Journal of Banking and Finance 154 (2023) 106918

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Banks, non-banks, and the incorporation of local information in CMBS loan pricing[☆]

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ARTICLE INFO

Article history:
Received 23 February 2021
Accepted 2 June 2023
Available online 11 June 2023

JEL classification:
G21
G32

Keywords:
CMBS
Non-bank lending
Geographical distance
Asymmetric information
Loan spread

ABSTRACT

Comparing banks to non-bank lenders, we investigate whether the geographical distance between lenders, borrowers, and their properties is reflected in the pricing of US mortgages that were included in US commercial mortgage-backed security (CMBS) pools during the 2000 to 2017 period. The difference in loan spreads when the bank-borrower distance increases from zero to the median of about 700 miles is 10 basis points, and this effect is more pronounced if the loan is collateralized by a riskier property. On the contrary, geographical distance does not seem to have any effect on the loan spread of mortgages granted by non-bank lenders. The difference in loan pricing across originator types (even after controlling for key mortgage and property characteristics) suggests that banks and non-bank lenders have different incentives, lending technologies, and/or different types of borrowers. Our results contribute to the emerging literature on non-bank lender behavior.

1. Introduction

Current research has provided mixed evidence regarding securitization practices of financial intermediaries and their incentives to appropriately screen and monitor borrowers (Keys et al., 2010; Dell'Ariccia et al., 2012). However, this line of work mostly studies the residential mortgage-backed securities (RMBS) market. In this paper, we study the effect of geographic distance on loan pricing and performance in the commercial mortgage-backed securities (CMBS) market, and test whether this effect differs for loans originated by banks and non-bank lenders.

We argue that the answers to these questions are important for two reasons. First, much less is known about the CMBS market, which has very different characteristics than the RMBS market. For example, unlike RMBS asset pools, which contain many residential mortgages, CMBS asset pools generally contain far fewer mortgages, because of the large size of commercial mortgages (Baghai and Becker, 2020). Therefore, CMBS asset pools have more concentrated real estate risk, and understanding the quality of each of the underlying loans and their real estate collateral becomes more important, especially since a commercial mortgage is much more heterogeneous in terms of property type than is a residential mortgage.

Second, the CMBS market has some key advantages for studying this research question. It involves a rather homogeneous product: loans without covenants, collateralized by rent-generating real estate assets. We can observe and control for the characteristics of these assets, which allows for a much cleaner comparison than

☆ We would like to thank anonymous referees, Jaap Bos, Hans Degryse, Iftekhar Hasan, David Martinez-Miera, Klaas Mulier, Peter Schotman, Markus Simeth, and Daniel Streitz as well as the seminar participants at Maastricht University (2017), the Barcelona GSE Summer School (2018), the 1st Ph.D. Consortium of Spanish Finance Association (AEFIN) (2018), the 15th Corporate Finance Day (2018), the 4th Benelux Banking Research Day (2018), XXVII International Rome Conference on Money, Banking and Finance (2018), the 27th Finance Forum (2019), and Lund University (2021) for helpful comments. We are grateful to Real Capital Analytics (RCA) for providing the CMBS data. Disclaimer: This paper should not be reported as representing the views of Nordea Asset Management (NAM). The views expressed are those of the authors and do not necessarily reflect those of NAM.

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https://doi.org/10.1016/j.jbankfin.2023.106918
0378-4266/

would be possible for other types of commercial loans, which differ more strongly in loan covenants and collateral assets. This offers an ideal setting in which to study the effects of heterogeneity in loan underwriters, comprising banks as well as non-bank lenders such as finance companies, pension funds, and insurance companies, on loan pricing.

Geographic distance has been considered as a proxy for access to such local information (see for example Knyazeva and Knyazeva, 2012; Hollander and Verriest, 2016), which on the CMBS market could take the form of, for example, private information about local economic and social conditions, proprietary information about the nature and the pieces of real-estate involved, and/or soft information about the borrower's character and professionalism.

In this paper, we study the impact of geographic distance on loan pricing and performance, comparing banks and non-bank lenders. In particular, we focus on two dimensions of distance: the distance between the originator and the borrower, and the distance between the borrower and the real estate collateral. We first hypothesize that loan spreads increase in distance between the lender and the borrower due to the information asymmetry.[1] Benefiting from observing collateral asset characteristics, we also hypothesize that the effect of originator-borrower distance on the spreads should be more pronounced for riskier collateral assets. If the information asymmetry is increasing in originator-borrower distance, this should matter most when the loan is collateralized by a risky property type such as industrial or office, because it will be repaid from the cash flows generated by this property (Conklin et al., 2018). Furthermore, we also evaluate the impact of distance between the borrower and the property. As suggested by Garmaise and Moskowitz (2004), for borrowers located farther away from their properties, asymmetric information about local market conditions should be more marked. For example, it might be difficult for those borrowers to distinguish between immediate income and the future value of the cash flows generated by those properties. To fully assess the quality of a building or its location, one needs to visit it, talk to tenants, and stroll around the area. Since lenders know this, we hypothesize that loan spreads increase with distance between the borrower and the property.

We use a dataset of loans issued in the US over the period 2000–2017 that are subsequently securitized. The dataset covers 31,270 conduit loans originated by US banks, bank holding companies, and non-bank lenders exclusively for direct sale into the secondary market, and includes rich information on the loans and the properties, as well as information about the borrowers and the lenders.

In the loan pricing analysis, we estimate a reduced-form model of commercial mortgage-treasury rate spreads. We define the mortgage spread as a function of geographical distance, mortgage and property characteristics, and capital market conditions. Our results show that a greater lender-borrower distance is associated with higher loan spreads. Moreover, this effect is more pronounced for banks relative to non-bank lenders. We find that the spread difference between a typical loan extended by a lender located in the direct vicinity of the borrower and a loan extended by a bank 772 miles away—the median distance in our sample for banks—is 10 basis points. To put this in perspective, the median loan size in the sample is USD 6 million, so this additional spread implies approximately USD 6000 in additional annual interest costs. We also find that this effect is more pronounced for riskier collateral assets, such as industrial and office properties. For example, the additional annual interest cost to finance industrial properties is on average USD 276,000 higher than for apartments. We also analyze whether the distance between borrower and property matter for loan pricing, and we do not find any consistent evidence.

Additionally, we explore how the effect of distance on the spread varies with the degree of information asymmetry. This effect is less pronounced if the borrower obtains a previous loan from the same originator, and if it is a large loan. We then explain the default probabilities by estimating a Cox proportional hazard model. Our results show that the probability of default decreases with the distance, when the originator is a bank.

In sum, commercial mortgage lenders, in particular banks, do well to consider distance in their loan pricing, to reflect the cost of acquiring local information about borrowers and their collateral assets. We suggest that originator reputation is a possible mechanism for distance being priced at loan origination in the CMBS market. Due to the repeated nature of securitization, lenders seem to care about originating high quality loans, and hence they continue investing in information collection across distance.

The remainder of the paper is organized as follows. Section 2 presents the theoretical motivation for our empirical analysis. Section 3 describes the data and the measurement of the variables. Section 4 presents our empirical results. Section 5 presents additional analyses, and Section 6 discusses the possible mechanism. Section 7 gives the results of robustness tests. Section 8 concludes.

2. Theoretical framework and hypotheses

We study the effect of distance on loan spread in the CMBS market by testing hypotheses based on information asymmetry theory. Distance has mainly been employed as a proxy for access to local information in the banking literature, and it is well established that it affects the ability of lenders to collect soft (private) information (see for example Sussman and Zeira, 1995; Almazan, 2002; Degryse and Ongena, 2005; Alessandrini et al., 2009; Agarwal and Hauswald, 2010; Knyazeva and Knyazeva, 2012; Hollander and Verriest, 2016).

In CMBS origination, basically hard and public information and standardized assessments play a central role for the loan approval. For example, lenders assessing credit quality look at a property's debt yield, loan-to-value ratio (LTV), and debt service coverage ratio (DSCR) to measure the ability of the property to meet the loan obligations. These three measures already incorporate hard and public information, such as property type, property size, and location of the property, which may be easy to verify. However, although CMBS loans are regarded as transactional loans, soft (private) information, which is generally obtained through relationship lending—such as reliability of the owners and the creditworthiness of their tenants, the quality of a location, and possible alternative uses of a property—plays an important role in commercial mortgage origination (Titman and Tsyplakov, 2010). Lenders have to exert costly effort to collect such local information by visiting the borrowers and the site of the property (Stein, 2002). Since gathering such local information is likely to be difficult and more costly over longer distances, geographic distance becomes important in the CMBS market.

One could argue whether information and, hence, distance should matter in the first place in the CMBS loan setting, because all the cash flows and risks are passed on to outside investors. Lenders might have no incentive to collect information on loan quality due to the lack of their own "skin in the game" in the loans originated for securitization. However, Rajan et al. (2015) argues that, the securitization process is a repeated game, in which a lender repeatedly originates loans that are then sold to CMBS purchasers. Due to this repeated nature of securitization, lenders have an incentive to build and preserve a good reputation for originating high-quality loans (Rajan et al., 2015). The lender knows

[1] Economic theory suggests two causal factors in the role of geographical distance in loan transactions: transportation costs and information costs. As the two channels are not mutually exclusive, we do not try to distinguish between the two.

that originating low-quality loans with a higher likelihood of poor performance will hurt his reputation and may lead to a loss of future profits (Gopalan et al., 2011). For example, if loan defaults are too high for a specific lender in a given year, CMBS purchasers can discipline the lender by not buying his loans in the future (Titman and Tsyplakov, 2010; Rajan et al., 2015). Thus, the need to build and preserve a good reputation could provide lenders with a non-contractual incentive to collect and screen local information, and to use it in their loan acceptance and pricing. If lenders extend loans to more distant borrowers, it is expected that they pass on the cost of acquiring information to the borrower, which results in higher loan spreads. On the other hand, if securitization leads to lax screening, distance should not play any role in loan pricing.

Moreover, we also consider the competition between banks and non-banks. Conduit lenders are even willing to extend loans to faraway borrowers because of the high competition in the CMBS market, driving them to expand their radius. In the CMBS market, banks are competing with each other, but also increasingly with non-bank lenders operating in the regulatory shadows. Carey et al. (1998) suggests that banks are special in their ability to screen borrowers, whereas non-bank lenders, namely finance companies, have been reputed to make high-interest loans to borrowers who have been rejected by banks. Thus, we additionally expect that the positive relationship between spread and distance is more pronounced for banks compared to non-bank lenders.

Hypothesis 1. The loan spread increases in distance between lender and borrower, and this effect is more pronounced for banks as opposed to non-bank lenders.

Next, we consider how the loan spread varies with the property type. Commercial mortgage default varies systematically with property type (Vandell et al., 1993; Ciochetti et al., 2002; An et al., 2011). Apartments are characterized by lower levels of uncertainty and less sensitivity to the business cycle than retail and office (An et al., 2011), so multi-family loans are the least risky loans. If risk increases with the originator-borrower distance, this should matter most when the loan is also collateralized by a risky property type, because the loans will be repaid from cash flows generated by those properties (Conklin et al., 2018). Therefore, we argue that the effect of geographical distance on the loan spread should be more pronounced if loans are collateralized by a risky property type such as hotel, industrial or retail property.

