university of groningen

faculty of economics and business

2020014-EEF

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

April 2021

(update of the September 2020 version)

Mark van der Plaat

university of groningen

faculty of economics and business

SOM is the research institute of the Faculty of Economics & Business at the University of Groningen. SOM has six programmes:
- Economics, Econometrics and Finance
- Global Economics & Management
- Innovation & Organization
- Marketing
- Operations Management & Operations Research
- Organizational Behaviour

Research Institute SOM
Faculty of Economics & Business
University of Groningen

Visiting address:
Nettelbosje 2
9747 AE Groningen
The Netherlands

Postal address:
P.O. Box 800
9700 AV Groningen
The Netherlands

T +31 50 363 9090/7068/3815

www.rug.nl/feb/research

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

Mark van der Plaat
University of Groningen, Faculty of Economics and Business, Department of Economics, Econometrics and Finance
m.t.van.der.plaat@rug.nl

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

Mark van der Plaat†

This Version: April 20, 2021

Original Version: September 28, 2020

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 on average increase the lending distance with approximately 47%, which corresponds to 206.9 km (128.6 miles). Loan sales are able to increase lending distances because they allow lenders to reduce their loan rates, which allows them to compete for loans in remote markets. We find that loan sales almost completely offset higher loan rates of remote lenders.

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

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

*I am grateful to Laura Spierdijk, Jakob de Haan, Peter van Santen, and Asad Rauf for helpful comments and suggestions. Furthermore, I would like to thank the participants of the EEF PhD Seminar series, and the NEW (*Nederlandse Economenweek*), and the discussant Matteo Bonetti in particular. I also would like to thank the Center for Information Technology of the University of Groningen for their support and for providing access to the Peregrine high performance computing cluster.

†Affiliation: University of Groningen, Faculty of Economics and Business, Department of Economics, Econometrics and Finance. Address Nettelbosje 2, 9747 AE Groningen. m.t.van.der.plaat@rug.nl

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, that are somewhere inside the local market, was a result of the close proximity of local lenders to their clientele, which made obtaining and verifying good-quality information much easier. Such an information advantage 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, which are somewhere outside the local market, 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 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 the theoretical predictions 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 of half of the loans in our sample are originated by local lenders.

We test the hypothesis that loan sales reduce lending distance by regressing log lending distances on a loan sales indicator variable and various control variables. Our empirical results confirm the prediction that loan sales increase a lender's lending distance. We find that loan sales increase the expected average lending distance by approximately 47%, which corresponds to 206.9 km (128.6 miles). The relation between loan sales and lending distance remains significantly positive after controlling for possible endogeneity by means of instrumental variable techniques. In addition, splitting the loan sales indicator into three separate indicators for loan sales to government-sponsored entities, loan sales to private entities and securitized loan sales (securitization), we find that all three indicators increase the expected average lending distance, with securitization having the largest impact. Our results, therefore, are unlikely to be driven by one type of loan sales or securitization.

Our study also provides evidence for the underlying mechanism that Frankel and Jin (2015) describe. They conjecture that loan sales increase lending distances by allowing remote lenders to severely reduce their loan rates. The corresponding reduction in remote loan rates turns out large enough for offering competitive loan offers in local markets. Our empirical findings are consistent with these additional predictions of Frankel and Jin (2015), which provide an explanation for the increased lending distance induced by loan sales.

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 discuss 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 lender 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. At the same time, local lenders charge more to these firms. In addition, the authors find that remote borrowers are more likely to default than local borrowers. The reliance on individual lenders by small businesses gives local lenders market power, the argument goes, allowing them to set higher loan rates. On the other hand, using data on syndicated lending in the U.S., Knyazeva and Knyazeva (2012) find that loans to remote borrowers have higher interest rate spreads. The authors argue that since large firms are less reliant on individual lenders local lenders do not gain market power. As a result, the information advantage of the local lender translates to lower loan rates. 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 convenants, 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 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. In addition, technology innovation 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 also 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 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

[1] Hard 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.

[2] Securitization 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).

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.

The main prediction by Frankel and Jin (2015) is 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. Our main hypothesis thus states 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 states that remote lenders are able to enter local markets because loan sales allow them to substantially reduce their loan rates. We therefore formulate the following 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 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.

[3] This 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).

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 is of yearly frequency. From 2018 onward, the HMDA include 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.[5] 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.

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, 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

[4]An 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.

[5]An 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.

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.

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 For all other county-level data we use the following databases. 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 from the US Census Bureau on the types of internet in households.

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 $\{jk\}$ 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:

$$D_{ij} = \arg\min_{b} d(L_j, L_b^{(i)}), \quad b = 1, 2, ..., B,$$

where D_{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. We take the log of distance D_{ij}.

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

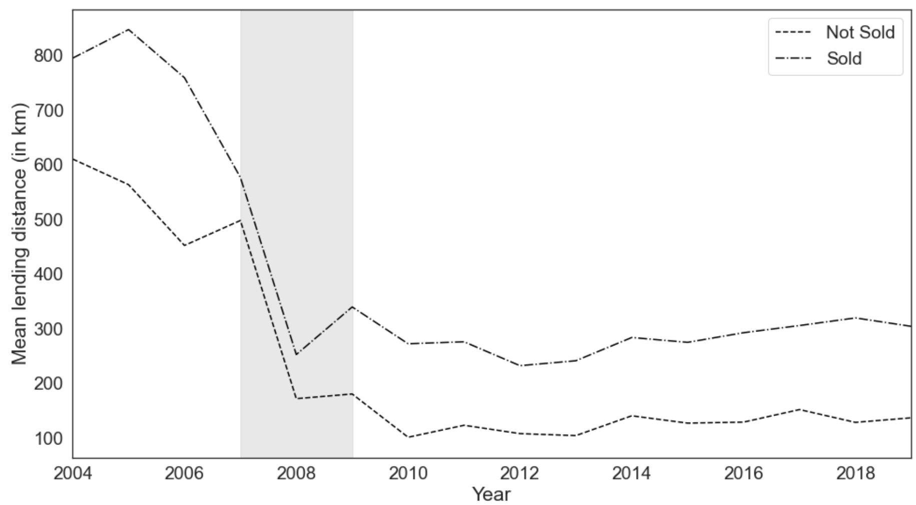
Frankel and Jin (2015) essentially model securitization as loan sales by allowing lenders to transfer loans of their balance sheets. Such a mechanism is identical to the mechanism of loan sales. The main differences between them is that securitization alters the patterns of cash flows, and converts the 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 lonas. 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%).

