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

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Abstract

Using de-identified cellphone mobility data to infer bank–borrower proximity, we study how distance to branches shapes mortgage access. Within-bank and within-tract identification shows that proximity materially raises approval probabilities; effects are twice as large for minority applicants. Proximity's impact concentrates in riskier borrowers, loans with greater information asymmetry, and lenders with less soft information. Matched-sample and instrumental-variable tests support causal inference. Heterogeneity tests reject statistical-discrimination channels in favor of taste-based mechanisms: proximity's benefits for minorities are strongest in high hate-crime, low social-capital counties. As branch networks contract, our results highlight an equity-relevant cost of reduced proximity in mortgage markets.

1. Introduction

Borrower proximity to banks expands credit access by facilitating soft-information production (Petersen and Rajan, 2002) and reducing transportation costs (Degryse and Ongena, 2005). Yet, proximity is dwindling as U.S. branch networks contract: 17,167 branches (18%) closed during 2013–2022.[1] Despite this retrenchment, branches remain salient: the Survey of Household Use of Banking and Financial Services reports that nearly 80% of households visited a branch in the prior year, and over 33% did so 10 times or more.[2] We examine how proximity to branches affects mortgage access. Leveraging de-identified mobile-device location data on bank visits, we construct a granular proximity measure for each bank-county. We find that proximity improves mortgage access on average, with much stronger effects for minority applicants.

This study addresses two gaps. First, we analyze how proximity affects retail mortgage credit, which is an underexplored setting. Although the benefits of proximity are well documented for corporate borrowers (Petersen and Rajan, 2002; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010), evidence for residential mortgages is scarce.[3] Given homeownership's central role in consumption, upward mobility, and wealth accumulation (Sodini, Van Nieuwerburgh, Vestman, and von Lilienfeld-Toal, 2023), our work adds policy-relevant findings.

Our second, and arguably more consequential, contribution is to quantify the heterogeneous effects of proximity across demographic groups. Branch retrenchment is disproportionately concentrated in low-income and minority areas: post-pandemic losses in low-

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[1] Industry research even claimed that branches may be 'extinct' within two decades. See: https://www.usatoday.com/story/money/2024/09/17/bank-branches-closing-study/75265819007/

[2] https://www.fdic.gov/household-survey/household-survey-archives

[3] In the nascent literature in this area, some notable studies are Nguyen (2019), Mayer (2024), Lim and Nguyen (2024), Frame, Huang, Jiang, Lee, Liu, Mayer, and Sunderam (2025) and Hampole, Jørring, and Monteiro (2025).

/moderate-income tracts (5.9%) exceeded those in higher-income areas (5.4%), and majority-Black areas are significantly more likely to be banking deserts (10.1%) than the national rate (6.4%).[4] Coupled with recent evidence of possible lending discrimination (Bartlett, Morse, Stanton, Wallace, 2022; Frame et al., 2025), these patterns motivate our inquiry into whether branch closures differentially restrict minority credit.

We build on the literature associating proximity to better *commercial* lending outcomes. Scholars argue that local banks can better assess soft information about borrowers (Hauswald and Marquez, 2006), which allows them to extend credit at preferential terms, relative to distant lenders. Proximity may also affect commercial lending by reducing borrowers' transportation costs to lenders and facilitate onsite monitoring (Degryse and Ongena, 2005 and 2009; Herpfer, Mjøs, and Schmidt, 2023). These findings from the commercial lending literature remain underexplored in residential lending. The proximity–credit nexus in commercial lending may not generalize to mortgages for several reasons. First, relative to commercial lending, mortgage underwriting relies more heavily on hard information (e.g., credit and employment histories), potentially attenuating the marginal value of proximity in applicant assessment.[5] Onsite monitoring is also less prevalent for residential mortgages than for small-business loans. Most importantly, banks commonly offload interest-rate risk by selling originated mortgages, which weakens screening incentives (Rajan, Seru, and Vig, 2015; Choi and Kim, 2021). No such secondary market exists for small

[4] See https://www.philadelphiafed.org/community-development/credit-and-capital/u-s-bank-branch-closures-and-banking-deserts. Examining a longer period (2001 to 2023) Narayanan, Ratnadiwakara, and Strahan (2025) show that local financial sophistication predicts branch closures, as local depositors show interest-rate sensitivity.

[5] See Liberti and Petersen (2018) for a clear distinction between hard and soft information, and Foote, Loewenstein, and Willen (2019) for a comprehensive survey on the information sources used for mortgage lending.

business loans. Consistent with these institutional differences, evidence on how proximity affects mortgage markets is mixed.[6] This study provides new evidence to fill that gap.

We use novel, high-frequency mobility data to quantify borrower–bank proximity and evaluate heterogeneity by race/ethnicity—minority (Black, Native, Asian, and/or Hispanic) versus non-minority (White, non-Hispanic). Our proximity construct uses Advan (formerly SafeGraph) device-location data, which record trillions of cell-phone pings from an estimated 15%[7] of the U.S. population, and map foot traffic to over seven million points of interest (POIs). We compute distances between device owners' residences and bank branch POIs. Aggregating to the bank–county level forms *Proximity*, the average distance between a bank and its customers in a county.

We merge *Proximity* to the 2022 Home Mortgage Disclosure Act (HMDA) near-universe of applications. Our sample comprises over 500,000 applications submitted to 827 banks – about 87% of mortgage-lending banks in 2022. We then estimate how local customer-to-branch distance affects an application's approval probability. Bank fixed effects isolate within-bank variation by comparing the applications to same lender across counties with closer versus more distant customers; census-tract fixed effects absorb unobserved neighborhood attributes (e.g., distressed vs. gated communities) that, among other things, correlate with credit-worthiness.

[6] For example, Mayer (2024) and Hampole et al. (2025) show that distance reduces mortgage approval rates while Nguyen (2019) finds that it does not. The first two papers measure distance between the application property's census tract centroid and the lending bank's nearest branch. Our distance measure, built from granular data on all bank customers in the county, can better avoid endogeneity concerns about applicant-bank matching. The third study does not measure distance, per se, but uses branch closures as shocks to distance. We also diverge from these papers in using a broader set of mortgage applications. Unlike Nguyen (2019) and Mayer (2024), our sample includes federally guaranteed loans, which allows us to capture a relevant subset of low-income borrowers. Unlike Hampole et al. (2025), our sample includes loans that the bank retains in its portfolio, reflecting heterogeneity in credit-underwriting incentives. Unlike Nguyen (2019), we use loan-level data instead of bank-county data, capturing loan- and applicant-level heterogeneity. Generally speaking, we believe our broader sample better represents the U.S. mortgage market.

[7] In older Adavan data, coverage was lower, see Li, Ning, Jing, and Lessani (2024). For more recent Advan data, coverage has substantially increased, see the "Scalability" section in their data description section here.

Our tests yield several insights. First, we document that geographic proximity significantly increases mortgage approval probability. The fact that this result parallels commercial lending evidence is noteworthy. Despite strong institutional predispositions against proximity having any effect on residential lending (i.e., greater reliance on hard information and weakened underwriting incentives through the secondary mortgage market), the effect bears out in the data. The finding is also policy-relevant: ongoing branch retrenchment mechanically increases borrower–lender distance, thereby eroding approval odds for all affected applicants.

