; Petersen and

[1] See Keil and Ongena (2024) for the U.S. and Legran et al. (2024) for Europe.

Figure 1: Number of Bank Branches in Japan



Note: The figure shows the total number of bank branches in Japan from 2009 to 2024.

Rajan, 2002). On the borrower side, empirical works highlight that greater distance can increase borrowers' costs through higher transportation costs, consistent with the classic Hotelling framework (e.g., Degryse and Ongena, 2005). This mechanism is also intuitive, as firms must physically visit bank branches to, for example, negotiate and manage loan contracts.

Given these effects on lenders' and borrowers' costs, the empirical literature has extensively documented the role of distance in loan pricing, primarily using reduced-form methods. Our structural estimation approach makes a marginal but distinct contribution to this literature by offering several advantages over reduced-form methods, in particular through the explicit joint modeling of interest-rate competition among banks and firms' endogenous lender choices. First, our framework allows us to examine why distance matters for loan pricing under explicit structural assumptions. In particular, we distinguish between the effects of distance on lenders' costs and on borrowers' costs, exploiting a theoretical implication that distance to a firm's own lender and distance to other nearby banks both affect loan rates through these two channels, but in different ways. This structure enables our empirical analysis to quantify the contribution of each channel by estimating the corresponding parameters. Second, our Monte Carlo simulations show that while our structural estimation properly identifies the marginal effects of

distance on borrowing costs, simple reduced-form regressions may yield attenuated estimates due to firms' endogenous lender selection. Although competition among nearby banks is known to affect loan pricing, directly identifying the relevant competitors from the data is challenging. Our model addresses this issue by allowing each bank branch to become a potential rival to the current lender with a certain likelihood, thereby capturing the role of rival branches in determining equilibrium loan rates. Third, in the counterfactual analysis, our framework examines how loan rates adjust endogenously in response to shocks such as bank branch closures, while accounting for firms' endogenous lender choices.

Our main findings are summarized as follows. First, our estimation results indicate that distance significantly affects loan pricing through both banks' lending costs and firms' perceived utility. We identify these effects through two distinct channels by exploiting variation in firms' borrowing rates and their distances not only to the lending branch but also to nearby rival branches. The estimates imply that a 1 kilometer increase in the distance to nearby bank branches raises borrowing costs by approximately 8.7 bps, which is economically significant given Japan's low-interest environment. In contrast, the effect of distance to the lending branch is more moderate, at about -2.2 bps per additional kilometer, underscoring the central role of competition among banks in determining loan rates. Second, our counterfactual simulations indicate that bank consolidation can lead to sizable increases in loan rates when accompanied by large-scale branch closures that alter the geographic distance between lenders and borrowers. This finding implies that, while bank consolidation may yield benefits such as reduced operating costs, it can also impose welfare costs by increasing firms' borrowing costs. Moreover, the magnitude of these effects varies substantially across firms and regions, reflecting differences in the availability of nearby alternative banks. In particular, the market share of the largest bank in a region is a useful predictor of the regional impact of branch closures, suggesting that policymakers can use such concentration measures to anticipate the adverse effects of bank consolidation.

Our study contributes to several strands of the banking research literature. First, this paper is closely related to recent studies that apply structural estimation in banking, such

as Egan et al. (2017), Pavanini et al. (2022), and Wang et al. (2022). In particular, Allen et al. (2019) investigate bank competition in the Canadian mortgage market, and our likelihood-based estimation framework, which models Bertrand competition among banks, closely follows their methodology. In addition, our approach to separating two distinct determinants of financial contracts is similar in spirit to Yasuda (2005). Second, our study builds on the traditional empirical literature examining the role of distance in loan pricing, including Petersen and Rajan (2002), Alessandrini et al. (2009), and Granja et al. (2022). Among these studies, Degryse and Ongena (2005) and Agarwal and Hauswald (2010) are particularly relevant, as they show that firms' borrowing costs depend not only on their distance to the lending bank but also on their distance to competing banks. In contrast to these reduced-form studies, we adopt a structural estimation approach that jointly models firms' bank choice and loan pricing, thereby uncovering the mechanism through which distance shapes competitive pressure in loan markets. Third, this paper contributes to the literature on bank consolidation and loan pricing, including DeYoung et al. (1999), Sapienza (2002), Degryse et al. (2011), and Nguyen (2019). Our structural framework allows us to quantify the effects of consolidation on loan pricing while taking into account firms' endogenous bank choice and the competitive structure they face.

The remainder of the paper is organized as follows. Section 2 explains the data used for empirical analyses in this study, as well as the institutional background of the banking system in Japan. Section 3 presents reduced-form evidence to motivate our structural model. Section 4 presents the structural model, and the estimation results are demonstrated in Section 5. Section 6 concludes.

2 Data and Background

This study primarily utilizes two datasets: the Teikoku Databank database and Kinyu Meikan (Financial Directory). We first describe these data sources, outlining their structure. Additionally, we provide institutional background on the Japanese commercial banking sector, explaining its market structure.

2.1 Teikoku Databank and Financial Directory (Kinyu Meikan)

Our firm-level data is provided by Teikoku Databank LTD., a leading business credit bureau in Japan. We utilize various datasets from the Teikoku Databank: the corporate financial database, the corporate profile database, and the corporate credit research database. The corporate financial database contains financial information on firms, including interest payments, profitability, and asset and loan sizes. The corporate profile database provides firm-level information, including its address. The corporate credit research database provides the bank-branch code of the bank branch with which the firm primarily transacts.[2]

Financial Directory (Kinyu Meikan) is an annual dataset that comprehensively lists branches of financial institutions in Japan. Although Japanese private financial institutions can be categorized in various ways, they are generally classified into five main groups: large banks, first-tier regional banks, second-tier regional banks, credit associations, and credit cooperatives. We refer to these bank categories as "Bank Type." The dataset contains detailed information on each branch, including its address and bank-branch code. For our analysis, we collected data from 2011 to 2020 and structured it as a panel dataset.

These two databases are merged using the bank-branch code. We then calculate the distance between each firm and its lending branch, as well as the distance between the firm and the 20 nearest bank branches as a potential "rival branch." Because our focus is on bank accessibility for small businesses in regional areas, we examine only firms in those areas that borrow from regional banks. Specifically, we exclude some firms from our sample if: (i) they are located in Tokyo or Osaka, or (ii) they borrow from large banks.[3]

[2]When the firm transacts with multiple bank branches, the list of bank branches is supposed to be ordered by loan volume. Thus, we designate the top-listed bank branch as the firm's lender in our study, following the methodology in Hosono et al. (2016).

[3]We also exclude firms that borrow from credit cooperatives, as they tend to be too small—primarily individual businesses—to be comparable with other firms.

Table 1: Descriptive Statistics

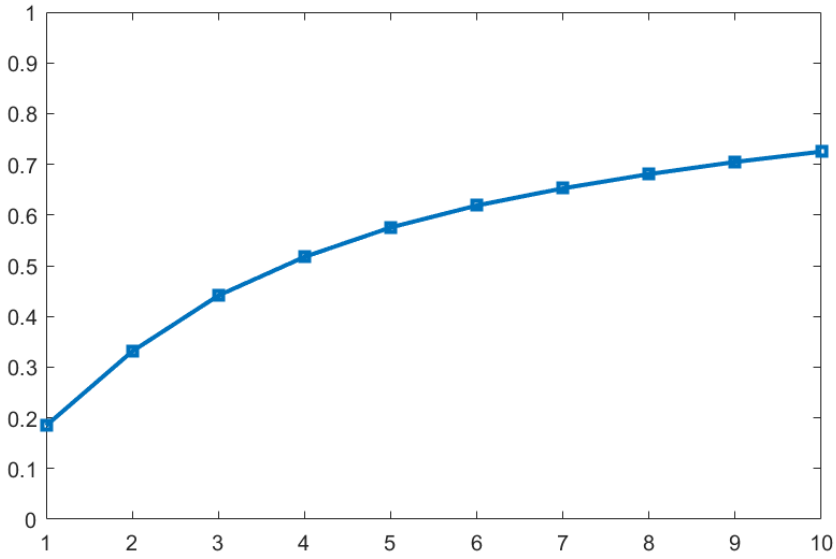
	Obs.	Mean	S.D.	p5	p50	p95
Lending Bank						
Distance (km)	993,284	3.20	3.94	0.25	1.93	10.40
Distance to rivals						
The closest (km)	993,284	1.35	1.88	0.12	0.79	4.26
Second closet (km)	993,284	2.01	2.88	0.26	1.20	6.18
Third closest (km)	993,284	2.74	5.44	0.40	1.56	8.14
Forth closes (km)	993,284	3.28	6.14	0.51	1.87	9.64
Fifth closest (km)	993,284	3.84	8.80	0.61	2.16	11.13
Other variables						
Interest Rate (%)	993,284	1.87	1.27	0.38	1.66	4.02
Assets (mil. yen)	993,284	1.11	10.20	0.02	0.23	3.64
ROA	993,284	0.03	0.08	-0.09	0.02	0.17
Capital Ratio	993,284	0.31	0.21	0.03	0.27	0.72

