Going the Distance?
Bank-customer proximity, applicant demographics, and credit access

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September 2026

Abstract

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Keywords: Mortgage Markets, Proximity, Minority Credit Access, Soft Information Lending

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Abstract

Does soft information matter equally for minority and nonminority loan applicants? Using cell-phone pings to measure bank-customer proximity, a proxy for soft information, we find that greater proximity is associated with higher mortgage approval rates, with a relationship nearly twice as large for minority applicants. Three patterns indicate a soft-information channel: the association is stronger for loans where soft information matters more, segments where banks bear greater underwriting risk, and banks that produce less relationship-based information. Multiple identification tests strengthen causal interpretation. The benefit of proximities to minorities is larger in areas with higher racial animus and lower social capital.

1. Introduction

Borrower proximity to banks expands credit access by facilitating soft-information production (Petersen and Rajan, 2002). As U.S. bank branch networks contract, customer distances to bank branches increase. Yet branches remain salient: two in three banked households visited a branch in the prior year, while one in six unbanked households cited inconvenient branch locations as a reason for not having an account.[1] We examine how bank-customer proximity affects mortgage access. Using de-identified mobile-device location data on bank visits, we construct a proximity measure for each bank-county. We find that proximity improves mortgage access, with stronger effects for minority applicants.

Our study addresses two gaps. First, although the benefits of proximity are documented for corporate borrowers (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010), evidence for residential mortgages is scarce and inconclusive. Second, we examine whether proximity matters differently for minority and non-minority applicants, motivated by evidence of mortgage-market discrimination (Bartlett, Morse, Stanton, Wallace, 2022; Frame, Huang, Jiang, Lee, Liu, Mayer, and Sunderam, 2025) and barriers to banking access.[2]

We build on the literature associating proximity to better *commercial* lending outcomes. Local banks can better assess soft information about borrowers (Agarwal and Hauswald, 2010), allowing them to extend credit at preferential terms. However, this intuition may not generalize to home mortgages. Mortgage underwriting relies more on hard information like credit and employment histories (Liberti and Petersen, 2018). Moreover, banks commonly sell originated

[1] 17,167 branches (18%) closed during 2013–2022 (FDIC National Survey). Industry research even claimed that branches may be extinct within two decades (USA Today).
[2] Majority-Black areas are more likely to be banking deserts (10.1%) than the national rate (6.4%) (Philadelphia Fed Report).

mortgages, weakening incentives for screening (Keys, Mukherjee, Seru, and Vig, 2010; Choi and Kim, 2021) and monitoring (Gryglewicz, Mayer, and Morellec, 2024). Consistent with these differences, evidence on how proximity affects mortgage approvals is mixed.[3]

We use high-frequency mobility data to quantify bank–customer proximity. Our construct uses SafeGraph (now Advan) device-location data, which record trillions of cell phone pings from an estimated 15%[4] of the U.S. population, and map foot traffic to over seven million points of interest (POIs). We aggregate distances between device owners' residences and bank branch POIs to the bank–county level and create the variable *Proximity*, the average distance between a bank and its customers in a county.[5] We merge *Proximity* to the 2022 Home Mortgage Disclosure Act (HMDA) data, which provides minority (Black, Hispanic, Native, or Asian vs. white, non-Hispanic) status and outcome (approved vs. denied) for the near-universe of U.S. mortgage applications, along with many relevant application-level variables.

In our sample of over 1,200,000 applications to 821 mortgage-lending banks (84% of banks in HMDA), we test whether *Proximity* associates with an application's approval probability. We control for observable loan and borrower characteristics and include bank and census-tract fixed effects to absorb lender- and neighborhood-level heterogeneity. Bank fixed effects compare applications to the same lender across counties where its customers are more or less proximate, while census-tract fixed effects compare applicants from the same neighborhood and absorb local characteristics that may correlate with creditworthiness.

[3] We know of only direct studies: Nguyen (2019), Mayer (2024), and Hampole, Jørring, and Monteiro (2025). The former finds no effect of proximity on mortgage approval rates while the other two document a positive effect.
[4] In older SafeGraph data, coverage was lower; see Li, Ning, Jing, and Lessani (2024). Coverage has substantially increased for more recent years (see the "Scalability" section in their data description section here).
[5] Specifically, *Proximity* is the log of the average distance multiplied by -1. This transformation linearizes the right-skewed distribution of raw distances and gives the variable a more intuitive interpretation, with larger values indicating a more proximate, rather than more distant, customer base.

We find that greater bank-customer proximity is associated with a higher probability of mortgage approval. This result is notable because residential mortgage lending relies heavily on hard information and because the secondary mortgage market weakens lenders' incentives to screen borrowers intensively. Yet proximity remains strongly related to approval outcomes. This finding also has policy relevance: as branch networks contract and customers live farther from physical branches, mortgage access may become more difficult.

Motivated by evidence of racial disparities in mortgage credit outcomes (Munnell, Tootell, Browne, and McEneaney, 1996; Wei and Zhao, 2022; Butler, Mayer, and Weston, 2023), we examine whether the relationship between proximity and approval differs across applicant groups. Minority applicants have lower approval rates, consistent with prior work. More importantly, the positive association between proximity and approval is substantially larger for minority applicants. As a result, greater proximity is associated with a narrower minority–nonminority approval gap. To the best of our knowledge, this is the first evidence that bank-customer proximity is associated with a narrower racial gap in mortgage approvals.

Figure 1 illustrates this pattern. Panel A plots the within-bank minority approval gap across counties sorted into quintiles by the distance of the bank's customers, while Panel B makes the analogous comparison across banks within census tracts. In both panels, the gap widens sharply with distance, more than doubling between the closest and farthest quintiles in Panel B, even though overall approval rates do not decline similarly with distance. This pattern is consistent with our regression results later: lower proximity is associated with reduced approval rates, with a disproportionately larger decline for minority applicants.

[Figure 1]

Our regression results suggest that a one standard deviation increase in customer–branch proximity raises approval probability by 1.15 (0.61) percentage points for minority (non-minority) applicants. These differences are sizeable compared to other approval determinants. For example, our model suggests that a one standard deviation decrease in the loan-to-value ratio raises approvals by 0.66 (1.58) percentage points for minorities (non-minorities), while conforming loan applications are 0.60 (1.90) percentage points more likely to be approved. For comparison, Frame et al. (2025) find that minority applicants are 3% less likely to be approved by a non-minority loan officer than by a minority one, and Chu, Xiao, and Zheng (2025) find that approvals are 40 basis points higher for banks with expertise in local industries.

We address the endogenous matching between borrowers and lenders through several strategies. Our baseline specification incorporates three safeguards beyond the standard controls. Proximity is constructed from the average distance traveled by the general population of device-carrying customers to a bank's branches in a county, rather than from any individual applicant's distance to her chosen lender, limiting mechanical applicant-level sorting. Bank fixed effects restrict comparisons to applications made to the same lender, absorbing cross-bank differences such as underwriting standards or risk appetite. Census-tract fixed effects absorb fixed neighborhood characteristics, reducing the scope for credit-relevant tract-level differences to confound our estimates.

Despite these safeguards, causal inference may still be affected by differences between minority and non-minority applicants and by differences between applicants who select more versus less proximate banks. We address these concerns in two ways. First, we use propensity-score matching. Within census tracts, we match minority applicants to non-minority applicants with similar loan and borrower characteristics. We then separately match applications to more proximate banks with applications to less proximate banks in the same tract, again on observable characteristics. Both exercises show that our results are not driven by observed differences between minority and non-minority applicants or between applicants choosing more versus less proximate banks within the same tract.

We also use an instrumental-variables approach, instrumenting Proximity with a bank's local deposit share 15 years earlier. Historical market share is relevant insofar as a longer-standing local presence facilitates the accumulation of soft information, while the exclusion restriction requires that historical market share affect current underwriting only through this channel. This exercise produces estimates that are consistent with a causal interpretation of our baseline findings.

Another identification concern is that banks may pursue different underwriting strategies across local markets. For example, a bank may be more permissive in markets where its customer base is more proximate for reasons unrelated to soft information. We therefore replace bank fixed effects with bank × MSA and bank × county-characteristic-quintile fixed effects, where the county characteristics include population, median income, and banking competition. The estimated relationship between proximity and approval, including its stronger association for minority applicants, is robust to these alternative fixed-effect structures.

As a final step in assessing the plausibility of a causal interpretation, we examine three theory-motivated settings in which the soft-information channel should be especially important. Soft information should matter more for less-standardized loan products (Rajan and Petersen, 2002), and indeed the proximity–approval relationship is concentrated in home improvement loans, where prior work suggests soft information is particularly valuable (Agarwal, Ambrose, Chomsisengphet, and Liu, 2011). It should also matter more when banks bear greater underwriting risk (Keys, Mukherjee, Seru, and Vig, 2010). Consistent with this prediction, our results are strongest for loan types with limited secondary markets—nonconforming loans, lines of credit, and junior liens—and are weaker elsewhere. Finally, soft information should be most valuable where banks have less of it to begin with. In line with this idea, our results are driven by large banks, which tend to rely more on transactional lending and are less likely to cultivate relationship-based soft information through other channels (Berger, Miller, Petersen, Rajan, and Stein, 2005; Stein, 2002). Taken together, these patterns are difficult to reconcile with a single omitted-variable explanation and appear more consistent with a soft-information mechanism.