Motivated by evidence of differential or discriminatory credit outcomes (Munnell, Tootell, Browne, and McEneaney, 1996; Wei and Zhao, 2022; Butler, Mayer, and Weston, 2023), we analyze demographic heterogeneity, finding two noteworthy results. First, minority applicants exhibit lower baseline approval rates, consistent with the studies mentioned above. Second, proximity has a large impact in counteracting these differences, a novel finding. Our results suggest that doubling customer–branch distance raises rejection probability by 3.73 (7.05) percentage points for non-minority (minority) applicants. These estimates obtain conditional on a rich set of controls and fixed effects to absorb confounding loan, bank, and borrower heterogeneity.

Next, we validate these results by assessing credit risk. If proximity reduces information frictions, the applicants that benefit most should be the marginal ones, whose approval likelihood can improve from proximity-driven soft information. To explore if proximity relates to approved applicants' credit risk, we use loans' rate spreads over prime to proxy for credit risk (Goplan, Nanda, and Yerramilli, 2009; Bayer, Ferreira, and Ross, 2013). Supporting our conjecture, proximity predicts higher rate spreads, suggesting that it facilitates lending to riskier borrowers. This effect concentrates in minority applicants. Generally, minorities pay lower spreads, consistent with credit rationing toward safer minority applicants (Hurtado and Sakong, 2024). [8] However, for minorities who apply to banks with more soft information about their borrowers (i.e., greater bank-customer proximity) approved loan spreads increase. Thus, proximity appears to relax credit rationing for riskier minority applicants.

We next examine heterogeneity by loan characteristics. Because standard mortgages can be readily securitized, lenders can transfer credit risk, diminishing the marginal value of soft information; by contrast, nonstandard loans (e.g., lines of credit, junior liens, adjustable-rate mortgages (ARMs), and nonconforming loans) are less liquid and more likely to remain on balance sheet, increasing the value of proximity when approving such loans. Home improvement loans are a particular type of mortgage banks are likely to retain.

We find that proximity effects are especially pronounced for nonstandard mortgages and for home improvement loans. Minority applicants face substantially higher rejection rates in these segments; however, consistent with the soft-information channel, proximity exerts a larger marginal effect for minorities than for non-minorities here, materially attenuating these disparities. By contrast, for standard loans the proximity effect is muted and similar across groups. These results underscore the importance of proximity where securitization is limited and lenders retain greater credit risk.

We also examine heterogeneity by lender scale, drawing on the relationship-versus-transactional lending distinction (DeYoung, Hunter, and Udell, 2004). Two competing predictions

[8] Hurtado and Sakong (2024) show large access disparities (lower approval for minorities) but near-zero cost disparities conditional on origination. This access gap with little/no price gap is exactly what a credit-rationing model predicts: if screening is stricter for minority applicants, accepted minority loans are safer on average, yielding no premium and sometimes even a discount. These authors also show substantially lower default among same-race borrowers at minority-owned banks, reinforcing the selection channel.

arise: small community banks may already possess abundant soft information, thereby diminishing the incremental value of proximity, or proximity might instead be more valuable precisely for small banks reliant on face-to-face screening, with large banks leaning more on standardized ("hard") underwriting. We classify lenders by assets, and, recognizing that asset size may not map cleanly to mortgage-market prominence, also by application volume.

We find that small banks approve minority applicants at lower rates, but proximity has no incremental predictive power for their approvals. For mid-sized banks, neither proximity nor minority status is systematically associated with approval probabilities. By contrast, for large banks, proximity significantly increases approval likelihoods, with disproportionately larger effects for minority applicants. These results are more consistent with proximity substituting for, rather than complementing, preexisting relationships. We further consider non-bank lenders (credit unions and non-depositories, including FinTech lenders). Minority applicants have higher approval probabilities at non-banks, consistent with evidence that FinTech intermediation mitigates racial disparities in credit access (Bartlett et al., 2022; Howel, Kuchler, Snitkov, Stroebel, and Wong, 2024). However, proximity has no additional effect, consistent with CUs behaving like small banks and FinTechs relying mainly on hard information.

Prompted by persistent minority–non-minority differentials, we investigate whether particular demographic groups drive these effects. We estimate separate models for Black, Native American, Asian, and Hispanic applicants, for male and female applicants, and for applicants <40, 40-69, and >69 years old. For all groups but the oldest applicants, minority applications are approved less frequently. For all groups, proximity benefits loan approval. However, the incremental effect on minority applicants exists only for Black, Asian, male, and middle-aged applicants (with a marginally significant effect for younger applicants).

Establishing causal identification is central because borrower–lender matching on unobservables can bias cross-sectional distance–credit estimates (Herpfer, Mjøs, and Schmidt, 2023). We employ several mechanisms to address omitted variables, reverse causality, and selection. First, bank fixed effects absorb lender heterogeneity (e.g., underwriting stringency, risk appetite, market positioning), so minorities applying to systematically stricter lenders cannot mechanically drive our estimates. Second, census-tract fixed effects net out local demand, risk, and neighborhood attributes (e.g., racial composition, housing stock), mitigating concerns that minority clustering or localized credit demand shocks confound the results. Third, our proximity construct is defined at the bank–county level from general customer–branch distances (derived from device-location data), not from applicant–bank choices. Thereby, it cannot reflect applicant sorting. Despite these safeguards in our baseline analysis, we go further by implementing within-tract propensity-score matching on (i) minority versus non-minority applicants and (ii) applications to above- versus below-median proximity banks; treatment-effect magnitudes remain stable and closely track our baseline, consistent with selection on observables not explaining the findings. Finally, in a two-staged least squares framework we instrument for 2022 branch-customer proximity with the bank's 2007 market share to corroborate the baseline coefficients, reinforcing a causal interpretation.

We do not take a stand on the existence of discrimination, per se; a negative coefficient on the minority indicator is consistent with discrimination but also with omitted-variables (e.g., selective lenders marketing to high-quality minority borrowers for Community Reinvestment Act purposes). However, if discrimination is at play and proximity alleviates it, it is important to distinguish between statistical (screening on group means when individual quality is noisy; Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977) and taste-based discrimination (disutility from transacting with minorities; Becker, 1957). If proximity mitigates statistical discrimination via more soft information, effects should be larger where mismeasurement is more severe (low-income tracts / applicants) and at lenders with less experience with minority applications. We find the opposite: while proximity consistently matters, its incremental effect for minorities concentrates in the upper income quintiles. Likewise, the *Minority* × *Proximity* interaction is indistinguishable from zero at lenders with low minority exposure and strongest where minority exposure is high. These results weigh against proximity as an antidote to statistical discrimination.

We then consider taste-based mechanisms. If racial/ethnic mistrust depresses approvals for minorities, proximity may foster repeated interaction and build relationship capital that attenuates such preferences. If proximity counters taste-based discrimination, its minority-specific effect should be larger in areas with greater per-capita hate crime and lower social capital (proxy for local trust), which is what we find. We conclude from these tests that if discrimination exists in the mortgage market and proximity can reduce it, it is more likely to operate on taste-based than statistical discrimination.