2.2 Descriptive Statistics

Table 1 demonstrates the descriptive statistics of our merged data, pooling all years. The number of observations is 993,284 over 11 years, implying that about 90,000 firms are included in each year. The figure presents the distance to the lending branch and the distribution of bank types of the lending branches. The first row shows that the average distance to the lending branch is about 3.2 km, with a standard deviation of 3.9 km and a median distance of 1.9 km. These results suggest that firms tend to select lending branches relatively close to their locations.

The table also displays the distances to the closest branch, as well as the second-, third-, fourth-, and fifth-closest branch, excluding the lending branch. The average distance to the closest bank branch, excluding the lending branch, is 1.35 km, with a median of 0.79 km, and the average distance to the second-closest branch is 2.01 km, with a median of 1.20 km. This indicates that the distance to the second-closest bank is slightly longer than the distance to the lending branch on average. Looking at the median, though, the distance to the second-closest branch is shorter than the distance to the lending branch. The average distance to the fifth-closest bank branch is 3.72 km, implying that there are more than five financial institutions, on average, within a radius of

Figure 2: Rank of Lending Branch by Distance (Cumulative)



Note: The figure shows the cumulative share of firms selecting the x-th closest bank branch as their main lender. It implies that around 20% of firms choose the nearest branch as their lender.

4.0 km.

Lastly, the table presents descriptive statistics for the control variables. The average interest rate is very low at 1.87%, with a median of 1.27%. Although not shown in the table, note that average loan rates in Japan have declined over the last few decades. The table also presents descriptive statistics for additional financial variables, such as asset size, ROA, and capital ratios, that may influence interest rates.

3 Motivating Facts

In this section, we perform descriptive and reduced-form analyses to motivate our structural models, using the data described in Section 2. In our analysis, we particularly focus on how firms' choice of lending branches, as well as their loan pricing, are affected by the geographical distance between firms and bank branches.

3.1 Does Distance Matter When Choosing a Lending Branch?

To begin our descriptive analysis, we ask the following question: Do firms actually borrow from nearby bank branches? In other words, does the distance between borrowers and lenders matter when firms choose their lender? If a greater distance between borrowers and lenders entails costs for borrowers and/or lenders, as suggested by the theoretical and empirical literature, we would expect firms to be more likely to borrow from closer banks.

As a first step toward answering this question, Figure 2 reports the number of firms borrowing from the xth closest bank branch and plots the corresponding *cumulative* shares. The figure shows that approximately 20% of firms choose the nearest branch as their lender, while 12% choose the second-nearest branch. Moreover, more than 70% of firms select their lender from among the ten closest bank branches, suggesting that distance to bank branches is an important determinant of firms' lender choices.

While Figure 2 suggests that distance is an important factor in firms' lender choices, it also indicates substantial heterogeneity across firms in the extent to which proximity is valued. What explains this heterogeneity? If the costs associated with greater distance reflect transportation or monitoring costs, as suggested by the existing literature, firms with larger loan volumes may be less sensitive to distance due to economies of scale. To examine this hypothesis, we define $Select_{i,j}$ for $j = 3, 5,$ and 10 as dummy variables that take the value one if firm i selects its lending branch from among the j nearest branches. We then conduct a logit analysis in which these indicators are regressed on loan volume and the number of nearby branches. Table 2 shows that, after controlling for the availability of nearby branches, firms with larger loan volumes are less likely to choose their lender from among nearby branches for all cases of $j = 3, 5,$ and 10. These results imply that distance is more important for firms with smaller loan volumes when selecting their lender, consistent with the hypothesis that borrowers' distance-related costs exhibit economies of scale.

Table 2: Firm's Lender Choice by Loan Size

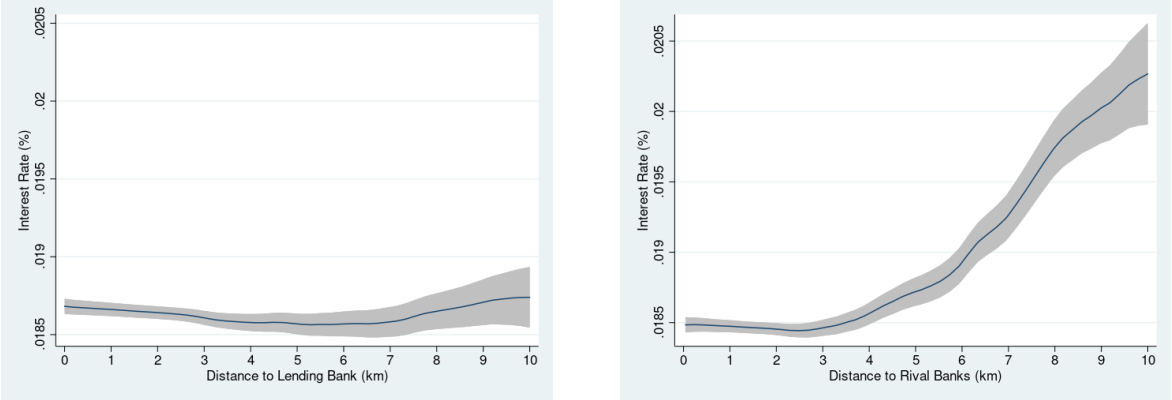
	(1) $Select_3$	(2) $Select_5$	(2) $Select_{10}$
Loan	-0.173***	-0.184***	-0.193***
	(-132.08)	(-137.06)	(-17.41)
# of Rivals	-0.128***	-0.134***	-0.150***
	(-225.71)	(-231.55)	(-231.16)
N	880345	880345	880345

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: $Select_{i,j}$ for $j = 3, 5,$ and 10 are dummy variables that take the value one if firm i chooses its lending branch from among the j nearest bank branches. The table shows the estimation results of a logit analysis in which these dummy variables are regressed on loan volume and the number of nearby branches.

Figure 3: Distance and Borrowing Costs



Note: The figure shows the relationship between borrowing costs and distance to the lending and rival bank branches. The horizontal axis represents the distance to the lending branch (the left panel) and the distance to the average distance to the five nearest branches (the right panel).

3.2 Does Distance Matter When Setting Loan Rates?

To understand how banks set loan rates, it is important to examine (i) the relationship between the loan rate and the distance to the lending branch, and (ii) the relationship between the loan rate and the distance to rival bank branches. Figure 3 illustrates these relationships using local polynomial regressions. The horizontal axis in the left panel represents the distance to the lending branch, while that in the right panel represents the distance to rival branches.[4] Figure 3 shows that, while there is no clear relationship between borrowing costs and the distance to the lending branch, borrowing costs increase significantly with the distance to nearby rival branches. Specifically, as the distance to nearby branches increases from 3 km to 8 km, borrowing costs rise by approximately 15 bps on average. This finding suggests that the distance to nearby bank branches—potential competitors to the current lending bank—is an important determinant of firms' borrowing costs.