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), which is quite considerable. For more half than 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, most loans (63%) are originated by local lenders, and 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 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.

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:

$$ln(Distance_{icmt}) = \beta LS_{icmt} + X_{icmt}\gamma + \alpha_i + \rho_c + \delta_{mt} + u_{icmt}, \tag{1}$$

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.

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 if loan sales on the log lending distance. Following hypothesis H1 we expect β to be positive and significant.

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 equation (1) using the within estimator 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. As robustness check we use an Instrumental variable approach to account for possible endogeneity, and we add variables for technological innovation to test the conjecture of Petersen and Rajan (2002), see section 6.

4.2. Rate Spread Model

In our rate spread model we focus on our second hypothesis, H2, which explains the mechanism why loan sales are able to increase lending distances. As dependent variable we use 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):

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

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 (see section 2.3) we expect these to be positive and negative, respectively. β_3 measures the marginal effect of loan sales of remote banks on the rate spread, and is our variable of interest. We expect this coefficient to be negative, indicating that loan sales allow remote lenders to reduce their loan rates. We estimate equation (2) 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. By estimating 2018 and 2019 separately, we can get a sense of whether there are unobserved time effects in the 2018–2019 sample that we do not take into account.

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.

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.

5. Empirical Results

Table 5 displays the results of our benchmark model. We find a positive and significant estimate for loan sales of approximately 0.39 in the full sample, and 0.17 in the post-Great Recession sample. Loan sales in the full (post-Great Recession) sample are associated with a 47% (11%) increase in lending distance.[6] An increase of 47% corresponds to an increase of approximate 206.9 km (128.6 miles). These results, therefore, show that loan sales are associated with greater lending distances, and provide evidence for hypothesis H1.

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 negative, 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 estimates of the rate spread model. Consistent with hypothesis H2 we find a negative and significant estimate for β_3, which implies that loan sales allow remote lenders to reduce their loan rate.

[6] $exp(0.3854) - 1 \approx 0.47$ and $exp(0.1706) - 1 \approx 0.11$.

Table 5: Estimation Results Benchmark Model

	(2004–2019)	(2010–2019)
Loan Sold (β)	0.3854	0.1706
	(0.0000)	(0.0000)
LTI	-0.0475	0.0274
	(0.6362)	(0.8412)
Loan Value	0.1155	0.0171
	(0.0024)	(0.7521)
Income	-0.0418	0.0974
	(0.4479)	(0.1536)
Subprime	0.4017	0.1401
	(0.0000)	(0.0001)
Lien	-0.4651	0.011
	(0.0000)	(0.9326)
Co-applicant	0.0374	-0.0676
	(0.0000)	(0.0000)
Size	-0.3047	-0.9509
	(0.0426)	(0.0000)
Employees	1.004	1.6151
	(0.0000)	(0.0000)
Branches	-0.9188	-0.8035
	(0.0000)	(0.0000)
Bank	-1.6681	-0.8569
	(0.0000)	(0.0000)
Observations	28096497	12734935
Adj. R^2	0.2194	0.0909
FE	MSA-year, FIPS & Lender	MSA-year, FIPS & Lender

Notes. Estimation results of the benchmark model. The model is estimated with the within estimator and includes clustered standard errors on the MSA-level. P-value in parentheses. P-value in parentheses. LTI = loan-to-income ratio. The model is estimated with clustered standard errors on the MSA-level.

The reduction is considerable, given that the total effect ($\beta_2 + \beta_3$) is 0.0166. In other words, loan sales seem to allow remote lenders to almost completely offset their informational disadvantage. The resulting remote loan rates are likely to be low enough to compete with loan rates offered by local lenders. Without loan sales, remote lenders offer significantly higher loan rates (β_2). Also consistent with the mechanism of Frankel and Jin, we find that loan sales do not benefit local lenders (β_1). In all columns of Table 6 we find insignificant estimated coefficients for loans sold. 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.

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

Table 6: Estimation Results Rate Spread Model

	(2018–2019)	(2018)	(2019)
Loan Sold (β_1)	0.0199	0.0285	0.0123
	(0.3064)	(0.1873)	(0.5147)
Remote (β_2)	0.1176	0.1217	0.117
	(0.0000)	(0.0000)	(0.0000)
Remote X LS (β_3)	-0.101	-0.1099	-0.0945
	(0.0000)	(0.0000)	(0.0000)
LTI	-0.9535	-0.7858	-1.2081
	(0.0000)	(0.0000)	(0.0000)
LTV	0.8154	0.805	0.8453
	(0.0000)	(0.0000)	(0.0000)
Loan Value	0.2955	0.2089	0.4359
	(0.0000)	(0.0044)	(0.0000)
Income	-0.576	-0.461	-0.7442
	(0.0000)	(0.0000)	(0.0000)
IO	0.1912	0.1318	0.2454
	(0.0000)	(0.0000)	(0.0000)
Balloon	0.1692	0.0802	0.2775
	(0.1355)	(0.4913)	(0.0205)
MAT	-0.1401	-0.1351	-0.147
	(0.0000)	(0.0000)	(0.0000)
Lien	0.3246	0.3836	0.2347
	(0.0000)	(0.0000)	(0.0008)
Co-applicant	-0.002	-0.0036	-0.0014
	(0.4695)	(0.1927)	(0.6189)
Observations	2112561	1073729	1038832
Adj. R^2	0.116	0.1118	0.1261
FE	FIPS & Lender	FIPS & Lender	FIPS & Lender

Notes. Estimation 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.

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 B for all robustness results.