Our study makes several contributions. First, we construct a new measurement for bank–borrower proximity, built from large-scale device-location data. Linked to HMDA mortgage applications, this setting enables identification with bank and tract fixed effects while mitigating applicant–lender sorting concerns. This advances the distance-in-lending literature into retail mortgages and complements work on branch retrenchment and local credit supply (Nguyen, 2019) and on technology's role in mortgage origination (Fuster, Plosser, Schnabl, and Vickery, 2019).

Second, we show that proximity remains economically meaningful in a market dominated by "hard-information" underwriting and credit risk offloading via securitization. Proximity significantly raises approval likelihood, and its effect is nearly twice as large for minority applicants. The impact concentrates where we expect it to if proximity mitigates information frictions: riskier applicants, loans with high information asymmetry, and banks with less soft information from relationships. As a placebo test, proximity does not affect credit decisions at nonbank lenders, which are considered strict hard information lenders (Liberti and Petersen, 2019).

Third, we distinguish possible statistical from taste-based discrimination. If proximity primarily corrects informational noise, effects should be largest in low-income strata and at lenders with low minority exposure; we find the opposite. Also, proximity's interaction with local hate-crime incidence and (low) social capital indicates attenuation of preference-based frictions, aligning with taste-based discrimination. These results refine recent evidence on access versus pricing gaps in mortgages (Hurtado and Sakong, 2024; Frame et al., 2025).

2. Data and Sample

Our sample is the intersection of two 2022 datasets: (i) de-identified Advan (formerly 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 Advan, we retain U.S. establishments in financial NAICS 522110/522120/522130/522310; exclude locations fully enclosed within other establishments; require polygon footprints (non-zero area), and drop POIs with "ATM" in the name. De-duplicating within POI-weeks leaves 7.9M.[9] We aggregate to annual branch-level averages. In HMDA, we keep applications to banks/thrifts with final status approved-accepted,

[9] We de-duplicate observations within a POI-week as follows: (i) select the observation with the most visits within a week, (ii) if multiple observations remain, select the one the greatest average distance from visitors, (iii) if multiple observations remain, select the one with the greatest dwell time from visitors, (iv) if multiple observations remain, select the one lowest NAICS code, (v) if multiple observations remain, select the one with the shortest length of the POI name, (vi) if multiple observations remain, select the one with the greatest latitude, (vii) if multiple observations remain, select the one with the greatest longitude. Selection criteria are arbitrary but necessary to remove duplicates.

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, single-family properties with positive reported 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. Advan also contains geocoordinates and names for all POIs. We first merge SOD to HMDA using lenders' RSSD identifiers. Next, we merge to Advan on branch name and geocoordinates.[10] To construct the *Proximity* variable (from Advan) we note the average distance people travel 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*). In other analysis, we also consider the interest rate spread over the prime rate (*Spread*). 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

[10] Specifically, we retain only matches where geocoordinates fall within 100 feet or those within 300 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 established 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.

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*), and type of loan (new purchase origination, *NPO*; home improvement, *HI*; or refinance, *Refi*). HMDA also provides information on lender type (bank, credit union, or nondepository institution), applicant income, and census tracts used in our study.

To illustrate the distance metric, consider Midwest BankCentre, a St. Louis, MO bank with $2.431B in assets. In June 2022, it operated 17 branches in four Missouri counties (Figure 1). Fourteen SOD branches in three counties match Advan; in the figure these are white squares (black are unmatched). Matched branches account for 82.3% of 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 1]

Our main sample includes 1,274,803 loan applications to 833 banks that collectively have 46,310 branches covered in Advan. This represents 85.5% of 2022 HMDA banks with our sample restrictions and 79.3% of these banks' branches. It includes applications from 77,007 census tracts within 2,383 counties across all 50 states.

[Table 1]

Table 1 shows the means, medians, and standard deviations for our variables. We report customer loan approval rates, loan spreads (observed only for approved loans), branch-customer distance (the basis for *Proximity*), several loan characteristics as well as demographic and census tract characteristics, 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 (66.23% versus non-minorities' 80.44%). This 14.22% approval gap is close to the 12.1% gap from An, Bushman, Kleymenova, and Tomy (2023). Our sample's overall approval rate (75.87%) 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%. Conditional on approval, minorities pay lower spreads. In unreported analysis, we show that important differences exist between minority types: Black, Hispanic, and Native American (Asian) borrowers pay a higher (lower) average spread than white Non-Hispanics, echoing the same pattern as Bhutta and Hizmo (2021), Willen and Zhang (2023), and Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022).

Minority applicants are linked to banks with more distant customer bases, seek higher leverage (LTV) and payment burdens (DTI), and submit applications less likely to meet secondary-market guidelines, with greater FHA/VA guarantees. They more often request lines of credit, junior liens, variable-rate, and longer-term loans; despite lower reported incomes, they seek larger loan amounts. A smaller (larger) fraction of minority mortgage applications is for refinances (new purchase originations and home improvement loans). They also apply much more frequently to larger banks, regulated by the CFPB. They disproportionately reside in urban tracts—higher median income, larger populations, and roughly double the minority share—and are roughly evenly split among Black, Asian, and Hispanic borrowers (<5% Native American); about one-third also identify as White. The minority sample is younger and has more female primary applicants.

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:

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

where i, b, c, and t index the mortgage application, bank, county, and census tract, respectively. *Approved* is an indicator flagging one if the application was approved, zero otherwise. *Proximity* measures how far customers travel to a given bank's branches in a given county. $\boldsymbol{X}$ 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 nonminorities (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 like resident 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 status), 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; Bartlett et al., 2022; Wei and Zhao, 2022; Willen and Zhang, 2023).

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_3= -0.109), also significant at 1%. More importantly, the coefficient on the *Proximity* × *Minority* interaction is positive and significant (0.008, p<0.01), implying that proximity's marginal effect is larger for minority applicants: The

[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.

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 disproportionate approval boost to minority applicants.

To interpret the economic magnitude of this effect, consider two otherwise identical applications to the same bank's branches in different counties, the only difference being one branch's customers live half as far from it as the other branch's. If the applicants are white, non-Hispanic, the application to the branch with closer customers is 3.73% (=0.009/(1-0.758707)) less likely to be rejected but if the applicants are minorities, that probability increases to 7.045%.[14] This comparison accounts for tract-level differences between the applicants.

3.2 Proximity and risk

To explore which minority applicants benefit from proximity, we next 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 information frictions may be at play. We estimate the model in Equation 1 by replacing the dependent variable with *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). This is especially true

[14] We follow related papers (e.g., Frame et al., 2025; Mayer, 2024) in reporting our estimated effect's economic magnitude but note that point estimates from linear probability models should be interpreted with caution as probabilities are not bounded by 0 and 1.

considering our fixed effect structure: within the same bank, controlling for neighborhood-level risk price differences. Note that spreads are only observed for approved mortgages, so these tests estimate how proximity correlates with the risk profile of approved applicants. Table 3 reports the results, omitting control variables for brevity.