Next, following Degryse and Ongena (2005), we run the following regression to assess the relationship between borrowing costs and the distance to the lending and rival bank branches:

$$\text{Interest Rate}_i = \beta_0 + \beta_1 D_{Lend,i} + \beta_2 D_{Rival,k,i} + \text{ Controls}_{it} + \text{Year}_t + \epsilon_{ij}$$

Here, Interest Rate$_i$ denotes the loan rate for firm i, and $D_{Lend,i}$ is the distance between firm i and its lending branch. As proxies for the distance to rival branches, $D_{Rival,k,i}$, we consider four alternative measures indexed by $k = 1, 2, 3, 4$. First, $D_{Rival,1,i}$ is the distance to the nearest bank branch for firm i (or the second-nearest branch if the lending branch is the nearest). Second, $D_{Rival,2,i}$ is the distance to the nearest branch within the same bank type. For example, when the lender for firm i is a tier-one regional bank, $D_{Rival,2,i}$ denotes the distance to the nearest branch of tier-one regional banks (or the second-nearest branch if the lending branch is the nearest). This second measure captures the possibility that firms may prefer particular types of banks over others. Third, $D_{Rival,3,i}$ is

[4] As a proxy for the distance to rival branches, we use the average distance to the five nearest branches. Using alternative proxies, such as the average distance to the three nearest branches, yields qualitatively similar results.

Table 3: Distance and Borrowing Cost

	(i)	(ii)	(iii)	(iv)
D_{Lend}	.0015***	.0016***	.0007*	.0005
	(4.09)	(4.17)	(2.02)	(1.45)
$D_{Rival,1}$	.0068***			
	(6.75)			
$D_{Rival,2}$		.0080***		
		(17.52)		
$D_{Rival,3}$			.0122***	
			(17.18)	
$D_{Rival,4}$				.0129***
				(23.08)
Controls	√	√	√	√
Year FE	√	√	√	√

The numbers in parentheses show the t-values.
*, **, and *** denote $p < 0.1, 0.05,$ and 0.01.

Note: The table the estimation results, where each column uses a different measure of distance to rival bank branches: (1) $D_{Rival,1,i}$ is the distance to the nearest bank branch for firm i (or the second-nearest branch if the lending branch is the nearest), (2) $D_{Rival,2,i}$ is the distance to the nearest branch within the same bank type, (3) $D_{Rival,3,i}$ is the average distance to the three closest bank branches for firm i, (4) $D_{Rival,4,i}$ is the average distance to the five closest bank branches for firm i. The estimation also includes dummy variables for the bank type of the lending branch, return on assets (ROA), capital ratios, liquidity ratios, the logarithm of total assets, and long-term loan ratios for firm i in year t. We also include time fixed effects, denoted by Year$_t$, to capture macroeconomic factors affecting interest rates.

the average distance to the three closest bank branches for firm i, and fourth, $D_{Rival,4,i}$ is the average distance to the five closest bank branches for firm i. These latter measures address the possibility that the relevant rival branch is not necessarily the nearest one, but rather one of several branches in the vicinity. Controls$_{it}$ includes dummy variables for the bank type of the lending bank, return on assets (ROA), capital ratios, liquidity ratios, the logarithm of total assets, and long-term loan ratios for firm i in year t. We also include time fixed effects, denoted by Year$_t$, to capture macroeconomic factors affecting interest rates.

Table 3 reports the estimation results. Each column uses a different measure of distance to rival bank branches. When we use the distance to the nearest bank branch, $D_{Rival,1}$, shown in the first column, the coefficients on both the distance to the lending

Table 4: Distance and Borrowing Cost for Firms Borrowing from Five Nearest Banks

	(i)	(ii)	(iii)	(iv)
D_{Lend}	.0055***	.0051***	-.0037**	-.0052***
	(3.93)	(4.21)	(-2.88)	(-4.40)
$D_{Rival,1}$	.0074***			
	(4.53)			
$D_{Rival,2}$		.0087***		
		(15.04)		
$D_{Rival,3}$			.0169***	
			(16.04)	
$D_{Rival,4}$				.0175***
				(22.38)
Controls	√	√	√	√
Year FE	√	√	√	√

The numbers in parentheses show the t-values.
*, **, and *** denote $p < 0.1, 0.05,$ and 0.01.

Note: The table reports the estimation results for firms borrowing from one of the five nearest banks. The same notes as in the previous table apply.

branch and the distance to the rival branch are positive and statistically significant. However, the effect of rival distance is larger in magnitude and more statistically significant. Using the distance to the nearest branch within the same bank type, $D_{Rival,2}$, shown in the second column, yields qualitatively similar results. When we instead use average distances to nearby branches, as shown in the third and fourth columns, the estimated effects of rival distance become larger and more statistically significant, while the effects of distance to the lending branch become smaller and statistically less significant. The average distances to nearby branches may more appropriately capture rival distance by accounting for the possibility that the nearest bank branch is not a relevant competitor. Accordingly, the results in the third and fourth columns indicate that the distance to the lending branch is not a significant determinant of borrowing costs once the distance to rival branches is controlled for. Overall, these estimation results suggest that competition among bank branches plays a central role in determining equilibrium loan rates.

Figure 2 shows that some firms borrow from distant banks rather than nearby banks, and Table 2 suggests that firms with different loan sizes exhibit different preferences re-

garding distance. To examine whether firms that are more sensitive to distance when choosing their lender are also sensitive to distance in loan pricing, we re-estimate regression (1) using only firms that borrow from one of the five nearest bank branches. The estimation results in Table 4 show that, while most results are qualitatively similar to those obtained using the full sample in Table 3, a key difference is that, in columns (3) and (4), the distance to the lending branch has statistically significant and *negative* effects on borrowing costs. Although this result contrasts with the estimates in Table 3, it is more consistent with the findings in the previous literature, such as Degryse and Ongena (2005). In the next section, we use a structural model of bank competition to discuss a possible mechanism underlying these reduced-form results in Tables 3 and 4.

4 Structural Model of Bank Competition

This section presents our structural model to investigate the relationship between distance and firms' borrowing costs. In the model, firms select their lender from nearby banks based on the interest rate offered, geographic distance, and other characteristics such as bank type. The equilibrium interest rate is determined through an English auction in Bertrand's competition among banks. In what follows, first, we describe the bank's loan supply. We then describe how firms choose their lenders and how their lending rates are determined in equilibrium. Finally, we discuss parameter identification and construct a likelihood function to estimate those structural parameters.

4.1 Bank's Lending Cost and Distance

Bank j extends loans to firms in its vicinity, incurring lending costs. The cost for bank j to lend to firm i is denoted by $\underline{r}_{ij}$ and defined as

$$\underline{r}_{ij} \equiv c_i + \omega_{ij}, \tag{1}$$

where c_i is a deterministic firm-specific lending cost shared by all banks and ω_{ij} is a stochastic and idiosyncratic lending cost for bank j to extend loans to firm i. We assume that both are observed by all banks and the borrower, but not by econometricians. The firm-

specific lending cost is modeled as a function of firm i's characteristics and is defined as $c_i \equiv x_i\beta$, where x_i is a vector of firm i's characteristics, including profitability, capital ratios, and asset size.

The stochastic and idiosyncratic lending cost ω_{ij} is assumed to follow a Type I extreme value distribution,

$$\omega_{ij} \sim \text{TIEV}(\xi_{ij}, \sigma_\omega). \tag{2}$$

where σ_w is a scale parameter that determines the variance of the distribution. We assume that distance from borrowers affects banks' lending costs by influencing the location parameter, ξ_{ij}, which determines the mean of the cost distribution. Specifically, we assume that ξ_{ij} is a function of the distance between bank j and firm i, d_{ij}, bank type T_j (regional I, regional II, or cooperative), and the interaction between bank type and firm size $Size_i$:

$$\xi_{ij} = \xi(d_{ij}, T_j, T_j \times Size_i).$$

The empirical and theoretical literature argues that lending costs may increase with distance because banks must incur higher monitoring costs for more distant borrowers (e.g., Petersen and Rajan, 2002). This implies that $\partial\xi_{ij}/\partial d_{ij} > 0$, so that greater distance from borrowers increases the idiosyncratic lending cost ω_{ij} in Equation (1) by shifting the mean of the distribution, ξ_{ij}. We further allow ξ_{ij} to depend on bank type T_j and its interaction with firm size, reflecting segmentation in lending markets across bank types and firm sizes.

