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Loan Sales and the Tyranny of Distance in U.S. Residential Mortgage Lending*

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Abstract

The distance between lenders and borrowers in the U.S. has increased considerably since the 1970s. This paper analyzes whether the use of loan sales by lenders has caused this increase. Using data on U.S. residential mortgage lending, we find that loan sales are associated with a 179% higher expected lending distance, which corresponds to an extra distance of 789.6 km (490.3 miles). We provide indirect evidence that loan sales facilitate higher lending distances because they allow lenders to compete in more remote markets by reducing their loan rates.

JEL classification: C33, C36, C55, G21, G23, R31

Keywords: Lending Distance; Remote Lending; Loan Sales; Securitization; Residential Mortgage Lending; Loan Rate Spreads; Great Recession; Multidimensional Panel Data; Instrumental Variable Analysis

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1. Introduction

Historically, lending in the U.S. was predominantly a local trade, where households and firms used to depend on their local lenders for credit. The dependence on local lenders was a result of their close proximity of these lenders to their clientele, which meant obtaining and verifying good-quality information took little effort. The resulting information advantage in relation to remote lenders allowed local lenders to offer favorable loan contracts, and carve out a local lending market (Agarwal and Hauswald, 2010; Petersen and Rajan, 2002). Remote lending was not attractive, since there were always local lenders offering more competitive loan contracts.

Empirical evidence suggests that the dependence on local lenders, known as the *tyranny of distance*, is diminishing in the U.S. That is, several studies have found that the distances between lenders and borrowers (referred to as lending distances) have been increasing over time. Best documented is the increase in small business lending since 1978 (Adams et al., 2020; Brevoort and Hannan, 2006; Brevoort et al., 2010; Brevoort and Wolken, 2008; DeYoung et al., 2008a; DeYoung et al., 2011; DeYoung et al., 2008b; Granja et al., 2019; Petersen and Rajan, 2002). The estimates vary from an increase of 25.1 km (15.6 miles) (DeYoung et al., 2008b, p. 125) to an increase of 281.6 km (175 miles) (Granja et al., 2019, p. 3).

The theoretical study of Frankel and Jin (2015) provides a possible explanation for the reduced importance of the tyranny of distance in the U.S. as observed in the aforementioned literature. Their main prediction is that remote lenders use loan sales to reduce their loan rates, which allows them to enter the local loan market. As a result, their lending distances increase.

This study provides an empirical test of one of the implications of Frankel and Jin (2015) by assessing whether U.S. lenders use loan sales to lend at greater distances. Loan sales refer to the sale of a (part of a) single loan or a pool of loans by writing a new claim that is linked to the loan or loan pool (Gorton and Metrick, 2013). Such sales are potentially attractive to financial institutions who want to transfer risk, but lack specialized expertise about securitization. To our best knowledge, we are the first to empirically test this implication of Frankel and Jin (2015).

Our empirical test uses data on U.S. residential mortgage lending from the Home Mortgage Disclosure Act's Loan Application Register (HMDA LAR) and various other data sources between 2004 and 2019. The mean lending distance in this sample is approximately 440.3 km (273.7 miles), which corresponds to about 235 minutes of travel time on a U.S. interstate. More than half of the loans in our sample are originated by local lenders.

The first part of our empirical analysis tests the hypothesis that loan sales increase lending distance by regressing log lending distances on a loan sales indicator and various control variables. We control for possible endogeneity of loans sales by means of instrumental variable techniques. We find that the expected lending distance of loans sold is approximately 179% higher than for loans that were not sold, which corresponds to an extra distance of 789.6 km (490.3 miles). The effect of loan sales on lending distance seems mostly driven by loan sales to private parties and securitization. Loan sales to government-sponsored entities are not associated with higher expected lending distances.

The second part of our empirical analysis provides evidence for the underlying mechanism that Frankel and Jin (2015) describe. They conjecture that loan sales allow remote lenders to reduce their loan rates by an amount that is sufficient to offer competitive loan offers in local markets. We regress loan rate spreads on indicators for loan sales and remote lenders, as well as their interaction and several additional control variables. We confirm that loan sales allow remote lenders to reduce their loan rates, which is consistent with the above conjecture of Frankel and Jin (2015). Loans sold by remote lenders have expected loan rates 28 basis points lower than loans held by remote lenders.

The remainder of this study is as follows. Section 2 reviews relevant literature and formulates testable hypotheses. Next, section 3 and 4 presents the data and method, respectively. Section 5 discusses our main results, after which section 6 offers some robustness checks. Section 7 concludes.

2. Literature review and hypotheses

This section reviews the relevant literature. First, we discuss the advantages of the close proximity of lenders to borrowers. Second, we review the effect of technological change on lending distance in U.S. banking markets. Third, we discuss Frankel and Jin (2015) and formulate the hypotheses that will be tested in our empirical analysis.

2.1. Lender proximity

The close proximity of a lender to a borrower is beneficial for lenders as well as for their borrowers. Lender proximity reduces information costs for lenders, and transportation costs for both lenders and borrowers (Brevoort and Wolken, 2008). Information costs include all costs lenders make to obtain, verify and store information about their customers. Transportation costs include all costs lenders or borrowers incur for conducting business in person. Because both costs are difficult to measure, empirical studies often rely on

indirect evidence.

Various empirical papers present evidence that local lenders have an information advantage. Using data on small business lending in the U.S., Agarwal and Hauswald (2010) find that nearby firms are more likely to be offered credit, and that loan rates decrease in the lender's proprietary credit assessment of firms. At the same time, firms located close to a (local) lender pay higher loan rates. In addition, firms located farther away from the local lender are more likely to switch lender when they have higher credit scores, or pay higher loan rates. The authors argue that, because these firms are primary targets for rent extraction, carving out a local market fails at the periphery due to diminishing information quality. As a consequence, competitors compete more aggressively at the periphery of the local market, resulting in more firms switching. Conversely, local lenders do not face much competition at the core of their market, allowing them to extract higher rents from their borrowers. Using data on syndicated lending in the U.S., Knyazeva and Knyazeva (2012) find that loans to remote borrowers have higher interest rate spreads than loans to local borrowers. The authors argue that local lending is associated with lower information costs than remote lending. And since large firms can switch lenders more easily than small firms, local lenders cannot use their market power to extract higher rents. As a result, and contrary to small business lending, a local information advantage translates to lower loan rates for large firms. Last, Hollander and Verriest (2016) show that contracts for remote borrowers include more and tighter loan covenants. Since covenants facilitate information collection, the authors argue that it is more difficult for lenders to obtain information on remote borrowers. Lenders do not require loans to local borrowers to include more and tighter loan covenants, since lenders have sufficient information on these borrowers, which is consistent with a local information advantage.

Other papers find empirical evidence that distance increase transportation costs. Using data on Belgian small business lending, Degryse and Ongena (2005) show that loan rates decrease with the distance between a firm and its lender. At the same time, increasing distance between a firm and alternative lenders significantly relaxes price competitions. As a result, borrowers have to travel further to an alternative lender. The lender knows this, and increases their loan prices. Bellucci et al. (2019) show using data on Italian small business lending that lenders require more collateral for local borrowers. Their findings are consistent with theory predicting that collateral requires frequent monitoring, which means that transportation costs increase in distance.

2.2. Lending distance and technological change

Petersen and Rajan (2002) show that lending distances in U.S. small business lending steadily grew between 1973 and 1993. This finding cannot be explained by a change in the number of branches per lender or by changes in credit standards and is therefore attributed to technological innovation. Innovation allows lenders to collect, store, and distribute more and different information. As a result, the nature of lending changes from strict ex ante screening, and costly ex post monitoring, to a continuous monitoring process in which quick intervention is possible. In other words, technological innovation reduce the information costs of lenders. Technology innovation also makes the collection of hard information at a distance easier, easing the ability to lend at a distance.¹

The findings of Petersen and Rajan (2002) have been corroborated and refined by various other studies. DeYoung et al. (2008a), DeYoung et al. (2011), and DeYoung et al. (2008b) show that credit score models and automated lending have facilitated lending at greater distances. Brevoort and Hannan (2006) and Brevoort et al. (2010) find that technological innovation only had an effect on remote lending. According to Brevoort and Wolken (2008), median lending distances have barely increased, while Adams et al. (2020) finds that the increase in mean lending distances is mostly due to a small group of high-volume, small loan lenders. Similar results have been found for markets other than the U.S. For instance, Felici and Pagnini (2008) focuses on Italian small business lending and find that technological innovations have enabled lenders to open branches in distant markets.

2.3. Testable hypotheses

Frankel and Jin (2015) focus on securitization and remote lending.² Since they model securitization as loan sales, we formulate our hypotheses in terms of loan sales. In contrast to technological innovation, loan sales do not reduce information costs but transfer them to a third party.

The theoretical model of Frankel and Jin (2015) specifies how loan sales allow lenders to lend at greater distances. They consider a local and a remote lender, who compete for loans in the local market. The local

¹Hard information is easily reduced to numbers, which means that it can be collected, stored, and transmitted efficiently and electronically (Liberti and Petersen, 2019). The quantitative nature of hard information makes its collection easy to automate and standardize, introducing greater economies of scale.