[Table 3]

Once again, we first show the effects of proximity, ignoring minority status (Column 1) and of being a minority, ignoring proximity (Column 2), before estimating Equation 1 with both effects and their interaction. The coefficient on *Proximity* is positive and significant (0.006, $p<0.05$) in Column 1, consistent with Degryse and Ongena (2005) and Agarwal and Hauswald (2010), who document higher interest rates for closer commercial borrowers.[15] Column 2 shows that minority applicants pay a lower spread, on average, consistent with credit rationing against minorities (Jo and Liu, 2024; Ambrose, Conklin, and Lopez, 2021; Hurtado and Sakong, 2024).[16] If banks ration credit against minorities then the subset of approved minorities should be safer and thereby have lower average loan spreads. When modeling both effects in Column 3, minorities continue to exhibit lower loan spreads (β_2) but proximity un-interacted no longer predicts spreads significantly (β_1). This suggests that for non-minority applicants, proximity does not affect spreads. In contrast, a strong positive effect emerges in on the interaction term (β_3).[17] That is, approved

[15] These papers explain the positive relationship between proximity and corporate interest rates as a form of 'borrower capture'. Because local lenders sink costs into producing soft information about local borrowers, a local borrower seeking credit from a distant lender raises adverse selection concerns that would be priced into their loan. Consequently, borrowers should prefer local lenders, who can then charge them higher rates.

[16] 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.

[17] In unreported analysis, we separately consider the four minority types in our sample. For Asian, Native, and Hispanic borrowers, β_2 is positive and significant but for Black borrowers, it is negative and significant. Thus, our overall inference of credit rationing seems most pertinent for Black borrowers. Notably, recent literature is mixed on whether minorities pay higher rate spreads: Bhutta and Hizmo (2021) show no significant differences while Bartlett et al.

minority applicants pay higher spreads if they are closer, consistent with proximity facilitating credit toward a riskier set of minority borrowers than might otherwise obtain it. Columns 4 and 5 provide more context by splitting the sample into loans the bank retains or sells on the secondary market, respectively. We find that in the sample of retained loans (Column 5), each of our three focal relationships strengthen, while in the sample of sold loans, neither proximity nor minority status affects spreads. Overall, this table is consistent with prior evidence suggesting credit rationing against minority applicants, but incrementally shows that being closer to branches relaxes this constraint. Proximity may produce soft information that alleviates information frictions impeding minority credit access.

3.4 Proximity and loan characteristics

Studies show that proximity is most valuable when screening is harder and standardization/securitization of loans is limited (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Nguyen, 2019). In mortgages, standard products are readily sold in secondary markets, reducing lenders' incentive to expend effort on collecting soft information. In contrast, less standard loans are more likely to remain on balance sheet, heightening the value of soft information. Relatedly, secondary market sales is not uniform across mortgage types: In our sample, banks held a third of new purchase originations, half of refinances, but 97% of home-improvement loans at the end of the origination year. Recent evidence on access gaps (Bartlett et al., 2022; Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2022) further motivates testing whether proximity disproportionately helps minority applicants where screening frictions are greater. Our next test addresses this by estimating approval models across product segments. We

(2022) do find differences. Most relevant to our study's focus (i.e., *Proximity*), β_3 remains positive and significant for all minority types, suggesting that proximity helps banks lend to all types of riskier minority borrowers, whether or not they are systematically discriminated against.

estimate Equation 1, now separately for standard versus non-standard loans, and for NPOs, HIs, and Refis. Nonstandard loans are defined as lines of credit, junior liens, adjustable-rate mortgages, or nonconforming loans. Table 4 presents our results.

[Table 4]

Effects are strongest for nonstandard loans (Column 1) and here minorities face substantially higher rejection rates. Consistent with our previous results, for nonstandard loans proximity confers a relatively larger approval boost for minority applicants than for non-minorities. By contrast, for standard products that can easily be securitized, proximity has only a modest, marginal effect (Column 2). Minorities are approved more, plausibly reflecting Community Reinvestment Act (CRA)-related incentives and securitization; notably proximity does not provide additional minority-specific gains. Further differences emerge when considering mortgage types separately in Columns 3-5. In NPOs, results resemble those for standard loans: Proximity has a marginal effect, minorities are approved more frequently, and proximity does not confer an incremental effect on minority approvals (Column 3). Results are similar in the refinance sample (Column 5), but proximity's effect is stronger. Column 4 shows that proximity confers the strongest benefit to HI approvals. Finally, minorities do derive an incremental benefit from proximity in HI applications, consistent with proximity supplying the soft information pertinent to these disproportionately on-balance-sheet loans. Taken together, our results paint a clear picture: Proximity materially relaxes approval frictions where screening is hardest, particularly for riskier, nonstandard loans, which lack deep secondary markets. HI loans exhibit the largest overall and minority-specific gains. In Column 6, we combine NPO and Refi samples to show that, with more statistical power in this combined sample, our tests detect an incremental benefit of proximity to minorities. However, the effect is still smaller than for HI loans.

3.4 Proximity and bank size

Since proximity enables lending relationships (Rajan and Petersen, 2002), we next examine how our results fare by bank size. Small banks are known to be relationship lenders (Elyasiani and Goldberg, 2004) while larger banks are considered transactional lenders that use hard information to make credit decisions (Berger and Black, 2011). If proximity builds relationships, its effects should be larger at small banks; if, however, proximity substitutes for relationships by generating incremental soft information, its effects should be larger for bigger banks. To test these predictions, we divide banks into small (assets <$10Bn), medium ($10-$100Bn), and large (>$100Bn). Since not all banks invest equally in mortgage lending as a business line, we also divide them along mortgage application thresholds, <10K, 10-50K, and >50K applications in 2022.[18]

[Table 5]

Results in Table 5 show that for the asset-based bank classification, small banks approve minorities (marginally) less, and proximity is irrelevant at small banks; at medium banks, neither proximity nor minority status predict approvals; at large banks, however, proximity raises approval rates, especially for minorities. Similar inferences hold for the volume-based classification. Thus, both classifications are consistent with proximity substituting for, rather than complementing, relationship lending.

3.5 Proximity and non-bank lenders

Recent literature in banking assesses whether credit unions (CUs; Li and van Rijn, 2024; Jun, 2025) and non-depository institutions (NDIs; Bartlett et al., 2022; Allen, Shan, and Shen, 2023; Chu, Zhang, and Zhang, 2023; and Cespedes, Jiang, Parra, and Zhang, 2024) bridge gaps in

[18] These thresholds ensure that the fraction of banks in each bin resembles the asset size classification above.

credit access in the traditional banking system (Bartlett et al., 2022; Allen, Shan, and Shen, 2023; Chu, Zhang, and Zhang, 2023; and Cespedes, Jiang, Parra, and Zhang, 2024). In our context, a relevant question is whether distance should matter for these lenders and, particularly, for their minority applicants. We expect proximity not to matter for both types of non-bank but for different reasons. Table 5 suggests that proximity can substitute for soft information produced from relationship lending. We expect CUs to behave like smaller community banks and organically gather sufficient soft information, rendering proximity irrelevant. NDIs, by contrast, are known to use primary hard information for underwriting decisions (Liberti and Petersen, 2019). As such, proximity may matter less for them.