4.2 Firm Preference and Equilibrium Interest Rate

Firm i maximizes the following indirect utility by choosing a lender to finance its business investment,

$$\max_{j \in \mathcal{J}_i} \; v_{ij} - r_{ij}$$

where $\mathcal{J}_i$ is the set of nearby bank branches, v_{ij} is firm i's perceived benefit on borrowing from branch j, and r_{ij} is the interest rate offered by branch j to firm i. The firm's perceived

benefit v_{ij} is assumed to be a function of distance,

$$v_{ij} = v(d_{ij}),$$

where d_{ij} is distance between firm i and bank branch j. The previous literature argues that borrowers may incur higher costs when borrowing from more distant lenders due, for example, to higher transportation costs (e.g., Degryse and Ongena, 2005). If greater distance entails higher borrowing costs, we expect $\partial v(d_{ij})/\partial d_{ij} \leq 0$. Note that the effect of distance on v_{ij} captures costs and benefits *for borrowers*, over and above the effect of distance on lending costs *for banks*, which is reflected in r_{ij}.

In addition, the estimation results in Table 2 indicate that firms with larger loan volumes are less sensitive to distance when choosing their lender. To capture such heterogeneity by loan size, we allow the marginal effect of distance on v_{ij} to vary with loan size. In particular, if distance is less important for firms with larger loans, we expect

$$\frac{\partial^2 v(d_{ij})}{\partial d_{ij}\, \partial Loan_{ij}} \leq 0,$$

where $Loan_{ij}$ denotes the loan size between firm i and branch j. This assumption is natural, as v_{ij} and r_{ij} represent the benefit and cost per dollar of the loan. Given that transportation costs are largely invariant to loan size, their importance per dollar borrowed should decline as loan size increases.

Firm i chooses its lender from nearby branches that compete under Bertrand competition. We assume that the lending branch has bargaining power in loan negotiations and sets the loan rate to maximize its profit under Bertrand competition. Accordingly, the equilibrium interest rate, r_i^*, is determined through an English auction, in which the most efficient branch offers the interest rate that makes firm i indifferent between borrowing from the most efficient branch and the second-efficient branch under the zero-profit condition.

To characterize the equilibrium interest rate more formally, bank branches in $\mathcal{J}_i$ are sorted in descending order according to the benefit they provide to firm i under $r_{ij} = \underline{r}_{ij}$

(i.e., under the zero-profit condition) and are numbered sequentially.

$$v_{i(1)} - \underline{r}_{i(1)} > v_{i(2)} - \underline{r}_{i(2)} > \cdots > v_{i(n)} - \underline{r}_{i(n)}$$

Then, we can show that, in equilibrium under Bertrand competition, firm i chooses its lender b_i^* to realize the (potentially) highest benefit,

$$b_i^* = b_{i(1)} \equiv \underset{j \in \mathcal{J}_i}{\operatorname{argmax}} \; v_{ij} - \underline{r}_{ij}$$

and the equilibrium interest rate r_i^*, which by definition is equal to the interest rate offered by the lending branch, $r_{i(1)}$, is determined as

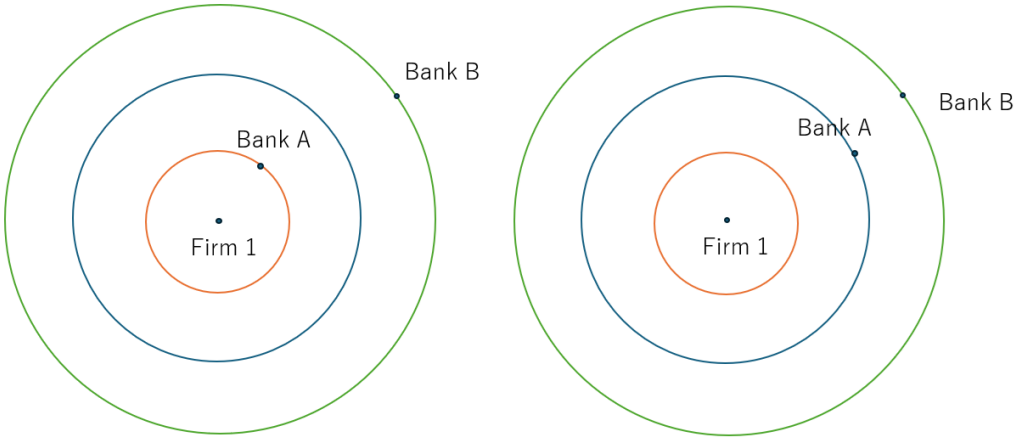
$$r_i^* = r_{i(1)} = v_{i(1)} - v_{i(2)} + \underline{r}_{i(2)}, \tag{3}$$

while all other banks offer interest rates equal to their zero-profit levels, $r_{i(k)} = \underline{r}_{i(k)}$ for $k = 2, \cdots, n$. Equation (3) implies that the equilibrium interest rate is determined through an English auction among banks. Specifically, the most efficient bank raises its offered interest rate $r_{i(1)}$ up to the point at which firm i is indifferent between borrowing from the most efficient bank and borrowing from the second-efficient bank under the zero-profit condition, that is, $v_{i(1)} - r_{i(1)} = v_{i(2)} - \underline{r}_{i(2)}$. The pair (b_i^*, r_i^*) constitutes an equilibrium outcome, as neither the lending bank nor the other banks have an incentive to deviate from their offered interest rates, and firm i likewise has no incentive to switch lenders.

4.3 Identification for Borrowers' and Lenders' Cost of Distance

In this model, an increase in the distance between borrowers and lenders affects the equilibrium interest rate and, consequently, firms' lender choices through two distinct channels: by increasing banks' lending costs and by lowering borrowers' perceived utility. We construct a unique dataset by merging firm-level microdata with a financial institution directory, which enables us to separately identify the effects of distance on borrowers' costs (e.g., transportation costs) and lenders' costs (e.g., monitoring costs) through these channels.

Figure 4: Identification for Lending and Borrowing Costs



Note: The figure illustrates how to separately identify the effects of distance on borrowers' costs (e.g., transportation costs) and lenders' costs (e.g., monitoring costs).

To understand the identification issue in our model, consider two firms, A and B, whose distances to their second-efficient branches are identical (after controlling for other observable factors), but whose distances to their respective lending branches differ (Figure 4). In equilibrium, the interest rates for firms A and B are given by $r_A^* = v_{A(1)} - v_{A(2)} + \underline{r}_{A(2)}$ and $r_B^* = v_{B(1)} - v_{B(2)} + \underline{r}_{B(2)}$, respectively. Since the distances to the second-efficient branches are the same for firms A and B, we have

$$r_A^* - r_B^* = v_{A(1)} - v_{B(1)}.$$

Now suppose that the relationship between distance and a firm's perceived utility is linear. Under this assumption, the equation above implies that we can identify the effect of distance on firms' perceived utility by comparing the equilibrium interest rates of firms X and Y. Finally, once the effect of distance on firms' perceived utility is identified, we can recover the effect of distance on banks' lending costs, $\underline{r}_{i(2)}$, from the equilibrium pricing condition in (3).

4.4 Likelihood Function for Estimating Structural Parameters

As we describe in Section 2, our dataset consists of the following items for firm i where $i = 1, \cdots, n$. First, the firm-level microdata provide firm i's borrowing cost r_i, the address of its headquarters, and a vector of characteristics x_i, such as profitability, firm size, and debt levels. Second, the financial institution directory provides the bank branch addresses and the bank types of the lender, T_m, as well as other banks T_j where $j \in \mathcal{J}_i \backslash \{m\}$. Third, by combining those two datasets, we can calculate the distance between firm i and its lender, d_{im}, as well as other banks in its neighborhood, d_{ij}, where $j \in \mathcal{J}_i \backslash \{m\}$. We focus only on firms outside Tokyo and Osaka prefectures that borrow from tier-one or tier-two regional banks or Shinkin banks (i.e., credit associations), as our interest lies in the effects of bank accessibility on regional economies. As shown in Figure 2, firms exhibit heterogeneous preferences regarding distance—some are sensitive to it, while others do not care about it at all. Therefore, we exclude firms that borrow from banks beyond their ten nearest banks, as their preferences differ from those of others.