6.1. Instrumental Variable Analysis

Even though there is a clear causality from loan sales to distance in the model of Frankel and Jin (2015), there might be some endogeneity concerns with respect to loan sales. For this reason, we instrument loan sales in the benchmark model and utilize a 2SLS estimator with the same fixed effects as our benchmark model, and cluster the standard errors at the MSA-level. As instrumental variable we use a measure of the depth of the loan sales market. For each lender i and county c we calculate the percentage of loans sold by all other lenders than lender i in county c.[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 it originates in county c. This measure for market depth has no direct effect on the lending distance of lender i. Moreover, this instrument does not vary with changing lending distances of lender i. We therefore believe this instrument is exogenous.

Table A2 contains the results for the IV model for the full sample and the post-2009 sample. The first-stage results show our instrument is strong.[8] The second-stage results demonstrate that loan sales are positively and significantly related to lending distance in the full sample. After 2009, the estimated coefficient of loan sales is only significant at the 10% level. In addition, we run a Durbin-Hausman-Wu (DHW) test to determine whether LS is endogenous. For both samples we cannot reject the null-hypothesis that our loan sales variable is exogenous.

The estimated coefficients of the benchmark model and the IV model are qualitatively very similar. There are some quantitative differences between the estimated coefficients in both models, but in general these differences are minor. Taking into account the insignificant DHW tests we have no reason to believe that the estimates in the benchmark model are inconsistent due to endogeneity.

6.2. 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 securitizated loan sales (private securitization). Previously we argued that 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. In this robustness check we split the loan sales indicator in three distinct indicators to study whether any such differences exists (see Table A5 column (3)). For all types we find positive and significant estimated coefficients, similar to our benchmark findings. To test whether the three estimated coefficients differ significantly we

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

[8] Since our IV model is exactly identified, i.e. the number of instruments equals the number of endogenous variables, we follow Wooldridge (2010) and use the t-statistic of LS Other. The t-statistics for the full and post-2009 sample are 30.68 and 26.17, respectively. Using the rule of thumb of $F > 10$, we conclude that our instrument is strong in both samples.

perform a Wald test where $\beta_{GSE} = \beta_{Private}$ and $\beta_{Private} = \beta_{Securitization}$. We reject this test at the 1%-level (p-value = 0.00), and conclude that the coefficients differ significantly. The coefficient for securitization has the highest magnitude. A coefficient of approximately 0.83 means that securitization is associated with an increase in lending distance of 130%, which corresponds to an increase of 527.8 km (355.9 miles). However, since both types of loan sales lead to higher lending distances as well, it is unlikely that our results are driven by securitization in particular.

The impact of securitization on lending distance appears to be the strongest of the three. This interpretation, however, is not without difficulties. Private securitization in the U.S. is done by a select group of large banks. The size of these banks makes them likely to have great lending distances regardless of their securitization activities. It is therefore possible that Securitization captures, at least in part, the size of this group of banks.

6.3. 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 and A4 display the robustness results. In general we find no effect of automated lending and credit scoring on distance. The estimated coefficients for loan sales stay positive and significant when we include either automated lending and credit scoring. In addition, we find no real effects of internet subscriptions on distance (the estimated coefficients are significant, but very close to zero). Probably the variation left in these variables is low due to inclusion of many fixed effects. Again we find that the estimated coefficients for loan sales stay positive and significant. In conclusion, our loan sales variables does not capture technological changes on the lender side, nor on the borrower side.

6.4. 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. We regress Loan Sold on Loan Costs, 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 A5 column (1) presents the robustness results of loan costs as dependent variable. Consistent with Frankel and Jin (2015), we find that loans sold have 0.09% lower loan costs. Given that the mean loan costs in our sample is 1.87%, such a reduction is quite considerable. We interpret this as further evidence that loan sales have an impact on the information advantage of local lenders.

6.5. 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 A5 columns (1)–(2), and Table A6 columns (1)–(2)). In addition, we find that remote loans are more likely to be sold, which is consistent with the predictions of Frankel and Jin (2015).

7. Conclusions

Lending distances in the U.S. residential mortgage market have been increasing in the past few decades. A possible explanation of why this has happened are loan sales. Loan sales allow remote lenders, which are somewhere outside the local market, to considerably reduce their loan rates, facilitating lending at greater distances. To the best of our knowledge, this paper is the first to test the relationship between loan sales and lending distance empirically. Using data on the U.S. residential mortgage origination between 2004–2019, we found that loan sales increase the expected average distance with approximately 47%, which corresponds to an increase of about 206.9 km (128.6 miles). The relation between loan sales and lending distance remains significantly positive after controlling for possible endogeneity by means of instrumental variable techniques. We furthermore showed that loan sales and securitization both increase the expected average lending distance.

Our study also provided evidence for the underlying mechanism why loan sales increase lending distances. We found that loan sales reduce the loan rates of remote loans considerably. The corresponding reduction in remote loan rates is large enough for offering competitive loan offers in local markets.

The use of loan sales and the subsequent geographic expansion 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. It is very likely, however, that growing lending distances impact inter-bank competition. In fact, Frankel and Jin 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. Other papers, however, argue the other way around, and predict the securitization and loan sales could cushion competition by allowing banks to ask higher loan rates. Future research might study these predictions empirically.

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 Coordinates borrower: HMDA	$\arg\min_b d(L_j, L_b^{(i)})$, where d is the geographical distance between j and b
Distance (CDD)	Log minimum distance between lender and borrower	Applicant-lender-year	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 if $MSA_{it} = MSA_{jt}$ 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	$ln(\frac{\text{\$loan value}_{ijt}}{\text{income}_{ijt}} + 1)$
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)	$\frac{\text{\$loan value}_{ijt}}{\text{property value}_{ijt}}$
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. Results Robustness Checks

See Tables A2, A3, A4, A5, and A6.