Hypothesis 2. The increase in loan spread in the distance between lender and borrower is more pronounced for riskier property types.

In a similar fashion to Garmaise and Moskowitz (2004), we also consider the distance between borrower and property as an indirect proxy for asymmetric information. Garmaise and Moskowitz (2004) argues that information considerations are important in real estate markets for two reasons: First, due to the illiquidity of the real estate market, conveyance of information to market participants is a slow process. Second, real estate assets are difficult for non-locals to value. They suggest that market participants resolve information asymmetries by purchasing nearby properties.

In our setting, the distance between borrower and property is also highly relevant, since the CMBS market allows investors to invest easily in a variety of geographic locations for diversification reasons. As the information diffusion is slow in the real estate market, it is natural to expect that borrowers located closer to the properties have more information about local market conditions. Therefore, lenders may take into account those borrowers' understanding and knowledge of local market conditions where the property is located. For example, a lender possibly believes that a borrower located in Florida buying real estate in Florida has more local market information than does a borrower located in Florida buying real estate in California. If the lenders predicate their loan pricing on the borrowers' access to local information, borrowers who purchase nearby properties obtain more favorable pricing conditions. This would imply a positive relationship between loan spread and borrower-property distance.

Hypothesis 3. The loan spread increases in distance between borrower and property.

We now turn to the dataset we use to test these three hypotheses.

3. Data and variables

3.1. Sample construction

We use a dataset of commercial mortgages provided by Real Capital Analytics Inc. (RCA), a leading data provider in commercial real estate. Our primary sample of CMBS conduit loans includes 48,173 commercial mortgages that were originated between January 2000 and August 2017 with the explicit intention of possible securitization.[2] The loan originators in the larger dataset are heterogeneous in terms of their financial activities. The categories include banks, corporate, developer/owner/operator, equity fund, finance, government, insurance, investment manager, pension fund, REIT, REOC, and religious institutions. The largest category in the dataset is "Bank." We classify all other types of originators as "Non-bank."[3]

We exclude syndicated loans and focus exclusively on sole-lender loans. For some loans, we have multiple borrowers. We keep these loans if all borrowers are located in the US. We exclude loans to borrowers located outside the US, loans to Real Estate Investment Trusts (REITs), and banks from the sample. The final sample includes 31,270 loans for 29,756 unique real estate properties to 9,754 unique borrowers.

Table 1 presents the top ten lenders in our sample. In the bank sample, the top ten originators constitute 84 percent of our bank sample. On the non-bank side, the top ten originators comprise 57 percent of our non-bank subsample.

3.2. Variables

Our sample provides information on the loans, the collateralizing properties, the lenders, and the borrowers. We will use this subsection to present and discuss all variables, beginning with distance, which is our key explanatory variable. Appendix A provides information regarding the definition of all variables used in this study.

3.2.1. Measurement of distance

We calculate "as the crow flies" distances using geographic coordinates. RCA data contains latitudes and longitudes for the borrower, property, and headquarters of the lender. CMBS loans are typically so large and complex in comparison to other mortgages. We therefore focus on the locations of the lenders' headquarters since it is likely that the decision to grant a loan is made at the

[2] An et al. (2009, p.308–309) defines the conduit loans as follow: "..., conduit loans are originated specifically with the intention of sales into CMBS structures in the secondary market. At loan origination, originators know with certainty that these loans will be sold to CMBS issuers".

[3] Our results hold when Goldman Sachs is classified as non-bank before November 2008 and as bank thereafter.

Table 1
Top ten lenders.

Number of loans by top ten lender types	
Banks	Number of loans by banks
Wells Fargo	2319
Citigroup	1823
JP Morgan	1793
Morgan Stanley	1313
Bank of America	1227
Goldman Sachs	1165
KeyCorp	831
PNC Financial Services	693
M&T Bank	460
BB&T	388
Total	12,012
Non-banks	Number of loans by non-banks
Ladder Capital	1346
CBRE	1263
Cantor Comm'l RE Lending	1262
Berkadia	1249
Walker & Dunlop	1240
Greystone	901
Arbor Commercial	794
Starwood Property Trust	672
NorthMarq	546
Lennar Corporation	528
Total	9801

Notes: This table reports the top ten lenders in the bank and the non-bank sample. Sample period 2000:Q1–2017:Q3.

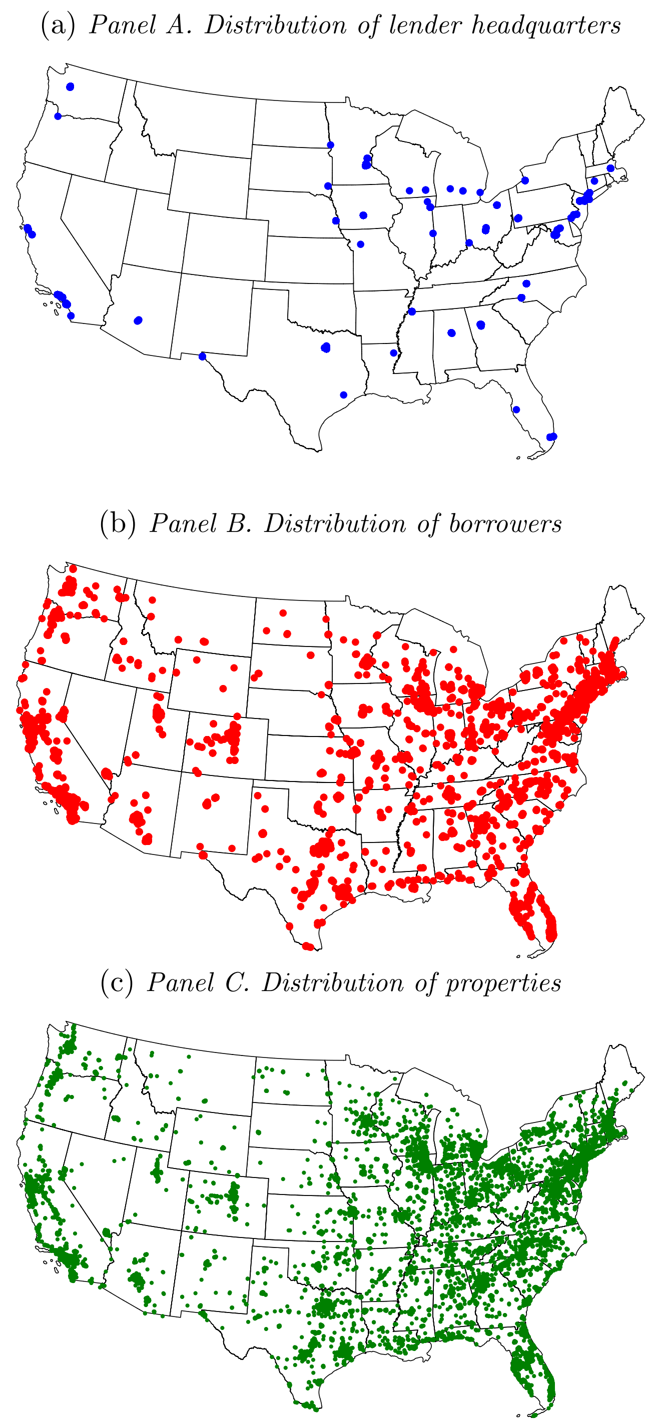

Fig. 1. Distribution of lenders, borrowers and properties.
Panel A shows the location of the 134 lender headquarters. Panel B shows the location of the 9754 unique borrowers. Panel C shows the location of the 29,756 unique properties. Alaska and Hawaii are not shown.

headquarters level.[4] Besides geographic distance, we also calculate the travel distance "a car would drive" as an alternative measure.

Because of the possible nonlinearity of the economic impact of distance, we employ a logarithmic transformation of distance. From an economic perspective, this transformation implies that the impact of a marginal increase of distance between 0 and 50 miles is not equal to an increase between 1000 and 1050 miles. Ln(1 + $\text{Distance}_{Originator-Borrower}$) is defined as the natural logarithm of one plus the distance (in miles) between the originator's headquarter and the borrower. Similarly, we define Ln(1 + $\text{Distance}_{Originator-Property}$) and Ln(1 + $\text{Distance}_{Borrower-Property}$).

Panel A of Fig. 1 shows a map of the US depicting the headquarter locations of the originators. New York accounts for thirty observations, including the headquarters of Citigroup, JP Morgan, Ladder Capital, and Morgan Stanley, which are among the top ten originators in our sample. Another relevant concentration is in California with twenty observations, including Wells Fargo. First National Bank Alaska is headquartered in Alaska, which is not shown on the map.

Panel B of Fig. 1 shows the distribution of the 9754 borrowers of our sample across the US. Although we observe clusters of borrowers in the major urban areas in the West and the North East, we also have a sizable number of borrower observations in other regions. Of all loans in the sample, 22 percent are to borrowers in California, mostly clustered in the major urban centers such as the San Francisco Bay area and Los Angeles. New York and Texas are the other two states with major borrower clusters, with 11.43 percent and 7.09 percent of our sample located in these states, respectively.

Panel C of Fig. 1 shows the distribution of locations for the 29,756 properties in the sample. The map shows that the main US urban areas are all represented in the sample, with California, Texas, and Florida being the most important locations: 32.43 percent of the loans are collateralized by properties located in these states.

3.2.2. Mortgage loan characteristics

Our dependent variable *Spread* is the mortgage spread. We define the mortgage spread as the difference between the mortgage rate and the Treasury bond rate with the same maturity, at the mortgage origination date. We restrict our sample to fixed-rate

[4] Unlike in studies on small business lending, top management involvement in the lending decisions is also the standard in the syndicated loan market (see for example Knyazeva and Knyazeva, 2012; Hollander and Verriest, 2016).

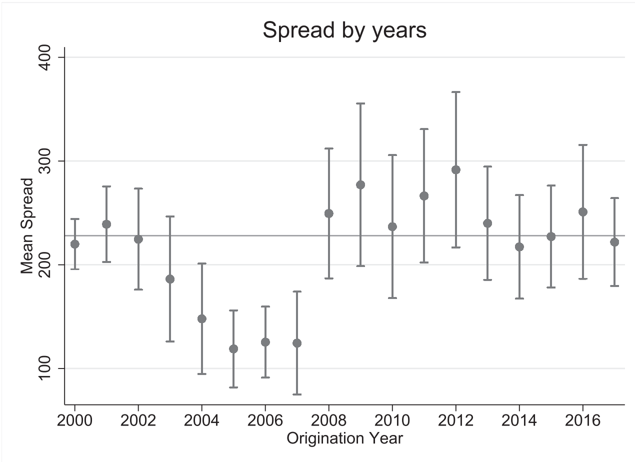

Fig. 2. Distribution of spread.
This graph shows the average loan spread over time, plus and minus one standard deviation. For each year, the dot depicts the mean spread, and the bar shows the plus and minus one standard deviation range. The horizontal line shows the average spread, 228 bps, for the whole sample period.

mortgages. Figure 2 shows the average loan spread over time, plus and minus one standard deviation. For each year, the dot depicts the mean spread, and the bar shows the plus and minus one standard deviation range. The horizontal line shows the average spread, 228 bps, for the whole sample period. We see that there is a sharp increase in the average spread during the 2008 financial crisis, and that the standard deviation of loan spreads is very large in 2009. Although spreads have come back down after the crisis, they are not as low as they were between 2003 and 2007, and seem to be hovering around their average level for the sample period.