[Table 6]

To test for non-bank lending, we select a sample of HMDA mortgage applications to nonbanks and estimate Equation 1 separately for applications to CUs, to NDIs, and to fintech lenders, a subset of NDIs.[19] Table 6 reports the results. We find that minorities are approved more by these non-bank institutions, but consistent with our priors, proximity has no incremental effect.

3.6 Proximity and borrower demographics

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. One logical starting place is along racial/ethnic lines. If proximity benefits minority borrowers, which minorities, specifically, drive this relationship? We estimate equation (1) separately for Black, Native, Asian, and Hispanic applicants. In these

[19] We use Fuster, Plosser, Schnabl, and Vickery's (2019) list to designate fintech lenders; they require that the application be processed without ever interfacing with human loan officers.

specifications, 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 that examines gender differences in lending outcomes (Goldsmith-Pinkham and Shue, 2023; Tsouderou and Tüzel, 2024). Finally, we also examine age-based partitions (Mayer and Moulton, 2022; Doerr, Kabas, and Ongena, 2024). Table 7 reports the results.

[Table 7]

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 coefficient on the interaction of *Minority x Proximity* is positive and significant for Blacks and Asians, only. Columns 5 and 6 show that the incremental minority beneficial of proximity generally accrues to male, not female, applicants. Finally, Columns 7-9 show that proximity has less effect for older applicants. Because older adults likely have a longer credit history, this heterogeneity further points to some credit-relevant soft information that proximity can help banks gather.

3.7 Addressing endogenous borrower-bank selection

Although we have saturated our models with powerful fixed effects and controls for variations in applicants, banks, and locations, we provide evidence from other additional tests to support causal inference.

First, we conduct propensity score matched (PSM) analysis. The identifying assumption is that units closely matched on observables via PSM are more likely to be similar along unobservables, as well. We split and PSM our sample in two ways: First we take all census tracts with at least (i) one minority applicant and (ii) at least 10 applications total and, within each tract, use PSM to match minorities to non-minorities. Matching variables include all controls from our baseline regressions. This (minority-based) matching can partly allay concerns that minorities might be inherently different from non-minorities, by selecting subsets of minority and non-minority applications that are at least similar on observable characteristics.

Second, we take all census tracts with at least (i) one minority applicant and (ii) at least 10 applications total and, within each tract, use PSM to match applications to banks above the within-tract median proximity measure to applications below the median proximity measure. This (distance-based) matching can partly allay the concern that applicants choosing banks with closer customers are inherently different than those selecting banks with further-away customers, by selecting subsets of close-customer-bank applications and far-customer-bank applications that are similar on observable characteristics.

[Table 8]

Table 8, Panel A shows the matching success. While, in the unmatched sample, minorities differ from non-minorities across all fifteen control variables and both focal variables, in the first matched sample, all differences go away except very small differences in *LTV*, *DTI* and *Fixed rate*.[20] In the second matched sample, more differences remain but most still dissipate. The ones that remain are: Minority (the closer sample has 586 fewer minorities), LTV (on a $300,000 home, the closer sample borrows $3,750 less), and Conforming. The relative differences are economically small. Panel B shows that our baseline findings on *Proximity* and *Minority x Proximity* hold. For both PSM samples, proximity continues to increase approval rates, especially for minorities.

[20] The economic magnitudes for the remaining differences are: For LTV minorities borrow ~$570 more than non-minorities on a $300,000 house; for DTI a minority borrower pays $5 more for debt service for every $1000 in income; for Fixed Rate, in our sample of 170,040, there are 731 fewer minorities with fixed rate loans than non-minorities.

To provide further causal evidence, we employ an instrumental variable test (Nguyen, 2019; Lim and Nguyen, 2021). Since *Proximity* is a proxy for relationship capital, soft information, trust, or rapport between a branch and its customers, to address endogeneity, we instrument for *Proximity* with the bank's 2007 local market share. The 2007 share is plausibly relevant – longstanding presence in the community fosters durable information and trust that translate into greater proximity – and excludable – historical market position should not directly affect a specific applicant's 2022 approval, except through its effect on proximity / relationship capital. Table 9 shows the results of this analysis.

[Table 9]

The instrument and its interaction with Minority strongly predict *Proximity* and *Minority x Proximity*, establishing relevance: First-stage F-statistics and Sanderson–Windmeijer under-identification (χ^2) and weak-identification (F) tests are large, ruling out under- and weak-instrument concerns. In the second stage, coefficients retain their original signs but increase in magnitude, consistent with attenuation in OLS and an IV local average treatment effect that is larger for minorities. Finally, in Column 3, *Minority x Proximity* has a positive and significant coefficient, corroborating our main results.

3.8 Taste-based versus statistical discrimination

The most robust and consistent result in this study is that proximity incrementally benefits minority applicants in the mortgage market. A natural follow-up question is: why? Do lenders have a tendency to discriminate and the soft information collected via proximity helps alleviate that? While establishing discrimination of any kind requires data beyond the scope of this study, we provide some tests to distinguish the mechanisms that may be at play. We borrow language from the taste-based discrimination (TBD) versus statistical discrimination (SD) literature to frame these tests. Under SD (Phelps 1972; Arrow 1973; Aigner and Cain 1977), proximity should matter most where underwriting noise is greatest, e.g., lower-income applicants/tracts, and lenders with little exposure to minorities. In these settings, more soft information helps separate high- from low-risk types. By contrast, under TBD (Becker 1957), proximity should attenuate preference-based frictions (animus/mistrust), so the minority-specific proximity premium should be larger precisely where local animus or mistrust is higher, regardless of risk proxies.

To test for SD, we identify subsamples that are more or less 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 SD by supplying finer risk information, its coefficient should be more positive in lower-income quintiles. We plot the focal coefficients in Figure 2.

[Figure 2]

In contrast to that prediction, Panels A and B of Figure 2 show the opposite. Although proximity is economically and statistically relevant in four of the five quintiles (untabulated), its incremental effect for minority applicants is concentrated in the top two income quintiles, as shown in the dashed lines. In fact, both lines show the highest value in the highest quintile, indicating the proximity effects are highest for the highest income minorities. This pattern is inconsistent with proximity primarily mitigating SD against poorer, therefore riskier, minorities.

We also examine whether proximity relaxes SD by exploiting lender heterogeneity in experience with minority borrowers. If lenders disproportionately reject minority applications because they cannot distinguish creditworthy from non-creditworthy minority applicants as well as they can for non-minorities, 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) a deposit-weighted county minority share, 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–D of Figure 2 again yield the opposite of the SD prediction. At banks with low minority exposure, the *Minority* × *Proximity* interaction is indistinguishable from zero; by contrast, proximity matters for minorities precisely at banks that frequently serve minority applicants. Taken together, these tests provide evidence against the view that proximity helps minority applicants overcome statistical discrimination.