Table A2: Robustness Results IV Benchmark Model

	(1)	(2)	(3)	(4)
LS Other	0.888	0.8411		
	(0.0000)	(0.0000)		
$\hat{LS}$			1.0273	0.6732
			(0.0254)	(0.0553)
LTI	-0.2183	-0.1586	0.0645	0.1349
	(0.0000)	(0.0000)	(0.6420)	(0.3747)
Loan Value	0.1245	0.0798	0.0611	-0.0285
	(0.0000)	(0.0000)	(0.3727)	(0.6596)
Income	-0.202	-0.1868	0.1033	0.2148
	(0.0000)	(0.0000)	(0.3254)	(0.0308)
Subprime	-0.0094	-0.0277	0.4035	0.1587
	(0.1368)	(0.0001)	(0.0000)	(0.0000)
Lien	0.2698	0.3336	-0.6494	-0.1721
	(0.0000)	(0.0000)	(0.0000)	(0.3256)
Co-applicant	0.0121	0.0209	-0.1031	-0.081
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size	-0.0505	-0.0874	-0.2045	-0.8055
	(0.0000)	(0.0000)	(0.1932)	(0.0000)
Employees	0.095	0.15	0.8596	1.426
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Branches	-0.034	-0.0433	-0.8835	-0.7714
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bank	-0.0281	0.0434	-1.6086	-0.8648
	(0.0616)	(0.0127)	(0.0000)	(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 Model results of the distance model. The model 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. 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)).

Table A3: Robustness Results Technological Innovation: Automated Lending and Credit Scoring

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Loan Sold	0.134			0.1479	0.1341		0.148
	(0.0000)			(0.0000)	(0.0000)		(0.0000)
Automated		0.0396		-0.0455		0.0398	-0.0457
		(0.2388)		(0.1581)		(0.2376)	(0.1550)
CSM			0.0014		-0.0023	-0.0026	0.0019
			(0.9500)		(0.9193)	(0.9100)	(0.9336)
LTI	0.2067	0.199	0.1932	0.2014	0.2067	0.1989	0.2015
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loan Value	-0.0739	-0.0805	-0.0775	-0.07	-0.0738	-0.0804	-0.0701
	(0.0010)	(0.0004)	(0.0006)	(0.0018)	(0.0010)	(0.0004)	(0.0018)
Income	0.2331	0.2206	0.2145	0.2281	0.2331	0.2206	0.2281
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Subprime	-0.0024	0.011	0.014	-0.0007	-0.0024	0.0111	-0.0008
	(0.8804)	(0.5061)	(0.3917)	(0.9660)	(0.8834)	(0.5010)	(0.9630)
Lien	0.1671	0.2076	0.2299	0.186	0.167	0.2074	0.1862
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Co-applicant	-0.0508	-0.0485	-0.0477	-0.0504	-0.0512	-0.049	-0.0501
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size	-0.6772	-0.6915	-0.6945	-0.6789	-0.6774	-0.6916	-0.6788
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Employees	1.6584	1.6816	1.6895	1.6644	1.6587	1.6819	1.6642
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Branches	-1.3087	-1.3223	-1.3259	-1.3111	-1.3088	-1.3224	-1.311
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bank	-1.2051	-1.2105	-1.2111	-1.2053	-1.2053	-1.2107	-1.2052
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	23771	23771	23771	23771	23771	23771	23771
Adj. R^2	0.056	0.0552	0.0552	0.056	0.056	0.0552	0.056
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 A4: Robustness Results Technological Innovation: Internet Subscriptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loan Sold	0.6421				0.6374	0.6259	0.6321		0.6285
	(0.0000)				(0.0000)	(0.0000)	(0.0000)		(0.0000)
Dail-up		-0.0			-0.0			0.0	0.0
		(0.0469)			(0.0722)			(0.7410)	(0.8066)
Broadband			-0.0			-0.0		-0.0	-0.0
			(0.0256)			(0.0614)		(0.2492)	(0.5206)
No Internet				-0.0			-0.0	-0.0	-0.0
				(0.0345)			(0.0629)	(0.6263)	(0.5295)
LTI	2.1086	2.5248	2.5013	2.5115	2.14	2.1245	2.1303	2.5009	2.1261
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loan Value	-1.0474	-1.3238	-1.2821	-1.3105	-1.053	-1.0222	-1.0431	-1.2884	-1.0325
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Income	1.333	1.5221	1.5072	1.5166	1.3526	1.3413	1.3484	1.5086	1.3447
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Subprime	0.2138	0.2026	0.2332	0.2097	0.1868	0.2156	0.1943	0.2277	0.2045
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Lien	0.9333	1.5171	1.4215	1.4913	0.922	0.8531	0.9042	1.4393	0.8794
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0001)
Co-applicant	-0.0663	-0.0495	-0.0584	-0.0564	-0.0725	-0.079	-0.0783	-0.0592	-0.0798
	(0.0002)	(0.0060)	(0.0014)	(0.0015)	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0000)
Size	-0.3496	-0.38	-0.3807	-0.3788	-0.3563	-0.3567	-0.3552	-0.3797	-0.3556
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Employees	1.2053	1.2979	1.3006	1.2983	1.2179	1.2205	1.2185	1.2996	1.2195
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Branches	-1.2879	-1.3401	-1.341	-1.3412	-1.2908	-1.2923	-1.2921	-1.3413	-1.2925
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bank	-0.883	-0.8322	-0.8429	-0.837	-0.8898	-0.8972	-0.8934	-0.8418	-0.8958
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	8563517	8563517	8563517	8563517	8563517	8563517	8563517	8563517	8563517
Adj. R^2	0.3369	0.3278	0.3285	0.3284	0.3379	0.3383	0.3383	0.3286	0.3384
FE	MSA-year, FIPS & Lender	MSA-year, FIPS & Lender	MSA-year, FIPS & Lender	MSA-year, 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 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 Benchmark Model: Loan Costs, Alternative Distance, and Loan Sales Split