²Securitization refers to the process of selling pools of legally segregated, specified, cash flows to a special purpose vehicle (SPV), which issues securities whose principal and interest payments are exclusively linked to these pools (Gorton and Metrick, 2013).

lender serves its own local loan market. The remote lender lends at some distance outside the local market. The local lender enjoys an informational advantage in its local market since it observes an applicant's real profitability (or creditworthiness), where the remote lender only observes an applicant's credit score, which is an imperfect representation of an applicant's profitability.

Without the possibility of loan sales, the local lender always outbids the remote lender. The local lender offers all profitable applicants a competitive loan rate, which is slightly lower than the loan rate of the remote lender, and does not serve the unprofitable applicants. Because the remote lender knows the local lender will serve all profitable applicants, it decides not to make any offers. Consequently, without the possibility of loan sales a local market is characterized by the tyranny of distance.

If local and remote lenders can sell their loans, ignorance is bliss for the remote lender. Since the local lender observes the profitability of the applicants, it has the incentive to sell only the unprofitable applicants. Investors know this and do not buy the local lender's securities unless the local lender signals asset quality, which is costly. Because the remote lender does not exactly know the profitability of the applicants, it sells all its loans, which it is able to do without costly signaling. Thanks to the possibility of loan sales, the remote lender does not need to hold these loans on its balance sheet and therefore does not need to provide the same level of scrutiny.³ As a result, remote lenders can reduce their loan rates and start competing for local loans.

In sum, the model of Frankel and Jin (2015) predicts that remote lenders use loan sales to enter the local market and to start lending. As a result, the lending distances of remote lenders increase.

We use Frankel and Jin (2015) to formulate our main hypothesis, stating that:

Hypothesis 1 (H1) *Loan sales allow lenders to lend at greater geographical distances.*

Our second hypothesis relates to the underlying mechanism described by Frankel and Jin (2015), which conjectures that remote lenders are able to enter local markets because loan sales allow them to substantially reduce their loan rates. This leads to our second hypothesis:

Hypothesis 2 (H2) *Loan sales allow remote lenders to offer applicants more favorable loan rates.*

3. Data

We obtain our data from multiple sources. For all loan-level information we use the data from the Home Mortgage Disclosure Act's Loan Application Register (HMDA LAR) between 2004 and 2019. Our sample

³This prediction of declining lending standards is consistent with the findings of Agarwal et al. (2012), Beltran et al. (2017), Berndt and Gupta (2009), Dell'ariccia et al. (2012), Elul (2016), Jiang et al. (2014), Keys et al. (2010), Maddaloni and Peydró (2011), Mian and Sufi (2009), and Purnanandam (2011).

starts in 2004 due to a number of important changes have been made to the reporting requirements in 2004 (cf. Avery et al., 2007). For all information about FDIC-insured financial institutions and their branches, we use the Statistics on Depository Institutions (SDI) and the Summary of Deposits (SOD), respectively, from the Federal Deposit Insurance Corporation (FDIC). For other county-level information we use data from the US Census Bureau and the National Bureau of Economic Research (NBER). We only include FDIC-insured thrifts and banks. See Table A1 for a overview of which data sources are used for which variables.

Home Mortgage Disclosure Act Data The HMDA requires all eligible financial institutions in the U.S. to maintain, report, and publicly disclose loan-level information about their residential mortgage lending activities.⁴ The data provide information about how lenders are serving the housing needs of U.S. residents (Bhutta et al., 2017), and cover approximately 90% of all originated mortgages in the U.S. (Dell’ariccia et al., 2012). The data contain extensive coverage on sold and held mortgages, and has yearly frequency.⁵ From 2018 onward, the HMDA includes more detailed loan-level information such as loan-to-value ratios, loan terms, and rate spreads. We exploit this information in our analysis, see section 4.2.

Following Bikker et al. (2012), Ho and Ishii (2011), and Müller and Noth (2018), we define a banking market to be a metropolitan statistical area (MSA) or a metropolitan division (MD), which is a subdivision of an MSA.⁶ Since the HMDA coverage of rural counties is sparse, we cannot ensure continuous data coverage, and exclude all loans originated outside of MSAs and MDs. We include only originated loans with the purpose of home purchase. We remove all loans from non-U.S. states or unknown counties and MSAs, and remove all loans with applicants with zero or negative incomes. Next, we remove loans with outliers or missing values in the variables for loan amount, applicant income, and employees, respectively. Last, using the HMDA lender file (a.k.a. ‘the Avery file’, cf. Bhutta et al. (2017)) we match the HMDA data with the other sources of data.

⁴An institution reports to the HMDA if 1) it is a bank, credit union, or savings association, 2) its total assets exceed the coverage threshold (\$39 million in 2010), 3) it has a home or branch in an MSA, and 4) it has originated at least one residential loan secured by a first lien on a one-to-four-family dwelling.

⁵There are similar data available on small business lending in the U.S. supplied by the FFIEC in accordance with the Community Reinvestment Act (CRA). These data are intensely studied by the literature, but do not include information on whether loans are sold or securitized. Because of this, we use the HMDA LAR instead.

⁶An MSA is defined by the US Census Bureau as an area containing a core area with a substantial population nucleus (> 50.000 inhabitants), and adjacent communities that have a high degree of economic and social integration with the core. MSAs with a core population of at least 2.5 million can contain Metropolitan Divisions (MDs), which consists of one or more counties that represent an employment center, plus adjacent counties.

The HMDA data provide detailed information about residential mortgage origination in the U.S., but is not without limitations. All mortgage-originating organizations that fall below a certain threshold are not in the data. Even though these organizations originate only a small fraction of the mortgages, they might play an important role in local markets. Moreover, we do not observe the date of origination, the exact location of the borrower and lending branch, and borrower's credit score. And before 2018 we do not observe the value of collateral, and the interest rate spread. We overcome most of these limitations by combining the HMDA data with data from other sources about lenders. In addition, we cannot track the loans through time. As a result, we miss loans sold in a year that it is not their origination year. Loans originated in a specific year and sold in the next year are tagged as *not sold* in the HMDA data. This measurement error, or attenuation bias, might lead to an underestimation of the effects of loan sales on lending distance. Avery et al. (2007) acknowledge this problem, but argue that this bias is likely to be small. Many end-of-year applications, the argument goes, are carried over into the following reporting year. As a result, end-of-year applications are low and start-of-year applications are high. For most lenders, the difference in the number of applications will balance out. For this reason, we do not correct for attenuation.

Last, the HMDA LAR lacks the detail to construct county-level competition measures like the Lerner index. For this reason we cannot directly test Frankel and Jin's conjecture that a reduction in loan rates due to loan sales increases competition in the local market, which increases lending distances. We can, however, indirectly test this conjecture by estimating the effect of loan sales on distance and loan rates, respectively.

Statistics on Depository Institutions and Summary of Deposits The SDI contain information about income statement, balance sheet, and off-balance sheet items for all FDIC-insured institutions. The SOD is a mid-year, annual survey of branch offices for FDIC-insured institutions, of which we only use location information of the branches. We match both datasets with the HMDA data on FDIC-certificate number, and exclude all institutions with missing or zero values for total assets, and number of employees.

Other County-level Data We use the Centers of Population from the US Census Bureau to get the population-weighted geographic centers of all U.S. counties. In addition, we use the NBER County Distance Database to get the unweighted geographic centers of all U.S. counties, which we use as robustness test. Last, we use data about the types of internet in households from the U.S. Census Bureau, which we also use in our robustness checks.

3.1. Variable Description

In this subsection we describe how we construct our main variables of interest: lending distance, and loan sales. See table A1 for an overview of the construction of all variables.

3.1.1. Lending Distance

The variable for lending distance measures the straight-line distance in kilometers between a mortgage borrower and a mortgage lender. Suppose lender i lends to borrower j in county c via its branch b . We observe in which county the borrower resides, we observe the resident county of all branches of each lender, and we observe from which lender borrower j borrows. We do not, however, observe from which branch of lender i borrower j borrows.

Following Brevoort and Hannan (2006) and Ho and Ishii (2011), we assume that borrower j borrows from the closest branch of lender i . For each borrower-lender pair $\{ij\}$ we can calculate the minimum distance between borrower j and branch b of lender i . Then, for some distance operator $d(\cdot)$ the minimum distance for borrower-lender pair $\{ij\}$ is:

$$Distance_{ij} = \arg \min_b d(L_j, L_b^{(i)}), \quad b = 1, 2, \dots, B,$$

where $Distance_{ij}$ is the minimum distance for borrower-lender pair $\{ij\}$, L_j is the location of borrower j , and $L_b^{(i)}$ is the location of branch b of lender i . For $d(\cdot)$ we use a haversine formula, where the geographic location is measured by the respective latitude and longitude. We calculate the distance for all originated loans.

The locations of the borrower and branches are at the county-level. For each county, we assign population-weighted latitudes and longitudes from the US Census Bureau, which we use in all our methods. As a robustness check, we use the NBER County Distance Database, which is based on the centroids of U.S. counties by the US Census Bureau, and is not corrected for population density.