Overall, these tests yield a consistent result: greater proximity is associated with higher mortgage approval rates, with a significantly stronger relationship for minority applicants. The different empirical approaches address the identification problem from distinct angles, including measurement, within-bank and within-tract comparisons, covariate balancing, instrumentation, and theory-motivated mechanism tests. Although no single strategy can rule out unobserved confounds, the persistence of our central findings across these exercises substantially narrows the set of alternative explanations consistent with the evidence. Overall, we view this evidence as making a causal interpretation of our results more plausible.[6]

We next ask what mechanism might account for the minority approval gap and its attenuation through *Proximity*. The fact that greater proximity is associated with a narrower approval gap is consistent with at least two distinct economic channels. Under statistical discrimination, lenders rely on group-level information when individual borrower quality is imperfectly observed (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977). If proximity provides additional information about individual applicants, lenders should rely less on group membership

[6] In additional tests, we address bank competition, transportation costs, and an alternative definition of bank proximity used in prior literature. In all these tests, our main results continue to hold.

as a proxy for unobserved risk, narrowing the approval gap. By contrast, under taste-based discrimination, lenders derive disutility from transacting with minority borrowers independent of applicant risk (Becker, 1957), so additional information need not narrow the gap. Distinguishing between these explanations helps clarify whether proximity operates primarily by alleviating an information problem or through a different relational channel.[7]

We therefore conduct a set of exploratory tests, not intended to conclusively distinguish between these mechanisms, but to assess which interpretation is more consistent with the patterns in our data. If proximity mitigates statistical discrimination, its minority-specific benefit should be larger where credit-quality differences are more consequential for repayment risk, such as among lower-income applicants and tracts, and where lenders have less experience evaluating minority borrowers. We find the opposite: the incremental association between *Proximity* and minority approvals appears only among higher-income minority applicants and at banks with greater minority exposure. These patterns weigh against the specific statistical-discrimination channel we test. In contrast, if racial or ethnic mistrust depresses minority approvals, repeated interactions associated with proximity may help build relationships and attenuate such preferences. Consistent with this interpretation, the minority-specific association is stronger in areas with higher rates of hate crime and lower social capital, our proxies for animus and local trust.[8]

Having documented that approval rates are higher when proximity is greater, especially for minority applicants, we next ask which minority applicants appear to benefit. A useful benchmark comes from Hurtado and Sakong (2024), who document large disparities in access to credit

[7] More generally, a large and growing literature alludes to discrimination in mortgage markets (Munnell et al., 1996; Bartlett et al., 2022; Frame et al., 2025; Ambrose et al., 2026). We inform this research stream by exploring why proximity might alleviate discriminatory gaps in minority credit access.

[8] These results echo Butler, Mayer, and Westin (2023) and Conklin, Gerardi, and Lambie-Hanson (2025), who show larger minority approval gaps in auto and home improvement loans, respectively, in areas with greater racial animus.

alongside little to no disparity in the cost of credit conditional on origination. Their evidence suggests that observed loan terms reflect a selected subset of applicants rather than a random draw from the applicant pool: when screening is more stringent, borrowers who clear the approval threshold are safer on average, so prices reveal less about the underlying applicant pool than approval decisions do. Applied to our setting, this logic suggests that if proximity facilitates soft-information production, the applicants drawn into the approved pool should be those whose risk is more difficult to assess from hard information alone.

We examine three market outcomes that can shed light on the composition of these approved borrowers: interest-rate spreads, which partly reflect lenders' assessment of default risk (Bayer, Ferreira, and Ross, 2013); the bank's propensity to retain a loan, which is related to its assessment of loan quality and balance-sheet risk (Gopalan, Nanda, and Yerramilli, 2009); and loan origination costs, which increase with underwriting effort (Ambrose and Conklin, 2014). If proximity expands minority approvals by improving the screening of harder-to-assess applicants, approved minority loans in high-proximity settings should tend to carry higher spreads, be retained less often, and involve greater origination costs. These are the patterns we find. We interpret them as supplementary evidence on the composition of the marginal borrower rather than as a test of any particular lending theory.

Given the continuing contraction of U.S. bank branch networks, we explore how the proximity–approval relationship varies with branch dynamics. We distinguish counties with growing, stable, and shrinking branch networks and consider changes at three levels: overall branch activity, the focal bank's own branch network, and the branch networks of its competitors. Two patterns emerge. The proximity–approval relationship is absent in markets that the focal bank has recently entered, consistent with soft information taking time to accumulate. Also, the association between proximity and minority approvals is stronger where the focal bank and competitors are reducing branch presence, highlighting that proximity to remaining branches is even more salient where branches are disappearing.

A battery of additional tests supports the internal consistency of our main results. Proximity retains its explanatory power after controlling for branch distance from the property census tract and for local transportation costs, suggesting that it captures something beyond simple geography and travel costs. Consistent with a soft-information mechanism, the minority benefit of proximity is stronger in less competitive banking markets and becomes larger at higher levels of proximity. Our finding relating to the association between proximity and minority applicants also holds when we re-estimate the analysis using data from 2020 and 2021.

Our study makes several contributions. First, we construct a measure of bank-customer proximity that reduces mechanical applicant–lender sorting concerns and provides a cleaner setting in which to study the role of soft information in mortgage approvals. We show that greater proximity is associated with higher approval rates, with a substantially stronger relationship for minority applicants, contributing to the emerging literature on distance in mortgage lending (Nguyen, 2019; Mayer, 2024; Hampole et al., 2025). Second, we show that proximity remains economically relevant even in a market dominated by hard-information underwriting and extensive credit-risk offloading. The relationship is concentrated in settings where soft information should be especially valuable: loan products with greater information asymmetry, thinner secondary markets, and large, more transactional lenders that are less likely to generate relationship-based information through other channels. Third, we contribute to the literature on discrimination in mortgage lending (Bartlett et al., 2022; Frame et al., 2025) by identifying bank-customer proximity as a potential force that can narrow minority approval gaps. Proximity's effect is stronger in areas with high hate crime and low social capital, suggesting a role for proximity where racial mistrust may be more salient. These findings complement recent evidence on racial disparities in mortgage access and pricing (Hurtado and Sakong, 2024; Conklin, Gerardi and Lambie-Hanson, 2025).

2. Data and Sample

Our data come from several sources. Our main sample is the intersection of two 2022 datasets: (i) de-identified SafeGraph device pings that record weekly visits to bank branches, from which we construct our proximity measure; and (ii) the HMDA modified Loan Application Register, which covers the near-universe of U.S. mortgage applications. In SafeGraph, we retain U.S. establishments in financial NAICS 522110, 522120, 522130, and 522310; exclude locations fully enclosed within other establishments; require polygon footprints (non-zero area); and drop POIs with "ATM" in the name. Removing duplicates within POI-weeks leaves 7.9M observations.[9] We aggregate to annual branch-level averages. In HMDA, we keep applications to banks/thrifts with final status approved-accepted, approved-not-accepted, or denied (dropping incomplete/withdrawn, preapproval-stage, and purchased loans); exclude non-/negative-amortizing products; and restrict to one-unit, owner-occupied, 1-4-family properties with positive reported applicant income.

We merge these two datasets, employing the Federal Deposit Insurance Corporation's (FDIC's) Summary of Deposits (SOD) dataset as a crosswalk. SOD provides geocoordinates for all bank branches under each identifier. SafeGraph also contains geocoordinates and names for all

[9] We remove duplicate observations within a POI-week by the following algorithm: (i) select the observation with the most visits within a week, (ii) if multiple observations remain, select the one with the greatest average visitor distance, (iii) if multiple observations remain, select the one with the greatest average visitor dwell time, (iv) if multiple observations remain, select the one with the lowest NAICS code, (v) if multiple observations remain, select the one with the shortest POI name length, (vi) if multiple observations remain, select the one with the greatest latitude, (vii) if multiple observations remain, select the one with the greatest longitude.

POIs. We merge SOD to HMDA using lenders' RSSD identifiers and then merge to SafeGraph on branch name and geocoordinates.[10] To construct the *Proximity* variable, we note the average distance from a cell phone's home address (as determined by SafeGraph) to a particular bank branch.[11] Because the measure is highly skewed, we use its natural logarithm and multiply by -1 for a measure of proximity (not distance). *Proximity* is computed for each bank branch and averaged across all branches in a county to obtain a bank-county measure. In many of our tests, the variable of interest is an interaction between *Proximity* and an application-level indicator, *Minority*, equal to one if the primary applicant identifies as Black, Hispanic, Native, or Asian.[12]

Our main dependent variable in an indicator for whether the application was approved (*Approved*). Our control variables also come from HMDA: the loan to value ratio (*LTV)*, the debt to income ratio (*DTI)*, the natural logarithm of the loan's term in months (*Term*), and indicators for whether the loan conforms to secondary market guidelines (*Conforming*), whether it is not guaranteed by the Federal Housing Administration or Veterans Administration (*Conventional*), whether it is structured as a line of credit (*LOC*), whether it represents a junior lien (*Junior*), whether its rate is fixed (*Fixed*), loan purpose (new purchase origination, *NPO*; home improvement, *HI*; rate-and-term refinance, *Refi*, and cash-out refinance, *CO Refi*); and the lender's regulator (OCC, FDIC, FRB, and CFPB). Beyond our main analysis, we also integrate data on applicant income; and county population, median income, and percent minority (all from HMDA); county deposit market shares (from Summary of Deposits); reported hate crime data (from the FBI

[10] Specifically, we retain only matches where geocoordinates fall within one hundred feet or those within three hundred feet with similar names in both datasets. Names are considered similar if the edit distance between them, using SAS's SPEDIS function, is below 50, a threshold set manually by examining false positive and false negative matches.
[11] This is averaged once across customers within a week and a second time across weeks within the year.
[12] We assign each application to the bank–county of the financed property because the submitting branch is unknown. This logic necessarily excludes applications where the property is outside counties in which the lending bank has a branch (i.e., applications to banks with no local branch are unassigned). Even so, the procedure retains over 55% of HMDA applications meeting our sample restrictions.

crime-data explorer); and social capital (from Penn State's Northeast Regional Center for Rural Development).

To visualize the *Proximity* metric, consider Midwest BankCentre, a St. Louis, MO bank with $2.431B in assets. In June 2022, it operated seventeen branches in four Missouri counties (Figure 2). Fourteen SOD branches in three counties match SafeGraph; in the figure these are white squares (black are unmatched). Matched branches account for 82.3% of its deposits. In St. Louis County, seven of eight branches match. For each, we average the home-to-branch distances of visiting devices (e.g., 4.48 miles at Branch 1). Averaging branch distances within the county yields the bank–county distance (10.713 miles). We repeat this for the two other counties with matched branches. Our tests relate such within-bank, cross-county distance variation to differential application outcomes.

[Figure 2]

Our main sample includes 1,261,218 loan applications to 821 banks that collectively have 51,073 branches that can be matched in SafeGraph. This represents 84.3% of 2022 HMDA banks with our sample restrictions and 86.1% of these banks' branches. It includes applications from 76,649 census tracts within 2,318 counties across all 50 states.

