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Banks, alternative institutions and the spatial–temporal ecology of racial inequality in US cities

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Research has made clear that neighbourhood conditions affect racial inequality. We examine how living in minority neighbourhoods affects ease of access to conventional banks versus alternative financial institutions (AFIs) such as check cashers and payday lenders, which some have called predatory. Based on more than 6 million queries, we compute the difference in the time required to walk, drive or take public transport to the nearest bank versus AFI from the middle of every block in each of 19 of the largest cities in the United States. The results suggest that race is strikingly more important than class: even after numerous conditions are accounted for, the AFI is more often closer than the bank in low-poverty racial/ethnic minority neighbourhoods than in high-poverty white ones. Results are driven not by the absence of banks but by the prevalence of AFIs in minority areas. Gaps appear too large to reflect simple differences in preferences.

Recent research on racial inequality in the United States has made clear that the ecology of the city matters, specifically that the spatial distribution of people and resources across neighbourhoods contributes to unequal life outcomes[1,2]. Studies based on millions of tax records and on field experiments have made clear that racial differences in both upward mobility and well-being reflect differences in the neighbourhoods where different people live[3–5]. What makes disadvantaged neighbourhoods difficult places to live?

The answer to this question is likely to be complex, given documented differences across high-poverty and racial/ethnic minority neighbourhoods both in their everyday conditions and in how they shape those living in them[6,7]. However, one important way that living in a high-poverty, minority neighbourhood may make life difficult is by undermining access to resources such as high-quality grocery stores, highly resourced schools or conventional banks[8,9]. The scarcity of such establishments in many disadvantaged neighbourhoods has led commentators to refer to such neighbourhoods as "food deserts", "school deserts", or "banking deserts"[10–12]. In what follows, we study 'banking deserts' and ask whether such establishments are in fact more difficult to access in high-poverty or minority neighbourhoods.

Access to conventional banking is essential to understanding economic inequality. Banks provide indispensable financial services necessary for both upward mobility (educational loans, business start-up funds, etc.) and general financial well-being (mortgages and refinancing services, check cashing, international transactions, emergency loans, etc.). Researchers have documented major differences across racial/ethnic and socio-economic groups in the use of conventional banking and even having a basic checking account [current account][13,14].

In banking, space matters. To be sure, banking services have increasingly become available electronically, and the number of brick-and-mortar branches has naturally declined. Nevertheless, physical establishments have remained so critical that between 2009 and 2019 more than 17,000 new offices have opened[15]. There are several reasons why. One is customer preferences. In spite of dramatic technological advances between 1989 and 2013, over that period the proportion of Americans who reported location as the most important reason for choosing the financial institution for their checking account remained largely unchanged. It stands at about 44%, and is by far the most cited reason[13,16]. These expressed preferences are consistent with what happens in practice. A 2016 Federal Deposit Insurance Corporation report found that 86% of households used a teller [cashier] at least once in the previous year[13,17]. In fact, "visiting a teller remains the most common way for households to access their accounts" (p. 43)[18]. Even among those households that preferred online banking, a majority reported visiting a teller in the previous year[17,19]. Another reason is that many needs, such as resolving disputes or opening or closing accounts, must be done in person, which continues to drive demand for physical banks. A final reason is that, from the bank's perspective, brick-and-mortar establishments provide an entry point to customers to whom mortgage, refinancing, credit card, investment and other services can be sold. It is easier for a teller to succeed in selling refinancing or investment services to a client after an in-person transaction than for an automated teller machine (ATM) [cash machine] to do so after a client has mechanically withdrawn their cash.

In addition, from the perspective of the individual, physical proximity to a bank affects banking practices. A 2017 study based on nationally representative data found that "households with reasonable geographic access to bank branches are more likely to have a bank account" (p. 91)[13]. Lacking a bank in one's neighbourhood reduced the probability of having an account, the entry point to many conventional services. The effects were largest among households "more likely to be on the margin of bank account ownership", the particular populations most likely to be affected by disadvantage (p. 91)[13].

Although neighbourhoods with few or no banks are referred to as 'banking deserts', this term can be misleading in two ways. First, although a 'desert' is a barren landscape, many disadvantaged neighbourhoods are not deprived of brick-and-mortar establishments[8]. Instead, as ethnographic researchers have reported, what many have are alternative financial institutions (AFIs), such as check-cashing stores and payday lenders[20–22]. While AFIs provide important financial services to consumers such as cashing checks,

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transferring money and short-term lending, they often do so with high fees and under strict terms[23,24]. Researchers have described many of these establishments as "predatory"[25], and a large literature has documented the negative consequences of repeated AFI use on household finances, particularly for those most economically vulnerable[26–30]. For example, one study using nationally representative data on ~42,000 households found that "40% of [payday loan] borrowers face an annual interest burden of at least $500, while 10% of borrowers pay upwards of $1000 in interest annually… a substantial allocation of resources for households with other financial commitments and only $15,000 to $50,000 of annual income" (p. 519)[31].