We construct a likelihood function to estimate the parameter values in the following two steps. First, the probability for firm i to choose bank m as its lending bank, $\mathcal{L}^1(b_i = m)$, is computed by,

$$\mathcal{L}^1(b_i = m) \quad = \quad \mathbf{Pr}\left[v_{im} - \underline{r}_{im} \geq v_{ij} - \underline{r}_{ij}, \quad \forall j \in \mathcal{J}_i \backslash \{m\}\right]$$

Next, under the condition that firm i chooses bank m as their lender, we compute the conditional probability that the equilibrium interest rate equals r_i, $\mathcal{L}^2(r_i|b_i = m)$. Given the equilibrium interest rate is determined by Equation (3), $\mathcal{L}^2(r_i|b_i = m)$ is,

$$\begin{aligned} \mathcal{L}^2(r_i|b_i = m) \quad &= \quad \mathbf{Pr}\left[r_i = v_{im} - v_{i(2)} + \underline{r}_{i(2)}\right] \\ &= \quad \mathbf{Pr}\left[\omega_{i(2)} = -v_{im} + v_{i(2)} + r_i - x_i\beta\right] \end{aligned}$$

where the variables $v_{i(2)}, \underline{r}_{i(2)}$, and $\omega_{i(2)}$ are variables for second-efficient banks. Note that while we can observe which bank is the lender for firm i in data, we cannot identify which bank is the second-efficient bank for firm i from the dataset. Thus, in constructing the likelihood function, we need to consider all cases where one of the nearby banks other

than the lender is the second-efficient bank for firm i. Specifically, let bank m and k be the lender and the second-efficient bank for firm i, respectively. Then, given that bank m is the lender for firm i, the conditional probability for bank k to become the second-efficient bank is,

$$\begin{aligned}
\mathbf{Pr}\left[v_{ik} - \underline{r}_{ik} \geq v_{il} - \underline{r}_{il}, \quad \forall l \in \mathcal{J}_i \backslash \{m,k\}\right] &= \mathbf{Pr}\left[v_{im} - r_i \geq v_{il} - \underline{r}_{il}, \quad \forall l \in \mathcal{J}_i \backslash \{m,k\}\right] \\
&= \mathbf{Pr}\left[\omega_{il} \geq -v_{im} + v_{il} + r_i - x_i\beta, \quad \forall l \in \mathcal{J}_i \backslash \{m,k\}\right] \\
&= \prod_{l \in \mathcal{L}_i \backslash \{m,k\}} \{1 - G_{il}(x_{iml})\}
\end{aligned}$$

where G_{ij} is a cdf of TIEV(ξ_{ij}, σ_w) for firm i and bank j, and $x_{imj} \equiv -v_{im} + v_{ij} + r_i - x_i\beta$. The equality in the first line utilizes the fact that the equilibrium interest rate is determined by an English auction in Equation (3). The second and third lines come from the assumption that the lending cost $\underline{r}_{il}$ is additively separable as described in Equation (1), and the idiosyncratic component ω_{il} follows TIEV(ξ_{il}, σ_w). Note that any variable for the second-efficient bank k does not show up in the right-hand side of the above equation. Then, given the probability for each bank to be the second-efficient bank, the conditional likelihood for interest rate, $\mathcal{L}^2(r_i|b_i = m)$, is rewritten as

$$\mathcal{L}^2(r_i|b_i = m) = \sum_{k \in \mathcal{L}_i \backslash \{m\}} g_{ik}(x_{imk}) \left[\prod_{l \in \mathcal{L}_i \backslash \{m,k\}} \{1 - G_{il}(x_{iml})\} \right]$$

where g_{ij} is a pdf of TIEV(ξ_{ij}, σ_w) for firm i and bank j. That is, we can compute the weighted average of $g_{ik}(x_{imk})$, the probability for each bank k's lending cost to be consistent with r_i, using the probability for bank k to be a second-efficient bank as their weight in the weighted average.

Finally, by computing the product of $\mathcal{L}^1(b_i = m)$ and $\mathcal{L}^2(r_i|b_i = m)$, we can compute

the likelihood for estimation as follows,

$$
\begin{aligned}
& \mathcal{L}(b_i = m, r_i) \\
= \; & \mathcal{L}^1(b_i = m) \times \mathcal{L}^2(r_i | b_i = m) \\
= \; & \mathbf{Pr}\left[v_{im} - \underline{r}_{im} \geq v_{ij} - \underline{r}_{ij}, \quad \forall j \in \mathcal{J}_i \backslash \{m\}\right] \times \sum_{k \in \mathcal{L}_i \backslash \{m\}} g_{ik}(x_{imk}) \left[\prod_{l \in \mathcal{L}_i \backslash \{m,k\}} \{1 - G_{il}(x_{iml})\}\right] \\
= \; & G_{im}(r_i - x_i\beta) \sum_{k \in \mathcal{L}_i \backslash \{m\}} g_{ik}(x_{imk}) \left[\prod_{l \in \mathcal{L}_i \backslash \{m,k\}} \{1 - G_{il}(x_{iml})\}\right]
\end{aligned}
$$

where $x_{imj} \equiv -v_{im} + v_{ij} + r_i - x_i\beta$. The equality in the last line utilizes the fact that the equilibrium interest rate is determined by an English auction in Equation (3). In the next section, we use this likelihood function for estimating structural parameters by maximum likelihood estimation.

5 Structural Estimation

In this section, we conduct quantitative analysis using the structural model described in the previous section. First, we parameterize the relationship between distance and lending costs, as well as perceived utility. Second, before estimating the model parameters using microdata, we conduct a Monte Carlo simulation to understand the model properties. Third, we estimate the model parameters using our dataset and interpret the estimation results. Fourth, we conduct a counterfactual simulation for bank branch closures to assess their impact on the equilibrium interest rate.

5.1 Parameterization

To investigate the structural relationship between distance and the interest rate, we assume the following specifications for utility v_{ij} when firm i borrows from bank j and lend-

ing costs c_i and ξ_{ij}.

$$
\begin{aligned}
v_{ij} &\equiv \gamma_{Dist} d_{ij} + \gamma_{Dist \times Loan} d_{ij} \cdot \log(\text{Loan}_i) \\
c_i &\equiv \beta_{Size} \log(\text{Asset}_i) + \beta_{ROA} \text{ROA}_i + \beta_{Liq} \text{Liquidity}_i + \beta_{cap} \text{CapRatio}_i + \beta_{long} \text{LongRatio}_i \\
\xi_{ij} &\equiv \theta_{Dist} d_{ij} + \sum_b \left[\theta_{T,b} \text{BankType}_{b,j} + \theta_{TS,b} \text{BankType}_{b,j} \times \log(\text{Asset}_i) \right]
\end{aligned}
$$

In this specification, the distance between borrowers and lenders, d_{ij}, affects the interest rate through both borrowers' perceived utility and banks' lending costs, captured by γ_{Dist} and θ_{Dist}, respectively. The effect of distance on borrowers' perceived utility is allowed to vary with loan size, as captured by the interaction term coefficient $\gamma_{Dist \times Loan}$. With respect to bank type, we classify all banks into one of three categories, $b \in \{\text{Regional I}, \text{Regional II}, \text{Shi}$

Using this specification, we first conduct a Monte Carlo simulation to assess whether our likelihood-based estimation can recover the true parameter values and to examine its relationship with the reduced-form estimation in Section 3. We then estimate the structural parameters by maximum likelihood and conduct counterfactual simulations based on the estimated parameter values.