Standard risk considerations of commercial loan underwriting involve the loan-to-value (LTV) ratio. The LTV ratio of a loan is measured as the loan amount divided by the appraised value of the real estate collateral. Previous studies find that the LTV is correlated with loan performance (Archer et al., 2002; Ambrose and Sanders, 2003), and that the LTV is an important predictor of default risk (An et al., 2011). We therefore expect the LTV to be positively related to the mortgage spread.

We also control for observable loan characteristics such as loan size and loan maturity. We expect that loan size is negatively related to the spread due to economies of scale in lending. That is, the relative costs of making loans to small borrowers tend to be greater than the relative costs of making loans to large borrowers. We similarly control for loan maturity and expect that this negatively affects spreads on CMBS loans. Commercial mortgages with a longer maturity have a lower default risk than those with a shorter maturity (An, 2007).

3.2.3. *Property characteristics*

Our data on the collateral properties is quite rich. We have six property types in the dataset: rental apartment, hotel, industrial, office, retail, and other. We construct six indicator variables for these property types.[5] Table B.1 shows the sample distribution by property type. Apartment is the most common type of collateral property we observe in the sample and it constitutes 30.68 percent and 65.22 percent of the collaterals for the loans originated by banks and non-banks, respectively. We use “apartment” as the base

Table 2
Summary statistics.

	Mean	Median	SD	N
Panel A: Full Sample				
Spread	228.14	226.27	70.36	31,270
Ln(1 + Distance$_{Originator-Borrower}$)	1126.91	925.63	892.09	31,270
Ln(1 + Distance$_{Originator-Property}$)	1084.13	931.20	784.33	31,270
Ln(1 + Distance$_{Borrower-Property}$)	525.10	193.76	670.24	31,270
Loan-to-value (LTV)	0.65	0.69	0.13	31,270
HHI	0.04	0.01	0.07	31,270
Maturity (in months)	118.12	120.00	34.75	31,270
Loan size ($ million)	12.14	6.30	22.47	31,270
11–20 years	0.19	0	0.39	31,270
21–30 years	0.17	0	0.38	31,270
31–40 years	0.15	0	0.35	31,270
41–50 years	0.13	0	0.34	31,270
Over 50 years	0.12	0	0.32	31,270
Central business district	0.07	0	0.26	31,270
Number of stories > 1	0.38	0	0.49	31,270
Renovated	0.28	0	0.45	31,270
Panel B: Banks				
Spread	220.94	222.10	73.35	14,238
Ln(1 + Distance$_{Originator-Borrower}$)	1125.06	771.59	911.38	14,238
Ln(1 + Distance$_{Originator-Property}$)	1086.64	870.13	816.30	14,238
Ln(1 + Distance$_{Borrower-Property}$)	615.25	316.25	721.57	14,238
Loan-to-value (LTV)	0.64	0.67	0.14	14,238
HHI	0.04	0.02	0.08	14,238
Maturity (in months)	116.90	120.00	35.12	14,238
Loan size ($ million)	13.40	6.18	29.38	14,238
11–20 years	0.21	0	0.40	14,238
21–30 years	0.17	0	0.38	14,238
31–40 years	0.13	0	0.34	14,238
41–50 years	0.11	0	0.31	14,238
Over 50 years	0.10	0	0.30	14,238
Central business district	0.08	0	0.27	14,238
Number of stories > 1	0.31	0	0.46	14,238
Renovated	0.29	0	0.45	14,238
Panel C: Non-banks				
Spread	234.16	230.00	67.18	17,032
Ln(1 + Distance$_{Originator-Borrower}$)	1128.46	967.40	875.66	17,032
Ln(1 + Distance$_{Originator-Property}$)	1082.04	965.55	756.59	17,032
Ln(1 + Distance$_{Borrower-Property}$)	449.74	114.23	614.05	17,032
Loan-to-value (LTV)	0.67	0.70	0.12	17,032
HHI	0.03	0.01	0.07	17,032
Maturity (in months)	119.14	120.00	34.41	17,032
Loan size ($ million)	11.10	6.45	14.27	17,032
11–20 years	0.18	0	0.38	17,032
21–30 years	0.17	0	0.38	17,032
31–40 years	0.16	0	0.37	17,032
41–50 years	0.16	0	0.36	17,032
Over 50 years	0.13	0	0.34	17,032
Central business district	0.06	0	0.24	17,032
Number of stories > 1	0.45	0	0.50	17,032
Renovated	0.27	0	0.44	17,032

Notes: Panel A reports the summary statistics for the full sample, Panel B reports for the banks, and Panel C reports for the non-bank sample. Sample period 2000:Q1–2017:Q3. All variables are defined in the Appendix.

case in the regressions as apartments are characterized by lower levels of uncertainty and less sensitivity to the business cycle than retail and office properties (An et al., 2011), whereas properties with volatile and cyclical cash flows such as industrial and hotels are viewed as the riskiest forms of commercial property collateral (Titman et al., 2005). We therefore expect loans to finance apartments to have lower spreads, followed by office, retail, and hotel, and with industrial property loans having the higher spreads.

Titman et al. (2005) finds that newer properties have lower spreads. This is likely because property age is a proxy for quality. Older properties are likely to be of lower quality, with a lower structure value relative to land value, increasing the moneyness of the redevelopment option, and therefore enhancing the like-

[5] Black et al. (2012) argues that it is possible that the effect of property types are captured by the LTV and DSCR variables. They nonetheless include them in the model specification to address the potential concern that lenders may concentrate on certain property types. Similarly, we also include property types in our model in order to account for any lender specialization.

lihood of redevelopment, and this flexibility is likely to increase the spread (Titman et al., 2004; 2005). Moreover, the age of a property is also a proxy for the degree of information asymmetry; properties with longer cash flow histories provide investors with more information about the property and local market conditions (Garmaise and Moskowitz, 2004). We have the age of the properties at the mortgage origination date. Since it is likely that the age of the property does not affect the spread linearly, we use indicator variables for different age categories: less than 10 years old, between 10 and 20, between 20 and 30, between 30 and 40, between 40 and 50, and more than 50 years old.

The argument about higher spreads for mortgages on properties with more investment flexibility also applies to properties that can be renovated. We therefore include an indicator variable equalling one if the property has been renovated.

We also control for the height of the properties. The number of stories can be associated with the loan spread for a variety of reasons. First, properties with a large number of stories generate additional rental income. For example, in some cities such as New York City, where land costs are high, building height is more important for total rentable space than the horizontal area (Barr, 2010). Second, there may be economies of scale associated with lower transaction costs in making loans to larger properties. For 65 percent of our sample, the number of stories is equal to one. Therefore, we define an indicator variable, *Number of Stories>1*, for the properties that have more than one story.

A final important factor in real estate quality and risk is the location. Assets located in or near a city's central business district tend to have less vacancy risk in down markets. This implies that their rental cash flows are less dependent on the business cycle. We therefore define an indicator variable for whether the property is located in the central business district (CBD). We expect the spread to be lower for loans involving properties located in CBDs.

3.2.4. Other control variables

In addition to these mortgage and property-specific variables, we also include a set of other variables that are known to affect loan spreads. Specifically, we include year-quarter time fixed effects to control for interest rate conditions that vary from quarter to quarter. We also include indicator variables for stated loan purposes: property acquisition or refinance. Following the literature (e.g., Ciochetti et al., 2002; Ambrose and Sanders, 2003; Titman and Tsyplakov, 2010; An et al., 2011), we also introduce fixed effects for the state where the property is located, as commercial mortgage default varies with geographic location. As a proxy for the level of commercial mortgage market competition in a state, we include the log of the Herfindahl–Hirschman Index (HHI) of the originator concentration in the state in which the borrower is located. We construct the HHI based on the market share by loan amount of each originator in a given state and year. A higher HHI means that the concentration is high, possibly increasing spreads.

Existing research, for example An et al. (2011), argues that investors pay a substantial premium for CMBS loans originated by lenders who have a strong reputation for strict underwriting in the commercial mortgage market. In order to take lender reputation into account, we include lender-fixed effects in all models.

3.3. Summary statistics

Table 2 provides summary statistics of the key variables. The spread has a mean value of 228 bps and a median value of 226 bps. The spread on non-bank loans is on average significantly higher than the spread on bank loans.

The average originator-borrower distance is 1126 miles, and lenders are located, on average, 1084 miles away from the property collateral. The shortest distance is the one between borrower and property and it is, on average, 525 miles. The distance series are skewed; the median originator-borrower distance is 925 miles, the median originator-property distance is 931 miles, and the median borrower-property distance is 193 miles.

In Fig. 3, we present mean and median distances between the loan originator, the borrower, and the property. The distance between the originator and the borrower is highly correlated (0.64) with the distance between the originator and the property. For 401 observations, the minimum value of the distance between the borrower and the property is 0. In most cases, these properties are apartments and offices.

The average LTV is 65 percent, with apartments having the highest LTV ratios at an average of 68 percent, and hotels the lowest, at an average of 61 percent. This pattern supports the view that LTV ratios are endogenously chosen, taking account of the riskiness of the property type (Titman et al., 2005). The average loan maturity is 118 months. The average loan size is USD 12 million, with a median size of USD 6 million, and the largest loan, for an open-air shopping mall in Hawaii, of USD 1.34 billion.

On average, 7 percent of the loans are collateralized by the properties located in a central business district (CBD), and 28 percent of the properties are renovated. The HHI equals 0.04, on average.

4. Results

4.1. Baseline results

We now turn to our estimation results. We start with testing whether the distance between lenders and borrowers is priced after controlling for observable mortgage and property characteristics. Column (1) of Table 3 presents the ordinary least squares (OLS) estimates of Eq. (1):

$$\begin{aligned} Spread = {} & \beta_0 + \beta_1 Ln\left(1 + Distance_{Originator-Borrower}\right) \\ & + \Sigma \alpha_i Property\ Characteristics \\ & + \Sigma \gamma_i Mortgage\ Characteristics + X + \epsilon \end{aligned} \tag{1}$$

where *Spread* is the difference between the mortgage rate and the Treasury bond rate with the same maturity, observed on the mortgage origination date. $Ln(1 + Distance_{Originator-Borrower})$ is the geographic distance between the originator headquarters and the borrower, in miles. *Property Characteristics* include property types, property age, property height, whether a property is located in a central business district, and whether a property is renovated. *Mortgage Characteristics* include loan size, loan maturity, and LTV. *X* represents a vector of control variables including HHI, the loan purpose, the MSA, the state where the property is located, the originator, the borrower, and the year-quarter time fixed effects. ϵ is the error term.