As with traditional banks – and other establishments such as grocery stores[32], childcare centres[33] and fitness centres[34] – physical proximity to AFIs has been shown to affect consumer behaviour. In surveys and focus groups evaluating financial behaviour, consumers report that the convenience and location of AFIs is an important factor shaping their use of these services[35,36]. One recent study found that "higher density [of AFIs] was associated with more chronic use among lowest-income individuals" (p. 51)[26]. Indeed, the impact of proximity on use has prompted many jurisdictions to restrict their location near entities such as elderly care homes and churches[37]. Thus, given the presence of AFIs, those living in a 'banking desert' might be facing not so much the absence of financial institutions as the constrained choice set: a nearby AFI versus a distant conventional bank.

The second way the term can be misleading is that, from an ecological perspective, measuring access in a 'desert' would seem to require counting the number of banks in a given geographic area, such as a county or zip code. Such measures, however, only capture access crudely, since the extent to which a bank is accessible to a given individual is affected by the configuration of space and the person's ability to traverse it effectively. In many neighbourhoods, highways [trunk roads], railway tracks, rivers and other ecological obstacles might make ostensibly 'nearby' resources spatially difficult to access[38]. Recent researchers have improved on the traditional area-based approach by measuring the physical distance between the geographic centre of the neighbourhood and the nearest establishment 'as the crow flies'[10,13,39], but even this improved approach ignores that people do not travel through cities the way birds fly through the air. In addition to the physical configuration of the space, public transportation options and even traffic may affect how accessible a resource actually is, that is, how much time is required in practice to reach it. A person may live physically near a bank but, given the ecological configuration of the space and the transportation-induced difficulties, have great difficulty reaching it.

Thus, a more effective way to understand how individuals in a given neighbourhood actually experience access is to capture how difficult a bank is to reach and to compare that with the difficulty of reaching an AFI. We develop a measure of resource accessibility across neighbourhoods based on the time it would take to travel to the nearest brick-and-mortar bank versus AFI, in every block in 19 of the largest cities in the United States. To take into account that traffic, congestion and other factors may play a role, we compute and compare times by car, public transport and foot (details in replication code and data package). Our computed times are based on more than 6 million queries. Earlier studies have been limited to one or two cities or metropolitan areas[10,24,25,39], or at best a handful[23]. Moreover, none, that we know of, has compared accessibility of AFIs versus banks, which lies at the heart of why living in a high-poverty neighbourhood might be difficult from a banking perspective.

Our data were derived from Google Maps, Google Places application programming interface (API) and the US Census (American Community Survey 2015 5-Year Estimate). Following standard practice, our measure of the neighbourhood is the block group. For details on data, see Methods section.

Results

There are far more banks than AFIs. As a result, the average bank was 13.45 min away by foot, 11.91 min by public transport and 1.67 min by car, compared with 24.83, 21.00 and 2.61 min, respectively, for the average AFI. The difference in foot travel between the nearest bank and nearest AFI was 11.38 min, which translates roughly to one-half to three-quarters of a mile, depending on pace of walking, or between 2,600 and 3,000 ft. From the perspective of experience on the ground in an urban context, the distance is notable, and beyond the scale that has concerned policy-makers worried about AFI proximity. Many local jurisdictions enact ordinances restricting AFIs from locating within 500–1,000 ft of the nearest elderly care home, church or school[37]. The average difference between the nearest AFI and bank is roughly 2.5–6 times greater than that.

We calculate the probability that an AFI is faster to get to than a bank, for block groups of varying race/ethnicity and class composition. Our core variables of interest are the racial/ethnic composition and poverty level of the block group. Our outcome is dichotomous, and we estimate models that do not assume normality or equal variances. We specify a series of nested logit models that adjust for an increasing number of neighbourhood conditions. Our variables include the percentages of the population that is non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, Hispanic or Latino, of another ethnic background, living in poverty, homeowner, unemployed, at least college educated, and foreign born; and population density, vacancy rate, proportion of housing units built before 2000, number of housing units per square kilometre, and number of commercial establishments per capita. We estimate logit models where the outcome is the probability that the time-nearest AFI is closer than the time-nearest bank. Given the major differences across cities (for example, the walkability and ease of public transport use of New York City versus Los Angeles), we specify city random-effects models with robust standard errors that account for within-city clustering. All reported statistical tests are two tailed. Full set of results are available at replication link.