5.2 Monte Carlo Simulation

Before estimating our model with the Japanese data, we conduct a Monte Carlo simulation to assess whether the parameter values are properly identified. Furthermore, we aim to ensure that the generated data closely replicate the reduced-form results presented in Section 3, and we expect that the results of reduced-form estimation using the simulated data give some interpretations for the reduced-form estimation in Section 3. The Monte Carlo simulation proceeds as follows. First, we generate 100,000 artificial firms, specifying their geographic characteristics and financial environments. Then, according to the equilibrium conditions in the model, firms optimally choose their lender, and interest rates are determined through Bertrand competition among banks.

Given the generated data through the Monte Carlo simulation, we run the following

Table 5: Estimated Coefficients Using Simulated Data

	[i] $(\gamma, \theta) = (0.0, 0.1)$	[ii] $(\gamma, \theta) = (-0.1, 0.0)$	[iii] $(\gamma, \theta) = (-0.1, 0.1)$
D_{Lend}	0.021	-0.075	-0.052
D_{Rival}	0.067	0.042	0.128

Note: The table shows the estimation results using the artificial data generated by the Monte Carlo simulation. Columns 1, 2, and 3 show the three cases with different parameter values for the pecuniary effects of distance (i.e., the lending cost) and the non-pecuniary effects of distance (i.e., the perceived benefit), γ and θ.

reduced-form estimation:

$$\text{Interest Rate}_i = \beta_0 + \beta_1 D_{Lend,i} + \beta_2 D_{Rival,i} + \epsilon_i \tag{4}$$

where $D_{Lend,i}$ is the distance to the lending bank, and $D_{Rival,i}$ is the distance to the nearest bank for firm i (or the distance to the second nearest bank if the lender is the nearest bank). Since the definition of explanatory variables is the same as in the estimation in Section 3, the coefficients β_1 and β_2 correspond to the reduced-form estimation in Section 3.

Table 5 shows the estimation results using the artificial data generated by the Monte Carlo simulation. Columns 1, 2, and 3 show the three cases with different parameter values for the pecuniary effects of distance (i.e., the lending cost) and the non-pecuniary effects of distance (i.e., the perceived benefit), γ and θ. By differentiating the parameter values for the pecuniary and non-pecuniary effects of distance, we can assess how they affect reduced-form estimation results. In all cases, the first and second rows show the estimated values for β_1 and β_2 in Equation 4.

The estimation results in Table 5 provide useful insights into interpreting the reduced-form estimates. First, Table 5 indicates that when the absolute value of the non-pecuniary effects of distance, γ, becomes larger, the estimated values of β_1 and β_2 become more negative and positive, respectively. Specifically, the estimated value for β_1 is 0.021 in case (i) and -0.052 in case (iii), while the estimated value for β_2 is 0.067 in case (i) and 0.128 in case (iii). Second, the table also indicates that as the absolute value of the pecuniary effect of

distance, θ, increases, the estimated values of β_2 become more positive. Specifically, the estimated value for β_2 is 0.042 in case (ii) and 0.128 in case (iii). Those effects of pecuniary and non-pecuniary effects of distance, θ and γ, can be understood from the fact that the equilibrium interest rate is determined through an English auction. That is, given that the equilibrium interest rate is determined by the equation, $r_i^* = v_{i(1)} - v_{i(2)} + \underline{r}_{i(2)}$, the marginal effects of θ and γ on the equilibrium interest rate are determined by:

$$\frac{\partial r_i^*}{\partial D_{Lend}} = \gamma \quad \text{and} \quad \frac{\partial r_i^*}{\partial D_{Rival}} = \theta - \gamma \tag{5}$$

which implies that γ has negative and positive effects on the marginal effects of D_{Lend} and D_{Rival}, respectively, while θ has positive effects on the marginal effects of D_{Rival}. Those theoretical implications are consistent with our estimation results using the simulated data in Table 4. Furthermore, the negative estimates for D_{Lend} in Table 5 are consistent with the negative effects of distance to the lending bank in the reduced-estimation, as estimated in Section 3 and in many previous studies such as Degryse and Ongena (2005). The Monte Carlo simulation here implies that, in the real economy, there are non-pecuniary effects of distance, in addition to pecuniary effects through lending costs, leading to a negative impact of distance to the lending bank on borrowing costs.

While the estimation results in Table 4 are broadly consistent with the estimation results in Section 3, it implies that there are some biases in the reduced-form estimation. Specifically, the estimation of β_1 is positively biased, whereas the estimates of β_2 are negatively biased. Given the theoretical implications in Equation (5), in case (i), for example, the estimated values of β_1 and β_2 should be centered around 0.0 and 0.1, respectively. However, the estimated values are 0.021 and 0.067, implying that the reduced-form estimates of β_1 and β_2 are positively and negatively biased, respectively. The estimation of β_1 is positively biased because distance to the lender is positively correlated with unobservable lending costs for the second-efficient bank, $\omega_{i(2)}$. Specifically, when a near bank's lending cost is high for some reason (i.e., high $\omega_{i(2)}$), firms choose a distant bank as their lender (i.e., long $d_{i(1)}$), which leads to the positive correlation between $\omega_{i(2)}$ and $d_{i(1)}$. On the other hand, the estimation of β_2 is negatively biased due probably to attenuation bias caused by the error-in-variables problem. As mentioned, we cannot identify

Table 6: Estimation Results of Structural Parameters

	Model (i)	Model (ii)
Borrower's utility		
$\gamma_{Distance}$	-0.022 (0.014)	-0.241 (0.005)
$\gamma_{Distance \times Loan}$		0.019 (0.006)
Lender's cost		
$\theta_{Distance}$	0.065 (0.005)	0.059 (0.006)
$\beta_{FirmSize}$	-0.183 (0.007)	-0.165 (0.007)
β_{ROA}	1.398 (0.009)	1.410 (0.008)
$\beta_{Liquidity}$	0.264 (0.020)	0.261 (0.020)
$\beta_{CapitalRatio}$	-0.473 (0.011)	-0.538 (0.010)
$\beta_{LongRatio}$	0.351 (0.011)	0.352 (0.011)

Note: The numbers in parentheses show the standard errors.

the second-efficient bank from our dataset. Thus, the distance to the second nearest bank is a reasonable proxy for $d_{i(2)}$ but contains some measurement errors, leading to a negative bias for the estimation of β_2.

In sum, the Monte Carlo simulation indicates that reduced-form estimation is somewhat biased and that the negative coefficient on distance to the lender can be interpreted as non-pecuniary effects of distance on a firm's perceived utility. Therefore, it implies that our structural approach to estimating structural parameters is helpful for counterfactual simulations, as it enables us to measure the true marginal effects of distance on lending costs and perceived utility, and provides some guidance for interpreting the relationship between distance and firms' borrowing costs.

5.3 Estimation Results of Structural Parameters

We estimate the parameter values using maximum likelihood, based on the likelihood function presented in the previous section. Table 6 demonstrates the estimation results for parameter values. The first and second columns, labeled Model (i) and Model (ii), present estimates without and with the interaction term between distance and loan vol-

umes in firms' perceived utility, respectively.

First and most importantly, the results indicate that the distance between borrowers and lenders affects interest rates through both borrowers' perceived utility and banks' lending costs. The first column reports positive and negative estimates for γ and θ, respectively, indicating that greater distance lowers borrowers' perceived utility while increasing banks' lending costs. Second, the estimation results suggest that the effects of distance on perceived utility are heterogeneous across firms and are particularly pronounced for firms with smaller loan sizes. Specifically, the second column shows that the interaction term between distance and loan size, $\gamma_{Distance \times Loan}$, is positive and significant. Moreover, the estimate of γ in the first column, which imposes homogeneous sensitivity to distance, is negative but imprecisely estimated with a relatively large standard error, whereas the estimate in the second column yields clearer and more precise results. These findings are consistent with the reduced-form evidence reported in Table 2. Accordingly, in the counterfactual analysis, we use the specification that allows for heterogeneous effects of distance by loan size.

The estimated values suggest that distance has an economically significant impact on interest rates. Quantitatively, the estimate in the first column of Table 6 implies that a 1 km increase in the distance to the rival branch (i.e., the second-efficient branch) raises borrowing costs by approximately 8.7 bps ($= \theta - \gamma$). In contrast, the effect of distance to the lending branch is much more moderate, estimated at -2.2 bps ($= \gamma$) for each additional kilometer.