We therefore consider TBD as an alternative operative mechanism. Under TBD, lenders reject minority applicants owing to disutility or mistrust toward transacting with them, either overtly (racial animus), or more subtly (lower priors of 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 mitigates TBD, 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 proximity primarily benefits minority applicants by fostering banker–borrower relationships that attenuate the effects of racial animus and mistrust.

4. Conclusions

We show that bank–customer proximity materially increases the likelihood of mortgage approval and that 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 point to a causal interpretation. Proximity also correlates with higher pricing for approved minority loans, consistent with proximity relaxing credit rationing at the extensive margin by enabling approval of riskier-but-creditworthy minority applicants. These effects concentrate in product segments where screening is harder and balance-sheet exposure is greater, such as nonstandard and home-improvement loans, and are strongest at large, transactional lenders.

The findings matter because physical branch networks continue to contract, increasing borrower–lender distance and potentially widening access gaps. We document that proximity partially offsets the lower baseline approval rates faced by minorities; in counterfactual terms, halving customer–branch distance substantially reduces rejection risk for minority applicants relative to non-minorities. By linking high-frequency mobility data to the HMDA universe, we quantify an equity-relevant cost of branch retrenchment that is otherwise obscured in markets dominated by "hard-information" underwriting and securitization.

Methodologically, the 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, pinpoint where these gains arise (products, lenders, borrowers), and use heterogeneity tests to distinguish mechanisms. The evidence favors taste-based over statistical discrimination: 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 have immediate policy implications: merger reviews and CRA evaluations should consider equity-relevant distance effects; targeted support for branch presence or mobile/part-time branches in banking deserts may improve access; and supervisory analytics that monitor approval gaps by distance could guide fair-lending examinations.

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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*); approved applications' rate spreads, in basis points, over the prime rate (*Spread*); the distance, in miles, between the application-bank's branches in the county and branch-visitors' home addresses (*Distance*); 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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); its term, in months (*Term*); the primary applicant's stated income in $1000s (*Income*); the property value, in $1000s (*Property Value*); the property tract's median income in $1000s (*Median Income*), population (*Population*), and fraction minority population (*Percent Minority*); indicators for whether the primary applicant is Black, Hispanic, Native, Asian, and Female; and the applicant's age. Distance comes from Advan (formerly 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 Variables												
Approved	1,274,803	75.87%	1	42.79%	369,213	66.23%	1	47.29%	801,599	80.44%	1	39.66%
Spread (bps)	963,678	22.0254	21	87.3093	243,538	18.1399	17.6	91.4859	642,571	24.7242	23.1	85.7365
Independent Variables												
Distance (miles)	1,274,777	8.36	5.38	11.25	369,204	8.49	5.5	11.89	801,584	8.18	5.325	10.68
Minority	1,170,812	31.53%	0	46.47%	369,213	100.00%	1	0.00%	801,599	0.00%	0	0.00%
Application Controls												
LTV	1,248,228	68.31%	0.74	22.84%	359,875	70.77%	0.76	22.87%	786,450	67.00%	0.72	22.84%
DTI	1,274,803	37.25%	0.38	14.67%	369,213	40.57%	0.4	15.06%	801,599	35.75%	0.33	14.20%
Conforming	1,274,803	91.16%	1	28.39%	369,213	90.60%	1	29.19%	801,599	92.04%	1	27.07%
Conventional	1,274,803	94.31%	1	23.16%	369,213	92.52%	1	26.31%	801,599	95.18%	1	21.42%
Line of Credit	1,274,803	23.65%	0	42.50%	369,213	25.30%	0	43.47%	801,599	23.01%	0	42.09%
Junior Lien	1,274,803	21.91%	0	41.36%	369,213	23.22%	0	42.23%	801,599	21.27%	0	40.92%
Fixed Rate	1,274,803	67.28%	1	46.92%	369,213	65.33%	1	47.59%	801,599	68.28%	1	46.54%
Term	1,271,828	327.99	360	83.98	367,604	333.40	360	78.43	800,595	324.76	360	86.54

Table 1: Descriptive Statistics, continued

	Full Sample				Minority				White, non-Hispanic			
	N	Mean	Med.	S.D.	N	Mean	Med.	S.D.	N	Mean	Med.	S.D.
Application Controls, continued												
NPO	1,274,803	42.92%	0	49.50%	369,213	45.92%	0	49.83%	801,599	41.22%	0	49.22%
HI	1,274,803	21.98%	0	41.41%	369,213	24.19%	0	42.82%	801,599	21.15%	0	40.84%
Refi	1,274,803	35.10%	0	47.73%	369,213	29.90%	0	45.78%	801,599	37.63%	0	48.45%
OCC	1,274,803	9.32%	0	29.08%	369,213	5.77%	0	23.32%	801,599	11.48%	0	31.88%
FRB	1,274,803	3.59%	0	18.60%	369,213	2.26%	0	14.86%	801,599	4.32%	0	20.34%
FDIC	1,274,803	11.34%	0	31.71%	369,213	6.45%	0	24.56%	801,599	13.62%	0	34.30%
CFPB	1,274,803	75.75%	1	42.86%	369,213	85.52%	1	35.19%	801,599	70.57%	1	45.57%
Additional Application Information												
Income ($1000s)	1,245,210	139.50	100	124.11	359,551	131.95	92	118.54	784,504	139.40	100	123.29
Property Value ($1000s)	1,247,658	567.29	405	514.65	359,785	587.73	415	526.86	785,908	542.51	385	493.79
Additional Census Tract Information												
Median Income ($1000s)	1,274,800	96.38	92.40	20.92	369,213	99.33	95.60	22.69	801,597	94.57	91.30	19.78
Population	1,274,800	4756.94	4604	1670.55	369,213	4939.79	4780	1717.34	801,597	4670.26	4515	1639.44
Percent Minority	1,274,800	36.47%	29.02%	25.50%	369,213	56.70%	56.45%	26.31%	801,597	27.01%	21.76%	18.87%
Demographic Characteristics												
White	1,125,708	79.79%	1	40.16%	341,864	33.46%	0	47.18%	783,844	100.00%	1	0.00%
Black	1,125,708	9.97%	0	29.96%	341,864	32.82%	0	46.96%	783,844	0.00%	0	0.00%
Hispanic	1,145,003	12.40%	0	32.96%	360,403	39.40%	0	48.86%	784,600	0.00%	0	0.00%
Native American	1,125,708	1.41%	0	11.80%	341,864	4.65%	0	21.06%	783,844	0.00%	0	0.00%
Asian	1,125,708	10.43%	0	30.56%	341,864	34.34%	0	47.48%	783,844	0.00%	0	0.00%
Female	1,274,803	37.71%	0	48.47%	369,213	41.19%	0	49.22%	801,599	36.44%	0	48.13%
Age	1,274,803	48.25	50	14.75	369,213	46.79	50	13.78	801,599	49.04	50	15.25