The coefficient of $Ln(1 + Distance_{Originator-Borrower})$ is positive and statistically significant, suggesting that the initial loan spread increases in distance between the originator and the borrower. It implies that, when the originator-borrower distance increases from zero to the median of about 900 miles, the loan spread increases 7 basis points.

Banks have long been the main lenders in the commercial mortgage market. But that has been changing since the Great Recession. Non-bank lenders such as finance companies, pension funds, and insurance companies have become major players in the origination of commercial mortgage loans. For example, banks such as Bank of America, Citigroup, JP Morgan, Morgan Stanley, and Goldman Sachs collectively represented more than 90 percent of the CMBS loan origination business in 2012, but their share dropped to roughly 65 percent by the end of 2015.[6] As our sam-

[6] New CMBS risk rules threaten smaller lenders' access, 2016.

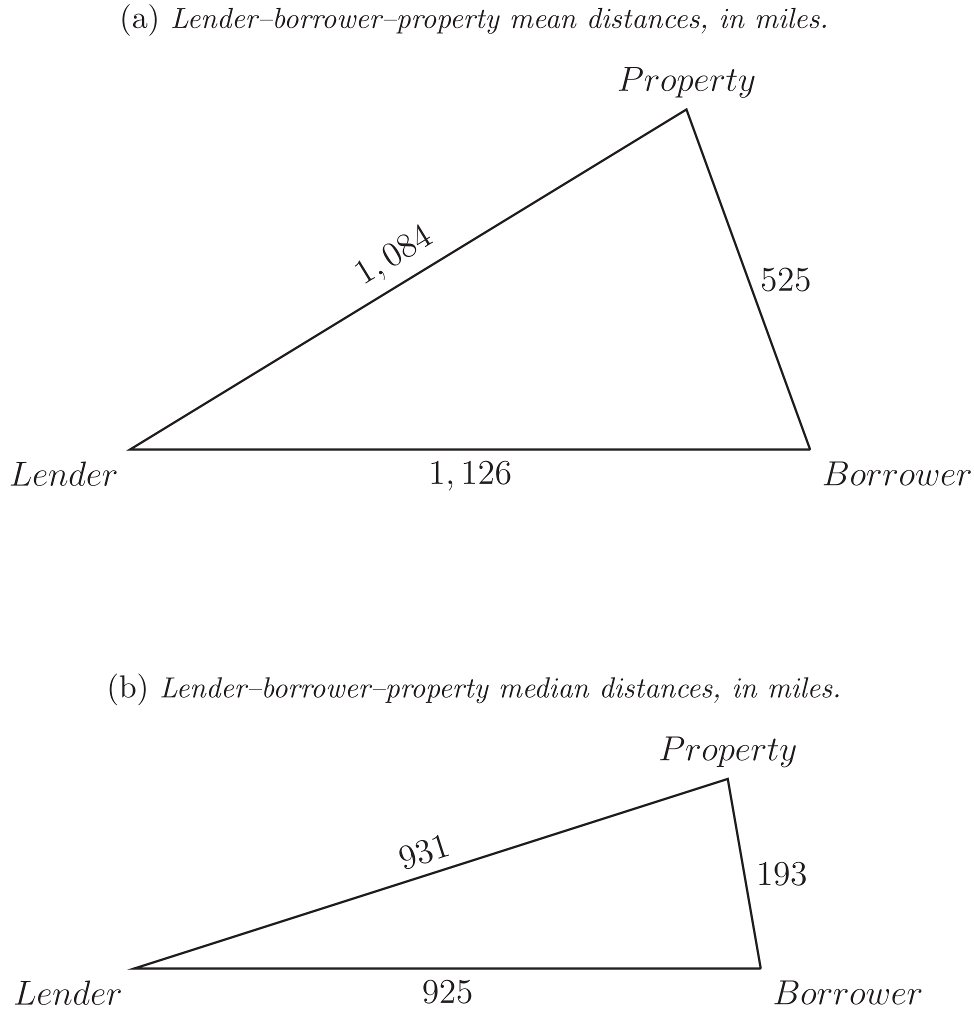

Fig. 3. Lender-borrower-property distances.
Panel A presents the mean distances, and Panel B presents the median distances.

ple consists of both bank and non-bank lenders, we also investigate whether the effect of distance on spread is different for the loans originated by banks and non-banks. To do so, we define an indicator variable, *Bank*, which is equal to one for the loans originated by banks, and zero otherwise. Similarly, we define an indicator variable, *Non-Bank*, which is equal to one for the loans originated by non-bank lenders, and zero otherwise. The interaction terms, $Ln(1 + Distance_{Originator-Borrower}) \times Bank$ and $Ln(1 + Distance_{Originator-Borrower}) \times Non\text{-}Bank$ measure the change in the spread with distance when the originator is a bank and when it is a non-bank, respectively. In Column (2), we find that the coefficient estimate for $Ln(1 + Distance_{Originator-Borrower}) \times Bank$ is significant at the 1% level while the estimate for $Ln(1 + Distance_{Originator-Borrower}) \times Non\text{-}Bank$ is insignificant. We also test for equality of the coefficients, and two coefficients are statistically different from each other at the 10% level. This suggests that local information is salient in the loan origination practices of banks. This implies that a 100 percent increase in distance is on average associated with a 1.5 basis point increase in spread for the loans originated by banks, all else being equal. Summary statistics in Panel B of Table 2 show a median distance of 772 miles, and our model would predict a 10 basis point increase in spread for borrowers at that distance relative to borrowers in the direct vicinity of the lender. For a median loan (USD 6 million), the increase in annual interest costs would be about USD 6000.

A natural question arises: If information acquisition over distances is costly for banks, why do they allocate loans to the distant borrowers in the first place? First, given the high competition in the CMBS market, conduit lenders tend to expand their radius. Moreover, while portfolio lenders are more comfortable making loans to borrowers who are nearby, conduit lenders can make loans for a borrower who is buying a property in a different state. Second, as the default rates vary across regions, lenders could seek geographic diversification in their loan portfolios.

The indicator variable *Bank* is positive and significant at the 5% level, which indicates that spread is on average higher for loans originated by banks. This result is consistent with our information search cost argument. Moreover, nonbank lenders compete with banks by cutting interest rate to increase their market share, and therefore nonbanks have been gaining ground on banks for the last decade. However, our finding is contrary to some of the existing results on differences in interest rates between bank and non-bank loans in the residential mortgage market and commercial and industrial (C&I) lending (see for example Chernenko et al., 2022), which are mainly attributed to bank regulations.

So it appears as if non-bank lenders either do not collect so much local information and/or if they do, they do not price its cost. We go one step further and also investigate the effect of distance on the loan spread for different types of non-bank lenders. The results of this test are presented in Table C.1 in the Appendix C.

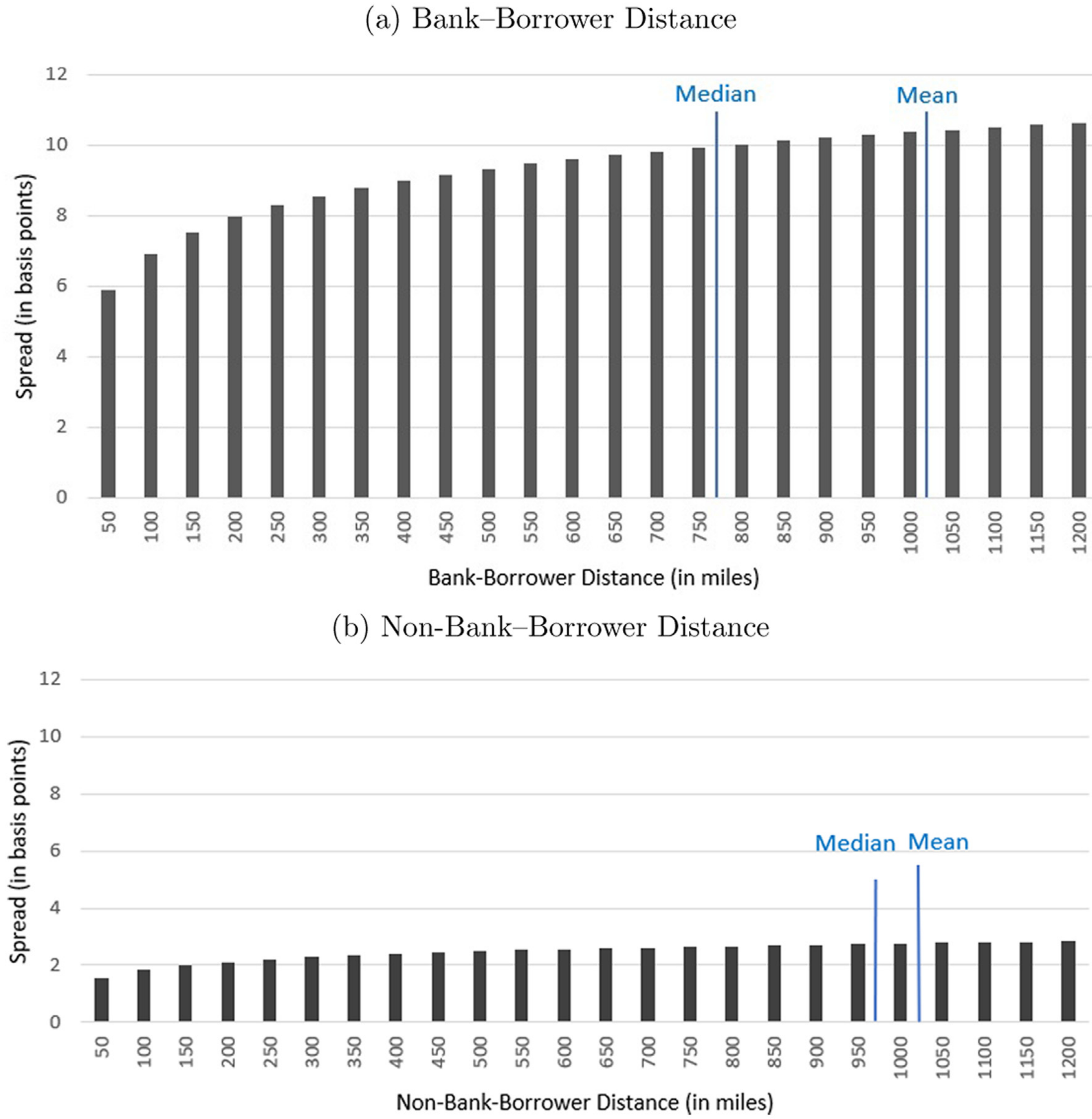

Fig. 4. Distance effects on spread.
The figure shows the impact of distance on spread by lender types based on the models presented in Table 3.

The coefficient of the distance variable is insignificant across the columns of Table C.1 except for insurance companies. These results can be explained by the fact that insurance companies are known for sophisticated underwriting and portfolio management approaches. It is likely that they tend to cherry-pick their borrowers and only provide loans to “low-risk” distant borrowers.