While these distance effects are broadly and qualitatively consistent with the reduced-form estimates reported in Section 3, their quantitative magnitudes differ substantially. In particular, the reduced-form estimates imply effects of at most 1.8 bps for distance to rival branches and -0.5 bps for distance to lending branches, which are much smaller in absolute value than the corresponding estimates based on Table 6. Indeed, the Monte Carlo simulation in the previous section suggests that simple reduced-form regressions may yield attenuated estimates, as they do not explicitly account for firms' endogenous lender choice. Therefore, to assess the potential effects of bank consolidation more accurately, counterfactual simulations based on the estimated structural model are partic-

ularly informative.

5.4 Counterfactual Simulation

This section conducts a counterfactual simulation based on the estimated structural parameters reported in Table 6. Motivated by policymakers' concerns about rising borrowing costs following bank branch closures, our counterfactual analysis examines how hypothetical large-scale closures affect firms' borrowing costs by influencing the geographic distance between lenders and borrowers. Specifically, the counterfactual simulation assumes that, in each prefecture in Japan, the bank ranked second by market share in the number of borrowers (hereafter, the"second-largest bank") closes all of its branches. Following these closures, we quantify the extent to which equilibrium interest rates increase as a result of reduced competition. Although this scenario is inspired by the fact that many bank consolidations involve first-tier banks acquiring second-tier banks, we do not view it as a realistic or likely outcome in Japan. Rather, it serves as a useful benchmark for assessing the quantitative impact of bank consolidation on borrowing costs and the underlying mechanisms.

A sketch of our counterfactual analysis is as follows. First, for all firms i and their potential lenders $j \in \mathcal{J}_i$ in our sample, we draw random shocks ω_{ij} following the extreme value distribution in (2) until we obtain M draws that are consistent with the observed lender choices and interest rates in 2019. Note that, since numerous combinations of shocks can rationalize the observed lender choices and interest rates, different branches are selected as the second- and third-efficient branches across draws. Second, we select the second-largest bank in each prefecture by the number of borrowers in 2019 and assume that it closes all of its branches in the prefecture where its headquarters are located. Third, we calculate the increase in borrowing costs for firm i following the branch closures. In our model, branch closures affect the equilibrium interest rate for firm i in the following two cases. The first case is the closure of the lending branch. In this case, the firm selects the second-efficient branch as a new lender, and the third-efficient branch (or the fourth-efficient branch if the third-efficient branch is closed) becomes a new rival branch. The second case is the closure of the second-efficient branch. In this

Table 7: Changes in Borrowing Costs in Counterfactual Analysis

	Mean	Std. Dev.	Median	[0.25, 0.75]
Borrowing cost increase (%)	0.42	0.44	0.30	[0.11, 0.63]

Note: The table reports summary statistics for changes in borrowing costs in the counterfactual analysis.

case, the third-efficient branch becomes a new rival branch. The equilibrium interest rate changes in the second case, even though the lender remains unchanged, as the interest rate is determined by an English auction. The increase in borrowing costs for firm i is then defined as the average increase over all M draws.

5.4.1 Firm-level Analysis

Table 7 presents summary statistics for the estimated increase in borrowing costs in the counterfactual analysis. The table shows that the average increase in the equilibrium interest rate is 42 bps, which is economically significant given Japan's low-interest environment. While bank consolidation has many benefits, including reduced operating costs, this result suggests that it may also be associated with sizable increases in firms' borrowing costs. The table further shows that the 25th percentile is only 11 bps, whereas the 75th percentile exceeds 63 bps, highlighting substantial heterogeneity in the magnitude of the increase in borrowing costs across firms.

To examine the sources of heterogeneity in the effects across firms, we conduct the following regression analysis:

$$\Delta r_i = \beta_0 + \beta_L Cl_{Lend,i} + \sum_{j=1}^{30} \beta_{R,j} Cl_{Rival,i,j} \tag{6}$$

where Δr_i is the change in the interest rate for firm i in the counterfactual simulation, $Cl_{Lend,i}$ is a dummy variable that takes the value one if the lending branch for firm i is closed, and $Cl_{Rival,i,j}$ is a dummy variable that takes the value one if the jth nearest branch for firm i is closed. In our counterfactual analysis, the interest rate changes only if the lending branch and/or nearby rival branches close. Therefore, in the regression above, β_L and $\beta_{R,j}$ capture the average effects of closures of the lending branch and nearby rival

Table 8: Effects of Closure of Lending Branch

Dependent Var.	Model (i) Δr_i	Model (ii) Δr_i
Cl_{Lend}	0.789***	1.028***
	(0.004)	(0.014)
$Cl_{Lend}\times$ # of Rivals		-0.0153***
		(-0.0008)
N	68,345	68,329

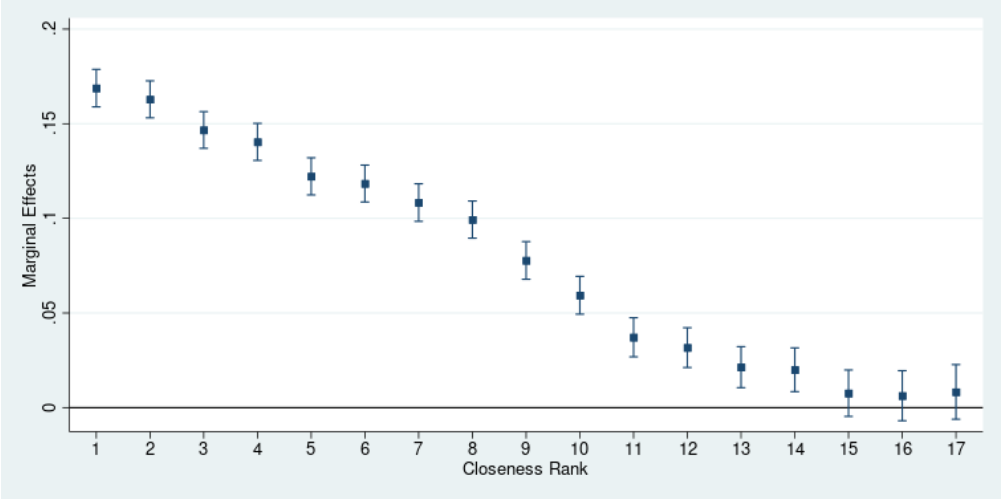
Note: The table shows the estimation results for β_L, the marginal effects of lending branches' closure, in (6). Columns (1) and (2) are the estimates in the specification without and with interaction terms. The numbers in parentheses show the standard errors. Significance levels are denoted by < 0.10 (*), < 0.05 (**), and < 0.01 (***).

branches, respectively.

Table 8 and Figure 5 show the estimation results for (6). First, Table 8 indicates that firms whose lending branches are closed would face a significant increase in borrowing costs. Specifically, the estimated value of β_L in column (1) implies that the interest rate increases by 87 bps on average when the lending branch is closed. Closures of lending branches, by definition, increase the distance to rival banks, thereby leading to higher equilibrium interest rates in our model. Furthermore, firms select their lenders based not only on distance but also on unobservable factors ω_{ij} in (2). Therefore, closures of lending branches result in the loss of lenders with favorable shocks to firm i, leading to further increases in borrowing costs.

Second, the regression analysis in (6) also implies that closures of nearby branches increase borrowing costs. Figure 5 plots the estimated values of $\beta_{R,j}$ for $j = 1, \cdots, 17$ in (6), which capture the marginal effects of closures of the jth nearest branches. The figure shows that the closure of the nearest bank branch for firm i raises its borrowing cost by 17 bps on average, and that the marginal effects decline gradually as the closed branch becomes more distant (i.e., as j increases). Since the interest rate increases in the counterfactual analysis only if the closed branch is the lending branch or the second-

Figure 5: Effects of Nearby Branches' Closures



Note: The figure plots the estimated values of $\beta_{R,j}$ for $j = 1, \cdots, 17$ in (6), which capture the marginal effects of closures of the jth nearest branches.

efficient branch, it may appear somewhat surprising that the closure of relatively distant branches still has economically significant effects on borrowing costs (for example, the closure of the 10th-nearest branch raises borrowing costs by around 6 bps). However, as shown in Figure 2, some firms choose relatively distant branches as their lending branches. Our estimates therefore allow for the possibility that such distant branches constitute the second-efficient branches for firm i as well.