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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); 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*; 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*. 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***	-0.109***
		(0.001)	(0.019)
Proximity x Minority			0.008***
			(0.001)
LTV	-0.060***	-0.053***	-0.067***
	(0.002)	(0.002)	(0.003)
LTV x Minority			0.038***
			(0.005)
DTI	-0.838***	-0.829***	-0.774***
	(0.003)	(0.003)	(0.004)
DTI x Minority			-0.149***
			(0.006)
Conforming	0.016***	0.017***	0.020***
	(0.001)	(0.001)	(0.002)
Conforming x Minority			-0.013***
			(0.003)
Conventional	0.028***	0.026***	0.027***
	(0.002)	(0.002)	(0.002)
Conventional x Minority			0.004
			(0.004)
LogTerm	0.045***	0.042***	0.038***
	(0.001)	(0.001)	(0.002)
LogTerm x Minority			0.021***
			(0.003)
Line of Credit	-0.162***	-0.165***	-0.150***
	(0.002)	(0.002)	(0.002)

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

Line of Credit x Minority			-0.051***
			(0.004)
Junior Lien	0.019***	0.018***	0.013***
	(0.002)	(0.002)	(0.002)
Junior Lien x Minority			0.018***
			(0.004)
Fixed Rate	0.004***	0.002**	-0.001
	(0.001)	(0.001)	(0.001)
Fixed Rate x Minority			0.016***
			(0.002)
FRB x Minority			0.010*
			(0.006)
FDIC x Minority			0.018***
			(0.004)
CFPB x Minority			-0.005
			(0.003)
Home Improvement	-0.194***	-0.195***	-0.178***
	(0.002)	(0.002)	(0.002)
Home Improvement x Minority	-0.085***	-0.087***	-0.079***
	(0.001)	(0.001)	(0.001)
Refinance			-0.044***
			(0.004)
Refinance x Minority			-0.026***
			(0.002)
Observations	1,241,997	1,140,178	1,140,161
Adj R2	0.298	0.302	0.305
Bank + Tract FE	Yes	Yes	Yes

Table 3: Approved Applicant Risk

This table reports OLS regression estimates from a modified version of Equation 1, in which the dependent variable is the approved loan's rate spread, in basis points, over prime. 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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); 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*; 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*. Columns 4 and 5 respectively estimate the model for approved applications retained and not retained on the bank's balance sheet as of year-end. 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) Spread	(3) Spread	(4) Spread	(5) Spread
Proximity	0.006**		0.001	0.009**	0.002
	(0.002)		(0.003)	(0.004)	(0.003)
Minority		-0.006***	-0.276***	-0.593***	-0.077
		(0.002)	(0.068)	(0.099)	(0.074)
Proximity x Minority			0.014***	0.016***	-0.001
			(0.003)	(0.005)	(0.004)
Observations	954,980	877,390	877,375	476,945	356,790
Adj R2	0.327	0.324	0.328	0.397	0.253
Sample	Approved	Approved	Approved	Retained	Sold
Controls	Yes	Yes	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes	Yes	Yes

Table 4: Loan Characteristics

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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); 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*; with new purchase origination, *NPO*, as the omitted category). Column 1 estimates the model over fixed-rate, senior lien, conforming, term loan (i.e., not a credit line) applications and Column 2 estimates the model for all other applications. Columns 3, 4, and 5 estimate the model for new purchase, home improvement, and refinance applications, respectively. Column 6 combines new purchase and refinance applications. 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	0.023***	0.003*	0.002*	0.026***	0.008***	0.006***
	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)
Minority	-0.364***	0.136***	0.125***	-0.277***	0.213***	0.100***
	(0.045)	(0.023)	(0.034)	(0.082)	(0.032)	(0.021)
Proximity x Minority	0.014***	0.003	0.002	0.014***	0.002	0.004***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)
Observations	179,744	172,343	714,835	329,892	180,394	603,603
Adj R2	0.167	0.232	0.321	0.205	0.288	0.305
Loans	Nonstandard	Standard	NPO	HI	Refi	NPO+Refi
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Bank Size

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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); 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*; with new purchase origination, *NPO*, as the omitted category). Column 1 (2, 3) estimates the model for applications to banks with <$10 ($10-$100, >$100) billion in assets. Column 4 (5, 6) estimates the model for applications to banks with <10 (10-50, >50) thousand applications in the previous year. 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	0.005	-0.004	0.016***	0.004*	0.002	0.016***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
Minority	-0.094*	-0.025	0.001	-0.091**	-0.036	0.064**
	(0.049)	(0.045)	(0.027)	(0.037)	(0.046)	(0.029)
Proximity x Minority	-0.003	0.003	0.015***	0.001	0.003	0.022***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	179,744	172,343	714,835	329,892	180,394	603,603
Adj R2	0.167	0.232	0.321	0.205	0.288	0.305
Size	Small	Medium	Large	Small	Medium	Large
Measure	Assets	Assets	Assets	Apps	Apps	Apps
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Non-bank Lenders

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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); 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*; with new purchase origination, *NPO*, as the omitted category). Column 1 (2) estimates the model for applications to credit unions (non-depository institutions, *Non-DI*s). Column 3 estimates it to a subset of NDIs, FinTech lenders, as defined by Fuster et al., 2019. 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) Approved	(2) Approved	(3) Approved
Proximity	0.002	-0.000	0.000
	(0.003)	(0.001)	(0.003)
Minority	0.121***	0.149***	0.248***
	(0.032)	(0.033)	(0.078)
Proximity x Minority	-0.001	0.002	0.004
	(0.003)	(0.001)	(0.003)
Observations	340,120	386,571	80,646
Adj R2	0.248	0.135	0.169
Lender	CU	Non-DI	Fintech
Controls	Yes	Yes	Yes
Lender + Tract FE	Yes	Yes	Yes

Table 7: 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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); 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*; 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; >59) 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***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.004)
Minority	-0.066***	-0.134***	-0.151***	-0.178***	-0.073**	-0.141***	-0.143***	-0.112***	0.063
	(0.023)	(0.028)	(0.031)	(0.024)	(0.031)	(0.026)	(0.053)	(0.024)	(0.061)
Proximity x 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)	(0.002)	(0.002)	(0.003)	(0.002)	(0.006)
Observations	978,842	913,024	883,948	982,517	423,812	703,981	229,692	717,840	156,668
Adj R2	0.293	0.293	0.280	0.284	0.323	0.295	0.327	0.302	0.310
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

Table 8: 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, *Line of Credit*, represents a junior lien on the property, *Junior Lien*, and offers a fixed rate, *Fixed Rate*; 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*, and refinance, *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