3.1.2. Loan Sales

Frankel and Jin (2015) essentially model securitization by allowing lenders to transfer loans off their balance sheets. Such a mechanism is identical to the mechanism of loan sales. The main difference between secu-

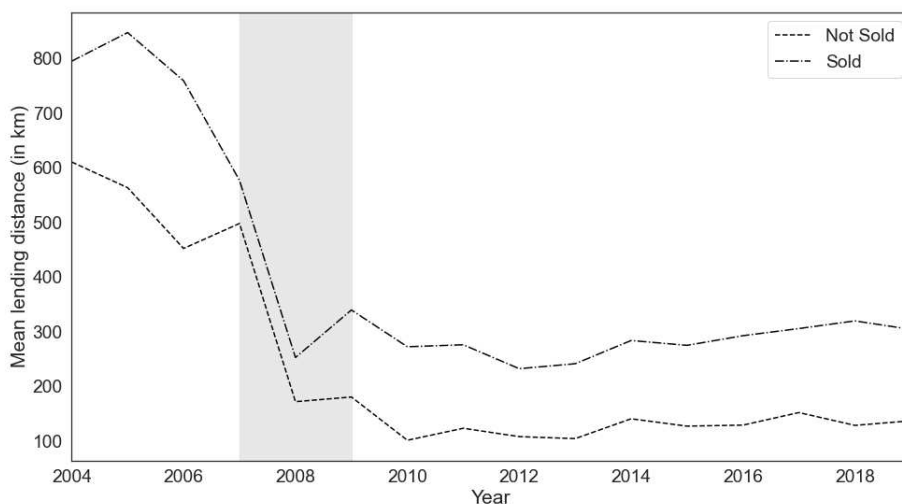
ritization and loan sales is that securitization alters the patterns of cash flows, and converts the loan pools into marketable securities (Greenbaum et al., 2019). These asset transformations, however, mainly affect the marketability of the underlying assets, and not so much the risk transferring capability of securitization. Because we are not interested in the marketability of securitization *vis-à-vis* loan sales, we consider both in our study. A practical benefit of loan sales is that it requires much less know-how than securitization.

For each loan in the HMDA data we observe whether the loan is sold to a GSE, sold to a third party, sold to a SPV (private securitization), or not sold by the lender. The variable *Loan Sales* equals one when a loan is sold or securitized and zero otherwise.

3.2. Summary Statistics

Figure 1 plots the mean lending distance through time. Prior to the Great Recession of 2007–2009, mean lending distances reached over 800 km (497.1 miles) for sold loans. Between 2007 and 2009 the U.S. housing bubble burst, and mean lending distances fell by more than half, indicating lending distances are pro-cyclical (see Granja et al. (2019)). Since 2009 lending distances have recovered slightly. Across all years sold loans have a higher mean distance than loans held on-balance sheet, which is consistent with our hypothesis H1.

Figure 1: Mean Distance Through Time



Notes. The figure plots the distance between lender and applicant for all loan originations between the years 2004–2019. The shaded area are the years during the GFC (2007–2009). Before the Great Recession (2007–2009) the mean lending distance was about 800 km (497.1 miles). Since the Great Recession mean lending distances have fallen to around 300 km (186.4 miles). Across all years sold loans have a higher mean distance than held loans.

Tables 1 and 2 presents the summary statistics of the full sample (2004–2019) and of the years 2018–2019. The full sample includes more than 28 million loan originations across 1,230 counties (FIPS), which are made by 5,874 lenders. Most of the originations in our sample are made by thrifts (approximately 79%).

Table 1: Summary Statistics Full Sample

	Mean	50%	S.E.
Distance Variables			
Distance (pop. weighted; log)	2.7748	0.0000	3.1931
Distance (CDD; log)	2.7854	0.0000	3.1952
Distance (pop. weighted; km)	440.257	0.0000	845.8528
Distance (CDD; km)	439.7295	0.0000	843.6009
Remote	0.3657	0.0000	0.4816
Loan Sales Variables			
Sold	0.7049	1.0000	0.4561
Sold to GSE	0.3822	0.0000	0.4859
Sold to private	0.2942	0.0000	0.4557
Securitized	0.0285	0.0000	0.1663
Loan Control Variables			
LTI	1.1302	1.1921	0.4138
Loan Value (log)	5.1171	5.1591	0.8447
Income (log)	4.4782	4.4188	0.7236
Subprime	0.1502	0.0000	0.3572
Lien	0.9208	1.0000	0.2700
Owner Occ.	0.8706	1.0000	0.3356
Co-applicant	0.47	0.0000	0.4991
Lender Control Variables			
Size (log)	17.4474	17.7495	2.7928
Employees (log)	8.7879	8.4822	2.5840
Branches (log)	4.7907	5.0039	2.9377
Bank	0.2088	0.0000	0.4065
Observations	28096497		
FIPS	1230		
MSA	436		
Lender	5874		
Years	16		

Notes. Summary statistics of the full sample. Mean, %50, and S.E. stand for the mean, median and standard deviation, respectively. FIPS stands for Federal Information Processing Standard, which is a five-digit code that uniquely identifies counties. For a description of all variables see subsection 3.1 and Table A1.

The log mean population-weighted lending distance of originated loans is 2.77, which translates to approximately 440.3 km (273.7). On a US interstate, 440.3 km corresponds to about 235 minutes of travel time at 113 kph (70 mph). For more than 60% of the originated loans, however, the lender and borrower are in the same county, indicating a still strong reliance on local lenders. The non-population-weighted lending distance is almost identical to the population-weighted distance. Moreover, in total roughly 70% of originated loans are sold, of which only a small part are securitized. Most loans are sold to government-sponsored entities.

Table 2: Summary Statistics 2018–2019

	Mean	50%	S.E.
Rate Spread	0.3798	0.2640	0.7426
LTV	0.8287	0.8452	0.1676
IO	0.0509	0.0000	0.2199
Balloon	0.01	0.0000	0.0997
MAT	0.9031	1.0000	0.2958
Loan Term	343.8796	360.0000	54.0418
Observations	2112561		
FIPS	1197		
MSA	409		
Lender	1144		
Years	2		

Notes. Summary statistics of the variables starting in 2018. Mean, %50, and S.E. stand for the mean, median and standard deviation, respectively. FIPS stands for Federal Information Processing Standard, which is a five-digit code that uniquely identifies counties. For a description of all variables see subsection 3.1 and Table A1.

4. Model Specification

4.1. Benchmark Model

In our benchmark model we focus on whether loan sales explain the increase in lending distance (hypothesis H1). For each loan application we observe the lender i , applicant j , county c of applicant j , and msa m of which county c is part at time t . As mentioned in section 3, we do not follow applicants through time. To save on notation, we drop subscript j . We estimate the effect of loan sales on lending distance:

$$\ln(\text{Distance}_{icmt}) = \beta LS_{icmt} + X_{icmt}\gamma + \alpha_i + \rho_c + \delta_{mt} + u_{icmt}, \quad (1)$$

where LS_{icmt} equals one when the loan is sold in the same year and zero otherwise, and X_{icmt} is a vector of control variables (see Table 3). β captures the effects of loan sales on the log lending distance. Following hypothesis H1 we expect β to be positive and significant.

LS_{icmt} in equation (1) is potentially endogenous. We therefore instrument LS_{icmt} with a measure for loan sales market depth. For some lender i , the measure of market depth captures the percentage of loans sold by all other lenders than lender i in county c :

$$MD_{icmt} = \sum_{l=1, l \neq i}^{i-1} \frac{LS_{lcm t}}{\text{Originated}_{lcm t}},$$

where MD_{icmt} captures the county-level yearly loan sales market depth, and $\sum_{l=1, l \neq i}^{i-1} \text{Originated}_{lcm t}$ are all

loans originated in county c at time t by all lenders other than i .⁷ When many lenders other than lender i sell their loans in county c , the market is deep, and investors have appetite for these loans. As a result, it is attractive for lender i to also sell loans originated in county c . This measure for market depth has no direct effect on the lending distance of lender i . Moreover, this instrument varies for each lender i , but does not depend on the lending distances of lender i . We believe this instrument is exogenous.

We include lender, α_i , and county, ρ_c , and MSA-year fixed effects, δ_{mt} . Lender fixed effects control for unobserved lender heterogeneity, and county fixed effects control for heterogeneity among counties. The MSA-year fixed effects absorb all market-wide time-specific effects. We include MSA-year fixed effects since each banking market is likely to have its own time trend. We do not include applicant fixed effect, since cannot follow applicants through time. Furthermore, we cluster the standard errors on the MSA-level. We estimate the model using a 2SLS within estimator (i.e. Fixed Effects 2SLS; Wooldridge (2010, pp. 353–358)) on the entire data set, spanning the years 2004 through 2019, and on the period after the Great Recession in order to check whether the relationship between distance and loan sales has changed since 2010. In the first stage we regress LS_{icmt} on MD_{icmt} and X_{icmt} , and obtain the fitted values $\hat{L}S_{icmt}$. In the second stage we plug in $\hat{L}S_{icmt}$ in equation (1) to obtain an estimate for β .