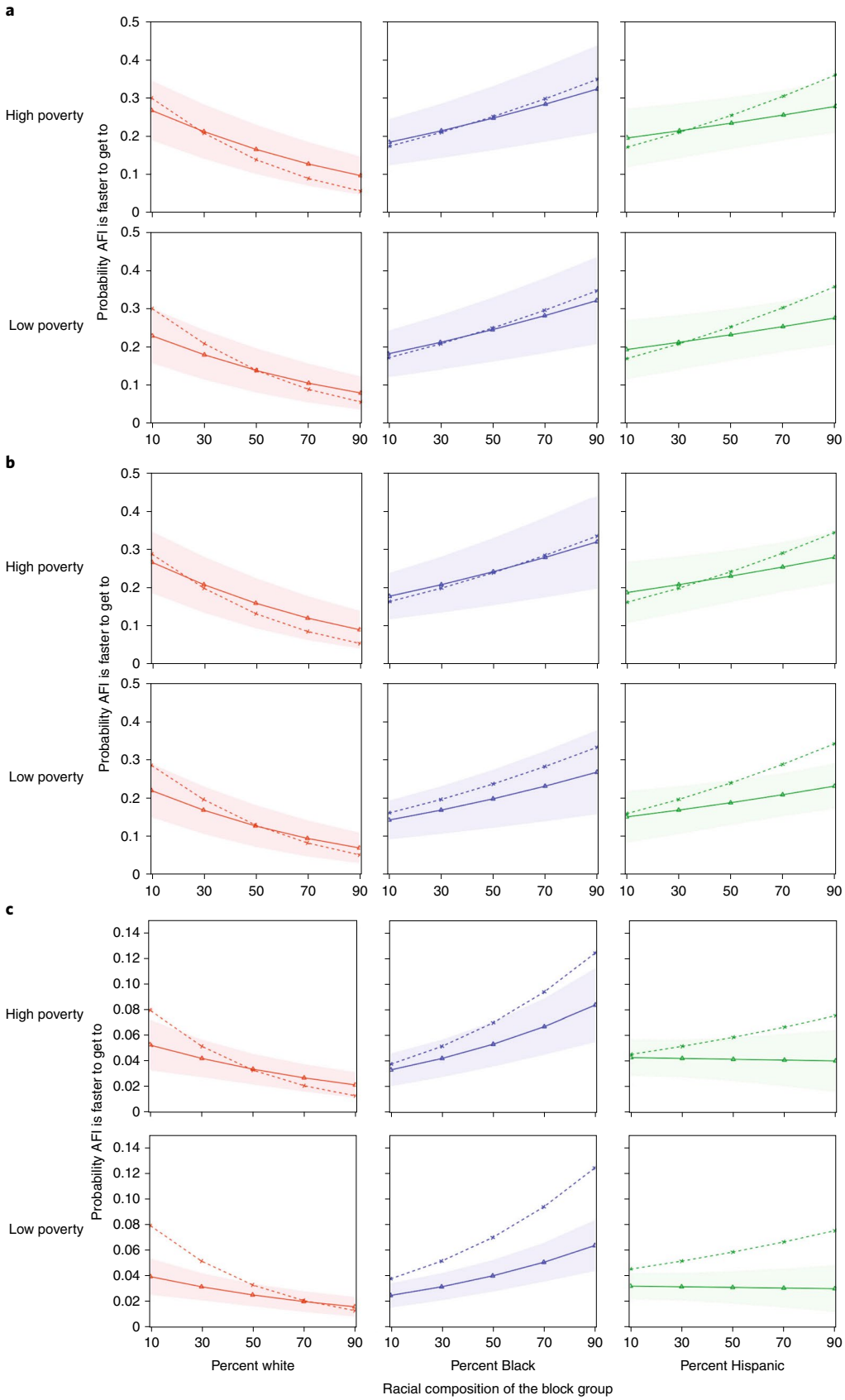
We note that our analysis is descriptive, not causal. Our aim is to identify a core characteristic of neighbourhoods of different racial/ethnic and class composition in the nation's largest cities.