[Table 1]

Table 1 shows the distribution of our variables for our full sample and for subsamples of minority and non-minority applications. There are roughly half as many minority applications in our sample as non-minority ones and they are approved at a substantially lower rate (66.12% versus non-minorities' 80.39%). This 14.28% approval gap is close to the 12.1% gap from An, Bushman, Kleymenova, and Tomy (2023). Our sample's overall approval rate (75.79%) also resembles An et al.'s (2023) (76.2%) and lies between Lim and Nguyen's (2021) (60.3%) and Bowen, Price, Stein, and Yang's (2024) and Frame et al.'s (2025) (92%). Minority applicants apply to banks with more distant customers, seek higher leverage (*LTV*) and payment (*DTI*), and submit applications less likely to meet secondary-market guidelines (*Conforming*), with greater FHA/VA guarantees (*Conventional*). They more often request lines of credit, junior liens, variable-rate, and longer-term loans. Minorities reside in areas with larger populations, are evenly split among Black, Asian, and Hispanic applicants with fewer Native Americans; about one-third also identify as White.

3. Empirical Analysis

3.1 Proximity and loan approval

The commercial lending literature suggests that proximity should increase approval likelihood (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010). Does that extend to the mortgage market? To test this, we estimate the following linear probability model:

$$Approved_i = \beta_1 \times Proximity_{b,c} + \beta_2 \times Minority_i + \beta_3 \times Proximity_{b,c} \times Minority_i + \boldsymbol{\gamma} \times \boldsymbol{X_i} \times Minority_{b,c} + \delta_b + \mu_t + \epsilon \qquad (1)$$

where i, b, c, and t index the mortgage application, bank, county, and census tract, respectively. *Approved* is an indicator that equals one if the application was approved, zero otherwise. *Proximity* is as explained earlier. **X** is the vector of controls described in the previous section. We opt for a 'fully specified' model, in which the effect of each covariate on approval is allowed to vary by minority status, because prior studies hint at potentially different underwriting processes for minorities and non-minorities (Bayer, Ferreira, and Ross, 2018; Alfaro, Faia, and Minoiu, 2022; Hurato and Sakong, 2024). δ and μ represent bank and census tract fixed effects, respectively. Bank fixed effects eliminate confounding bank-level heterogeneity, like corporate cultures, business models, or funding constraints. They compare Bank *B*'s likelihood to approve a mortgage application in County *C* to the same bank's likelihood to approve an application in a different county, where the two counties differ in how far local customers travel to that bank's branches. We include tract-fixed effects to account for tract-level differences (e.g., wealth, minority population, access to credit, etc. We cluster standard errors at the tract level (Gupta, 2019; Mayer, 2024).[13]

[Table 2]

Before estimating Equation 1, we estimate two pared down versions to better understand how proximity and minority status affect approvals. In the first (second), *Approval* is regressed on *Proximity* (*Minority*), ignoring *Minority* (*Proximity*) and the interaction effects. Columns 1 and 2 of Table 2 report results, respectively. Regardless of minority status, *Proximity* improves approval rates (Column 1) consistent with Mayer (2024) and Hampole et al. (2025) but inconsistent with Nguyen (2019), who finds no change in mortgage approval rates following increased distance due to branch closings. Irrespective of distance, minority applicants face lower approval rates (Column 2), consistent with most prior work (e.g., Mundell et al., 1996; Wei and Zhao, 2022; Willen and Zhang, 2023; Frame et al., 2025).

Having established these baseline relationships, we report estimates from our main specification, Equation 1, in Column 3. *Proximity* continues to load positively (β_1=0.009) and is significant at the 1% level. Within the same bank, closer customers associate with a higher mortgage approval probability, holding loan features constant and controlling for neighborhood differences through tract fixed effects. When controlling for branch-customer distance, minority applicants continue to have lower mortgage approval rates (β_2= -0.142), also significant at 1%.

[13] We expect the approval decision to correlate strongly to local economic conditions, yielding potentially correlated error terms within locales. Our models cluster standard errors at the most granular geography our data allows: the census tract. Many related papers (e.g., Nguyen, 2019; Bhutta and Hizmo, 2021; Lim and Nguyen, 2021) cluster by county. If we cluster by county, our main conclusions continue to hold.

More importantly for our purposes, the coefficient on *Proximity* × *Minority* is positive and significant (0.008, p<0.01), implying that proximity's marginal effect is larger for minority applicants: the total slope with respect to *Proximity* is about 0.017 (=0.009+0.008) for minorities versus 0.009 for non-minorities. Given the negative baseline association for *Minority*, this interaction indicates that proximity partially offsets the minority approval gap by delivering a disproportionately greater approval boost to minority applicants.

To interpret the economic magnitude, consider two otherwise identical applications to the same bank's branches in different counties, the only difference being one branch's customers live one standard deviation further than the other's. For white non-Hispanic applicants, the application to the branch with closer customers is 0.61 percentage points more likely to be accepted, but for minorities, that probability increases to 1.15 percentage points.[14] These effects are noteworthy in the context of prior literature. Frame et al. (2025) find that minority applicants are three percentage points less likely to be approved from a white loan officer than similar non-minority applicants are from the same individual. Chu, Xiao, and Zheng (2025) find that banks with expertise in local industries have 40-basis point higher mortgage approval rates. The estimates are also meaningful relative to known approval drivers. For example, conforming loans are 1.90% (0.60%) more likely to be approved for non-minority (minority) applicants. A standard deviation increase in LTV is associated with 1.58% (0.66%) lower approval probability. Finally, the estimates are meaningful when considering the unconditional minority-non-minority approval gap of 14.28%.

3.2 Additional identification tests

[14] We follow related papers (e.g., Frame et al., 2025; Mayer, 2024) in estimating economic magnitudes but note that point estimates from linear probability models should be interpreted with caution as they are not bounded by 0 and 1. A standard deviation in *Proximity* is 0.68. Multiplying by the *Proximity* coefficients yields an estimated 0.017*0.68=1.15% (0.009*0.68=0.61%) effect for minorities (non-minorities).

Although we measure *Proximity* in a way that severs the mechanical applicant sorting concerns, saturate our models with rich fixed effects, and control for variation in applicants, banks, and locations, we address causal inference through four further tests.

3.2.1 Propensity score matching

One concern is that minority borrowers inherently differ from non-minorities along unmeasurable characteristics that drive approval. Such differences, omitted from our model, might bias *Minority* and *Proximity x Minority* coefficients. We address this concern through propensity score matching (PSM). We take all census tracts with at least one minority applicant and at least ten total applications and, within each tract, PSM minorities to non-minorities.[15] Matching variables include all controls from our baseline regressions. By sampling similar minority and non-minority applications, this test reduces the chance that failing to capture credit-relevant minority-non-minority differences biases our focal estimates.

Similarly, one might be concerned about fundamental differences between banks with close vis-à-vis distant customers in a given area. To address this issue, we take all census tracts with at least one minority applicant and at least ten applications total and, within each tract, PSM applications to banks above the within-tract median proximity with applications to banks below median proximity. By sampling similar applications to banks closer to and further from their customer, this test reduces the chance that failing to capture differences between closer-customer and further-customer banks biases our focal estimates.

[Table 3]

[15] In this and the subsequent PSM test, we use 1:1 greedy matching within a 10% caliper.

Table 3, Panel A shows the matching efficacy. While in the unmatched sample, minorities differ from non-minorities across all sixteen control variables and approvals, in the first matched sample, all differences dissipate and nearly all lose statistical significance.[16] In the second matched sample, statistical differences remain for half of the controls but also become economically trivial.[17]. Panel B shows that for both PSM samples, proximity continues to increase approval rates, especially for minorities. These tests suggest that endogenous selection between minority and non-minority borrowers and between close-to-customer and far-from-customer banks is unlikely to drive findings.

3.2.2 Instrumental variable test

Another concern is that *Proximity* may indirectly capture something beyond soft information and that something, not soft information, affects approval. To provide further suggestive evidence, we employ an instrumental variable test as a complement to our fixed-effects and matching estimators. Our setting requires an instrument related to a bank's soft information about potential applicants, but otherwise unrelated to the applicant's approval likelihood.

We propose the bank's 2007 local market share as a candidate. The 2007 share is plausibly relevant, as longstanding presence in the community fosters durable information. We acknowledge that satisfying the exclusion restriction is inherently challenging in this setting, as historical market position might also capture franchise strength, reputation, branch quality, legacy customer composition, or local political embeddedness. Therefore, we do not view this test as definitive

[16] Minority applications flow to banks with customers one tenth of a mile closer; have LTVs 21 basis points higher, borrowing about $735 more on the 2022 median home price of $350,000; have DTIs 53 basis points higher, paying $34 more per month on the 2022 median monthly income of 6,400; apply for 1% fewer fixed rate mortgages; and apply for 30 bps fewer cash-out refinances.

[17] Applicants to banks with closer customers have lower LTVs, apply for more conforming and conventional mortgages, more lines of credit, more junior lien, home improvement and rate-term refinance loans, and fewer home improvement loans. The average difference in these is one percentage point.

proof of causality, but rather as a useful supplementary exercise. We estimate a two-stage least squares regression and report it in Table 4.

[Table 4]

The instrument and its interaction with *Minority* strongly predict *Proximity* and *Minority* × *Proximity*, establishing relevance. First-stage F-statistics and Sanderson–Windmeijer under-identification (χ^2) and weak-identification (F) statistics are large, alleviating underidentified and weak-instrument concerns. In the second stage, coefficients retain their original signs but increase in magnitude, consistent with attenuation in OLS. Finally, in Column 3, *Minority* × *Proximity* has a positive and significant coefficient. On balance, these IV estimates provide supportive evidence that points in the same direction as our baseline fixed-effects and PSM results.

3.2.3 Expanded fixed-effects

Another set of endogeneity concerns relate to banks pursuing different policies across markets. Our within-bank comparisons are susceptible to that issue. A given bank might be more likely to approve applications in areas with closer customers for market-related reasons beyond proximity. To address this, we swap bank for bank-MSA fixed effects. Table 5, Column 1 shows that when severely restricting variation to within bank-MSA (and continuing to control for tract differences), the incremental effect of proximity on minorities remains significant.