One possibility that explains these results is that non-bank lenders may have a different type of lending technology than banks have. For example, Black et al. (2012) suggests balance sheet lending as a potential channel by which to explain the average quality of securitized loans across originator types. They argue that the originators, such as banks, which are also active in balance sheet lending in addition to transaction lending, have better screening and monitoring abilities. Moreover, distance may matter relatively less to non-bank lenders if it is correlated with other dimensions of risk, which are priced into the loan scoring of non-banks. Alternatively, risk retention might be another channel explaining the observed pricing difference between banks and non-banks. If banks hold a larger share of the loan on their balance sheets, they have more incentive for careful screening.

Figure 4 presents the impact of the levels of distance on the spread by lender types based on the models presented in Table 3. In Panel (a), as the distance between a bank and a borrower increases, the spread also increases. For instance, while the spread is around 5 basis points on average when the distance is 50 miles, it increases to around 10 basis points when the distance is 1200 miles. On the other hand, the impact of distance is weaker for non-bank lenders. As distance increases, in general, the spread remains flat.

We re-estimate the regression models in columns (1) and (2) by replacing geographic distance with travel distance. The results are presented in columns (3) and (4), respectively. Similar results hold for travel distance. Columns (3) and (4) show that our results are robust to this alternative measure.

The control variables enter with the expected signs, consistent with the literature: We find a negative relationship between loan maturity and spread, and between loan size and spread. LTV is positively associated with spread. However, loan spread may be jointly determined with other loan terms such as LTV. For example, it is likely that the spread is higher for distant borrowers, because

Table 3
Originator-borrower distance and spread.

	Dependent variable: spread			
	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
Ln(1 + $Distance_{Originator-Borrower}$) × Bank		1.590***		1.406***
		(0.550)		(0.506)
Ln(1 + $Distance_{Originator-Borrower}$) × Non-Bank		0.458		0.293
		(0.572)		(0.553)
Ln(1 + $Distance_{Originator-Borrower}$)	1.047**		0.894**	
	(0.443)		(0.415)	
Bank		23.536**		23.516**
		(11.540)		(11.502)
Ln(1 + Maturity)	−53.574***	−53.629***	−53.709***	−53.760***
	(3.397)	(3.392)	(3.385)	(3.379)
Ln(Loan size)	−5.016***	−5.028***	−5.032***	−5.042***
	(0.462)	(0.460)	(0.463)	(0.462)
Loan-to-Value Ratio (LTV)	36.037***	36.138***	35.949***	36.017***
	(7.057)	(7.052)	(7.022)	(7.009)
Hotel	26.008***	26.261***	25.582***	25.858***
	(5.321)	(5.269)	(5.406)	(5.355)
Industrial	24.980***	25.146***	25.056***	25.213***
	(3.393)	(3.433)	(3.475)	(3.512)
Office	20.169***	20.264***	19.880***	19.968***
	(2.617)	(2.651)	(2.670)	(2.707)
Other	18.493***	18.402***	18.286***	18.173***
	(3.016)	(3.019)	(3.041)	(3.042)
Retail	18.921***	18.862***	18.887***	18.829***
	(2.131)	(2.109)	(2.194)	(2.174)
Central business district	−0.669	−0.756	−0.872	−0.960
	(2.216)	(2.245)	(2.299)	(2.329)
Renovated	−0.827	−0.792	−0.850	−0.817
	(0.815)	(0.806)	(0.823)	(0.815)
Ln(HHI)	0.466	0.468	0.323	0.325
	(1.019)	(1.021)	(1.018)	(1.019)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	31,270	31,270	31,195	31,195
Adjusted R^2	0.809	0.809	0.810	0.810

Notes: This table reports OLS regression results. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. Control variables include indicator variables for the age of the property, the number of stories, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

these borrowers have higher LTV ratios. To account for this, we investigate whether the loans which are allocated to distant borrowers have different LTVs than those are allocated to nearby borrowers. Following Titman and Tsyplakov (2010), we regress LTV on our variable of interest, *Ln(1 + $Distance_{Originator-Borrower}$)*. In untabulated results, we find that the coefficients of the distance variable are not significant which suggests that our result is not likely to be due to biased estimate of LTV.

The property type coefficients are in line with expectations in the sense that loans for the riskier property types have higher spreads, and loans financing apartments—the omitted category in the regression—have the lowest spreads, which is in line with their lower risk. Renovation and a central business district (CBD) location do not seem to play a significant role in CMBS loan spreads.

4.2. Difference-in-differences estimation

Since the 2008 financial crisis was caused by residential and subprime mortgages and not by commercial mortgages, one could argue that the resulting regulatory changes and industry consolidation primarily affect banks but not non-bank lenders. Hence, we define the treatment group as *Bank = 1* and the control group as *Bank = 0* (Non-bank). We construct an indicator variable, *Post-crisis*, which is equal to one for 2008 and the years after, and zero otherwise. Our analysis is based on the sample over the period of ± 4 years around the 2008 financial crisis (2003–2007, 2008–2012). We employ a difference-in-differences framework. Specifically, we estimate the model in Eq. (2):

$$\begin{aligned} Spread = {} & \beta_0 + \beta_1 Ln\left(1 + Distance_{Originator-Borrower}\right) \\ & + \beta_2 Bank \times Post\text{-}crisis + \beta_3 Bank + \beta_4 Post\text{-}crisis \\ & + \Sigma\alpha_i Property\ Characteristics \\ & + \Sigma\gamma_i Mortgage\ Characteristics + X + \epsilon \end{aligned} \quad (2)$$

where β_2 is a difference in differences. Column (1) of Table 4 presents the regression results. The estimate on *Bank × Post-crisis* is positive and statistically significant at the 1% level. This result implies that spreads increased since the 2008 financial crisis for bank originators.

In column (2), the coefficient of *Ln*(1 + *$Distance_{Originator-Borrower}$*) × *Post-crisis* is positive and statistically significant at the 1% level for banks (Bank = 1), and it is negative and statistically significant at the 5% level for non-banks (Bank = 0). These coefficients are significantly different from each other at the 1% level.

Table 4
Difference-in-differences estimation.

	Dependent variable: spread			
	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
Ln(1 + $Distance_{Originator-Borrower}$) × Post-crisis for Bank = 1		2.318***		1.850**
		(0.878)		(0.839)
Ln(1 + $Distance_{Originator-Borrower}$) × Post-crisis for Bank = 0		−1.973**		−2.123**
		(0.925)		(0.871)
Bank × Post-crisis	46.393***		45.739***	
	(7.027)		(6.860)	
Ln(1 + $Distance_{Originator-Borrower}$)	1.297**		1.142*	
	(0.632)		(0.607)	
Bank	0.287	11.390	0.898	12.611
	(11.185)	(11.133)	(11.036)	(11.050)
Post-crisis	40.829***	67.417***	40.931***	69.232***
	(15.468)	(15.888)	(15.500)	(15.967)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	11,147	11,147	11,124	11,124
Adjusted R^2	0.883	0.882	0.883	0.882

Notes: This table reports OLS regression results. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. The indicator variable *Post-crisis* is equal to one for 2008 and the years after, and zero otherwise. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of stories, central business district, renovated, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

In columns (3) and (4), we repeat the analyses with travel distance. The results are very similar.

4.3. The effect of property type

Next, we employ property type interactions. Mortgage loans collateralized by apartments have a more stable cash flow and are much more homogeneous, and therefore easier to judge, than are hotel, retail, office and industrial loans, suggesting that the salience of local information and thus the effect of distance should be stronger for the latter property types. To explore this hypothesis, we include interaction terms between the main property types and $Ln(1 + Distance_{Originator-Borrower})$.

Table 5 presents the results. In our estimation, the baseline property type is apartment (as in Titman et al., 2005). Column (1) presents the results estimated with geographical distance. The results are in line with our expectation; the estimated coefficients of the interaction terms are positive and statistically significant for industrial, office, and retail properties, and for the properties in the other category, suggesting that the effect of distance is more salient for loans collateralized with those type of properties.

In column (2), we employ three-way interactions with *Bank* and *Non-Bank* together with distance and property types. For the banks, the estimated coefficients of the interaction terms are positive and statistically significant for industrial, office, retail and other types, while for the non-banks only the estimated coefficient of the office is statistically significant. Next, we formally test the equality of the estimated coefficients. The coefficients for the industrial and retail types are significantly different from each other (at the 1% and 10% level, respectively).

This effect is also economically significant. For example, the coefficient of the interaction term, $Ln(1 + Distance_{Originator-Borrower}) \times Industrial \times Bank$ is 6.8. The additional annual interest cost for a median loan is USD 270,000 for industrial properties when the borrower is located at the median distance from the bank.

In columns (3) and (4), we replace geographic distance by travel distance, and obtain very similar results.

4.4. Borrower-property distance and spread

We also consider the distance between borrower and property as an indirect measure of information asymmetry, and we also expect that increasing distance is associated with higher spreads here. Garmaise and Moskowitz (2004) argues that buyers located closer to a property likely have a better understanding of local market conditions and can more easily and cheaply evaluate the property. Ling et al. (2018) shows that distant buyers tend to overpay in the commercial property market. Eichholtz et al. (2016) finds that office properties owned by distant investors have lower occupancy, resulting in a lower cash flow. If originators are aware of this, they will prefer borrowers that are close to their assets, which may be reflected in loan pricing. Thus, we add borrower-property distance to our model specified in Eq. (1). Our results in Table C.2 in the Appendix C show that borrower-property distance does not affect the spread. In order to investigate this finding in more detail, we differentiate by relative borrower distance to the originator. In particular, in Eq. (3), we create an indicator variable, D, which is equal to one if $Ln(1 + Distance_{Originator-Borrower})$ is smaller than $Ln(1 + Distance_{Originator-Property})$. We also define $Minimum_{Distance} = \{Ln(1 + Distance_{Originator-Borrower}), Ln(1 + Distance_{Originator-Property})\}$. In essence, we want to assess whether pricing is different if the borrower or the property is closer to the lender.

$$\begin{aligned} Spread = {} & \beta_0 + \beta_1 Minimum_{Distance} \times D \\ & + \beta_2 Ln\left(1 + Distance_{Borrower-Property}\right) \times D \\ & + \Sigma\alpha_i Property\ Characteristics \\ & + \Sigma\gamma_i Mortgage\ Characteristics + X + \epsilon \end{aligned} \tag{3}$$

We present the results in Table 6. In column (1), the only significant coefficient is the one of $Ln(1 + Distance_{Borrower-Property})$,

Table 5
The effect of property type.