4.2. Rate Spread Model

In our rate spread model we focus on our second hypothesis, H2, which explains the mechanism why loan sales enable increasing lending distances. As dependent variable we use loan rate spreads, which are calculated as the difference between a loan’s annual percentage rate and the average prime offer rate for a comparable transaction as of the date on which the interest rate is set. We regress rate spread on loan sales, LS_{icmt} , whether a loan is originated by a remote bank, $Remote_{it}$, an interaction term $LS_{icmt} \times Remote_{it}$ and a vector of control variables, X_{icmt} (see Table 4):

$$RateSpread_{icmt} = \beta_1 LS_{icmt} + \beta_2 Remote_{it} + \beta_3 LS_{icmt} \times Remote_{it} + X_{icmt}\gamma + \alpha_i + \rho_c + u_{icmt}. \quad (2)$$

β_1 captures the effect of loan sales of local banks on the rate spread, and β_2 the effect of a loan made by a remote lender on the rate spread. Following the predictions by Frankel and Jin (2015) (see section 2.3) we expect these to be negative and positive, respectively. β_3 measures the marginal effect of loan sales of remote

⁷Altunbas et al. (2019) uses similar instrumental variables.

banks on the rate spread, and is our variable of interest. We expect this coefficient to be negative, indicating that remote lenders use loan sales to reduce their loan rates. As in our benchmark model, LS_{icmt} in equation (2) is potentially endogenous. Since we believe our loan sales market depth instrument is also exogenous in this model, we use it to instrument LS_{icmt} and $LS_{icmt} \times Remote_{it}$. In the first stage we regress LS_{icmt} and $LS_{icmt} \times Remote_{it}$, respectively, on MD_{icmt} , $MD_{icmt} \times Remote_{it}$, and X_{icmt} , and obtain the fitted values \hat{LS}_{icmt} and $\hat{LS}_{icmt} \times Remote_{it}$. In the second stage we plug in the fitted values to obtain estimates for β_2 and β_3 . We estimate the model on the years 2018 and 2019, and 2018 and 2019 separately, and include lender and county fixed effects. Furthermore, we cluster the standard errors on the MSA-level. Since there are only two years, we do not include MSA-year fixed effects.

Table 3: Control Variables for the Benchmark Model

Variable	Exp. Sign	Explanation	Source
Loan Control Variables			
LTI	-	Due to information asymmetries, risky loans are less likely to be originated at greater distances.	DeYoung et al. (2011)
Loan Value	+	The greater the loan value, the greater the probability that a lender will lend at a distance.	Berger et al. (2005)
Income	+	Higher income signals lower credit risk, and hence the higher the income, the greater the lending distance.	DeYoung et al. (2008b) and Loutskina and Strahan (2011)
Subprime	-	Captures loans with excess loan rates, lenders are more likely to charge higher loan rates at greater distances.	Agarwal and Hauswald (2010) and Purnanandam (2011)
First Lien	+	Captures loans with high-quality collateral	Demyanyk and Loutskina (2016)
Co-applicant	+	Captures the lower risk of loan applications with a co-applicant	
Lender Control Variables			
Size	+	The more intense use of hard information makes large lender's lending technology less distance dependent.	Berger et al. (2005)
Employees	-	Is a proxy for personal communication. The more employees a lender has, the more personal contact is possible.	Petersen and Rajan (2002)
Branches	-	Captures the geographical reach of a lender. The more branches a lender has, the more likely it is to have a branch relatively close to the lender.	Berger et al. (2005)
Bank	-	Banks are often more closely located to their borrowers than non-banks.	Petersen and Rajan (2002)

Notes. The table contains all control variables for the benchmark model, including the expected sign (Exp. Sign) of the coefficients, a brief explanation, and, where possible, the source. See appendix ?? for the variable construction.

5. Empirical Results

Table 5 displays the results of our benchmark model. Columns (1) and (2) contain the estimates of the first stage. The estimated coefficients of our instrument are significant and positive (respective t-values: 30.7 and 26.2), indicating our instrument is strong. In the second stage we find a positive and significant estimate

Table 4: Control Variables for the Rate Spread Model

Variable	Exp. Sign	Explanation	Source
LTV	+	Lenders charge higher interest rates on risky loans	Antinolfi et al. (2016) and Justiniano et al. (2017)
LTI	+	Lenders charge higher interest rates on risky borrowers	DeYoung et al. (2011)
Loan Value	+	Large loans are riskier for the lender	Antinolfi et al. (2016) and Justiniano et al. (2017)
Income	-	Higher income signals less risky borrowers	DeYoung et al. (2008b) and Loutskina and Strahan (2011)
Interest Only (IO)	-	Interest-only loans often require lower interest rates	Justiniano et al. (2017)
Balloon Payment	-	Loans with a balloon payment require lower interest rates	Justiniano et al. (2017)
MAT	+	Loans with a long maturity have higher interest rates	Antinolfi et al. (2016)
First Lien	-	First lien loans are less risky and have lower interest rates	Antinolfi et al. (2016) and Justiniano et al. (2017)

Notes. The table contains all control variables for the rate spread model, including the expected sign (Exp. Sign) of the coefficients, a brief explanation, and, where possible, the source. See appendix ?? for the variable construction.

for loan sales of approximately 1.03 in the full sample, which means that loans sold in the full sample are associated with a 179% higher expected distance than loans not sold.⁸ 179% corresponds to 789.6 km (490.3 miles) of extra distance. In the post-Great Recession Sample, we find a significant estimated coefficient for loan sales at the 10%-level, indicating that the relationship between loan sales and lending distance has changed since the Great Recession. These results show that loan sales allow lending at greater distances over the entire sample, and are therefore consistent with hypothesis H1. After the Great Recession, this relationship seems to somewhat disappear.

Most estimated coefficients of the control variables have the expected sign. Subprime, lien, size, and number of employees, however, do not have the expected sign. The positive coefficients for subprime most likely capture the fact that remote loans more often have excess loan rate spreads. Lien is negative in the full sample, suggesting loans with better quality collateral are made at lower distances. This signals that local banks' information advantage allows them to 'steal' these loans from remote banks, and is consistent with the findings of Bellucci et al. (2019). Size is negative, which indicates that large banks originate at shorter distances. These findings correspond with the fact that many large banks have more branches. Last, employees is positive, meaning that the variable captures the size of the lender. In that case, an increase in employees is not a proxy for personal communication, but a proxy for lender size.

Table 6 displays the second-stage estimates of the rate spread model. For all first-stage regressions we find our instruments are strong ($F > 10$; see Appendix B), meaning the finite-sample bias of the 2SLS-estimator

⁸ $\exp(1.0273) - 1 \approx 179\%$.

Table 5: Robustness Results IV Benchmark Model

	(1)	First Stage (2)	(3)	Second Stage (4)
MD	0.888 (0.0000)	0.8411 (0.0000)		
$\hat{L}S$			1.0273 (0.0254)	0.6732 (0.0553)
LTI	-0.2183 (0.0000)	-0.1586 (0.0000)	0.0645 (0.6420)	0.1349 (0.3747)
Loan Value	0.1245 (0.0000)	0.0798 (0.0000)	0.0611 (0.3727)	-0.0285 (0.6596)
Income	-0.202 (0.0000)	-0.1868 (0.0000)	0.1033 (0.3254)	0.2148 (0.0308)
Subprime	-0.0094 (0.1368)	-0.0277 (0.0001)	0.4035 (0.0000)	0.1587 (0.0000)
Lien	0.2698 (0.0000)	0.3336 (0.0000)	-0.6494 (0.0000)	-0.1721 (0.3256)
Co-applicant	0.0121 (0.0000)	0.0209 (0.0000)	-0.1031 (0.0000)	-0.081 (0.0000)
Size	-0.0505 (0.0000)	-0.0874 (0.0000)	-0.2045 (0.1932)	-0.8055 (0.0000)
Employees	0.095 (0.0000)	0.15 (0.0000)	0.8596 (0.0000)	1.426 (0.0000)
Branches	-0.034 (0.0000)	-0.0433 (0.0000)	-0.8835 (0.0000)	-0.7714 (0.0000)
Bank	-0.0281 (0.0616)	0.0434 (0.0127)	-1.6086 (0.0000)	-0.8648 (0.0000)
Observations	28096474	12734912	28096474	12734912
Adj. R^2	0.1216	0.1952	0.217	0.0909
DHW p-val			0.1405	0.1245
FE	MSA-year, FIPS & Lender	MSA-year, FIPS & Lender	MSA-year, FIPS & Lender	MSA-year, FIPS & Lender

Notes. Instrumental Variable Benchmark Model results. The model is estimated with a 2SLS within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Distance. The instrument for LS is the depth of the loan sales market. P-value in parentheses. LTI = loan-to-income ratio. Columns (1)–(2) display the first stage results and column (3)–(4) the second stage results. The model is estimated on the full sample (columns (1) and (3)) and the post-2009 sample (columns (2) and (4)).

is relatively small. Consistent with hypothesis H2 we find a negative and significant estimate for β_3 . β_3 implies that loans sold by remote lenders have 28 basis points lower expected loan rates than loans held by remote lenders. The reduction is considerable, given that the total effect ($\beta_2 + \beta_3$) is -0.046 in 2018-2019. Without loan sales, remote lenders offer significantly higher loan rates (β_2). These estimates are consistent with the predictions of Frankel and Jin (2015). However, we do not directly test this channel. An alternative explanation is that monitoring and servicing remote loans is very costly. The ability to sell these loans, then, reduces lending costs for the remote lender, allowing it to offer more competitive rates. In either case, lower expected loan rates might lead to an increase in competition, which leads to an increase in lending distance. Since we find a positive relationship between loan sales and distance, and a negative one between loan sales by remote lenders and loan rates, our results are consistent with this channel.