We examine the adjusted probability that an AFI is faster to reach than a bank, as the racial/ethnic composition of the neighbourhood changes, for low-poverty and high-poverty neighbourhoods. In Fig. 1, we exhibit adjusted probabilities for neighbourhoods at the 10% and 50% poverty thresholds, at the 10%, 30%, 50%, 70% and 90% thresholds for proportion white, Black, and Latino; and at the grand mean for all other variables. To create Fig. 1, we include all race/ethnicity variables and suppress the constant. Each pair of rows represents a single regression with all neighbourhood conditions adjusted for (solid lines and confidence intervals), and a single

Fig. 1 | AFIs are easier to get to as proportion minority in neighbourhood increases, regardless of whether neighbourhood is high or low poverty. a–c, Adjusted probability that an AFI establishment is faster to get to when travelling by foot (**a**), public transport (**b**) or car (**c**). All variables are set at the grand mean except that block group poverty is set at either 10% (for low) or 50% (for high), and racial/ethnic composition is set at 10%, 30%, 50%, 70% and 90% for the primary group. At each race/ethnicity level, the remaining population is equally split between the two other major racial/ethnic groups, except that 8% is always set to Asian and 2% to other (for example, if the primary group is 50% Black, the remainder is 20% white, 20% Latino, 8% Asian and 2% other). Unadjusted probability in dotted lines. Shaded area represents 95% confidence intervals. Number of observations: 21,852 for travel by car, 21,313 by public transport, 21,800 by foot. For coefficients, standard errors and odds ratios, see Supplementary Table 1a–c.

regression with unadjusted results (dotted lines). Each graph represents predicted outcomes for neighbourhoods of different race/ethnicity and class composition with otherwise average characteristics.

Because there are far more banks than AFIs, the base probability that an AFI is closer is less than 50%. The question is how this rate changes with racial/ethnic and class composition.



The first column shows how a neighbourhood's predicted probability changes as its white population increases. To produce sensible marginal predictions, it is necessary to specify the full racial/ethnic composition of the neighbourhood; for example, if the neighbourhood is set to 10% white, we must specify what race/ethnicity the remaining 90% should be set to. At each level, we set the remaining population to be equally split between proportion Black and proportion Latino, except that 8% is always set to proportion Asian, and 2% always set to proportion other, given the typical distributions of the latter two groups. Thus, the predictions for a neighbourhood that is 10% white assume that the neighbourhood is 40% Black, 40% Latino and 10% of the other groups; if it is 70% white, then it is 10% Black, 10% Latino and 10% of the other groups. For the second and third columns, which focus on the proportion Black and proportion Latino, respectively, we perform the analogous process. In each case, the focal group determines the base rate, with the two other large groups splitting the difference, minus the Asian/other adjustment. Note that these specifications are necessary only for presentation purposes and do not alter the basic conclusions regarding the relative significance of race/ethnicity versus class.

The left column makes clear that, as the proportion white increases, the probability that an AFI is closer decreases dramatically, regardless of whether the neighbourhood is low or very high poverty. For example, the top-left figure shows that, if a neighbourhood is 70% white, the probability that one can walk to an AFI in less time than to a bank is only 10.4% (mean 0.104, s.e. 0.026, $Z=4.08$, $P<0.001$, 95% CI 0.054–0.155) if it has a 10% poverty rate, and only ~2 percentage points greater (mean 0.126, s.e. 0.029, $Z=4.33$, $P<0.001$, 95% CI 0.069–0.183) if it has a 50% poverty rate. The figures for taking public transport tell a similar story. The figures for driving tell an analogous story, albeit at much lower probabilities.

The second and third columns make clear the dramatic difference that race makes. As the neighbourhood increases in proportion Black (middle column), the probability that an AFI is closer rises rapidly, and the poverty level does not alter the findings dramatically. The top middle graph shows that, if a neighbourhood is 70% Black, the probability that an AFI is closer by foot is 24.1% (mean 0.241, s.e. 0.046, $Z=5.24$, $P<0.001$, 95% CI 0.151–0.331) at a 10% poverty rate and 28.1% (mean 0.281, s.e. 0.050, $Z=5.62$, $P<0.001$, 95% CI 0.183–0.379) at a 50% poverty level. In fact, an AFI establishment is 8 percentage points more likely to be closer if the neighbourhood is 70% Black and low poverty than if it is 70% white and high poverty. The pattern is similar across all modes of transportation. The Black–white difference in the predicted log odds that the AFI is closer is statistically significant for all modes of travel: foot ($b=0.017$, s.e. 0.002, $Z=9.61$, $P<0.001$, 95% CI 0.014–0.021), public transport ($b=0.018$, s.e. 0.002, $Z=10.24$, $P<0.001$, 95% CI 0.0145–0.021) and car ($b=1.016$, s.e. 0.003, $Z=5.83$, $P<0.001$, 95% CI 0.011, 0.022) (Supplementary Table 1a–c).