	Dependent variable: spread			
	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Apartment $\times$ Bank		−1.174		−1.183
		(0.736)		(0.717)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Apartment $\times$ Non-Bank		−0.295		−0.328
		(0.510)		(0.502)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Hotel $\times$ Bank		0.219		−0.058
		(1.863)		(1.643)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Hotel $\times$ Non-Bank		0.680		0.293
		(2.122)		(1.913)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Industrial $\times$ Bank		6.845***		6.493***
		(1.281)		(1.157)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Industrial $\times$ Non-Bank		2.294		1.850
		(1.990)		(1.863)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Office $\times$ Bank		2.809***		2.459***
		(0.752)		(0.703)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Office $\times$ Non-Bank		2.551***		2.118**
		(0.967)		(0.912)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Retail $\times$ Bank		3.060***		2.757***
		(0.817)		(0.773)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Retail $\times$ Non-Bank		1.463		1.090
		(1.238)		(1.222)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Other $\times$ Bank		2.845**		2.389**
		(1.119)		(1.114)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Other $\times$ Non-Bank		1.777		1.284
		(1.194)		(1.208)
$Ln(1 + Distance_{Originator-Borrower}) \times$ Apartment	−0.601		−0.625	
	(0.445)		(0.438)	
$Ln(1 + Distance_{Originator-Borrower}) \times$ Hotel	−0.139		−0.448	
	(1.897)		(1.675)	
$Ln(1 + Distance_{Originator-Borrower}) \times$ Industrial	5.824***		5.407***	
	(1.422)		(1.301)	
$Ln(1 + Distance_{Originator-Borrower}) \times$ Office	2.639***		2.313***	
	(0.729)		(0.688)	
$Ln(1 + Distance_{Originator-Borrower}) \times$ Retail	2.607***		2.307***	
	(0.862)		(0.827)	
$Ln(1 + Distance_{Originator-Borrower}) \times$ Other	2.381**		1.941*	
	(1.074)		(1.070)	
Hotel	22.536*		23.540**	
	(11.759)		(10.619)	
Industrial	−11.140		−9.309	
	(9.578)		(9.032)	
Office	0.808		1.962	
	(4.730)		(4.578)	
Retail	−0.412		0.909	
	(6.176)		(6.093)	
Other	−0.463		1.513	
	(7.956)		(8.246)	
Bank		29.770**		29.389**
		(11.594)		(11.574)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	31,270	31,270	31,195	31,195
Adjusted R^2	0.810	0.812	0.811	0.812

Notes: This table reports OLS regression results. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the age of the property, the number of stories, central business district, renovated, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

when the property is located closer to the originator relative to where the borrower is located (D=0). It is positive and statistically significant at the 5% level. The coefficient of $Ln(1 + Distance_{Borrower-Property})$ is insignificant when the borrower is closer to the originator relative to where the property is located. One possible explanation for these contradictory results is that the borrower-property distance does not matter for borrowers given their expertise and industry focus. Our findings are therefore more in line with those of Conklin et al. (2018) who argues that information asymmetries are likely to be relatively small for professional investors such as REITs when investing at a distance.

Table 6
Borrower-property distance and spread.

	Dependent variable: spread			
	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
Ln(1 + $Distance_{Borrower-Property}$) × Bank, when $Distance_{Originator-Property}$ > $Distance_{Originator-Borrower}$		−0.518		−0.602
		(0.438)		(0.396)
Ln(1 + $Distance_{Borrower-Property}$) × Non-Bank, when $Distance_{Originator-Property}$ > $Distance_{Originator-Borrower}$		0.506		0.550*
		(0.349)		(0.317)
Ln(1 + $Distance_{Borrower-Property}$) × Bank, when $Distance_{Originator-Property}$ < $Distance_{Originator-Borrower}$		0.407		0.443
		(0.519)		(0.493)
Ln(1 + $Distance_{Borrower-Property}$) × Non-Bank, when $Distance_{Originator-Property}$ < $Distance_{Originator-Borrower}$		1.127***		1.230***
		(0.397)		(0.319)
Ln(1 + $Distance_{Borrower-Property}$), when $Distance_{Originator-Property}$ > $Distance_{Originator-Borrower}$	−0.009		−0.042	
	(0.276)		(0.244)	
Ln(1 + $Distance_{Borrower-Property}$), when $Distance_{Originator-Property}$ < $Distance_{Originator-Borrower}$	0.785**		0.871***	
	(0.344)		(0.299)	
Ln(1 + $Distance_{Originator-Borrower}$), when $Distance_{Originator-Property}$ > $Distance_{Originator-Borrower}$	0.704	0.682	0.679*	0.651
	(0.429)	(0.433)	(0.393)	(0.400)
Ln(1 + $Distance_{Originator-Property}$), when $Distance_{Originator-Property}$ < $Distance_{Originator-Borrower}$	0.424	0.417	0.280	0.292
	(0.413)	(0.426)	(0.364)	(0.372)
Bank		35.914***		36.487***
		(10.435)		(10.241)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	31,270	31,270	30,720	30,720
Adjusted R^2	0.810	0.810	0.809	0.809

Notes: This table reports the OLS regression results of Eq. (3). The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Property}$ is the distance between the originator headquarters and the property, in miles. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. $Distance_{Borrower-Property}$ is the distance between the borrower and the property, in miles. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of stories, central business district, renovated, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Next, we are interested in finding out whether these results for the borrower-property distance differ for banks and non-banks. To do so, we include interaction terms as presented in column (2). When the property is located closer to the originator relative to where the borrower is located, the coefficient of the interaction between $Ln(1 + Distance_{Borrower-Property})$ and *Non-Bank* is positive and statistically significant at the 1% level, but it is not significant for banks. When we test for the equality of these two coefficients, the test results reveal that they are not significantly different from each other.

In columns (3) and (4), we replace geographic distance by travel distance, and obtain very similar results.

5. Heterogeneity in information asymmetry and loan default

In this section, we explore the role of asymmetric information, as proxied by distance, when there is more information available to the lenders due to the previous relationship between the lender and the borrower, and loan size. Moreover, we analyze the likelihood of loan default.

5.1. Repeat borrowers

In this section, we take into account the effect of repeated interaction of the borrowing firm with the lenders. It is well established in the banking literature that borrowers become more known to lenders as they repeatedly interact with each other (Sufi, 2007). As repeated interaction reduces the information asymmetry between lenders and borrowers, the effect of distance should be less pronounced for the repeat borrowers. Table 7 confirms this prediction.

We create a new variable, *Number of previous loans*, which is equal to one if the number of previous loans is in the top quintile, and zero otherwise. Column (1) examines the interaction of geographical distance with the number of previous loans. The coefficient of the distance variable implies that the spread increases with distance when the number of previous loans is zero, meaning that the spread is higher when there is less interaction between lender and borrower. The coefficient of the interaction term between the distance and the number of previous loans is negative and statistically significant at the 1% level. In column (2), we include triple interactions with *Bank* and *Non-bank* indicators. The results show that both coefficients are negative and statistically significant at the 5% level. These results imply that information about the borrower, such as the borrower's portfolio size and experience in the business, is also important while lending against real estate, besides property cash flow analysis. Lenders can learn more about these types of borrower-specific information through repeated interaction with the borrower.

The results in columns (3) and (4) repeat the analyses in columns (1) and (2) with travel distance, and find similar results.

5.2. The effect of loan size

Thus far, we find that loan spreads increase in originator-borrower distance only for banks. In this section, we analyze the impact of loan size on originator-borrower distance and loan pricing. Previous literature (see e.g., Wittenberg-Moerman, 2008) argues that loan size is typically positively correlated with borrower size. The effect of distance might be more pronounced for small-sized loans because small borrowers are more subject to asymmet-

Table 7
Repeat borrowers and information asymmetry.

	Dependent variable: spread			
	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
Ln(1 + $Distance_{Originator-Borrower}$) × Number of previous loans × Bank		−0.923**		−0.870**
		(0.459)		(0.428)
Ln(1 + $Distance_{Originator-Borrower}$) × Number of previous loans × Non-Bank		−1.092**		−1.041**
		(0.472)		(0.438)
Ln(1 + $Distance_{Originator-Borrower}$) × Number of previous loans	−1.489***			−1.441***
	(0.500)			(0.468)
Ln(1 + $Distance_{Originator-Borrower}$)	0.570**		0.573**	
	(0.268)		(0.251)	
Number of previous loans	4.155	1.155	4.082	0.999
	(3.407)	(3.072)	(3.279)	(2.929)
Bank		23.164*		23.179*
		(12.787)		(12.774)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	31,270	31,270	31,195	31,195
Adjusted R^2	0.650	0.650	0.650	0.650

Notes: This table reports OLS regression results. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. *Number of previous loans* is equal to one if the number of the borrowers' previous loans is in the top quintile, and zero otherwise. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of stories, central business district, renovated, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

ric information problems than are larger borrowers. Moreover, a larger loan could enjoy a lower spread due to economies of scale in underwriting. To investigate these predictions, we split our sample into two groups based on loan size and create two indicator variables: (i) *Small loan*, which takes a value of one if the loan size is smaller than the median loan size, and zero otherwise, and (ii) *Large loan*, which takes a value of one if the loan size is greater than the median loan size, and zero otherwise.

Table 8 presents the results. In column (1), the coefficient of the interaction term between distance and small loans is insignificant. In column (2), we include three-way interactions with *Bank* and *Non-Bank*. The interaction term *Ln(1 + $Distance_{Originator-Borrower}$) × Small loan × Bank* indicates that the effect of distance is more pronounced for small loans originated by banks, however the coefficient is insignificant for non-bank lenders. The coefficients are statistically different at the 5% level. On the other hand, even though the coefficient of the interaction term with *Large loan* is statistically significant for banks, it is not significantly different from the coefficient of non-bank interaction.

The results in columns (3) and (4) repeat the analyses in columns (1) and (2) with travel distance, and find similar results.

5.3. Default analysis

Our analysis consistently shows that the loan spread increases with originator-borrower distance. This effect is either due to the transportation cost or to the information cost caused by the distance, however it is very difficult to make this distinction in the absence of a natural experiment. Therefore we cannot distinguish the exact channel. Instead, we suggest that if the distant borrowers are more likely to default, this is supportive of the idea that distance dilutes the screening standards of the lenders. As distance relates the soft information, we test whether distant borrowers are more likely to default. We use loan performance based on the assumption that loan performance is positively correlated with borrower (unobservable) creditworthiness. If all the hard and soft information associated with borrower risk is captured by the lender, we would not expect the coefficient of the distance variable to be significant. Following Titman and Tsyplakov, 2010, we employ loan spread as a control variable in the regression. A statistically significant coefficient of the distance variable would suggest that not all the information relating to mortgage risk is captured by hard information at the time of origination.

We have information about the status of a total of 1119 mortgages that are defined as "Resolved," "Restructured/Extension" and "Troubled." We classify them all as defaulted mortgages. The 1119 mortgages that we label as defaulted represent 3.58 percent of our total sample. Because some loans in the sample had not reached maturity at the time of observation, we estimate a Cox proportional hazards (CPH) model, which accounts for a possible right-censoring problem. The CPH model is a standard tool for default analysis in mortgage studies (see e.g., Keys et al., 2010).

CPH tests the impact of distance on default likelihood. Table 9 presents the result. The estimates are expressed in terms of hazard ratios. A hazard ratio of less than one indicates a decrease in the probability of default, whereas a hazard ratio greater than one indicates an increase in the probability of default. In column (1), we analyze the effect of distance, and the hazard ratio on the distance variable remains insignificant. In column (2), we include the interaction terms with both *Bank* and *Non-Bank* indicators. The estimated effect of distance for bank lenders is 0.923 (significant at the 5% level), indicating that bank loans experience 5% lower default than do non-bank loans, if we double the distance.