We find also find that loan sold by local lenders (β_1) are associated with higher rate spreads. Since higher rate spreads often indicate higher-risk loans, these results are consistent with the prediction by Frankel and Jin (2015) that local lenders sell their unprofitable loans. Additionally, the similarity of the estimated coefficients in all three columns indicate that the omission of MSA-time fixed effects has no significant impact on the estimates in the 2018–2019 sample.

Table 6: Estimation Results Rate Spread IV Model: Second Stage

	(2018–2019)	(2018)	(2019)
$\hat{L}S$ (β_1)	0.2775 (0.0169)	0.3131 (0.0219)	0.2844 (0.0085)
Remote (β_2)	0.2279 (0.0009)	0.1943 (0.0052)	0.2418 (0.0030)
Remote X $\hat{L}S$ (β_3)	-0.2739 (0.0041)	-0.2314 (0.0191)	-0.2877 (0.0097)
LTI	-0.9106 (0.0000)	-0.7381 (0.0000)	-1.159 (0.0000)
LTV	0.7754 (0.0000)	0.764 (0.0000)	0.798 (0.0000)
Loan Value	0.3001 (0.0000)	0.2134 (0.0038)	0.4402 (0.0000)
Income	-0.5351 (0.0000)	-0.4142 (0.0000)	-0.6995 (0.0000)
IO	0.2739 (0.0000)	0.2248 (0.0001)	0.3335 (0.0000)
Balloon	0.2173 (0.0571)	0.1382 (0.2516)	0.3223 (0.0067)
MAT	-0.1487 (0.0000)	-0.1452 (0.0000)	-0.1563 (0.0000)
Lien	0.2272 (0.0042)	0.275 (0.0004)	0.1309 (0.1483)
Co-applicant	-0.0091 (0.0375)	-0.0114 (0.0207)	-0.0094 (0.0297)
Observations	2112557	1073729	1038828
Adj. R^2	0.1158	0.1115	0.126
DHW p-val	0.0	0.0	0.0
FE	FIPS & Lender	FIPS & Lender	FIPS & Lender

Notes. Estimation results of the rate spread IV model. The model is estimated with a 2SLS within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Distance. The instrument for LS is the depth of the loan sales market. P-value in parentheses. LS = Loan Sold, LTI = loan-to-income ratio, LTV = loan-to-value ratio, IO = Interest Only, MAT = Maturity loan 30 years and longer.

With respect to the control variables, LTI, IO, MAT, and lien have unexpected signs. LTI is negative and significant, indicating higher leveraged incomes have lower rate spreads. These findings are consistent with the fact that high-income applicants often apply for high loans. Even though the LTI is very high, then, these high-income applicants are still considered safe. IO is positive, meaning that these loans might be riskier. With IO-loans there is a higher chance for lenders not to retrieve the full principle amount. MAT is negative, showing that loans with a relatively standard maturity of 30 years are deemed safer than loans with

different maturities. Last, *lien* is positive, implying that loans with good collateral have higher rate spreads. These findings are consistent with the findings of Bellucci et al. (2019) and indicate that local lenders use their market power to extract higher rents.

6. Robustness Checks

In this section we perform several robustness checks. See appendix C for all robustness results.

6.1. Loan Sales Split

The loan sales indicator we use in our benchmark model includes three types of loan sales, namely (unsecuritized) loan sales to government-sponsored entities (GSEs), (unsecuritized) loan sales to private parties, and securitized loan sales (private securitization). Loan sales and securitization transfer risk in similar way. There are, however, some differences between loan sales and securitization when it comes to asset transformation which potentially lead to differential effects on lending distance. For example, pooling assets might allow lenders to sell loans they cannot sell individually or makes it easier to sell them. As a result, the effect of securitization on distance might be greater than the effect of loan sales.

In this robustness check we split the loan sales indicator in three distinct indicators to study whether any such differences exists. Due to the low variation in securitization (only 2.8% of the loans are securitized) our instrument does not have the level of detail required to make a strong instrument. As a result, we cannot directly estimate the effect of securitization on lending distance. We can, however, filter out securitization and study the changes in the parameter estimates.

For loan sales without securitization (*LSNoSec.*; column (4) Table A8) we find a positive, but insignificant estimated coefficient. When we further split this variable, we find that loan sales to GSEs are not associated with greater lending distances (column (5) Table A8). Loan sales to private parties, however, are positively and significantly associated with greater lending distances.⁹ These results suggest that both loan sales to private parties and securitization are important drivers of our results.

⁹All our instruments are strong (see Table A7 columns (4)-(6)). The F-statistics for columns (5) and (6) are 295902 and 628550, respectively.

6.2. Technological Innovation

It is possible that our loan sales variable actually captures technological innovation, and hence provides support for the hypothesis of Petersen and Rajan (2002). To rule this out, we add two sets of variables for technological innovation to the benchmark model. The first set of variables measure technological innovation by the lender. We add dummies for automated lending and credit scoring, which equal one if a loan has been originated automatically and whether a credit scoring method has been used, respectively. The data is from the HMDA LAR from 2018 onward. The second set of variables measure the adoption of technological innovation by borrowers. We add county-level data on internet subscriptions. We assume that individuals with an internet subscription are more tech-savvy (Corrocher, 2006; Kim et al., 2005). As such, the variables can be seen as an approximation of technology adoption by borrowers in a specific county. The data is from the US Census Bureau’s Presence and Types of Internet in Household data.

Tables A3 through A6 display the robustness results.¹⁰ In general we find no effect of automated lending and credit scoring on distance. The estimated coefficients for loan sales, however, are insignificant in all regressions. In addition, we find no real effects of internet subscriptions on distance (the estimated coefficients are significant, but very close to zero). We find that the estimated coefficients for loan sales are positive and significant at the 10%-level. Because we only use the years 2013 through 2018, these estimates are comparable to those in column (4) in Table 5. In conclusion, our loan sales variables most likely do not capture technological changes on the lender side, nor on the borrower side.

6.3. Loan Costs

Lending distance is a reasonable proxy for loan costs (see section 2.1). As a robustness check for the benchmark model we exchange Distance for loan-costs-to-loan-value from the HMDA LAR (from 2018 onward). Loan costs include costs such as appraisal fees, and costs for home inspection by the lender. Consistent with either information or transportation costs, we expect remote loans to have higher loan costs. Loan sales should be able to reduce the costs due to lower scrutiny, see section 2.3. We regress Loan Costs on Loan Sold, since it is very unlikely that a lender originates a high-costs loan without means to offset these costs (by loan sales in our case).

Table A8 column (1) presents the robustness results of loan costs as dependent variable. Consistent

¹⁰The instruments in all first stage regressions are strong (all t-values are above 10).

with Frankel and Jin (2015), we find that loans sold have 0.28% lower loan costs. Given that the mean loan costs in our sample is 1.87%, such a reduction is quite considerable. Similar to our benchmark results, these results are consistent with the conjecture Frankel and Jin (2015) that loan sales reduce the information or transportation costs.

6.4. Alternative Distance Measures

Next, we re-estimate the benchmark and rate spread models with unweighted distance measure from NBER's County Distance Database and a remote lender dummy to test the sensitivity of our results to our distance measure. In general we find our results to be robust to these different measures (see Table A8 columns (1)–(2), and Table A9 columns (5)–(6)). We do not, however, find that remote loans are more likely to be sold (see column (3) in Table A8).

7. Conclusions

Lending distances in the U.S. residential mortgage market have been increasing in the past few decades. According to Frankel and Jin (2015), loans sales provide a possible explanation for this phenomenon. If loan sales considerably reduce the loan rates of remote lenders, they facilitate lending at greater distances. To the best of our knowledge, this paper is the first to empirically test the relationship between loan sales and lending distance.

Using data on the U.S. residential mortgage origination between 2004–2019, the first part of our empirical analysis confirms the prediction by Frankel and Jin (2015) that loan sales increase lending distance. We have shown that loans sold turned out to have a 179% higher expected lending distance than loans that were not sold, which corresponds to an extra distance of 789.6 km (490.3 miles).

Our study can also help to explain why loan sales increased the expected lending distance. That is, the second part of our empirical analysis has found that loans sold by remote lenders have nearly 28 basis points lower expected loan rates than loans held by remote lenders. This finding is in line with the conjecture by Frankel and Jin (2015) that loan sales permit remote lenders to compete in local markets by reducing their loan rates.

Using loan sales to expand geographically is not without risk. Loan sales do not decrease the overall risk in the system, they merely transfer risk across the system. The information disadvantage of remote lenders *vis-à-vis* local lenders does not disappear. All else equal, remote loans are still riskier than local

loans, because they are based on lower-quality information. Loan sales allow these risky loans to flow to investors with a larger risk appetite than remote lenders. And as a result, remote lenders can substantially improve their loan offers. Loan sales do not reduce the information asymmetry between borrower and lender. In fact, loan sales most likely increase the total risk in the system by allowing lending at greater distances, which implies greater informational disadvantages for the lender and riskier loans.

Since we focus on lending distance, we cannot make any predictions about inter-bank competition. Frankel and Jin (2015) predict that securitization leads to more intense lending competition. Our results point in the same direction, by showing that remote lenders can offer competitive loan offers in local markets. Whether a reduction on expected loan rates really leads to more competition and subsequently higher lending distances is for future research to decide.