	(1)	(2)	(3)	(4)
Loan Sold	-0.0009	0.3908	0.0519	
	(0.0000)	(0.0000)	(0.0000)	
LS GSE				0.2958
				(0.0000)
LS Private				0.4693
				(0.0000)
Securitization				0.8334
				(0.0000)
LTI	0.0075	-0.0808	-0.009	-0.1101
	(0.0000)	(0.4213)	(0.4670)	(0.2725)
Loan Value	-0.0156	0.1391	0.0081	0.1369
	(0.0000)	(0.0003)	(0.1165)	(0.0004)
Income	0.0046	-0.0371	-0.0064	-0.0537
	(0.0000)	(0.4981)	(0.3665)	(0.3272)
Subprime	0.0013	0.3968	0.0729	0.3657
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Lien	0.0343	-0.4774	-0.0479	-0.4162
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Co-applicant	-0.0003	-0.0942	-0.0049	-0.0867
	(0.0000)	(0.0000)	(0.0166)	(0.0000)
Size	-0.0003	-0.311	0.0359	-0.3084
	(0.6107)	(0.0381)	(0.0747)	(0.0383)
Employees	0.0026	1.0046	0.0428	0.9956
	(0.0001)	(0.0000)	(0.0732)	(0.0000)
Branches	-0.0028	-0.9164	-0.1295	-0.9009
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bank	-0.0025	-1.6541	-0.2358	-1.6713
	(0.0017)	(0.0000)	(0.0000)	(0.0000)
Observations	2048391	28096497	28096497	28096497
Adj. R^2	0.0837	0.2179	0.195	0.2208
FE	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 colum (1), Distance (CDD) in column (2), Local in column (3) and Distance in column (4). 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 A6: Robustness Results Rate Spread Model

	(1)	(2)
Loan Sold	0.0227	0.0228
	(0.2298)	(0.2267)
Distance	0.0191	
	(0.0000)	
LS x Distance	-0.0167	
	(0.0000)	
Distance (CDD)		0.019
		(0.0000)
LS x Distance (CDD)		-0.0166
		(0.0000)
LTI	-0.9538	-0.9539
	(0.0000)	(0.0000)
LTV	0.8152	0.8152
	(0.0000)	(0.0000)
Loan Value	0.2957	0.2957
	(0.0000)	(0.0000)
Income	-0.576	-0.576
	(0.0000)	(0.0000)
IO	0.1913	0.1913
	(0.0000)	(0.0000)
Balloon	0.1685	0.1684
	(0.1379)	(0.1382)
MAT	-0.1401	-0.1401
	(0.0000)	(0.0000)
Lien	0.324	0.3241
	(0.0000)	(0.0000)
Co-applicant	-0.002	-0.002
	(0.4597)	(0.4584)
Observations	2112561	2112561
Adj. R^2	0.116	0.116
FE	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.

References

Adams, R. M., Brevoort, K., & Driscoll, J. C. (2020). Is lending distance really changing? Distance dynamics and loan composition in small business lending. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3604308

Agarwal, S., Chang, Y., & Yavas, A. (2012). Adverse selection in mortgage securitization. *Journal of Financial Economics*, *105*(3), 640–660. https://doi.org/10.1016/j.jfineco.2012.05.004

Agarwal, S., & Hauswald, R. (2010). Distance and private information in lending. *Review of Financial Studies*, *23*(7), 2757–2788. https://doi.org/10.1093/rfs/hhq001

Altunbas, Y., Marques-Ibanez, D., van Leuvensteijn, M., & Zhao, T. (2019). *Competition and bank risk the role of securitization and bank capital* (No. *140*). https://doi.org/10.5089/9781498318501.001

Antinolfi, G., Brunetti, C., & Im, J. (2016). Mortgage rates and credit risk: evidence from mortgage pools. *SSRN Electronic Journal*, 1–33. https://doi.org/10.2139/ssrn.2809367

Avery, R. B., Brevoort, K. P., & Canner, G. B. (2007). Opportunities and issues in using HMDA data. *Journal of Real Estate Research*, *29*(4), 351–380. https://doi.org/10.5555/rees.29.4.wn160840825t7077

Bellucci, A., Borisov, A., Giombini, G., & Zazzaro, A. (2019). Collateralization and distance. *Journal of Banking and Finance*, *100*, 205–217. https://doi.org/10.1016/j.jbankfin.2019.01.011

Beltran, D. O., Cordell, L., & Thomas, C. P. (2017). Asymmetric information and the death of ABS CDOs. *Journal of Banking and Finance*, *76*, 1–14. https://doi.org/10.1016/j.jbankfin.2016.11.008

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, *76*(2), 237–269. https://doi.org/10.1016/J.JFINECO.2004.06.003

Berndt, A., & Gupta, A. (2009). Moral hazard and adverse selection in the originate-to-distribute model of bank credit. *Journal of Monetary Economics*, *56*(5), 725–743. https://doi.org/10.1016/j.jmoneco.2009.04.002

Bhutta, N., Laufer, S., Ringo, D. R., & Kelliher, J. (2017). Residential mortgage lending in 2016: evidence from the Home Mortgage Disclosure Act Data. *Federal Reserve Bulletin*, *103*(6), 1–27.

Bikker, J. A., Shaffer, S., & Spierdijk, L. (2012). Assessing competition with the Panzar-Rosse model: The role of scale, costs, and equilibrium. *Review of Economics and Statistics*, *94*(4), 1025–1044. https://doi.org/10.1162/REST_a_00210

Brevoort, K. P., & Hannan, T. H. (2006). Commercial lending and distance: Evidence from community reinvestment act data. *Journal of Money, Credit and Banking*, *38*(8), 1991–2012.

Brevoort, K. P., Holmes, J. A., Wolken, J. D., & Holmes, J. A. (2010). *Distance still matters: The information revolution in small business lending and the persistent role of location, 1993-2003*. Washington D.C., Federal Reserve Board.

Brevoort, K. P., & Wolken, J. D. (2008). Does Distance Matter in Banking. In *Finance and economics*.