In subsequent columns, we absorb bank policy differences across markets with different wealth, population, and competition levels. We add fixed effects for bank *x* income quintile (bank *x* population quintile) in Column 2 (3), retaining tract fixed effects. In Column 4, we add bank *x* HHI quintile fixed effects, using application amounts to measure market share. In all three columns, proximity continues to predict approvals, especially for minorities. We conclude that differential bank policies across markets are unlikely to bias our findings.

[Table 5]

3.3 Validity tests based on theory

To further augment the plausibility of a causal interpretation, we examine three theory-motivated settings in which soft information should be especially important in assessing mortgage applicants.

3.3.1 Soft information and loan type

Hard information can be easily processed through credit underwriting software so soft information is most valuable for less standardized loan types (DeYoung, Glennon, and Nigro, 2008; Degryse and Ongena, 2005). Agarwal, Ambrose, Chomsisengphet, and Liu (2006, 2011) argue that home equity loans, many of which appear as home improvement loans in HMDA, are precisely these types of less standardized mortgages. Therefore, if soft information explains our findings, they should be stronger for home improvement loans than for other loan types. To test this, we separately estimate Equation 1 over subsamples of home improvement loans and all other loan types. Table 6, Columns 1 and 2 show that coefficients for both *Proximity* and the interaction term are larger for home improvement loans.

[Table 6]

3.3.2 Soft information and secondary market activity

The ability to sell loans on the secondary market reduces lenders' incentive to collect soft information because underwriting decisions are less consequential when the bank faces reduced loss potential. In contrast, soft information should be more valuable for loans that must be retained. If soft information drives the value of proximity, then the effects should be stronger (weaker) for loans that banks must retain (can sell). To test this, we separately estimate Equation 1 over subsamples of non-standard mortgages (lines of credit, junior liens, and nonconforming loans), which have much thinner secondary markets and are usually retained by the bank, and other loans, which are more commonly sold. Table 6, Columns 3 and 4 show an even starker contrast: Both *Proximity* and the interaction coefficients are over six times larger for non-conforming loans, and the interaction is only significant in for these loans.

3.3.3 Soft information and lender size

Because lending relationships produce soft information and large banks are less commonly relationship lenders (Elyasiani and Goldberg, 2004; Berger and Black, 2011), larger institutions should collect less soft information through the normal course of business. If so, and if soft information is the reason proximity relates to approvals, then our results should be stronger for larger banks, that would have more marginal benefit from proximity-driven soft information. Table 6, Columns 5 and 6 estimate Equation 1 over samples of banks with >$100Bn in assets and all other banks. As predicted, proximity only determines approvals at the largest banks, which are naturally soft-information-scare.[18]

3.4 Proximity and discrimination

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[18] We also divide banks by mortgage application volume, <50K and >50K applications, and inferences are identical. In addition, untabulated tests using non-bank lenders support the same interpretation. A recent literature asks whether credit unions (CUs) and non-depository institutions (NDIs) bridge credit access gaps left by traditional banks (Bartlett et al., 2022). If proximity substitutes for soft information, it should be largely irrelevant for both lender types, though for different reasons. CUs resemble smaller community banks and accumulate soft information through relationships. NDIs, by contrast, underwrite on hard information. Estimating Equation (1) separately for CUs and NDIs, we find that proximity is unrelated to approvals for either minority or non-minority applicants. These results function as placebo tests: proximity does not predict approvals precisely where soft information is either already abundant or not used.

All our results thus far point to a 'minority approval gap' – lower approvals for minorities – which many before us have found (e.g., Munnell et al., 1996; Wei and Zhao, 2022; Bhutta, Hizmo, and Ringo, 2025). Such a gap does not automatically imply discrimination, but when viewed in the context of concurrent evidence from multiple angles, discrimination becomes one likely explanation. For example, Bartlett et al. (2022) finds that minorities pay higher rates for the same GSE mortgage. Zhang and Willen (2021) find that minorities are offered a worse menu of mortgage options. Hanson, Hawley, Martin, and Liu (2016) conduct a field experiment showing that mortgage service originators respond less frequently to inquiries from minority-sounding names. Wei and Zhao (2022) show that black borrowers face longer processing times. Ambrose et al. (2021) and Frame et al. (2025) find more favorable outcomes when minority applicants work with brokers and minority loan officers. Collectively, these papers tell a story of the U.S. mortgage market that is, at least, consistent with discrimination.[19]

In our study, the most robust and consistent result is that proximity is associated with a stronger effect for minorities than for non-minorities. A natural follow-up question is why? If mortgage markets do discriminate against minorities, does proximity help alleviate that? We borrow ideas and language from the taste-based discrimination (TBD) versus statistical discrimination (SD) literature to frame tests that address this question. SD is the notion that minority status may be a useful proxy for credit-relevant unobservable factors. Under SD (Phelps 1972; Arrow 1973; Aigner and Cain 1977), proximity should matter most where underwriting noise is greatest. In contrast, TBD is racial animus against a group of people (Becker 1957). Under

[19] Two exceptions to these broad conclusions are Bhutta and Hizmo (2021), who attribute racial gaps in mortgage pricing to differential applicant sorting rather than differential treatment and Bhutta, Hizmo, and Ringo (2025), who argue that the approval gap is largely explained by observable and unobserved risk factors rather than differential treatment.

TBD, proximity should attenuate preference-based frictions precisely where local animus or mistrust is higher, regardless of risk proxies.

To test for an SD-based explanation, we identify subsamples that are differentially susceptible to it. Because SD operates through beliefs about default risk, we seek covariates correlated with both minority status and default probability. Income is a natural proxy, measured (i) in absolute terms (reported income on the application) and (ii) in relative terms (income scaled by the property tract's median income to capture cost-of-living differences). We partition the sample into quintiles on each measure and re-estimate the baseline approval regressions within each quintile. If proximity attenuates the minority credit access gap through the SD channel, for example by supplying finer risk information, its coefficient should be more positive in lower-income quintiles. We plot the focal coefficients in Figure 3.

[Figure 3]

In contrast to that prediction, Panels A and B of Figure 3 show the opposite results. Proximity's incremental effect for minority applicants is stronger in higher income quintiles, as shown by the solid line plotted within 95% confidence intervals. Both lines show the strongest effect in the highest quintile, indicating the greater proximity benefits for the highest – not lowest – income minorities. This pattern is inconsistent with proximity offsetting the minority gap through the SD channel.

We also examine whether proximity relaxes SD by exploiting lender heterogeneity in experience with minority borrowers. If lenders disproportionately reject minorities because they cannot distinguish creditworthy from non-creditworthy minority applicants as well, the problem should be most acute at banks with little minority exposure. We measure exposure in two ways:

(i) the minority share of 2021 HMDA applications received by the bank; and (ii) the deposit-weighted minority share of county residents, where weights equal the fraction of the bank's 2021 deposits sourced from each county. We again split the sample into quintiles on each measure and re-estimate the baseline regressions within quintiles.

Panels C and D of Figure 3 again yield the opposite of the SD prediction. At banks with low minority exposure, the *Minority* × *Proximity* interaction is indistinguishable from zero. In contrast, proximity matters for minorities precisely at banks that frequently serve minority applicants. These tests provide further evidence against the view that proximity operates through the SD channel.

We next consider TBD as an alternative mechanism. Under TBD, lenders reject minority applicants owing to disutility or mistrust toward transacting with them, either overtly (racial animus), or more subtly (lower trust relative to non-minorities). To test the overt channel, we proxy for local animus with cumulative hate crimes (2011–2021) at the county level, normalized by 2022 population. If proximity attenuates the minority credit access gap through the TBD channel, the *Minority* × *Proximity* effect should be larger where animus is higher; Panel E confirms this pattern. To test the subtler mistrust channel, we use social capital as a county-level proxy for generalized trust (acknowledging that an ideal, minority-specific mistrust measure is unavailable and that animus and mistrust are likely correlated). If proximity builds familiarity and rapport that offset mistrust, the incremental interaction should be stronger in low–social capital (high-mistrust) counties; Panel F supports this prediction, as well. We conclude that if proximity can reduce discriminatory access gaps, it can likely do so by fostering banker–borrower relationships that attenuate racial animus and mistrust.

3.5 Proximity and risk

To explore which minority applicants benefit from proximity, we examine how *Proximity* and *Minority* associate with a mortgage applicant's risk profile. If proximity provides soft information that expands credit access, the applicants most likely to benefit should be marginal ones, who would have been otherwise rejected; safer applicants were already likely to be approved. Indeed, Han (2011) finds no mortgage approval gap for minority borrowers with long credit histories, evidence that better information may facilitate minority lending.

We estimate Equation 1 by replacing the dependent variable with three proxies for applicant risk, each of which can only be observed for approved applications. The first is *Spread*, which is the loan's interest rate spread over the prevailing prime rate. Because risk is priced into the interest rate, *Spread* reflects the applicant's risk profile (Magri and Pico, 2011; Dunsky, Follain, and Giertz, 2021). The second is *Retained*, a measure of whether the loan was not sold during the calendar year. Intuitively, banks would want to retain safer credits, all else equal (Drucker and Puri, 2009; Keys et al., 2010). The third is *LogCosts*, the natural logarithm of loan costs. Ambrose and Conklin (2014) show that origination costs increase as credit score decreases. Thus, these three variables are each coarse but independent proxies for risk of approve loans. Table 7 reports the results, omitting control variables for brevity.

[Table 7]

Proximity predicts lower risk in Column 1 but higher risk in Columns 2 and 3. It is unclear how proximity affects credit access for non-minority applicants. The three columns are consistent, however, in their implications on the interaction term: proximity associates with riskier minorities being approved. This finding intersects with prior work documenting credit rationing against minorities (Jo and Liu, 2024; Ambrose, Conklin, and Lopez, 2021; Hurtado and Sakong, 2024).[20] In our setting, proximity matters more for riskier minority approvals, suggesting that soft information could better ease funding constraints for riskier minority applicants.

3.6 Proximity and branch dynamics

If proximity allows banks to better access soft information, then the dramatic reduction in branches over the past decade may well impede their ability to do so.[21] Where branches are closing, proximity may matter more if branch closures render soft information scarcer and more valuable for remaining lenders. On the other hand, it may matter less if banks choose to close branches precisely because soft information in those areas was not valuable. We explore this tension by separately estimating our model in counties where branches per one thousand residents increased, held steady, or decreased from 2021 to 2022. We do so at three levels of analysis. First, we examine the total number of bank branches in a county. Next, we examine changes in branch counts for the focal bank.[22] Finally, we examine changes for the focal bank's in-market competitors. Results are presented in the first, middle, and last three columns of Table 8, respectively.