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A. Variable Construction

See Table A1.

Table A1: Variable Description, Source and Construction

Variable	Description	Dimension	Data Source	Calculation
Dependent Variables				
Distance	Log minimum distance between lender and borrower	Applicant-lender-year	Coordinates lender: US Census Bureau, Centers of Population; SOD	$\arg \min_b d(L_j, L_b^{(i)})$, where d is the geographical distance between j and b
Distance (CDD)	Log minimum distance between lender and borrower	Applicant-lender-year	Coordinates borrower: HMDA NBER County Distance Database	
Local	Equals one when the lender is in the same MSA as the applicant	Applicant-lender-year	US Census Bureau, SOD	$1 \text{ if } MSA_{it} = MSA_{jt} \text{ else } 0$
Rate Spread	Difference between the the loan's annual percentage rate and the average prime offer rate	Applicant-lender-year	HMDA (> 2017)	
Loan Sales Variables				
Loan Sold	Equals one when the loan has been sold	Applicant-lender-year	HMDA	1 if loan is sold else 0
Loan Control Variables				
LTI	Log of the loan-to-income ratio	Applicant-lender-year	HMDA	$\ln(\frac{\$loan \text{ value}_{ijt}}{income_{ijt}} + 1)$
Loan Value	Log of the value of the loan	Applicant-lender-year	HMDA	$\ln(\text{loan value}_{ijt} + 1)$
Income	Log of the incomce of the borrower	Applicant-lender-year	HMDA	$\ln(\text{income}_{ijt} + 1)$
Subprime	Equals one the reported loan spread is above 3% for first-security loans and above 5% for all junior security loans (Purnanandam, 2011)	Applicant-lender-year	HMDA	
Lien	Equals one if the lender has first lien	Applicant-lender-year	HMDA	
Co-applicant	Equals one if the loan applicant has a co-applicant	Applicant-lender-year	HMDA	
LTV	Loan to value ratio	Applicant-lender-year	HMDA (> 2017)	$\frac{\$loan \text{ value}_{ijt}}{\text{property value}_{ijt}}$
IO	Equals one if the loan is an interest-only loan	Applicant-lender-year	HMDA (> 2017)	
Balloon	Equals one is the loan has a balloon payment	Applicant-lender-year	HMDA (> 2017)	
MAT	Equals one if the maturity of the loan is 30 years or more	Applicant-lender-year	HMDA (> 2017)	
Lender Control Variables				
Size	Log of the total assets of the lender	Lender-year	SDI	$\ln(TA_{it})$
Employees	Log of employees per lender	Lender-year	SDI	$\ln(\#\text{employees}_{it} + 1)$
Branches	Log of the number of branches per lender	Lender-year	SOD	$\ln(\#\text{branches}_{it} + 1)$
Bank	Dummy indicating whether the lender is a bank	Lender-year	SDI	1 if bank _{it} , else 0

Notes. The table contains the description of all variables used in the paper, including its source, dimension and calculation. # is the count of the specific variable. When the calculation is left blank, no computations have been done to the data or when the calculation is obvious.

B. First Stage Results Rate Spread Model

See Table A2

Table A2: Estimation Results Rate Spread IV Model: First Stage

	(2018–2019)		(2018)		(2019)	
	(1)	(2)	(3)	(4)	(5)	(6)
MD	0.5653 (0.0000)	0.001 (0.9538)	0.5897 (0.0000)	0.0129 (0.5082)	0.5547 (0.0000)	-0.0057 (0.7401)
Remote X MD	-0.345 (0.0000)	0.3824 (0.0000)	-0.3127 (0.0000)	0.393 (0.0000)	-0.374 (0.0000)	0.3773 (0.0000)
Remote (β_2)	0.2519 (0.0000)	0.4718 (0.0000)	0.2245 (0.0000)	0.4579 (0.0000)	0.2764 (0.0000)	0.4811 (0.0000)
LTI	-0.1373 (0.0000)	-0.0199 (0.0010)	-0.129 (0.0000)	-0.0123 (0.0662)	-0.1512 (0.0000)	-0.0278 (0.0001)
LTV	0.1252 (0.0000)	0.0127 (0.0001)	0.1108 (0.0000)	0.0123 (0.0003)	0.1418 (0.0000)	0.0137 (0.0004)
Loan Value	-0.0208 (0.0316)	0.0007 (0.7799)	-0.0204 (0.0314)	-0.0032 (0.2693)	-0.0181 (0.1313)	0.0051 (0.1566)
Income	-0.1512 (0.0000)	-0.0289 (0.0000)	-0.1474 (0.0000)	-0.024 (0.0000)	-0.158 (0.0000)	-0.0339 (0.0000)
IO	-0.3573 (0.0000)	-0.0442 (0.0000)	-0.3489 (0.0000)	-0.0363 (0.0000)	-0.3679 (0.0000)	-0.0517 (0.0000)
Balloon	-0.1906 (0.0000)	0.0182 (0.0009)	-0.2155 (0.0000)	0.0144 (0.0132)	-0.1634 (0.0000)	0.0225 (0.0001)
MAT	0.0428 (0.0000)	0.0078 (0.0000)	0.042 (0.0000)	0.0068 (0.0004)	0.045 (0.0000)	0.0089 (0.0000)
Lien	0.3715 (0.0000)	0.0431 (0.0000)	0.3655 (0.0000)	0.0478 (0.0000)	0.3729 (0.0000)	0.037 (0.0000)
Co-applicant	0.0278 (0.0000)	0.0071 (0.0000)	0.0251 (0.0000)	0.0064 (0.0000)	0.0305 (0.0000)	0.0077 (0.0000)
Observations	2112557	2112557	1073729	1073729	1038828	1038828
Adj. R^2	0.173	0.581	0.1712	0.5716	0.1783	0.5908
F-stat	15520.9097	15883.6111	8473.2423	9189.9948	7179.659	7017.8943
FE	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender

Notes. Estimation results of the rate spread IV model. The model is estimated with a 2SLS within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Distance. The instrument for LS is the depth of the loan sales market. P-value in parentheses. LS = Loan Sold, LTI = loan-to-income ratio, LTV = loan-to-value ratio, IO = Interest Only, MAT = Maturity loan 30 years and longer.

C. Results Robustness Checks

See Tables 5, A3, A4, A5, A6, A8, and A9.

Table A3: Robustness Results Technological Innovation: Automated Lending and Credit Scoring (First Stage)

	(1)	(2)	(3)	(4)
MD	0.3889 (0.0000)	0.2908 (0.0000)	0.3881 (0.0000)	0.2912 (0.0000)
Automated		0.5711 (0.0000)		0.574 (0.0000)
CSM			0.0268 (0.0000)	-0.0304 (0.0000)
LTI	-0.0816 (0.0000)	-0.0026 (0.8399)	-0.081 (0.0000)	-0.0029 (0.8196)
Loan Value	-0.028 (0.0047)	-0.0714 (0.0000)	-0.0287 (0.0037)	-0.0707 (0.0000)
Income	-0.1263 (0.0000)	-0.0424 (0.0000)	-0.1259 (0.0000)	-0.0423 (0.0000)
Subprime	0.1186 (0.0000)	0.0762 (0.0000)	0.1176 (0.0000)	0.0771 (0.0000)
Lien	0.4535 (0.0000)	0.1373 (0.0000)	0.4547 (0.0000)	0.1344 (0.0000)
Co-applicant	0.0192 (0.0000)	0.0115 (0.0000)	0.0237 (0.0000)	0.0063 (0.0000)
Size	-0.0781 (0.0000)	-0.0469 (0.0000)	-0.0766 (0.0000)	-0.0486 (0.0000)
Employees	0.1864 (0.0000)	0.0819 (0.0000)	0.1834 (0.0000)	0.0848 (0.0000)
Branches	-0.1274 (0.0000)	-0.0752 (0.0000)	-0.1265 (0.0000)	-0.076 (0.0000)
Bank	-0.0232 (0.2918)	-0.0183 (0.2889)	-0.0209 (0.3363)	-0.0208 (0.2278)
Observations	2377113	2377113	2377113	2377113
Adj. R^2	0.1341	0.2848	0.1344	0.2852
FE	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender

Notes. Robustness results of the benchmark model. The model includes dummies for technological innovation, and is estimated with the within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Distance. P-value in parentheses. LTI = loan-to-income ratio.