In column (3), we investigate for the different types of non-bank lenders on the likelihood of default. The results show that the risk of default increases with distance for the insurance and the investment manager types of non-bank lenders. Specifically, doubling the distance is associated with a 34% and a 27% increase in hazard for the loans originated by insurance companies and investment management companies, respectively, relative to the loans originated by finance companies.

Table 8
Loan size.

	Dependent variable: spread			
	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
Ln(1 + $Distance_{Originator-Borrower}$) × Small loan × Bank		2.026***		1.756***
		(0.659)		(0.603)
Ln(1 + $Distance_{Originator-Borrower}$) × Small loan × Non-Bank		0.674		0.453
		(0.586)		(0.578)
Ln(1 + $Distance_{Originator-Borrower}$) × Large loan × Bank		1.268**		1.136**
		(0.543)		(0.500)
Ln(1 + $Distance_{Originator-Borrower}$) × Large loan × Non-Bank		0.400		0.255
		(0.649)		(0.615)
Ln(1 + $Distance_{Originator-Borrower}$) × Small loan	0.582		0.486	
	(0.494)		(0.441)	
Ln(1 + $Distance_{Originator-Borrower}$)	0.833*		0.712	
	(0.475)		(0.438)	
Small loan	−2.460	−1.957	−1.936	−1.366
	(3.462)	(3.436)	(3.191)	(3.188)
Bank		24.414**		24.313**
		(11.530)		(11.501)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	31,270	31,270	31,195	31,195
Adjusted R^2	0.809	0.810	0.810	0.810

Notes: This table reports OLS regression results. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. The indicator variable *Large Loans* equals one if the loan size is greater than the median loan size, and zero otherwise. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of stories, central business district, renovated, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The results in columns (4), (5) and (6) repeat the analyses in columns (1), (2) and (3) with travel distance, respectively, and find similar results. In sum, we find that the greater the bank-borrower distance, the higher the probability of default.

6. Lender reputation

In this section, we analyze the underlying mechanism for distance being priced at loan origination in the CMBS market. One could argue that due to the originate-to-distribute model of securization, lenders do not bear the default risk of the loan, and hence why they should invest in information collection across distance. Even though lenders do not bear the default risk, they do bear the reputation risk. Defaulting loans would harm lender reputation and, consequently, future profits. This is due to the repeated game nature of securitization; a lender originating loans that are then sold to CMBS purchasers (Rajan et al., 2015). Therefore, lenders care about originating high quality loans by investing in screening across distance. In this context, reputation can function as a self-disciplining mechanism for lenders (Albertazzi et al., 2015; Rajan et al., 2015; Deku et al., 2019).

To test the relationship between lender reputation and loan default, we define an indicator variable, *Top issuer*, which takes a value of one if the market share of a lender is in the top quintile in a given year, and zero otherwise. The indicator variable, *Loan default*, equals one one when the mortgage is classiffied as either "resolved","re- structured/extension", or "troubled", and zero otherwise.

Table 10 presents the results in terms of hazard ratios. In column (1), the hazard ratio for the distance variable is 1.079, which indicates that the greater the distance between lender and borrower, the higher the probability of default. In other words, when the information asymmetry is severe, the loan is more likely to default. This result is consistent with Albertazzi et al. (2015). The hazard ratio for the interaction term between distance and top issuer is smaller than one. In particular, it is 0.77, indicating that the effect of the top issuer for default on the distance is 23% lower. In column (2), we introduce the interaction terms of $Ln(1 + Distance_{Originator-Borrower}) \times Top\ issuer \times Bank$ and $Ln(1 + Distance_{Originator-Borrower}) \times Top\ issuer \times Non-Bank$. Both coefficients are statistically significant at the 1% level, and they are significantly different from each other at the %5 level.

The results in columns (3) and (4) repeat the analyses in columns (1) and (2) with travel distance, and find similar results.

7. Robustness tests

7.1. Propensity score matching

The basic OLS regression results suggest that distance effect is more pronounced for the loans originated by banks. In this section, we address selection concerns with regard to the endogeneity of the originator-borrower matching (i.e., borrowing from a bank rather than from a non-bank lender). In the regressions, we include originator and borrower fixed effects which account for selection on time-invariant originator and borrower characteristics, while year-quarter time fixed effects account for aggregate time variation (Karolyi, 2018). However, our specification may still be subject to possible selection on the basis of time-varying borrower characteristics (Karolyi, 2018). Hence, in this section we employ

Table 9
Default analysis.

	Geographic distance			Travel distance		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(1 + $Distance_{Originator-Borrower}$)	0.976 (0.035)			0.981 (0.035)		
Ln(1 + $Distance_{Originator-Borrower}$) × Bank		0.923** (0.035)			0.931** (0.033)	
Ln(1 + $Distance_{Originator-Borrower}$) × Non-Bank		1.106 (0.088)			1.105 (0.087)	
Ln(1 + $Distance_{Originator-Borrower}$) × D/O/O			1.066 (0.435)			1.071 (0.445)
Ln(1 + $Distance_{Originator-Borrower}$) × Equity fund			1.144 (0.169)			1.140 (0.152)
Ln(1 + $Distance_{Originator-Borrower}$) × Finance			0.904 (0.113)			0.918 (0.106)
Ln(1 + $Distance_{Originator-Borrower}$) × Insurance			1.536** (0.306)			1.582** (0.316)
Ln(1 + $Distance_{Originator-Borrower}$) × IM			1.420** (0.244)			1.426** (0.245)
Ln(1 + $Distance_{Originator-Borrower}$) × REIT			1.049 (0.388)			1.013 (0.379)
Ln(1 + $Distance_{Originator-Borrower}$) × Other			0.858 (0.083)			0.863* (0.076)
Bank		2.757* (1.605)			2.660* (1.553)	
Developer/Owner/Operator			0.204 (0.542)			0.212 (0.589)
Equity fund			0.167 (0.194)			0.179 (0.196)
Insurance			0.041* (0.070)			0.033** (0.057)
Investment manager			0.070* (0.108)			0.068* (0.104)
REIT			0.089 (0.224)			0.120 (0.306)
Other			1.405 (1.384)			1.475 (1.370)
Spread	0.994*** (0.001)	0.994*** (0.001)	0.995*** (0.002)	0.994*** (0.001)	0.994*** (0.001)	0.995*** (0.002)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,224	31,224	16,353	31,149	31,149	16,309

Notes: This table reports the estimation results of the Cox proportional hazard models explaining loan default. The indicator variable *Loan Default* equals one when the mortgage is classified as either “resolved”,”restructured/extension”, or “troubled”, and zero otherwise. For each variable, we present the hazard ratio. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of stories, central business district, renovated, the loan purpose, and the state where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

propensity-score matching in order to take into account any selection bias. Since almost all loan terms such as LTV and DSCR are endogenous, we include variables based on the property characteristics. The difference in loan spreads between the matched loans shows significant loan cost savings for firms that borrowed from banks. The average difference in loan spread ranges is 10 bps. This estimate of a lower spread for bank loans is consistent with lower spreads for bank loans in our summary statistics (without controls).

Our matched sample includes 19,648 observations. We continue with the matched sample analysis and run the baseline regression on the matched sample. In untabulated results, we find that, for two comparable properties, the spread increases in distance for the bank loans but not for the non-bank loans, but we acknowledge that the propensity score matching (PSM) approach has some limitations. For example, our PSM analysis is based on the assumption that loans can be matched based on observable property characteristics. However, it is likely that loans might differ along unobservable characteristics, such as borrower characteristics.

7.2. Do out-of-state borrowers pay more?

Next, we investigate whether our results are robust to the inclusion of an additional measure of distance: distance in jurisdiction rather than in miles.

Existing studies show that out-of-state investors pay economically meaningful premiums relative to their in-state counterparts. This premium is found both for apartment complexes (Lambson et al., 2004), office buildings (Ling et al., 2018), and commercial real estate markets in general (Agarwal et al., 2018). The likely reason is that local investors have informational advantages relative to their out-of-state counterparts. For in-state investors, it is easier and cheaper to obtain local soft information by inspecting buildings and locations, reading local newspapers, and interacting with residents and building users (Agarwal et al., 2018). Thus, local investors have superior information relative to their non-local counterparts.

To test whether the previously found effect of distance on spread is due to the out-of-state effect, we define an indicator vari-

Table 10
Lender reputation.

	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
$\text{Ln}(1 + \text{Distance}_{Originator-Borrower}) \times$ Top issuer $\times$ Bank		0.833***		0.843***
		(0.036)		(0.032)
$\text{Ln}(1 + \text{Distance}_{Originator-Borrower}) \times$ Top issuer $\times$ Non-Bank		0.594***		0.618***
		(0.084)		(0.073)
$\text{Ln}(1 + \text{Distance}_{Originator-Borrower}) \times$ Top issuer	0.773***		0.777***	
	(0.044)		(0.042)	
$\text{Ln}(1 + \text{Distance}_{Originator-Borrower})$	1.079*		1.084*	
	(0.049)		(0.050)	
Bank		0.872		0.875
		(0.117)		(0.120)
Top issuer	4.354***	3.079***	4.304***	2.899***
	(1.515)	(0.764)	(1.455)	(0.662)
Spread	0.994***	0.994***	0.994***	0.994***
	(0.001)	(0.001)	(0.001)	(0.001)
Control Variables	Yes	Yes	Yes	Yes
Observations	31,224	31,224	31,224	31,149

Notes: This table reports the estimation results of the Cox proportional hazard models explaining loan default. The indicator variable *Loan Default* equals one when the mortgage is classified as either "resolved","restructured/extension", or "troubled", and zero otherwise. For each variable, we present the hazard ratio. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. *Top issuer* is an indicator variable and equals one if the market share of a lender is in the top quintile in a given year, and zero otherwise. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of properties, central business district, renovated, the loan purpose, and the state where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

able, "Out-of-State", that is equal to one if the borrower and the property are not located in the same state, and zero otherwise. Moreover, following Agarwal et al. (2018), we only include loan transactions in which the borrower appears for the first time in the host state.[7] That is, if the borrower has more than one loan collateralized with a property in a host state, we only include the first loan.

We present the estimated results in Table 11. In Panel A, we rerun our baseline regressions for the entire sample, controlling for "Out-of-State", and find similar results as in our baseline regression. The coefficient of the interaction term $Ln(1 + Distance_{Originator-Borrower}) \times$ *Bank* is positive and statistically significant at the 1% level, whereas the estimated coefficient of the interaction term $Ln(1 + Distance_{Originator-Borrower}) \times$ *Non-Bank* is insignificant. The test for the equality of these two coefficients reveals that they are significantly (at the 10% level) different from each other. "Out-of-State" remains insignificant across all the columns of Panel A.

In Panel B, we present the results based on the sample of "first-time borrowers". The coefficient of the interaction term $Ln(1 + Distance_{Originator-Borrower}) \times$ *Non-Bank* becomes statistically significant at the 5% level. However, comparison of the coefficients provides evidence that they are not statistically significant from each other.