	PSM on Minority Status						PSM on Distance					
	Unmatched Means			Matched Means			Unmatched Means			Matched Means		
Variable	Min	Non	p	Min	Non	p	Close	Far	p	Close	Far	p
Minority	1.00	0.00	0.00	1.00	0.00	0.00	0.34	0.33	0.00	0.37	0.37	0.04
Distance	8.49	8.18	0.00	8.06	8.10	0.49	4.72	15.46	0.00	5.30	14.07	0.00
LTV	0.71	0.67	0.00	0.72	0.72	0.05	0.67	0.71	0.00	0.70	0.71	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	0.44
Conforming	0.91	0.92	0.00	0.87	0.87	0.78	0.91	0.88	0.00	0.81	0.81	0.01
Conventional	0.93	0.95	0.00	0.95	0.95	0.48	0.95	0.93	0.00	0.97	0.96	0.00
LogTerm	5.77	5.73	0.00	5.81	5.81	0.32	5.75	5.76	0.00	5.80	5.81	0.13
Line of Credit	0.25	0.23	0.00	0.23	0.23	0.35	0.28	0.18	0.00	0.15	0.14	0.00
Junior Lien	0.23	0.21	0.00	0.22	0.22	0.49	0.25	0.19	0.00	0.15	0.14	0.00
Fixed Rate	0.65	0.68	0.00	0.69	0.70	0.00	0.64	0.69	0.00	0.70	0.70	0.37
New Purchase	0.46	0.41	0.00	0.52	0.52	0.80	0.39	0.51	0.00	0.54	0.56	0.00
Home Improvement	0.24	0.21	0.00	0.21	0.21	0.16	0.25	0.18	0.00	0.14	0.13	0.00
Refinance	0.30	0.38	0.00	0.27	0.27	0.12	0.36	0.30	0.00	0.32	0.31	0.00
FDIC	0.06	0.14	0.00	0.06	0.07	0.39	0.08	0.16	0.00	0.07	0.07	0.13
OCC	0.06	0.11	0.00	0.05	0.05	0.75	0.10	0.08	0.00	0.02	0.02	1.00
FRB	0.02	0.04	0.00	0.02	0.02	0.85	0.02	0.06	0.00	0.01	0.01	0.37
CFPB	0.86	0.71	0.00	0.87	0.87	0.62	0.80	0.71	0.00	0.90	0.90	0.12

Panel B: Propensity-score matched regressions

	(1) Approved	(2) Approved
Proximity	0.012***	0.011***
	(0.003)	(0.003)
Minority	-0.033	-0.026
	(0.049)	(0.084)
Proximity x Minority	0.007**	0.011**
	(0.003)	(0.004)
Observations	169,984	91,478
Adj R2	0.304	0.280
Matching	Minority	Distance
Controls	Yes	Yes
Bank + Tract FE	Yes	Yes

Table 9: Two-Staged 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 (*Line of Credit*), represents a junior lien on the property (*Junior Lien*), and offers a fixed rate (*Fixed Rate*); 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*; 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 x Proximity	Approved
2007 Market Share	0.876***	0.019***	
	(0.010)	(0.004)	
Minority	-0.017	-1.914***	-0.059**
	(0.016)	(0.020)	(0.025)
2007 Market Share x Minority	0.120***	0.983***	
	(0.010)	(0.015)	
$\widehat{Proximity}$			0.077***
			(0.006)
Minority x $\widehat{Proximity}$			0.035***
			(0.009)
Observations	1,116,442	1,116,442	1,093,538
Adj R2	0.710	0.902	0.173
F-statistic	5212.49	3054.82	
SW Chi2 statistic	7524.93	5116.55	
SW F statistic	7519.08	5112.58	
Controls	Yes	Yes	Yes
Bank + Tract FE	Yes	Yes	Yes

Figure 1: 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) Advan data that can be merged.

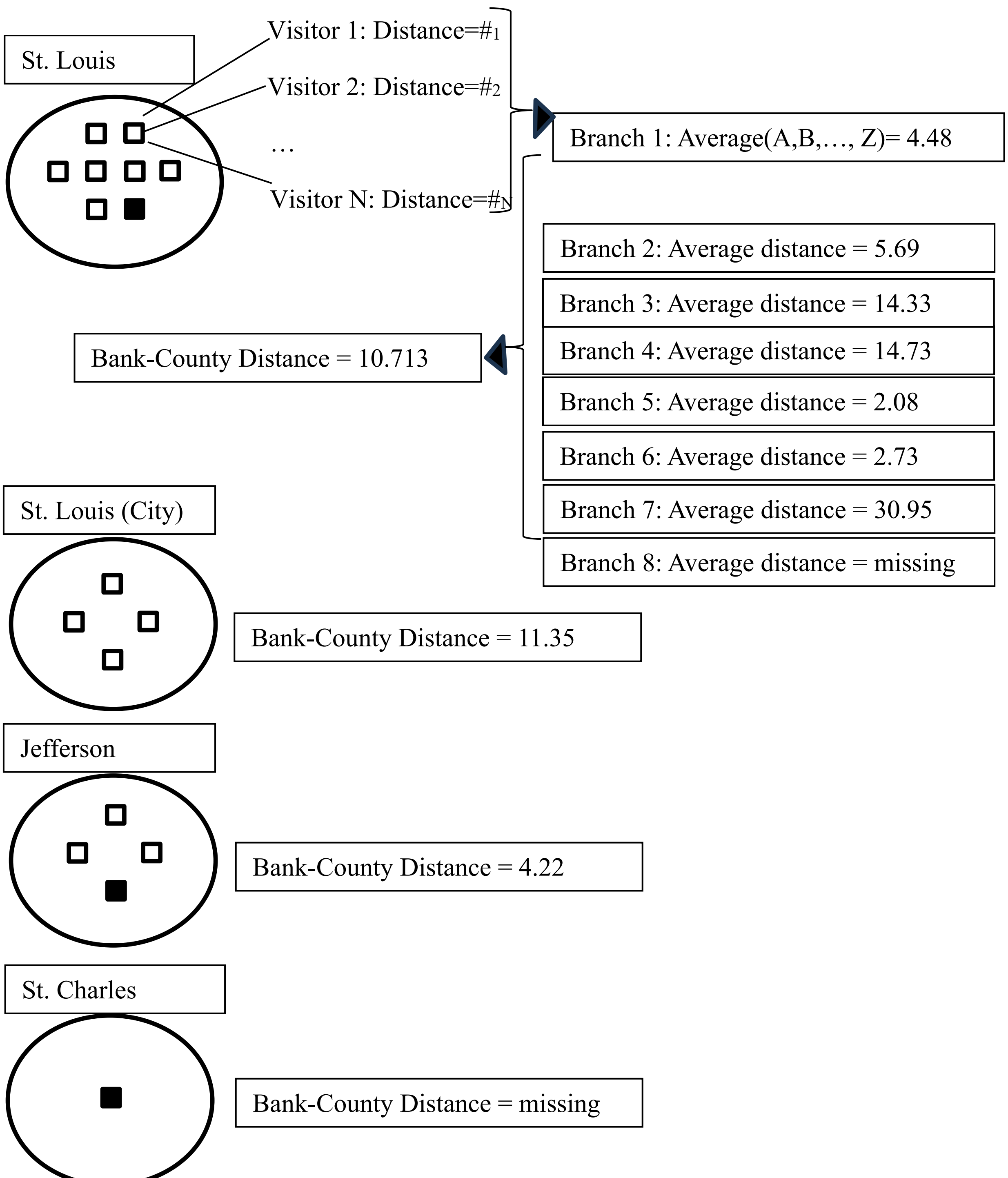

Figure 2: Statistical versus taste-based discrimination