Table A4: Robustness Results Technological Innovation: Automated Lending and Credit Scoring

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\tilde{L}S$	0.6134 (0.4086)			0.7989 (0.4214)	0.6146 (0.4089)		0.7979 (0.4214)
Automated		0.0396 (0.2388)		-0.4199 (0.4616)		0.0398 (0.2376)	-0.4214 (0.4613)
CSM			0.0014 (0.9501)		-0.0157 (0.6408)	-0.0026 (0.9099)	0.0214 (0.5213)
LTI	0.2553 (0.0012)	0.1989 (0.0000)	0.1932 (0.0001)	0.2124 (0.0000)	0.2551 (0.0011)	0.1989 (0.0000)	0.2126 (0.0000)
Loan Value	-0.0611 (0.0469)	-0.0804 (0.0004)	-0.0775 (0.0006)	-0.0241 (0.7471)	-0.0607 (0.0524)	-0.0804 (0.0004)	-0.0246 (0.7400)
Income	0.2996 (0.0023)	0.2205 (0.0000)	0.2145 (0.0000)	0.2613 (0.0000)	0.2995 (0.0023)	0.2205 (0.0000)	0.2613 (0.0000)
Subprime	-0.0613 (0.5193)	0.011 (0.5063)	0.014 (0.3918)	-0.0522 (0.5296)	-0.0609 (0.5192)	0.0111 (0.5012)	-0.0527 (0.5283)
Lien	-0.0573 (0.8693)	0.2076 (0.0000)	0.2299 (0.0000)	0.091 (0.5453)	-0.0586 (0.8673)	0.2074 (0.0000)	0.0933 (0.5285)
Co-applicant	-0.0608 (0.0004)	-0.0485 (0.0000)	-0.0477 (0.0000)	-0.0587 (0.0001)	-0.0635 (0.0038)	-0.049 (0.0000)	-0.055 (0.0000)
Size	-0.6152 (0.0009)	-0.6915 (0.0000)	-0.6945 (0.0000)	-0.6236 (0.0005)	-0.616 (0.0009)	-0.6916 (0.0000)	-0.6225 (0.0005)
Employees	1.5466 (0.0000)	1.6816 (0.0000)	1.6895 (0.0000)	1.5888 (0.0000)	1.5481 (0.0000)	1.6818 (0.0000)	1.5869 (0.0000)
Branches	-1.247 (0.0000)	-1.3223 (0.0000)	-1.3259 (0.0000)	-1.2617 (0.0000)	-1.2474 (0.0000)	-1.3224 (0.0000)	-1.2613 (0.0000)
Bank	-1.1834 (0.0000)	-1.2105 (0.0000)	-1.2111 (0.0000)	-1.1827 (0.0000)	-1.1847 (0.0000)	-1.2107 (0.0000)	-1.1809 (0.0000)
Observations	2377113	2377113	2377113	2377113	2377113	2377113	2377113
Adj. R^2	0.0553	0.0552	0.0552	0.0553	0.0553	0.0552	0.0553
DHW p-val	0.5161			0.5104	0.5161		0.5107
FE	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender

Notes. Robustness results of the benchmark model. The model includes dummies for technological innovation, and is estimated with the within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Distance. P-value in parentheses. LTI = loan-to-income ratio.

Table A5: Robustness Results Technological Innovation: Internet Subscriptions (First Stage)

	(1)	(2)	(3)	(4)	(5)
MD	0.7622 (0.0000)	0.767 (0.0000)	0.7724 (0.0000)	0.7645 (0.0000)	0.7769 (0.0000)
Dail-up		0.0 (0.2261)			-0.0 (0.0679)
Broadband			0.0 (0.1652)		0.0 (0.0091)
No Internet				0.0 (0.4539)	
LTI	-0.0051 (0.7882)	-0.0059 (0.7583)	-0.0071 (0.7105)	-0.0051 (0.7909)	-0.0082 (0.6630)
Loan Value	-0.0433 (0.0001)	-0.0434 (0.0001)	-0.0433 (0.0001)	-0.0434 (0.0000)	-0.0431 (0.0001)
Income	-0.0874 (0.0000)	-0.088 (0.0000)	-0.0887 (0.0000)	-0.0875 (0.0000)	-0.0895 (0.0000)
Subprime	0.103 (0.0000)	0.1032 (0.0000)	0.1031 (0.0000)	0.103 (0.0000)	0.1028 (0.0000)
Lien	0.4291 (0.0000)	0.43 (0.0000)	0.431 (0.0000)	0.4294 (0.0000)	0.4319 (0.0000)
Co-applicant	0.0179 (0.0000)	0.0181 (0.0000)	0.0183 (0.0000)	0.0181 (0.0000)	0.0185 (0.0000)
Size	-0.065 (0.0001)	-0.0659 (0.0001)	-0.0661 (0.0000)	-0.0656 (0.0001)	-0.0659 (0.0000)
Employees	0.154 (0.0000)	0.1527 (0.0000)	0.1515 (0.0000)	0.1535 (0.0000)	0.1505 (0.0000)
Branches	-0.0835 (0.0000)	-0.0821 (0.0000)	-0.0808 (0.0000)	-0.0827 (0.0000)	-0.08 (0.0000)
Bank	0.0398 (0.0145)	0.0401 (0.0141)	0.0405 (0.0130)	0.0404 (0.0134)	0.0409 (0.0119)
Observations	2254045	2254045	2254045	2254045	2254045
Adj. R^2	0.2656	0.2658	0.2659	0.2656	0.2659
FE	MSA- year, FIPS & Lender	MSA- year, FIPS & Lender	MSA- year, FIPS & Lender	MSA- year, FIPS & Lender	MSA- year, FIPS & Lender

Notes. Robustness results of the benchmark model. The model includes dummies for technological innovation, and is estimated with the within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Distance. P-value in parentheses. LTI = loan-to-income ratio.

Table A6: Robustness Results Technological Innovation: Internet Subscriptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
\hat{LS}	1.0838 (0.0147)				0.9217 (0.0558)	0.8373 (0.0942)	0.9177 (0.0605)		0.8935 (0.0726)
Dail-up		-0.0001 (0.0031)			-0.0001 (0.0048)			-0.0 (0.3843)	-0.0001 (0.2480)
Broadband			-0.0 (0.0050)			-0.0 (0.0089)		-0.0 (0.4826)	-0.0 (0.6883)
No Internet				-0.0 (0.0048)			-0.0 (0.0096)		
LTI	0.0701 (0.5861)	0.0073 (0.9585)	0.0322 (0.8228)	-0.0153 (0.9126)	0.0892 (0.4838)	0.1046 (0.4208)	0.0667 (0.5972)	0.0201 (0.8861)	0.094 (0.4605)
Loan Value	0.0091 (0.8619)	-0.0218 (0.6575)	-0.025 (0.6178)	-0.0166 (0.7341)	0.0046 (0.9308)	-0.0009 (0.9868)	0.0094 (0.8573)	-0.0233 (0.6392)	0.0029 (0.9566)
Income	0.2432 (0.0019)	0.1056 (0.1545)	0.123 (0.1107)	0.098 (0.1855)	0.2423 (0.0014)	0.2458 (0.0012)	0.234 (0.0020)	0.1146 (0.1248)	0.2433 (0.0013)
Subprime	-0.0978 (0.0747)	0.0052 (0.8746)	0.009 (0.7809)	0.0081 (0.8020)	-0.0848 (0.1404)	-0.0729 (0.2127)	-0.0816 (0.1607)	0.0069 (0.8326)	-0.0811 (0.1649)
Lien	-0.1947 (0.3436)	0.2823 (0.0009)	0.265 (0.0021)	0.2865 (0.0009)	-0.1476 (0.4969)	-0.1241 (0.5764)	-0.1412 (0.5227)	0.2732 (0.0010)	-0.1397 (0.5307)
Co-applicant	-0.094 (0.0000)	-0.075 (0.0000)	-0.0783 (0.0000)	-0.0809 (0.0000)	-0.0967 (0.0000)	-0.0977 (0.0000)	-0.1021 (0.0000)	-0.0767 (0.0000)	-0.097 (0.0000)
Size	-0.5124 (0.0165)	-0.7217 (0.0001)	-0.7069 (0.0002)	-0.7098 (0.0002)	-0.4992 (0.0201)	-0.5067 (0.0179)	-0.49 (0.0228)	-0.7129 (0.0002)	-0.501 (0.0193)
Employees	1.4508 (0.0000)	1.8348 (0.0000)	1.8317 (0.0000)	1.8251 (0.0000)	1.508 (0.0000)	1.535 (0.0000)	1.5002 (0.0000)	1.8333 (0.0000)	1.5172 (0.0000)
Branches	-1.2057 (0.0000)	-1.363 (0.0000)	-1.3742 (0.0000)	-1.3713 (0.0000)	-1.2554 (0.0000)	-1.2752 (0.0000)	-1.2631 (0.0000)	-1.3694 (0.0000)	-1.2623 (0.0000)
Bank	-1.0295 (0.0000)	-1.0315 (0.0000)	-1.0336 (0.0000)	-1.0541 (0.0000)	-1.0304 (0.0000)	-1.0324 (0.0000)	-1.0518 (0.0000)	-1.0325 (0.0000)	-1.031 (0.0000)
Observations	2254045	2254045	2254045	2254045	2254045	2254045	2254045	2254045	2254045
Adj. R^2	0.1334	0.136	0.1359	0.136	0.1377	0.1374	0.1377	0.1361	0.1377
DHW p-val	0.03				0.1	0.1586	0.1052		0.1256
FE	MSA- year, FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	MSA- year, FIPS & Lender	MSA- year, FIPS & Lender	MSA- year, FIPS & Lender	FIPS & Lender	MSA- year, FIPS & Lender

Notes. Robustness results of the benchmark model. The model includes dummies for technological innovation, and is estimated with the within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Distance. P-value in parentheses. LTI = loan-to-income ratio.