The results in columns (3) and (4) of Panels A and B repeat the analyses in columns (1) and (2) with travel distance, and find similar results.

8. Conclusion

In this paper, we study how geographical distance affects loan spread in the CMBS market. Benefiting from the non-bank lender's access the CMBS market, we analyze how banks and non-bank lenders deal with soft information – as proxied by borrower-lender distance – in CMBS loan pricing.

First, we show that the loan spread increases with distance between bank and borrower, and this effect is more pronounced for the riskier property types such as industrial and office properties. On the contrary, geographical distance does not seem to have any effect on the loan spread of mortgages granted by non-bank lenders.

Second, our default analysis indicates that bank loans experience lower default than do non-bank loans, if we double the distance. Moreover, we find that the probability of default is lower for reputable lenders. We argue that due to the repeated nature of securitization, originator reputation is a possible mechanism for distance being priced at loan origination in the CMBS market.

Credit author statment

All authors in their capacity contributed equally to the manuscript.

Data availability

The authors do not have permission to share data.

[7] Of course, we can only assess this as far as our dataset goes, and it may be possible that a borrower has been active in a state without appearing in our dataset. So this variable is estimated with some error.

Table 11
Out-of-state borrowers.

	Dependent variable: spread			
	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Ln(1 + $Distance_{Originator-Borrower}$) × Bank		1.585***		1.401***
		(0.548)		(0.505)
Ln(1 + $Distance_{Originator-Borrower}$) × Non-Bank		0.458		0.293
		(0.572)		(0.554)
Ln(1 + $Distance_{Originator-Borrower}$)	1.044**		0.892**	
	(0.444)		(0.416)	
Bank		23.576**		23.564**
		(11.525)		(11.488)
Out-of-state borrower	0.783	0.752	0.899	0.864
	(1.066)	(1.053)	(1.066)	(1.052)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	31,270	31,270	31,195	31,195
Adjusted R^2	0.809	0.809	0.810	0.810
Panel B: First-Time				
Ln(1 + $Distance_{Originator-Borrower}$) × Bank		1.369		1.133
		(1023)		(0.922)
Ln(1 + $Distance_{Originator-Borrower}$) × Non-Bank		1.841**		1.649**
		(0.854)		(0.808)
Ln(1 + $Distance_{Originator-Borrower}$)	1.606**		1.380**	1.652**
	(0.706)		(0.656)	
Bank		66.098***		67.161***
		(23.739)		(23.506)
Out-of-state borrower	0.217	0.215	0.229	0.228
	(1.561)	(1.561)	(1.570)	(1.570)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	17,927	17,927	17,869	17,869
Adjusted R^2	0.884	0.884	0.884	0.884

Notes: This table reports OLS regression results. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. The indicator variable *Out-of-state borrower* equals one if the borrower and the property are located in different states, and zero otherwise. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of stories, central business district, renovated, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix A. Variable definition

Variable	Definition
Geographical Distance	
Ln(1 + $Distance_{Originator-Borrower}$)	The natural logarithm of one plus the distance between the bank headquarter and the borrower. $Distance_{Originator-Borrower}$ is calculated from geographic coordinates, in miles.
Ln(1 + $Distance_{Originator-Property}$)	The natural logarithm of one plus the distance between the bank headquarters and the property. $Distance_{Originator-Property}$ is calculated from geographic coordinates, in miles.
Ln(1 + $Distance_{Borrower-Property}$)	The natural logarithm of one plus the distance between the borrower and the property. $Distance_{Borrower-Property}$ is calculated from geographic coordinates, in miles.
Mortgage Characteristics	
Loan-to-value (LTV)	The ratio of the loan to the value of the property.
Ln(1 + Maturity)	The natural logarithm of the maturity, in months.
Ln(Loan size)	The natural logarithm of the loan amount, in millions.
Small loan	An indicator variable that is equal to one if the loan size is smaller than the median loan size, zero otherwise.
Large loan	An indicator variable that is equal to one if the loan size is greater than the median loan size, zero otherwise.
Spread	The difference between the mortgage rates and the Treasury bond rates with the same maturities, in basis points.
Property Characteristics	
Age of the property	Indicator variables identifying the age group of the property. Age groups include less than 10, 10–20, 20–30, 30–40, 40–50, and more than 50 years.
Central business district	An indicator variable that is equal to one if the property is located in a central business district (CBD), zero otherwise.
Number of stories>1	An indicator variable that is equal to one if the number of stories is greater than one, zero otherwise.
Property Type	
Apartment	An indicator variable that is equal to one if the property type is apartment, zero otherwise.
Hotel	An indicator variable that is equal to one if the property type is hotel, zero otherwise.
Industrial	An indicator variable that is equal to one if the property type is industrial, zero otherwise.
Office	An indicator variable that is equal to one if the property type is office, zero otherwise.
Retail	An indicator variable that is equal to one if the property type is retail, zero otherwise.
Other	An indicator variable that is equal to one for another type of property, zero otherwise.
Renovated	An indicator variable and is equal to one if the properties have been renovated, zero otherwise.
Other Variables	
Ln(HHI)	The natural logarithm of the summed squares of the bank market shares, in each state.
Post-crisis	Post-crisis: An indicator variable that is equal to one for the loans originated in 2008 and the years after, zero otherwise
Out-of-state borrower	An indicator variable that is equal to one if the borrower and the property are located in different states, zero otherwise.
Loan Purpose	
Property acquisition	An indicator variable that is equal to one if the loan purpose is property acquisition, zero otherwise.
Refinance	An indicator variable that is equal to one if the loan purpose is to refinance, zero otherwise.
Metropolitan statistical area FE	Indicator variables identifying the metropolitan statistical area (MSA) where the property is located.
Property state FE	Indicator variables identifying the state where the property is located.
Year-quarter FE	Indicator variables identifying the origination year-quarter of the loan.

Appendix B. Sample

Table B.1
Distributions of property types.

Numbers of loans by property types		
Property types	Number of loans by banks	Number of loans by non-banks
Apartment	4386	11,099
Hotel	1397	552
Industrial	1032	628
Office	1843	871
Retail	3274	2160
Other	2306	1722
Total	14,238	17,032

Notes: This table reports the number of loans by property types. Sample period: 2000:Q1–2017:Q3.

Appendix C. Additional analyses

Table C.1
Types of non-bank lenders.

	Dependent variable: spread	
	Geographic distance (1)	Travel distance (2)
Ln(1 + $\text{Distance}_{Originator-Borrower}$) × Developer/Owner/Operator	3.086	2.926
	(2.018)	(1.970)
Ln(1 + $\text{Distance}_{Originator-Borrower}$) × Equity fund	2.369	2.296
	(4.209)	(4.051)
Ln(1 + $\text{Distance}_{Originator-Borrower}$) × Finance	0.260	0.145
	(1.077)	(1.036)
Ln(1 + $\text{Distance}_{Originator-Borrower}$) × Insurance	−5.237**	−5.403**
	(2.093)	(2.187)
Ln(1 + $\text{Distance}_{Originator-Borrower}$) × Investment manager	−0.991	−0.991
	(1.649)	(1.599)
Ln(1 + $\text{Distance}_{Originator-Borrower}$) × REIT	0.820	0.194
	(2.169)	(2.138)
Ln(1 + $\text{Distance}_{Originator-Borrower}$) × Other	0.439	0.563
	(0.913)	(0.884)
Developer/Owner/Operator	5.824	6.050
	(62.566)	(62.741)
Equity fund	33.214	32.580
	(31.297)	(30.917)
Insurance	50.977**	51.706**
	(25.102)	(25.441)
Investment manager	30.324**	29.794**
	(14.147)	(13.928)
REIT	11.345	14.576
	(15.087)	(15.484)
Other	−37.812	−40.303
	(36.841)	(36.358)
Control variables	Yes	Yes
Property state FE	Yes	Yes
Originator FE	Yes	Yes
Borrower FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	16,387	16,343
Adjusted R-squared	0.834	0.833

Notes: This table reports the OLS estimates for different types of non-bank lenders. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. Control variables include the loan maturity, the loan size, the loan-to-value (LTV) ratio, the HHI and indicator variables for the property type, the age of the property, the number of stories, central business district, renovated, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table C.2
Borrower-property distance and spread.

	Geographic distance		Travel distance	
	(1)	(2)	(3)	(4)
Ln(1 + $Distance_{Originator-Borrower}$) × Bank		1.1586***		1.497***
		(0.550)		(0.513)
Ln(1 + $Distance_{Originator-Borrower}$) × Non-Bank		0.454		0.308
		(0.571)		(0.544)
Ln(1 + $Distance_{Borrower-Property}$)	0.313	0.313	0.370	0.368*
	(0.241)	(0.238)	(0.225)	(0.221)
Ln(1 + $Distance_{Originator-Borrower}$)	1.043**		0.945**	0.309
	(0.444)		(0.413)	
Bank		23.525**		22.514*
		(11.537)		(11.401)
Ln(1 + Maturity)	−53.536***	−53.591***	−53.804***	−53.851***
	(3.393)	(3.388)	(3.414)	(3.408)
Ln(Loan size)	−5.011***	−5.023***	−5.063***	−5.074***
	(0.463)	(0.461)	(0.468)	(0.467)
Loan-to-value (LTV)	35.974***	36.075***	35.212***	35.295***
	(7.070)	(7.064)	(7.042)	(7.031)
Hotel	26.152***	26.405***	24.959***	25.268***
	(5.314)	(5.264)	(5.584)	(5.533)
Industrial	25.082***	25.248***	24.882***	25.050***
	(3.378)	(3.419)	(3.537)	(3.578)
Office	20.319***	20.414***	19.540***	19.649***
	(2.615)	(2.649)	(2.876)	(2.910)
Other	18.446***	18.356***	18.194***	18.078***
	(3.029)	(3.032)	(3.173)	(3.165)
Retail	18.915***	18.856***	18.411***	18.351***
	(2.128)	(2.106)	(2.293)	(2.269)
Central business district	−0.612	−0.699	−0.897	−0.992
	(2.197)	(2.224)	(2.413)	(2.446)
Renovated	−0.829	−0.794	−0.822	−0.783
	(0.815)	(0.807)	(0.815)	(0.807)
Ln(HHI)	0.467	0.468	0.387	0.391
	(1.020)	(1.021)	(1.003)	(1.004)
Control Variables	Yes	Yes	Yes	Yes
Property State FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	31,270	31,270	30,690	30,690
Adjusted R^2	0.809	0.809	0.809	0.809

Notes: This table reports OLS regression results. The dependent variable is the loan spread, between the mortgage rate and the Treasury bond rate with the same maturity, in basis points. $Distance_{Originator-Borrower}$ is the distance between the originator headquarters and the borrower, in miles. $Distance_{Borrower-Property}$ is the geographic distance between the borrower and the property, in miles. Control variables include indicator variables for the age of the property, the number of stories, the loan purpose, and the MSA where the property is located. All variables are defined in the Appendix. Robust standard errors, clustered at the MSA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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