[Table 8]

Proximity predicts higher approvals in markets with growing (Column 1) or shrinking (Column 3) branch networks. However, the incremental minority effect obtains only in Column 3. This is consistent with proximity helping minorities precisely in areas with increasing bank-customer distances. In Column 4, proximity does not significantly affect approvals for any

[20] Jo and Liu (2024) show that banks ration credit to minorities when they face seasonal capacity constraints; Ambrose, Conklin, and Lopez (2021) also show more severe credit rationing to minority applicants. Hurtado and Sakong (2024) show that even within the same loan officer, minorities are less likely to receive credit.

[21] A test of whether credit contracts where banks are disappearing is beyond this paper's scope. It would be difficult to attribute any credit access changes to increasing distance, per se, and not other factors that precipitated branch exit.

[22] A lender must have at least one branch in a county to measure proximity, so branch reductions are not market exits.

applicant in areas where the bank is growing branches. This could be because branches opened within one year may not yet generate the soft information needed to benefit lenders. In a bank's remaining markets, proximity improves approval rates, incrementally so for minorities. However, the strongest effects appear in markets the bank is actively leaving (Column 6). In communities that banks are actively leaving, proximity to remaining branches mitigates the negative effects on credit access, especially for minorities. The final three columns show that proximity's incremental minority effect exists only where competitors are also exiting (Column 9).

3.7 Robustness checks and alternative explanations

Table 9 presents six tests that probe whether the proximity–approval relationship reflects soft-information production rather than measurement, transportation costs, market structure, the functional form of our estimation equation, or sample period. To preview our results, *Proximity* continues to predict approvals positively when controlling for branch-census tract distance, transportation costs, and market power, and the relationship strengthens at closer distances. It relates to higher approvals in 2021 but not in 2020. Its incremental effect on minorities persists but is concentrated in less competitive markets and is stronger at closer distances. It holds in 2020 and 2021. We discuss each in turn.

In Column 1 we address whether our measure is simply a noisier proxy for the distance concept used by Hampole, Jørring, and Monteiro (2025), namely the distance from the application's census tract centroid to the nearest bank branch.[23] We construct that measure (*Tract Proximity*) and find it is only correlated with *Proximity* at under 10%, indicating the two capture

[23] We believe tracking cell-phone-home to branch distance can better reflect a bank's soft informational environment in an area because it measures existing banking relationships. Census tract centroid-branch distance, in contrast, is more likely to capture selection effects of a specific applicant. Nevertheless, to benchmark with the literature, we use this alternative for robustness check of our main results.

largely distinct variation. Adding *Tract Proximity* and its interaction with *Minority* leaves the *Proximity* and focal interaction coefficients unchanged. *Tract Proximity* predicts approvals to a lesser degree and no different for minorities.

We next address the transportation-cost interpretation of proximity, based on prior literature. The commercial-lending literature treats distance as capturing both soft information (Petersen and Rajan, 2002; Hauswald and Marquez, 2006) and travel costs borne by borrowers during application and servicing and by lenders during monitoring (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). Lender travel costs are less relevant here, as mortgage lenders rarely conduct onsite monitoring (Gryglewicz, Mayer, and Morellec, 2024), and the three studies of distance in mortgage lending we know of interpret proximity solely through the information channel (Nguyen, 2019; Mayer, 2024; Hampole et al., 2025). We nonetheless control directly for the interactions between county transportation costs and *Minority* and *Proximity*.[24] Column 2 presents the results and shows that both *Proximity* and *Proximity* × *Minority* remain significant. Proximity therefore predicts approvals beyond what travel costs alone would explain.

Columns 3 controls for local banking competition, adding the county's loan-amount HHI interacted with *Minority*, *Proximity*, and *Proximity* × *Minority*. *Proximity* retains significance, but the interaction term does not. However, the significantly positive triple interaction implies that the incremental minority effect does hold but predominantly in less competitive markets. This is consistent with Loutskina and Strahan's (2011) finding that soft information matters more in concentrated lending markets.

[24] Transportation costs come from the Center for Neighborhood Technology. Unlike *Proximity*, measured by bank-county, *Transportation Costs* are measured at the county level so they drop out of a regression with tract fixed effects.

In Column 4, we relax the linear structure of our estimation equation by adding a quadratic proximity term and its interaction with *Minority*. Both the level effect and the minority interaction survive, so our findings are not an artifact of imposing a linear relationship between logged distance and approval. Moreover, the positive quadratic interaction term implies that *Proximity*'s incremental effect on minority approvals strengthens at closer distances.

In Columns 5 and 6, we re-estimate Equation 1 on 2020 and 2021 HMDA applications (recall our main sample is 2022). Because 2020 and 2021 span an unusual refinance boom and pandemic-era underwriting, we do not merge the three years into our main sample.[25] *Proximity* is positive and significant in 2021 but indistinguishable from zero in 2020. However, the interaction effect holds in both years, which indicates that the association between proximity and minority approval is highly stable.

3.8 Proximity and borrower demographics

Finally, the heterogeneous effects between minority and non-minority borrowers motivate us to further explore demographic differences. We partition our main sample to test whether proximity benefits a specific type of borrower. We start along racial/ethnic lines. Which minorities, specifically, benefit? We estimate Equation (1) separately for Black, Native, Asian, and Hispanic applicants. Non-focal minorities are dropped from the sample so the counterfactual remains white, non-Hispanics. We also split our sample by gender following the literature on gender differences in lending outcomes (Goldsmith-Pinkham and Shue, 2023; Tsouderou and Tüzel, 2024) and on age (Mayer and Moulton, 2022; Doerr, Kabas, and Ongena, 2024). Table 10 reports the results.

[25] Our baseline findings are unchanged when estimating over the 2020-2022 panel and substituting for bank-year and tract-year fixed effects. However, sample coverage expanded dramatically with the number of bank branches nearly doubling from 2021 to 2022. For this reason, we prefer the 2022 cross-section as a more robust sample.

[Table 10]

In Columns 1 – 4, we find that all minority types have a lower overall approval rate and that proximity benefits non-minorities in all specifications. However, the interaction loads positively and significantly for Blacks and Asians, only. Columns 5 and 6 show that the incremental minority benefit accrues to male, not female, applicants, while Columns 7-9 show that proximity has less effect for older minority applicants. Because older adults likely have a longer credit history, this heterogeneity supports Han's (2011) finding that the minority approval gap dissipates for borrowers with longer credit histories.

4. Conclusions

We find that bank–customer proximity is associated with a materially higher likelihood of mortgage approval, and this effect is disproportionately large for minority applicants. Within-bank and within-tract designs, matched-sample analyses, and an IV strategy based on historical market share all support a causal interpretation. In addition, three separate mechanism tests based on predictions from theory corroborate these findings. Motivated by recent literature, we also examine whether the minority approval gap's attenuation through proximity is consistent with taste based or statistical discrimination and find results supporting the former channel. Minority proximity premia are largest in high–hate-crime, low–social-capital counties, and not in low-income strata or at lenders with little minority exposure that would suggest statistical discrimination.

Our findings matter because physical bank branch networks continue to contract, increasing borrower–lender distance and widening access gaps. We document that proximity partially offsets the lower baseline approval rates faced by minorities. Thus, we quantify an equity-relevant cost of branch retrenchment that is otherwise obscured in markets dominated by "hard-information" underwriting and securitization.

Methodologically, our paper introduces a scalable bank–county proximity measure from device-location data and ties it to application-level outcomes, advancing the distance–lending literature into retail mortgages. Relative to prior work on commercial credit and branch closures (e.g., Nguyen, 2019) and on technology and intermediation in mortgages (Fuster et al., 2019; Fuster et al., 2022; Bartlett et al., 2022; Frame et al., 2025), our contribution is to separate average proximity effects from minority-specific gains and pinpoint where these gains arise (products, lenders, borrowers).

Our findings have immediate policy implications: merger reviews and CRA evaluations might consider equity-relevant distance effects to ameliorate minority approval gaps, targeted support for branch presence or mobile/part-time branches in banking deserts may improve access, especially for minorities, and supervisory analytics that monitor approval gaps by distance could inform fair-lending considerations.

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Table 1: Descriptive Statistics

This table reports descriptive statistics for our main sample and for subsamples of minority and White, non-Hispanic applications. We report the number of observations (N), means, medians (Med.), and standard deviations (S.D.) for key variables in our paper. These include an indicator for whether application was approved (*Approved*); the distance, in miles, between the application-bank's branches in the county and branch-visitors' home addresses (*Distance*); the negative of that value's natural log (*Proximity*); an indicator for whether the primary applicant was Black, Hispanic, Native American, or Asian (*Minority*); loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); its term, in months (*Term*); approved applications' interest rate above prime (*Spread*), log loan costs (*Log(Costs)*), and an indicator for whether the loan was not sold in the calendar year it was accepted (*Retained*); indicators for whether the primary applicant is Black, Hispanic, Native, Asian, and Female; and the applicant's age. Distance comes from SafeGraph data and all other variables come from HMDA.