Table A7: Robustness Results Benchmark Model (First Stage): Loan Costs, Alternative Distance, and Loan Sales Split

	(1)	(2)	(3)	(4)	(5)	(6)
MD	0.2813 (0.0000)	0.888 (0.0000)	0.888 (0.0000)			
MD GSE					0.6388 (0.0000)	0.0974 (0.0023)
MD PRIV					0.0744 (0.0451)	0.8081 (0.0000)
MD No Sec.				1.6358 (0.0000)		
LTI	-0.0955 (0.0000)	-0.2183 (0.0000)	-0.2183 (0.0000)	-0.2103 (0.0000)	-0.2127 (0.0000)	-0.0041 (0.7109)
Loan Value	-0.0559 (0.0000)	0.1245 (0.0000)	0.1245 (0.0000)	0.1154 (0.0000)	0.0634 (0.0000)	0.0535 (0.0000)
Income	-0.1288 (0.0000)	-0.202 (0.0000)	-0.202 (0.0000)	-0.1998 (0.0000)	-0.1604 (0.0000)	-0.0428 (0.0000)
Subprime	0.0995 (0.0000)	-0.0094 (0.1368)	-0.0094 (0.1368)	-0.0505 (0.0000)	-0.0935 (0.0000)	0.0432 (0.0000)
Lien	0.5377 (0.0000)	0.2698 (0.0000)	0.2698 (0.0000)	0.2669 (0.0000)	0.3917 (0.0000)	-0.1186 (0.0000)
Co-applicant	0.0262 (0.0000)	0.0121 (0.0000)	0.0121 (0.0000)	0.015 (0.0000)	0.0326 (0.0000)	-0.0167 (0.0000)
Size	-0.0854 (0.0000)	-0.0505 (0.0000)	-0.0505 (0.0000)	-0.0849 (0.0000)	0.0068 (0.4989)	-0.0873 (0.0000)
Employees	0.1757 (0.0000)	0.095 (0.0000)	0.095 (0.0000)	0.1236 (0.0000)	0.0375 (0.0010)	0.0776 (0.0000)
Branches	-0.1195 (0.0000)	-0.034 (0.0000)	-0.034 (0.0000)	-0.0224 (0.0000)	-0.0009 (0.7463)	-0.0164 (0.0000)
Bank	-0.005 (0.8108)	-0.0281 (0.0616)	-0.0281 (0.0616)	-0.0278 (0.0767)	-0.0264 (0.1565)	-0.0101 (0.5837)
Observations	2048387	28096474	28096474	28096474	28096474	28096474
Adj. R^2	0.1412	0.1216	0.1216	0.1184	0.1157	0.1003
FE	FIPS Lender	& MSA-year, FIPS Lender	& MSA-year, FIPS Lender	& MSA-year, FIPS Lender	& MSA-year, FIPS Lender	& MSA-year, FIPS Lender

Notes. Robustness results of the distance model for the robustness checks loan costs, alternative distance, and loan sales split. The model is estimated with the within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Loan Costs-to-Loan-Value in column (1), Distance (CDD) in column (2), Remote in column (3) and Distance in the remaining columns. P-value in parentheses. LTI = loan-to-income ratio. The model in column (1) is estimated on the years 2018-2019, the rest of the models utilize the entire data set.

Table A8: Robustness Results Benchmark Model (Second Stage): Loan Costs, Alternative Distance, and Loan Sales Split

	(1)	(2)	(3)	(4)	(5)
$\hat{L}S$	-0.0282 (0.0000)	1.0246 (0.0260)	0.1213 (0.0864)		
$LS\hat{G}SE$					-0.6853 (0.3371)
$LSP\hat{r}ivate$					1.1715 (0.0239)
$LSN\hat{o}Sec.$				0.4366 (0.3614)	
LTI	0.0044 (0.0011)	0.0718 (0.6032)	0.0077 (0.7128)	-0.0809 (0.5448)	-0.368 (0.0200)
Loan Value	-0.017 (0.0000)	0.0618 (0.3667)	-0.0003 (0.9745)	0.1378 (0.0332)	0.1816 (0.0073)
Income	0.0008 (0.4326)	0.1064 (0.3107)	0.0093 (0.5750)	-0.0317 (0.7574)	-0.2068 (0.0878)
Subprime	0.0041 (0.0000)	0.404 (0.0000)	0.0737 (0.0000)	0.4151 (0.0000)	0.28 (0.0002)
Lien	0.0492 (0.0000)	-0.6552 (0.0000)	-0.0673 (0.0016)	-0.4873 (0.0008)	0.0881 (0.7404)
Co-applicant	0.0004 (0.0007)	-0.1037 (0.0000)	-0.0059 (0.0034)	-0.0962 (0.0000)	-0.0408 (0.1187)
Size	-0.0035 (0.0000)	-0.2062 (0.1887)	0.0474 (0.0202)	-0.292 (0.0789)	-0.185 (0.2474)
Employees	0.0081 (0.0000)	0.8605 (0.0000)	0.027 (0.3005)	0.9927 (0.0000)	0.9107 (0.0000)
Branches	-0.0061 (0.0000)	-0.8827 (0.0000)	-0.1258 (0.0000)	-0.9262 (0.0000)	-0.8743 (0.0000)
Bank	-0.003 (0.0003)	-1.5919 (0.0000)	-0.229 (0.0000)	-1.6739 (0.0000)	-1.765 (0.0000)
Observations	2048387	28096474	28096474	28096474	28096474
Adj. R^2	0.0841	0.2151	0.1926	0.216	0.2177
DWH p-val	0.0	0.1447	0.3007	0.0013	
FE	FIPS Lender	& MSA-year, FIPS Lender	& MSA-year, FIPS Lender	& MSA-year, FIPS Lender	& MSA-year, FIPS Lender

Notes. Robustness results of the distance model for the robustness checks loan costs, alternative distance, and loan sales split. The model is estimated with the within estimator and includes clustered standard errors on the MSA-level. The dependent variable is Loan Costs-to-Loan-Value in column (1), Distance (CDD) in column (2), Remote in column (3) and Distance in the remaining columns. P-value in parentheses. LTI = loan-to-income ratio. The model in column (1) is estimated on the years 2018-2019, the rest of the models utilize the entire data set.

Table A9: Robustness Results Rate Spread Model

	(1)	(2)	First Stage		(5)	Second Stage	
			(3)	(4)		(6)	
MD	0.5632 (0.0000)	0.0387 (0.6889)	0.5639 (0.0000)	0.0381 (0.6939)			
MD x Distance	-0.0498 (0.0000)	0.3611 (0.0000)					
Distance	0.0387 (0.0000)	0.497 (0.0000)			0.0382 (0.0008)		
MD x Distance (CDD)			-0.0495 (0.0000)	0.3627 (0.0000)			
Distance (CDD)			0.0385 (0.0000)	0.4947 (0.0000)			0.0376 (0.0009)
$\hat{L}S$					0.2875 (0.0117)		0.2876 (0.0115)
$\hat{L}S$ x Distance					-0.0469 (0.0028)		
$\hat{L}S$ x Distance (CDD)							-0.0462 (0.0030)
LTI	-0.1384 (0.0000)	-0.1539 (0.0000)	-0.1385 (0.0000)	-0.1556 (0.0000)	-0.9108 (0.0000)		-0.9107 (0.0000)
LTV	0.1247 (0.0000)	0.1007 (0.0000)	0.1248 (0.0000)	0.1032 (0.0000)	0.7754 (0.0000)		0.7755 (0.0000)
Loan Value	-0.0204 (0.0355)	0.0132 (0.4444)	-0.0204 (0.0356)	0.0128 (0.4623)	0.3006 (0.0000)		0.3005 (0.0000)
Income	-0.152 (0.0000)	-0.2036 (0.0000)	-0.1521 (0.0000)	-0.2054 (0.0000)	-0.5349 (0.0000)		-0.5348 (0.0000)
IO	-0.3566 (0.0000)	-0.3316 (0.0000)	-0.3565 (0.0000)	-0.3374 (0.0000)	0.2739 (0.0000)		0.2739 (0.0000)
Balloon	-0.1905 (0.0000)	0.057 (0.1187)	-0.1905 (0.0000)	0.0501 (0.1789)	0.2167 (0.0575)		0.2164 (0.0579)
MAT	0.0428 (0.0000)	0.0564 (0.0000)	0.0428 (0.0000)	0.0569 (0.0000)	-0.1487 (0.0000)		-0.1487 (0.0000)
Lien	0.3713 (0.0000)	0.2832 (0.0000)	0.3713 (0.0000)	0.2884 (0.0000)	0.2251 (0.0043)		0.2251 (0.0043)
Co-applicant	0.0279 (0.0000)	0.048 (0.0000)	0.0279 (0.0000)	0.0484 (0.0000)	-0.0091 (0.0379)		-0.0092 (0.0373)
Observations	2112557.0	2112557.0	2112557.0	2112557.0	2112557.0		2112557.0
Adj. R^2	0.1732	0.5565	0.1732	0.5553	0.1157		0.1158
F-stat	14929.9985	15513.8717	14931.431	15685.3327			
DHW p-val					0.0		0.0
FE	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender	FIPS & Lender

Notes. Robustness results of the rate spread model. The model is estimated with the within estimator and includes clustered standard errors on the MSA-level. P-value in parentheses. LS = Loan Sold, LTI = loan-to-income ratio, LTV = loan-to-value ratio, IO = Interest Only, MAT = Maturity loan 30 years and longer.