Corrocher, N. (2006). Internet adoption in Italian banks: An empirical investigation. *Research Policy*, *35*(4), 533–544. https://doi.org/https://doi.org/10.1016/j.respol.2006.02.004

Degryse, H., & Ongena, S. (2005). Distance, lending relationships, and competition. *Journal of Finance*, *60*(1), 231–266. https://doi.org/10.1111/j.1540-6261.2005.00729.x

Dell'ariccia, G., Igan, D., & Laeven, L. (2012). Credit booms and lending standards: Evidence from the subprime mortgage market. *Journal of Money, Credit and Banking*, *44*(2-3), 367–384. https://doi.org/10.1111/j.1538-4616.2011.00491.x

Demyanyk, Y., & Loutskina, E. (2016). Mortgage companies and regulatory arbitrage. *Journal of Financial Economics*, *122*(2), 328–351. https://doi.org/10.1016/j.jfineco.2016.07.003

DeYoung, R., Frame, W. S., Glennon, D., McMillen, D. P., & Nigro, P. (2008a). Commercial lending distance and historically underserved areas. *Journal of Economics and Business*, *60*(1), 149–164. https://doi.org/https://doi.org/10.1016/j.jeconbus.2007.08.004

DeYoung, R., Frame, W. S., Glennon, D., & Nigro, P. (2011). The information revolution and small business lending: The missing evidence. *Journal of Financial Services Research*, *39*(1-2), 19–33. https://doi.org/10.1007/s10693-010-0087-2

DeYoung, R., Glennon, D., & Nigro, P. (2008b). Borrower-lender distance, credit scoring, and loan performance: Evidence from informational-opaque small business borrowers. *Journal of Financial Intermediation*, *17*(1), 113–143. https://doi.org/10.1016/j.jfi.2007.07.002

Elul, R. (2016). Securitization and mortgage default. *Journal of Financial Services Research*, *49*(2-3), 281–309. https://doi.org/10.1007/s10693-015-0220-3

Felici, R., & Pagnini, M. (2008). Distance, bank heterogeneity and entry in local banking markets. *Journal of Industrial Economics*, *56*(3), 500–534. https://doi.org/10.1111/j.1467-6451.2008.00357.x

Frankel, D. M., & Jin, Y. U. (2015). Securitization and lending competition. *Review of Economic Studies*, *82*, 1383–1408. https://doi.org/10.1093/restud/rdv013

Gorton, G. B., & Metrick, A. (2013). Securitization. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the economics of finance* (pp. 1–70). Amsterdam, Elsevier BV. https://doi.org/10.1016/B978-0-44-453594-8.00001-X

Granja, J., Leuz, C., & Rajan, R. (2019). *Going the extra mile: distant lending and credit cycles*. Cambridge, Mass., National Bureau of Economic Research.

Greenbaum, S. I., Thakor, A. V., & Boot, A. W. (2019). Securitization. In S. I. Greenbaum, A. V. Thakor, & A. W. Boot (Eds.), *Contemporary financial intermediation* (4th, pp. 249–282). London, Academic Press. https://doi.org/10.1016/b978-0-12-405208-6.00011-5

Hauswald, R., & Marquez, R. (2006). Competition and strategic information acquisition in credit markets. *Review of Financial Studies*, *19*(3), 967–1000. https://doi.org/10.1093/rfs/hhj021

Ho, K., & Ishii, J. (2011). Location and competition in retail banking. *International Journal of Industrial Organization*, *29*(5), 537–546. https://doi.org/10.1016/j.ijindorg.2010.11.004

Hollander, S., & Verriest, A. (2016). Bridging the gap: The design of bank loan contracts and distance. *Journal of Financial Economics*, *119*(2), 399–419. https://doi.org/10.1016/j.jfineco.2015.09.006

Jiang, W., Nelson, A. A., & Vytlacil, E. (2014). Liar's loan? Effects of origination channel and information falsification on mortgage delinquency. *Review of Economics and Statistics*, *96*(1), 1–18. https://doi.org/10.1162/REST_a_00387

Justiniano, A., Primiceri, G., & Tambalotti, A. (2017). The Mortgage Rate Conundrum. *National Bureau of Economic Research*. https://doi.org/10.3386/w23784

Keys, B. J., Mukherjee, T., Seru, A., & Vig, V. (2010). Did securitization lead to lax screening? Evidence from subprime loans. *Quarterly Journal of Economics*, *125*(1), 307–362.

Kim, B.-M., Widdows, R., & Yilmazer, T. (2005). The determinants of consumers' adoption of Internet banking, In *Proceedings of the consumer behavior and payment choice 2005 conference, boston, ma.*

Knyazeva, & Knyazeva. (2012). Does being your bank's neighbor matter? *Journal of Banking and Finance*, *36*(4), 1194–1209. https://doi.org/10.1016/j.jbankfin.2011.11.011

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1–41. https://doi.org/10.1093/rcfs/cfy009

Loutskina, E., & Strahan, P. E. (2011). Informed and uninformed investment in housing: The downside of diversification. *Review of Financial Studies*, *24*(5), 1447–1480. https://doi.org/10.1093/rfs/hhq142

Maddaloni, A., & Peydró, J.-L. (2011). Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the Euro-area and the U.S. lending standards. *Review of Financial Studies*, *24*(6), 2121–2165. https://doi.org/10.1093/rfs/hhr015

Mian, A., & Sufi, A. (2009). The consequences of mortgage credit expansion: Evidence from the U.S. mortgage default crisis. *Quarterly Journal of Economics*, *124*(4), 1449–1496. https://doi.org/10.1162/qjec.2009.124.4.1449

Müller, C., & Noth, F. (2018). Market power and risk: Evidence from the U.S. mortgage market. *Economics Letters*, *169*, 72–75. https://doi.org/10.1016/j.econlet.2018.04.033

Petersen, M. A., & Rajan, R. G. (2002). Does distance still matter? The information revolution in small business lending. *Journal of Finance*, *57*(6), 2533–2570.

Purnanandam, A. (2011). Originate-to-distribute model and the subprime mortgage crisis. *Review of Financial Studies*, *24*(6), 1881–1915. https://doi.org/10.1093/rfs/hhq106

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance*, *47*(4), 1367–1400. https://doi.org/10.1111/j.1540-6261.1992.tb04662.x

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance*, *45*(4), 1069–1087. https://doi.org/10.1111/j.1540-6261.1990.tb02427.x

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). Cambridge, Mass., MIT Press.