	Full Sample				Minority				White, non-Hispanic			
	N	Mean	Med.	S.D.	N	Mean	Med.	S.D.	N	Mean	Med.	S.D.
Dependent Variable												
Approved	1,261,218	75.79%	1	42.84%	366,420	66.12%	1	47.33%	792,034	80.39%	1	39.70%
Independent Variables												
Distance (miles)	1,261,192	8.30	5.36	11.04	366,411	8.50	5.49	11.84	792,019	8.09	5.29	10.38
Proximity	1,261,192	-1.80	-1.68	0.68	366,411	-1.80	-1.70	0.69	792,019	-1.79	-1.66	0.66
Minority	1,158,454	31.63%	0	46.50%	366,420	100.00%	1	0.00%	792,034	0.00%	0	0.00%
Controls												
LTV	1,234,975	68.29%	0.74	22.85%	357,121	70.74%	0.76	22.89%	777,161	66.99%	0.72	22.84%
DTI	1,261,218	37.27%	0.38	14.68%	366,420	40.59%	0.4	15.07%	792,034	35.76%	0.33	14.21%
Conforming	1,261,218	91.17%	1	28.38%	366,420	90.72%	1	29.01%	792,034	92.00%	1	27.13%
Conventional	1,261,218	94.32%	1	23.14%	366,420	92.52%	1	26.30%	792,034	95.20%	1	21.38%
LOC	1,261,218	23.82%	0	42.60%	366,420	25.46%	0	43.56%	792,034	23.17%	0	42.19%
Junior	1,261,218	22.01%	0	41.43%	366,420	23.32%	0	42.29%	792,034	21.36%	0	40.98%
Fixed	1,261,218	67.22%	1	46.94%	366,420	65.36%	1	47.58%	792,034	68.18%	1	46.58%
Term (Months)	1,258,371	328.19	360	83.90	364,817	333.44	360	78.47	791,140	325.01	360	86.43

	Full Sample				Minority				White, non-Hispanic			
	N	Mean	Med.	S.D.	N	Mean	Med.	S.D.	N	Mean	Med.	S.D.
Controls (continued)												
NPO	1,261,218	42.85%	0	49.49%	366,420	45.79%	0	49.82%	792,034	41.17%	0	49.21%
HI	1,261,218	22.06%	0	41.47%	366,420	24.28%	0	42.88%	792,034	21.22%	0	40.89%
Refi	1,261,218	19.51%	0	39.63%	366,420	15.72%	0	36.40%	792,034	21.38%	0	41.00%
CO Refi	1,261,218	15.57%	0	36.26%	366,420	14.21%	0	34.91%	792,034	16.22%	0	36.87%
OCC	1,261,218	9.23%	0	28.95%	366,420	5.77%	0	23.32%	792,034	11.35%	0	31.72%
FRB	1,261,218	11.25%	0	31.59%	366,420	6.40%	0	24.47%	792,034	13.52%	0	34.19%
FDIC	1,261,218	3.55%	0	18.50%	366,420	2.25%	0	14.81%	792,034	4.28%	0	20.23%
CFPB	1,261,218	75.97%	1	42.72%	366,420	85.59%	1	35.12%	792,034	70.85%	1	45.44%
Additional Variables												
Spread	952,391	21.90	20.98	87.74	241,294	18.13	17.70	91.99	634,540	24.57	23.00	86.14
Retained	925,490	57.25%	1	49.47%	233,473	57.21%	1	49.48%	617,731	56.81%	1	49.53%
Log(Costs)	721,306	8.20	8.28	0.87	187,340	8.33	8.41	0.84	474,313	8.13	8.23	0.87
White	1,113,643	79.73%	1	40.20%	339,247	33.46%	0	47.18%	774,396	100.00%	1	0.00%
Black	1,113,643	10.03%	0	30.04%	339,247	32.93%	0	47.00%	774,396	0.00%	0	0.00%
Hispanic	1,132,935	12.45%	0	33.01%	357,687	39.43%	0	48.87%	775,248	0.00%	0	0.00%
Native American	1,113,643	1.41%	0	11.80%	339,247	4.64%	0	21.03%	774,396	0.00%	0	0.00%
Asian	1,113,643	10.43%	0	30.56%	339,247	34.22%	0	47.45%	774,396	0.00%	0	0.00%
Female	1,261,218	37.74%	0	48.47%	366,420	41.24%	0	49.23%	792,034	36.45%	0	48.13%
Age	1,261,218	48.27	50	14.75	366,420	46.81	50	13.79	792,034	49.06	50	15.24

Table 2: Proximity, Minorities, and Approval Rates

This table reports linear probability model estimates of Equation 1. The dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include the negative logged average distance between the application-bank and its customers in the application's county (*Proximity*), an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian (*Minority*), and the interaction between the two. Controls include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (*HI*), rate-and-term refinance (*Refi*), and cash-out refinance (*CO Refi*), with new purchase origination, *NPO*, as the omitted category). Columns 1 and 2 include the focal independent variables separately while column three includes both and their interaction. Column 3 also interacts each control with *Minority* for a fully specified model. All models include bank and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1) Approved	(2) Approved	(3) Approved
Proximity	0.011***		0.009***
	(0.001)		(0.001)
Minority		-0.056***	-0.142***
		(0.001)	(0.019)
Proximity × Minority			0.008***
			(0.001)
LTV	-0.060***	-0.053***	-0.069***
	(0.002)	(0.002)	(0.003)
LTV × Minority			0.040***
			(0.005)
DTI	-0.839***	-0.830***	-0.776***
	(0.003)	(0.003)	(0.004)
DTI × Minority			-0.147***
			(0.006)
Conforming	0.016***	0.017***	0.019***
	(0.001)	(0.001)	(0.002)
Conforming × Minority			-0.013***
			(0.003)
Conventional	0.028***	0.025***	0.028***
	(0.002)	(0.002)	(0.002)
Conventional × Minority			0.003
			(0.004)
LogTerm	0.046***	0.043***	0.037***
	(0.001)	(0.001)	(0.002)
LogTerm × Minority			0.026***
			(0.003)
LOC	-0.163***	-0.166***	-0.148***
	(0.002)	(0.002)	(0.002)

Table 2: Proximity, Minorities, and Approval Rates, continued

LOC × Minority			-0.059***
			(0.005)
Junior	0.019***	0.018***	0.014***
	(0.002)	(0.002)	(0.002)
Junior × Minority			0.017***
			(0.004)
Fixed	0.004***	0.003**	-0.001
	(0.001)	(0.001)	(0.001)
Fixed× Minority			0.016***
			(0.002)
FRB × Minority			0.013**
			(0.006)
FDIC × Minority			0.019***
			(0.004)
CFPB × Minority			-0.003
			(0.003)
HI	-0.193***	-0.194***	-0.181***
	(0.002)	(0.002)	(0.002)
HI × Minority	-0.084***	-0.086***	-0.084***
	(0.001)	(0.001)	(0.001)
Refi	-0.086***	-0.087***	-0.075***
	(0.001)	(0.001)	(0.001)
Refi × Minority			-0.036***
			(0.004)
CO Refi			-0.007**
			(0.003)
CO Refi × Minority			-0.041***
			(0.003)
Observations	1,228,721	1,128,114	1,128,097
Adj R^2	0.299	0.302	0.305
Bank + Tract FE	Yes	Yes	Yes

Table 3: Propensity Score Matching

This table summarizes two propensity-score matching exercises: matching across minority status and matching applications to closer-to-customer and further-from-customer banks, defined by above versus below within-tract means of application-bank to customer distance. Panel A presents group means on the two potentially endogenous variables (the average distance between the application-bank and its customers in the application's county, *Proximity*, and an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian, *Minority*) as well as the fifteen matching variables (the application's loan-to-value, *LTV*, and debt-to-income, *DTI,* ratios; indicators for whether the loan conforms to secondary market guidelines, *Conforming*, is not guaranteed by the FHA or VA, *Conventional*, is structed as a line of credit, *LOC*, represents a junior lien on the property, *Junior*, and offers a fixed rate, *Fixed*; its term, in months, *Term*; indicators for four bank regulators, *OCC*, *FRB*, *FDIC*, and *CFPB*; and indicators for loan type: new purchase origination, *NPO,* home improvement, *HI*, refinance, *Refi*, and cash-out refinance, *CO Refi*. Observations are matched within census tract across the matching variables. Panel B reports linear probability model estimates of Equation 1 over both propensity-score matched samples. The dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include the negative log of *Distance* (*Proximity*), *Minority*, and their interaction. Controls, unreported for brevity, include all remaining matching variables. Both models include bank and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Panel A: Group differences

	By minority status						By distance					
	Unmatched			PSM (Minority)			Unmatched			PSM(Distance)		
Variable	Mean	Mean	p-value	Min	NonMin	p-value	Closer	Further	p-value	Closer	Further	p-value
Minority	1.00	0.00	0.00	1.00	0.00	0.00	0.34	0.33	0.00	0.37	0.38	0.26
Distance	8.50	8.08	0.00	8.09	8.20	0.03	4.72	15.72	0.00	5.33	14.65	0.00
LTV	0.71	0.67	0.00	0.73	0.73	0.04	0.67	0.71	0.00	0.71	0.72	0.00
DTI	0.41	0.36	0.00	0.38	0.38	0.00	0.38	0.37	0.00	0.37	0.37	0.88
Conforming	0.91	0.92	0.00	0.87	0.87	0.92	0.92	0.88	0.00	0.81	0.80	0.06
Conventional	0.93	0.95	0.00	0.95	0.95	0.72	0.95	0.93	0.00	0.964	0.958	0.00
LogTerm	5.77	5.73	0.00	5.82	5.82	0.54	5.75	5.76	0.00	5.81	5.82	0.14
LOC	0.25	0.23	0.00	0.24	0.24	0.76	0.28	0.18	0.00	0.16	0.14	0.00
Junior	0.23	0.21	0.00	0.23	0.23	0.95	0.25	0.19	0.00	0.16	0.14	0.00
Fixed	0.65	0.68	0.00	0.68	0.69	0.00	0.65	0.69	0.00	0.69	0.69	0.87
NPO	0.46	0.41	0.00	0.54	0.54	0.71	0.39	0.52	0.00	0.57	0.60	0.00
HI	0.24	0.21	0.00	0.22	0.22	0.48	0.25	0.18	0.00	0.15	0.14	0.00
Refi	0.16	0.21	0.00	0.12	0.12	0.72	0.20	0.16	0.00	0.13	0.13	0.04
CO Refi	0.14	0.16	0.00	0.11	0.12	0.06	0.16	0.14	0.00	0.14	0.14	0.13
FDIC	0.06	0.14	0.00	0.07	0.07	0.32	0.08	0.16	0.00	0.06	0.07	0.21
OCC	0.06	0.11	0.00	0.05	0.05	0.94	0.10	0.08	0.00	0.02	0.02	0.81
FRB	0.02	0.04	0.00	0.02	0.02	0.81	0.02	0.05	0.00	0.01	0.01	0.20
CFPB	0.86	0.71	0.00	0.87	0.87	0.44	0.80	0.71	0.00	0.91	0.90	0.10