For firms whose lending branch, or second-efficient branch, is closed, the magnitude of the increase in borrowing costs should depend on the availability of alternative nearby branches. We examine this hypothesis by allowing β_L to vary with measures of availability captured by the number of bank branches within a 15 km radius. Column (2) of Table 8 reports the estimation results for the interaction terms between $Cl_{Lend,i}$ and the proxy for availability. The results indicate that the availability of nearby alternative branches significantly affects the marginal effects of lending-branch closures. In particular, for each additional nearby branch, the impact of a lending-branch closure is mitigated by 1.5 bps, underscoring the importance of nearby branches as alternative lenders or rivals.[5] Figure 6 presents the histogram of Δr_i by the number of nearby bank branches.

[5]While we do not report the estimation results for the interaction terms between $\beta_{R,j}$ and the number of nearby banks, these interaction terms also have statistically significant effects on changes in borrowing

Figure 6: Borrowing Costs and Number of Nearby Banks



Note: The figure presents the histogram of Δr_i by the number of nearby bank branches.

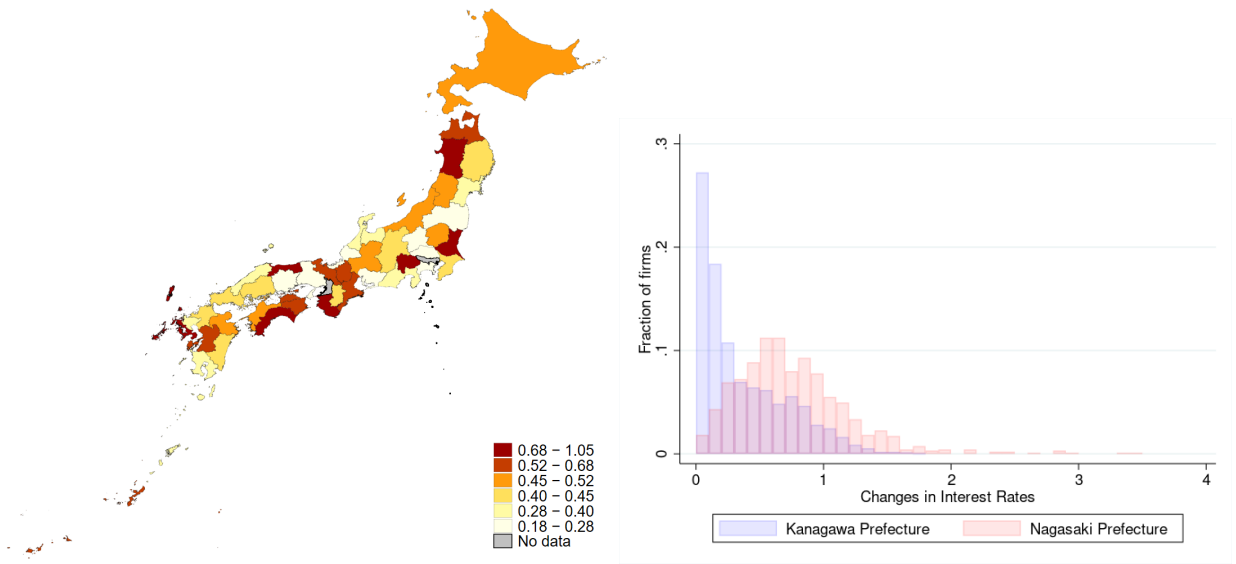
Consistent with the estimation results above, the figure indicates that the availability of nearby branches significantly affects the impact of branch closures on borrowing costs. Specifically, the magnitude of the impact is relatively large when the number of nearby branches is 10 or fewer (left panel), becomes substantially smaller when the number is between 11 and 20 (middle panel), and is quite limited when the number exceeds 20 (right panel).

5.4.2 Prefecture-level Analysis

Our counterfactual analysis assumes a common scenario across all prefectures in which the second-largest bank closes all of its branches. Nonetheless, the impact on borrowing costs varies across regions, reflecting the heterogeneous effects across firms discussed above. Indeed, the left panel of Figure 7 shows the average increase in borrowing costs by region in our counterfactual simulation, which indicates substantial heterogeneity across regions. As an example of this heterogeneity, the right panel of the figure focuses on two representative prefectures that experience large and small impacts in the counterfactual analysis and presents the histogram of Δr_i. The panel indicates that firms in Kanagawa Prefecture, which is adjacent to Tokyo and characterized by a highly competitive banking market, face much smaller increases in borrowing costs than firms in Na-

costs.

Figure 7: Changes in Borrowing Costs by Region



Note: The left panel shows the average increase in borrowing costs by region in our counterfactual simulation. The right panel focuses on two representative prefectures that experience large and small impacts in the counterfactual analysis, Kanagawa and Nagasaki, and presents the histogram of Δr_i.

gasaki Prefecture, where alternative banking options are relatively limited.

How can policymakers infer the heterogeneous effects of bank consolidation across regions? While the number of firms whose lending branches or second-efficient branches are closed can predict these effects, such information is not readily available to policymakers. Instead, we propose using the market shares of the first- and second-largest banks in each prefecture as practical predictors of the regional impact of bank consolidation. To examine this hypothesis, we run a prefecture-level regression of average changes in borrowing costs on the market shares of the first- and second-largest banks. The estimation results are as follows:

$$\Delta r_p = \beta_0 + \underset{[0.15]}{0.55} \times Share_{1,p} + \underset{[0.15]}{1.03} \times Share_{2,p} \qquad adj.R^2 = .65$$

where Δr_p is the average change in borrowing costs in prefecture p, and $Share_{1,p}$ and $Share_{2,p}$ denote the market shares of the first- and second-largest banks, respectively, measured by the number of borrowers in prefecture p. Numbers in brackets report standard errors. The results indicate that higher market shares of either the first- or second-

largest bank are associated with larger increases in borrowing costs following bank consolidation. This finding suggests that policymakers can use these readily observable concentration measures to assess and predict the regional impact of branch closures.

Why do the first- and second-largest banks' shares predict the effects of branch closures across regions? First, a higher second-largest bank's share, $Share_{2,p}$, leads to a larger impact simply because we assume that the second-largest bank closes all of its branches. That is, when the second-largest bank's share is high, its branches are more likely to be the lending branch or the second-efficient branch for firms, thereby generating larger increases in borrowing costs. Second, a higher first-largest bank's share, $Share_{1,p}$, also predicts a larger impact because it proxies the availability of nearby alternative branches. When the first-largest bank's share is high, branch closures by the second-largest bank make the regional banking market effectively monopolistic, thereby leading to larger increases in borrowing costs.

In sum, our counterfactual analysis indicates that if bank consolidation entails large-scale bank branch closures, it may substantially increase firms' borrowing costs. The analysis also shows that the impact on borrowing costs is highly heterogeneous across firms and regions, reflecting differences in the availability of nearby alternative banks. Accordingly, the share of the largest bank, in addition to the share of the bank conducting the consolidation, predicts the regional impact of branch closures. This finding suggests that policymakers can use these measures to predict, in advance, the effects of bank consolidation on regional borrowing costs.

6 Conclusion

In this paper, we examine how firms' borrowing costs are affected by geographic distance from bank branches. We develop a model where firms endogenously choose their lenders by considering loan rates determined à la Bertrand competition among banks, and estimate the structural parameters using a dataset that combines firm- and bank-level microdata from Japan. The estimation results indicate that distance affects loan pricing by influencing both banks' and borrowers' costs, and that a simple reduced-form

approach may yield biased estimates due to firms' endogenous lender choice. Counterfactual simulations indicate that the impact of bank consolidation depends on regional competitive conditions.

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