List of research reports

16001-GEM: Hoorn, A. van, How Are Migrant Employees Manages? An Integrated Analysis

16002-EEF: Soetevent, A.R., Te Bao, A.L. Schippers, A Commercial Gift for Charity

16003-GEM: Bouwmeerster, M.C., and J. Oosterhaven, Economic Impacts of Natural Gas Flow Disruptions

16004-MARK: Holtrop, N., J.E. Wieringa, M.J. Gijsenberg, and P. Stern, Competitive Reactions to Personal Selling: The Difference between Strategic and Tactical Actions

16005-EEF: Plantinga, A. and B. Scholtens, The Financial Impact of Divestment from Fossil Fuels

16006-GEM: Hoorn, A. van, Trust and Signals in Workplace Organization: Evidence from Job Autonomy Differentials between Immigrant Groups

16007-EEF: Willems, B. and G. Zwart, Regulatory Holidays and Optimal Network Expansion

16008-GEF: Hoorn, A. van, Reliability and Validity of the Happiness Approach to Measuring Preferences

16009-EEF: Hinloopen, J., and A.R. Soetevent, (Non-)Insurance Markets, Loss Size Manipulation and Competition: Experimental Evidence

16010-EEF: Bekker, P.A., A Generalized Dynamic Arbitrage Free Yield Model

16011-EEF: Mierau, J.A., and M. Mink, A Descriptive Model of Banking and Aggregate Demand

16012-EEF: Mulder, M. and B. Willems, Competition in Retail Electricity Markets: An Assessment of Ten Year Dutch Experience

16013-GEM: Rozite, K., D.J. Bezemer, and J.P.A.M. Jacobs, Towards a Financial Cycle for the US, 1873-2014

16014-EEF: Neuteleers, S., M. Mulder, and F. Hindriks, Assessing Fairness of Dynamic Grid Tariffs

16015-EEF: Soetevent, A.R., and T. Bružikas, Risk and Loss Aversion, Price Uncertainty and the Implications for Consumer Search

16016-HRM&OB: Meer, P.H. van der, and R. Wielers, Happiness, Unemployment and Self-esteem

16017-EEF: Mulder, M., and M. Pangan, Influence of Environmental Policy and Market Forces on Coal-fired Power Plants: Evidence on the Dutch Market over 2006-2014

16018-EEF: Zeng,Y., and M. Mulder, Exploring Interaction Effects of Climate Policies: A Model Analysis of the Power Market

16019-EEF: Ma, Yiqun, Demand Response Potential of Electricity End-users Facing Real Time Pricing

16020-GEM: Bezemer, D., and A. Samarina, Debt Shift, Financial Development and Income Inequality in Europe

16021-EEF: Elkhuizen, L, N. Hermes, and J. Jacobs, Financial Development, Financial Liberalization and Social Capital

16022-GEM: Gerritse, M., Does Trade Cause Institutional Change? Evidence from Countries South of the Suez Canal

16023-EEF: Rook, M., and M. Mulder, Implicit Premiums in Renewable-Energy Support Schemes

17001-EEF: Trinks, A., B. Scholtens, M. Mulder, and L. Dam, Divesting Fossil Fuels: The Implications for Investment Portfolios

17002-EEF: Angelini, V., and J.O. Mierau, Late-life Health Effects of Teenage Motherhood

17003-EEF: Jong-A-Pin, R., M. Laméris, and H. Garretsen, Political Preferences of (Un)happy Voters: Evidence Based on New Ideological Measures

17004-EEF: Jiang, X., N. Hermes, and A. Meesters, Financial Liberalization, the Institutional Environment and Bank Efficiency

17005-EEF: Kwaak, C. van der, Financial Fragility and Unconventional Central Bank Lending Operations

17006-EEF: Postelnicu, L. and N. Hermes, The Economic Value of Social Capital

17007-EEF: Ommeren, B.J.F. van, M.A. Allers, and M.H. Vellekoop, Choosing the Optimal Moment to Arrange a Loan

17008-EEF: Bekker, P.A., and K.E. Bouwman, A Unified Approach to Dynamic Mean-Variance Analysis in Discrete and Continuous Time

17009-EEF: Bekker, P.A., Interpretable Parsimonious Arbitrage-free Modeling of the Yield Curve

17010-GEM: Schasfoort, J., A. Godin, D. Bezemer, A. Caiani, and S. Kinsella, Monetary Policy Transmission in a Macroeconomic Agent-Based Model

17011-I&O: Bogt, H. ter, Accountability, Transparency and Control of Outsourced Public Sector Activities

17012-GEM: Bezemer, D., A. Samarina, and L. Zhang, The Shift in Bank Credit Allocation: New Data and New Findings

17013-EEF: Boer, W.I.J. de, R.H. Koning, and J.O. Mierau, Ex-ante and Ex-post Willingness-to-pay for Hosting a Major Cycling Event

17014-OPERA: Laan, N. van der, W. Romeijnders, and M.H. van der Vlerk, Higher-order Total Variation Bounds for Expectations of Periodic Functions and Simple Integer Recourse Approximations

17015-GEM: Oosterhaven, J., Key Sector Analysis: A Note on the Other Side of the Coin

17016-EEF: Romensen, G.J., A.R. Soetevent: Tailored Feedback and Worker Green Behavior: Field Evidence from Bus Drivers

17017-EEF: Trinks, A., G. Ibikunle, M. Mulder, and B. Scholtens, Greenhouse Gas Emissions Intensity and the Cost of Capital

17018-GEM: Qian, X. and A. Steiner, The Reinforcement Effect of International Reserves for Financial Stability

17019-GEM/EEF: Klasing, M.J. and P. Milionis, The International Epidemiological Transition and the Education Gender Gap

2018001-EEF: Keller, J.T., G.H. Kuper, and M. Mulder, Mergers of Gas Markets Areas and Competition amongst Transmission System Operators: Evidence on Booking Behaviour in the German Markets

2018002-EEF: Soetevent, A.R. and S. Adikyan, The Impact of Short-Term Goals on Long-Term Objectives: Evidence from Running Data

2018003-MARK: Gijsenberg, M.J. and P.C. Verhoef, Moving Forward: The Role of Marketing in Fostering Public Transport Usage

2018004-MARK: Gijsenberg, M.J. and V.R. Nijs, Advertising Timing: In-Phase or Out-of-Phase with Competitors?