Panel B: Propensity-score matched regressions

	(1)	(2)
	Approved	Approved
Proximity	0.010***	0.012***
	(0.003)	(0.003)
Minority	-0.034	0.037
	(0.053)	(0.094)
Proximity × Minority	0.007**	0.011**
	(0.003)	(0.005)
Observations	156,852	80,694
Adj R^2	0.310	0.285
Matching	Minority	Distance
Controls	Yes	Yes
Bank + Tract FE	Yes	Yes

Table 4: Two-Stage Least Squares

This table reports two-stage least squares linear probability model estimates of Equation 1. Columns 1 and 2 report first-stage estimates in which we respectively regress the potentially endogenous variables (negative logged average distance between the application-bank and its customers in the application's county, *Proximity*, and that variable interacted with an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian, *Minority*) on their instruments and control variables. We instrument for the potentially exogenous *Proximity* and its interaction with *Minority* with a bank's 2007 deposit market share in a county and its interaction with *Minority*. Controls, unreported for brevity, include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); and its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (home improvement, *HI*; refinance, *Refi*; and cash-out refinance, *CO Refi*; with new purchase origination, *NPO*, as the omitted category). Below coefficient estimates, we report the F-statistics and Sanderson–Windmeijer under-identification (χ^2) and weak-identification (F) test statistics. In Column 3, the dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include *Minority* and fitted values from the two first-stage regressions. Controls are the same as in the first stage. All models include lender and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
	Proximity	Minority × Proximity	Approved
2007 Market Share	0.921***	0.019***	
	(0.010)	(0.004)	
Minority	-0.031*	-1.911***	-0.144***
	(0.016)	(0.021)	(0.020)
2007 Market Share × Minority	0.110***	1.010***	
	(0.010)	(0.015)	
$\widehat{Proximity}$			0.009***
			(0.001)
Minority × $\widehat{Proximity}$			0.006***
			(0.002)
Observations	1,083,897	1,083,897	1,083,897
Adj R^2	0.705	0.904	0.178
F-statistic	5669.09	3136.53	-
SW Chi^2 statistic	8658.02	5435.73	-
SW F statistic	8651.29	5431.50	-
Controls	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes

Table 5: Expanded fixed effects

This table summarizes tests that model bank policy heterogeneity across markets. To do so, we swap our baseline model's bank fixed effects for bank × market fixed effects, where market is defined as MSA in Column 1 and as three market characteristic quintiles in Columns 2-5. In Column 2 (3), we study tract income (population) quintiles. In Column 4, we study the mortgage loan HHI quintiles, computing market shares through the dollar amount of loan applications. The dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include the negative logged average distance between the application-bank and its customers in the application's county (*Proximity*), an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian (*Minority*), and the interaction between the two. Controls, unreported for brevity, include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); and its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (home improvement, *HI*; refinance, *Refi*; and cash-out refinance, *CO Refi*; with new purchase origination, *NPO*, as the omitted category). All models also include census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1) Approved	(2) Approved	(3) Approved	(4) Approved
Proximity	-0.002	0.007***	0.009***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)
Minority	-0.148***	-0.137***	-0.140***	-0.139***
	(0.019)	(0.019)	(0.019)	(0.019)
Proximity x Minority	0.005***	0.008***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,128,017	1,128,078	1,127,999	1,128,078
Adj R2	0.309	0.306	0.305	0.306
Controls	Yes	Yes	Yes	Yes
FEs	Bank × MSA + Tract	Bank × Income Quintile + Tract	Bank × Population Quintile + Tract	Bank × Loan HHI ($) Quintile + Tract

Table 6: Heterogeneity Analysis

This table reports linear probability model estimates of Equation 1. The dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include the negative logged average distance between the application-bank and its customers in the application's county (*Proximity*), an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian (*Minority*), and the interaction between the two. Controls, unreported for brevity, include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); and its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (home improvement, *HI*; refinance, *Refi*; and cash-out refinance, *CO Refi*; with new purchase origination, *NPO*, as the omitted category). Column 1 (2) estimates the model home improvement loans (all other loans); Column 3 (4) estimates the model for non-conforming loans, more likely to be retained (all other loans); Column 5 (6) estimates the model for banks over $100 billion in assets (all other banks). All models include bank and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1) Approved	(2) Approved	(3) Approved	(4) Approved	(5) Approved	(6) Approved
Proximity	0.025***	0.006***	0.026***	0.004***	0.015***	-0.001
	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Minority	-0.283***	0.068***	-0.387***	0.110***	-0.054**	-0.075**
	(0.083)	(0.021)	(0.050)	(0.023)	(0.027)	(0.032)
Prox. × Min.	0.014***	0.004***	0.014***	0.002	0.015***	-0.001
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	228,301	884,059	388231	726400	711,382	359,715
Adj R^2	0.106	0.152	0.251	0.131	0.248	0.070
Loans	Home Improve.	Other Types	Likely Retained	Likely Sell	Large Banks	Other Banks
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Applicant Risk

This table reports OLS regression estimates from a modified version of Equation 1. In Column 1 (2, 3) in which the dependent variable is the approved loan's rate spread, in basis points, over prime (*Spread*; an indicator flagging one if the loan is not sold in the calendar year, *Retained*; the natural log of reported loan costs, *LogCosts*). Independent variables include the negative logged average distance between the application-bank and its customers in the application's county (*Proximity*), an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian (*Minority*), and the interaction between the two. Controls include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); and its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (home improvement, *HI*; refinance, *Refi*; and cash-out refinance, *CO Refi*; with new purchase origination, *NPO*, as the omitted category). All models include bank and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1) Spread	(2) Retained	(3) LogCosts
Proximity	0.002	0.009***	-0.027***
	(0.003)	(0.001)	(0.003)
Minority	-0.274***	-0.962***	1.242***
	(0.070)	(0.022)	(0.054)
Proximity × Minority	0.015***	-0.017***	0.015***
	(0.003)	(0.002)	(0.004)
Observations	867,115	842,237	653,203
Adj R^2	0.330	0.560	0.493
Sample	Approved	Approved	Approved
Controls	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes

Table 8: Changes in Branch Presence

This table reports linear probability model estimates of Equation 1 for different subsamples of local branch dynamics. The dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include the negative logged average distance between the application-bank and its customers in the application's county (*Proximity*), an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian (*Minority*), and the interaction between the two. Controls, unreported for brevity, include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); and its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (home improvement, *HI*; refinance, *Refi*; and cash-out refinance, *CO Refi*; with new purchase origination, *NPO*, as the omitted category). Columns 1-3 consider counties in which the net number of branches per one thousand residents increased, stayed flat, and decreased, respectively. Column's 4-6 (7-9) consider bank-county dyads in which the bank (bank's competitors) increases, does not change, or decreases net branches, respectively. All models include bank and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Approved	Approved	Approved	Approved	Approved	Approved	Approved	Approved	Approved
Proximity	0.011***	0.002	0.010***	0.016	0.007***	0.015***	0.009***	-0.002	0.010***
	(0.003)	(0.003)	(0.001)	(0.013)	(0.001)	(0.005)	(0.003)	(0.003)	(0.002)
Minority	-0.124**	-0.084	-0.123***	-0.062	-0.140***	-0.053	-0.115**	-0.122**	-0.104***
	(0.052)	(0.052)	(0.023)	(0.137)	(0.024)	(0.039)	(0.050)	(0.049)	(0.024)
Proximity × Minority	-0.003	0.005	0.008***	-0.004	0.005***	0.012***	-0.002	0.003	0.008***
	(0.004)	(0.004)	(0.002)	(0.009)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)
Observations	180,584	199,906	747,597	31,738	754,483	327,505	200,051	215,642	707,342
Adj R^2	0.313	0.272	0.311	0.322	0.293	0.333	0.307	0.274	0.315
Net branch/1000 residents	>0	0	<0	>0	0	<0	>0	0	<0
		In county			By bank in county			By bank's competitors in county	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank + Tract FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Robustness

This table reports linear probability model estimates of Equation 1. The dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include the negative logged average distance between the application-bank and its customers in the application's county (*Proximity*), an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian (*Minority*), and the interaction between the two. Controls, unreported for brevity, include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); and its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (home improvement, *HI*; refinance, *Refi*; and cash-out refinance, *CO Refi*; with new purchase origination, *NPO*, as the omitted category). Column 1 adds the application census tract distance to the nearest bank branch (*Tract Proximity*) and its interaction with *Minority*. Column 2 adds estimated county transportation costs (*Transportation Costs*) as a fraction of median county income and its interactions with *Minority* and *Proximity*. Column 3 controls for the interactions of county loan amount Hirschman-Herfindahl Index (*HHI*) with *Minority*, *Proximity*, and *Minority* × *Proximity*. Column 4 adds a quadratic proximity measure and its interaction with Minority. Column 5 and 6 estimate the model over 2020 and 2021 HMDA samples. All models include bank and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Approved	Approved	Approved	Approved	Approved	Approved
Proximity	0.008***	0.033***	0.011***	0.012***	-0.000	0.004***
	(0.001)	(0.005)	(0.002)	(0.004)	(0.001)	(0.001)
Minority	-0.144***	-0.094***	-0.149***	-0.123***	0.190***	0.097***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.017)	(0.015)
Proximity × Minority	0.006***	0.007***	0.002	0.028***	0.021***	0.010***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.002)	(0.001)

Table 9: Robustness (continued)

Tract Proximity	0.002***					
	(0.001)					
Tract Proximity × Minority	0.000					
	(0.001)					
Proximity × Transportation Costs		-0.002***				
		(0.000)				
Minority × Transportation Costs		-0.001***				
		(0.000)				
HHI × Proximity			-0.063			
			(0.054)			
HHI × Minority			0.235*			
			(0.143)			
Minority × Proximity × HHI			0.176**			
			(0.076)			
Proximity × Proximity				0.000		
				(0.001)		
Minority × Proximity × Proximity				0.005***		
				(0.001)		
Observations	1,084,687	981,463	1,128,011	1,128,097	2,022,157	2,017,905
Adj R^2	0.314	0.307	0.305	0.305	0.262	0.285
Sample Period	2022	2022	2022	2022	2020	2021
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Demographics

This table reports linear probability model estimates of Equation 1. The dependent variable is an indicator for whether the loan was approved (*Approved*). Independent variables include the negative logged average distance between the application-bank and its customers in the application's county (*Proximity*), an indicator for whether the primary applicant identifies as Black, Hispanic, Native American, and/or Asian (*Minority*), and the interaction between the two. Controls, unreported for brevity, include the application's loan-to-value (*LTV*) and debt-to-income (*DTI*) ratios; indicators for whether the loan conforms to secondary market guidelines (*Conforming*), is not guaranteed by the FHA or VA (*Conventional*), is structed as a line of credit (*LOC*), represents a junior lien on the property (*Junior*), and offers a fixed rate (*Fixed*); and its term, in months (*Term*); indicators for three bank regulators (*FRB*, *FDIC*, and *CFPB*; with *OCC* as the omitted category); and indicators for loan type (home improvement, *HI*; refinance, *Refi*; and cash-out refinance, *CO Refi*; with new purchase origination, *NPO*, as the omitted category). Column 1 (2, 3, 4, 5, 6) estimates the model for applications with Black (Hispanic, Native American, Asian, male, female) primary applicants. Columns 7 (8, 9) estimates it for primary applicants <40 (40-59; >69) years old. All models include bank and census tract fixed effects and cluster standard errors by tract. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Approved	Approved	Approved	Approved	Approved	Approved	Approved	Approved	Approved
Proximity	0.007***	0.008***	0.008***	0.009***	0.009***	0.009***	0.008***	0.008***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.004)
Minority	-0.079***	-0.169***	-0.173***	-0.212***	-0.094***	-0.181***	-0.149***	-0.152***	0.074
	(0.024)	(0.029)	(0.032)	(0.025)	(0.031)	(0.026)	(0.054)	(0.024)	(0.062)
Proximity × Minority	0.005**	-0.001	0.002	0.009***	0.004	0.009***	0.005*	0.008***	0.007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.006)
Observations	968,333	902,729	873,803	971,283	419,523	696,157	226,544	710,637	154,957
Adj R^2	0.293	0.293	0.281	0.285	0.324	0.296	0.328	0.303	0.311
Included Minority	Black	Hispanic	Native	Asian	Female	Male	<40	40-69	>69
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Approval Gaps by Bank-County Distance Quintile

This figure plots the minority-non-minority approval gap by distance quintile. In Panel A (B) the gap is computed by comparing the same bank's (tract's) minority and non-minority approval rates.

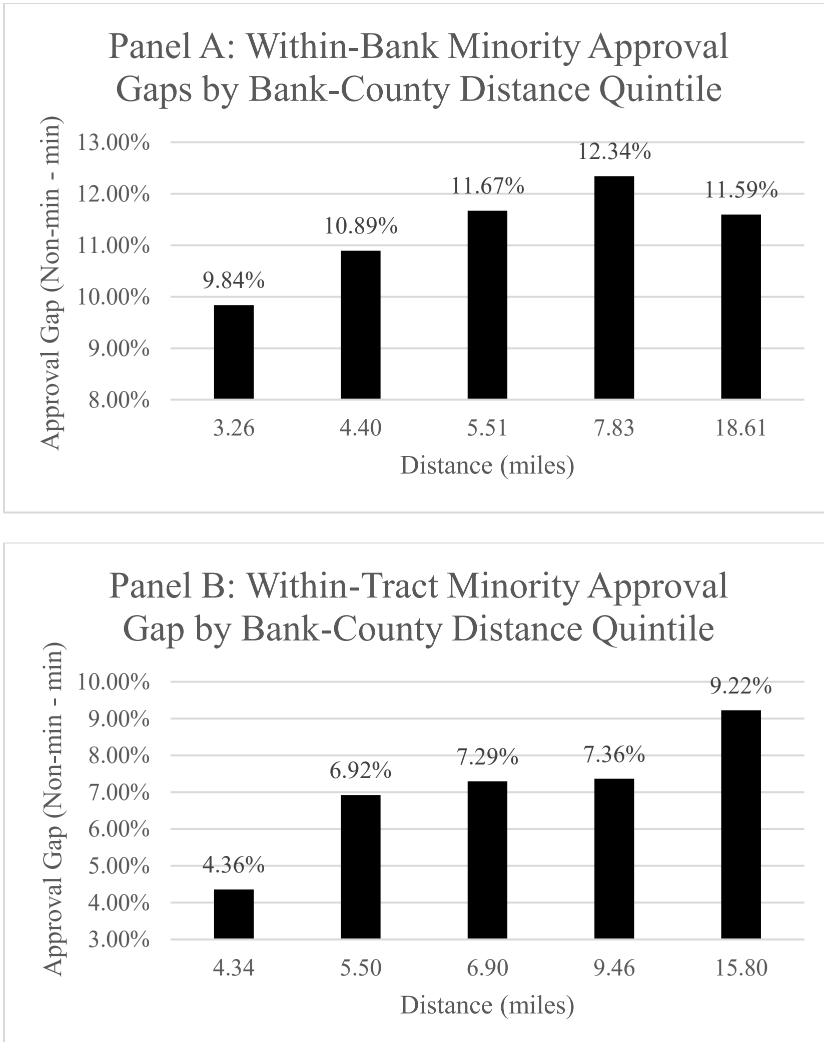

Figure 2: Example of Distance Measure Construct for Midwest BankCentre

This figure illustrates how we compute our focal construct, bank-county customer distance for one bank, Midwest BankCentre. Circles represent counties in which the bank operates, and squares represent its branches. White (black) squares denote branches with (without) SafeGraph data that can be merged.

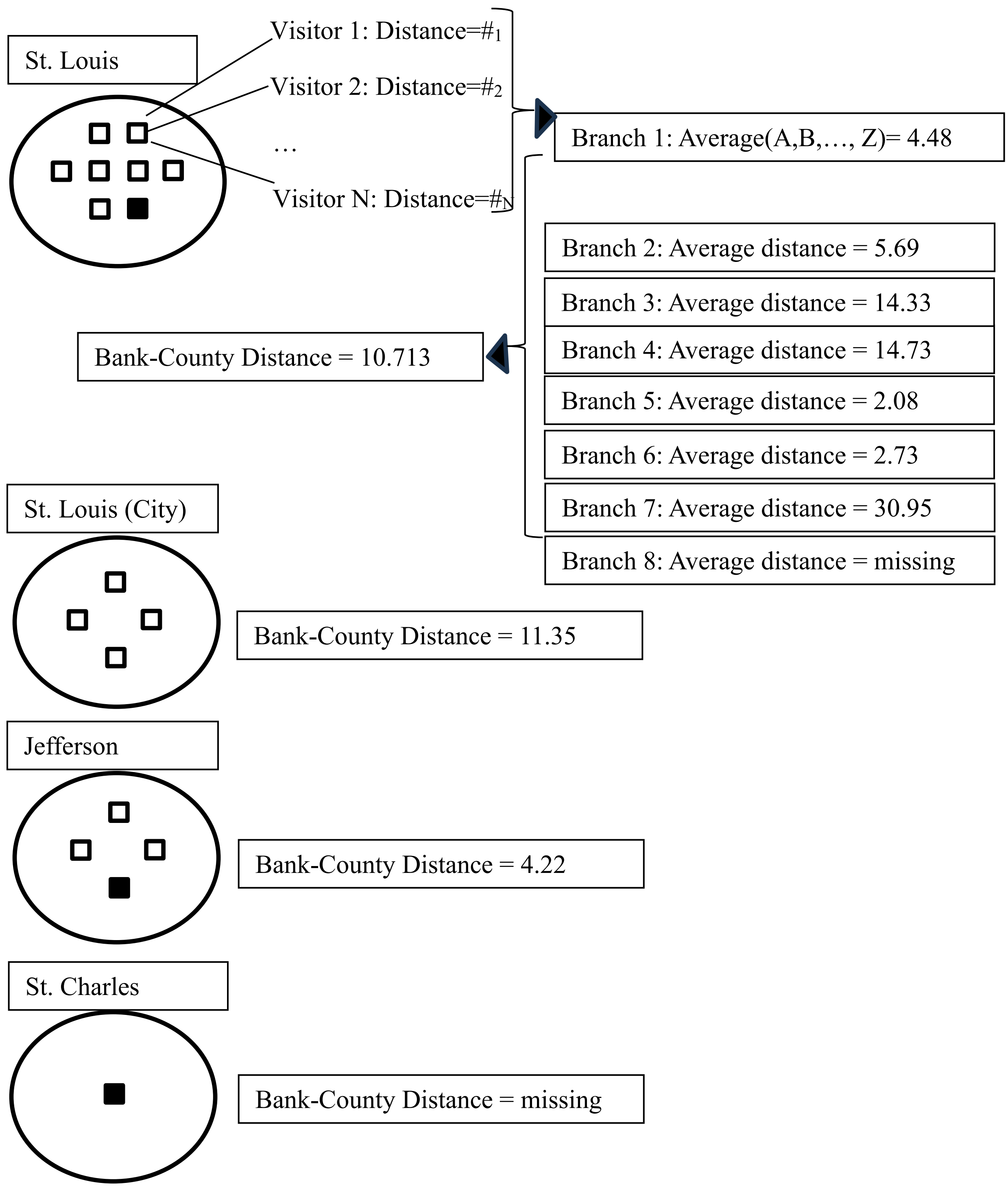

Figure 2: Statistical versus taste-based discrimination

This figure presents tests to distinguish statistical discrimination (SD) from taste-based Discrimination (TBD). To test for SD, we identify subsamples by income, measured (i) in absolute terms (reported income on the application) (Panel A) and (ii) in relative terms (income scaled by the property tract's median income to capture cost-of-living differences) (Panel B), and by minority exposure, measured by: (i) the minority share of 2021 HMDA applications received by the bank (Panel C); and (ii) a deposit-weighted county minority share, where weights equal the fraction of the bank's 2021 deposits sourced from each county (Panel D). To test for TBD, we proxy for local animus with cumulative hate crimes (2011–2021) at the county level, normalized by 2022 population (Panel E), and also the degree of social capital (Panel F). We partition the sample into quintiles on each measure and re-estimate the baseline approval regressions within each quintile. In each panel, we plot the focal coefficients with the statistical significance shown by the shaded areas.