2018005-EEF: Hulshof, D., C. Jepma, and M. Mulder, Performance of Markets for European Renewable Energy Certificates

2018006-EEF: Fosgaard, T.R., and A.R. Soetevent, Promises Undone: How Committed Pledges Impact Donations to Charity

2018007-EEF: Durán, N. and J.P. Elhorst, A Spatio-temporal-similarity and Common Factor Approach of Individual Housing Prices: The Impact of Many Small Earthquakes in the North of Netherlands

2018008-EEF: Hermes, N., and M. Hudon, Determinants of the Performance of Microfinance Institutions: A Systematic Review

2018009-EEF: Katz, M., and C. van der Kwaak, The Macroeconomic Effectiveness of Bank Bail-ins

2018010-OPERA: Prak, D., R.H. Teunter, M.Z. Babai, A.A. Syntetos, and J.E. Boylan, Forecasting and Inventory Control with Compound Poisson Demand Using Periodic Demand Data

2018011-EEF: Brock, B. de, Converting a Non-trivial Use Case into an SSD: An Exercise

2018012-EEF: Harvey, L.A., J.O. Mierau, and J. Rockey, Inequality in an Equal Society

2018013-OPERA: Romeijnders, W., and N. van der Laan, Inexact cutting planes for two-stage mixed-integer stochastic programs

2018014-EEF: Green, C.P., and S. Homroy, Bringing Connections Onboard: The Value of Political Influence

2018015-OPERA: Laan, N. van der, and W. Romeijnders, Generalized aplha-approximations for two-stage mixed-integer recourse models

2018016-GEM: Rozite, K., Financial and Real Integration between Mexico and the United States

2019001-EEF: Lugalla, I.M., J. Jacobs, and W. Westerman, Drivers of Women Entrepreneurs in Tourism in Tanzania: Capital, Goal Setting and Business Growth

2019002-EEF: Brock, E.O. de, On Incremental and Agile Development of (Information) Systems

2019003-OPERA: Laan, N. van der, R.H. Teunter, W. Romeijnders, and O.A. Kilic, The Data-driven Newsvendor Problem: Achieving On-target Service Levels.

2019004-EEF: Dijk, H., and J. Mierau, Mental Health over the Life Course: Evidence for a U-Shape?

2019005-EEF: Freriks, R.D., and J.O. Mierau, Heterogeneous Effects of School Resources on Child Mental Health Development: Evidence from the Netherlands.

2019006-OPERA: Broek, M.A.J. uit het, R.H. Teunter, B. de Jonge, J. Veldman, Joint Condition-based Maintenance and Condition-based Production Optimization.

2019007-OPERA: Broek, M.A.J. uit het, R.H. Teunter, B. de Jonge, J. Veldman, Joint Condition-based Maintenance and Load-sharing Optimization for Multi-unit Systems with Economic Dependency

2019008-EEF: Keller, J.T. G.H. Kuper, and M. Mulder, Competition under Regulation: Do Regulated Gas Transmission System Operators in Merged Markets Compete on Network Tariffs?

2019009-EEF: Hulshof, D. and M. Mulder, Renewable Energy Use as Environmental CSR Behavior and the Impact on Firm Profit

2019010-EEF: Boot, T., Confidence Regions for Averaging Estimators
2020001-OPERA: Foreest, N.D. van, and J. Wijngaard. On Proportionally Fair Solutions for the Divorced-Parents Problem

2020002-EEF: Niccodemi, G., R. Alessie, V. Angelini, J. Mierau, and T. Wansbeek. Refining Clustered Standard Errors with Few Clusters

2020003-I&O: Bogt, H. ter, Performance and other Accounting Information in the Public Sector: A Prominent Role in the Politicians' Control Tasks?

2020004-I&O: Fisch, C., M. Wyrwich, T.L. Nguyen, and J.H. Block, Historical Institutional Differences and Entrepreneurship: The Case of Socialist Legacy in Vietnam

2020005-I&O: Fritsch, M. and M. Wyrwich. Is Innovation (Increasingly) Concentrated in Large Cities? An Internatinal Comparison

2020006-GEM: Oosterhaven, J., Decomposing Economic Growth Decompositions.

2020007-I&O: Fritsch, M., M. Obschonka, F. Wahl, and M. Wyrwich. The Deep Imprint of Roman Sandals: Evidence of Long-lasting Effects of Roman Rule on Personality, Economic Performance, and Well-Being in Germany

2020008-EEF: Heijnen, P., On the Computation of Equilibrium in Discontinuous Economic Games

2020009-EEF: Romensen, G.J. and A.R. Soetevent, Improving Worker Productivity Through Tailored Performance Feedback: Field Experimental Evidence from Bus Drivers

2020010-EEF: Rao, Z., M. Groneck, and R. Alessie, Should I Stay or Should I Go? Intergenerational Transfers and Residential Choice. Evidence from China

2020011-EEF: Kwaak, C. van der, Unintended Consequences of Central Bank Lending in Financial Crises

2020012-EEF: Soetevent, A.R., Determinants choice set variation in demand estimation – with an application to the electric vehicle public charging market

2020013-EEF: Kwaak, C. van der, Old-Keynesianism in the New Keynesian model

2020014-EEF: Plaat, m. van der, Loan Sales and the Tyranny of Distance in U.S. Residential Mortgage Lending

2020015-I&O: Fritsch, M., and M. Wyrwich, Initial Conditions and Regional Performance in the Aftermath of Disruptive Shocks: The Case of East Germany after Socialism

2020016-OPERA: Laan, N. van der, and W. Romeijnders, A Converging Benders' Decomposition Algorithm for Two-stage Mixed-integer Recourse Models

2021001-OPERA: Baardman, L., K.J. Roodbergen, H.J. Carlo, and A.H. Schrotenboer, A Special Case of the Multiple Traveling Salesmen Problem in End-of-aisle Picking Systems

2021002-EEF: Wiese, R., and S. Eriksen, Willingness to Pay for Improved Public Education and Public Health Systems: The Role of Income Mobility Prospects.

2021003-EEF: Keller, J.T., G.H. Kuper, and M. Mulder, Challenging Natural Monopolies: Assessing Market Power of Gas Transmission System Operators for Cross-Border Capacity

2021004-EEF: Li, X., and M. Mulder, Value of Power-to-Gas as a Flexibililty Option in Integrated Electricity and Hydrogen Markets

2021005-GEM: Rozite, K., J.P.A.M. Jacobs, and D.J. Bezemer, Investor Sentiment and Business Investment www.rug.nl/feb