The pattern as the proportion Latino increases is similar to that as proportion Black increases, though the Latino–white difference is smaller; it is statistically significant for travel by foot ($b=0.015$, s.e. 0.003, $Z=4.96$, $P<0.001$, 95% CI 0.009–0.020) and public transport ($b=0.016$, s.e. 0.003, $Z=4.92$, $P<0.001$, 95% CI 0.009–0.022). By car, the observed Latino–white difference does not reach statistical significance ($b=0.007$, s.e. 0.004, $Z=1.76$, $P=0.079$, 95% CI −0.001 to 0.015), and no statistically significant change is detected in the predicted probability for a neighbourhood at the mean of all other variables as the proportion Latino increases. Nevertheless, by car the base probabilities that AFIs are closer are quite low for all racial/ethnic groups (see above and Supplementary Table 1a–c). Cars dampen the time-of-travel difference between the two kinds of establishments, which means that the consequences of the patterns we report are greatest for those without access to stable cars, among the lowest-income populations.

Though our analysis deliberately focused on within-city differences, between-city differences can be large. For example, while in New York City the average nearest bank is 8.77 min closer by foot than the nearest AFI, in Detroit the nearest AFI is actually closer than the bank, by 1.28 min. Adjusting for observed characteristics tempers but does not eliminate such differences. For example, for the average New York City neighbourhood that is otherwise 70% Black with a 10% poverty level, the adjusted probability that an AFI is closer by foot is 13.5% (mean 0.135, s.e. 0.010, $Z=13.43$, $P<0.001$, 95% CI 0.116–0.155), while for the average Detroit neighbourhood with those characteristics, it is 47.6% (mean 0.476, s.e. 0.075, $Z=6.36$, $P<0.001$, 95% CI 0.329–0.623).

In separate analyses, we examined independently the proximities to each kind of establishment. After adjusting for most neighbourhood conditions, proportion Black played no role in proximity to banks but a major role in proximity to AFIs. Proportion Latino shortened time to banks, but shortened time to AFIs at dramatically higher rates (available in replication file). Thus, the differences reported in Fig. 1 are due less to an absence of banks than to a surplus of AFIs in places accessible to minorities, even high-income minorities (Supplementary Table 2a,b).

We note that, across the main models, education and poverty were the most consistently important controls. AFIs are especially likely to be faster to get to when the population has few college graduates. Indicators related to the built environment were important as well (Supplementary Table 3a–c).

We performed additional analyses. We examined the possibility that the relationship between race/ethnicity and the outcome was non-linear. Though we found some evidence of concavity, incorporating non-linearity did not improve most models and overall did not notably change the results. We also examined whether the substantive conclusions were changed or modified by including specific interactions between race/ethnicity and poverty variables, by replacing proportion living in poverty with average household income, by separating cities with especially aggressive AFI restrictions from others, by separating cities in Texas and California (the two most common states in our sample) from others or by taking into account the reliability of American Community Survey estimates. Across these analyses, the overall story remained unchanged. For full details on robustness checks and supplementary analyses, see Supplementary Sect. 5 and full output in replication file.

We probed further. Unravelling the full set of supply-side and demand-side factors producing this distribution is a matter for future research. An extensive body of work on financial institutions, banking, redlining and other structural conditions is illuminating, and should guide future work on the spatial distributions of banks and AFIs[40–42]. Still, a natural question is whether these differences reflect not inefficiencies in the market but primarily racial/ethnic differences in the extent to which individuals prefer AFIs.

We present an additional descriptive analysis that suggests that such factors are unlikely to account for the observed spatial patterns. For the analysis, consider that, as researchers have repeatedly confirmed, most of the unique services offered by AFIs, such as immediate loans with minimal credit checks, are designed to appeal to high-poverty households with unstable incomes, weak credit or both[25,27]. A high-income household led by a college-educated homeowner is far less likely to fall into that category. In addition, such a homeowner is likely to have repeatedly needed conventional banking services, at a minimum, and nearly by default, for mortgage and education loans.

On this basis, comparing conditions at the two extremes is instructive: We can compare those predominantly white neighbourhoods for which AFIs would be most economically appealing with those predominantly minority neighbourhoods for which they would be least economically appealing. We estimate adjusted probabilities that the AFI is closer for neighbourhoods that are 70% white,

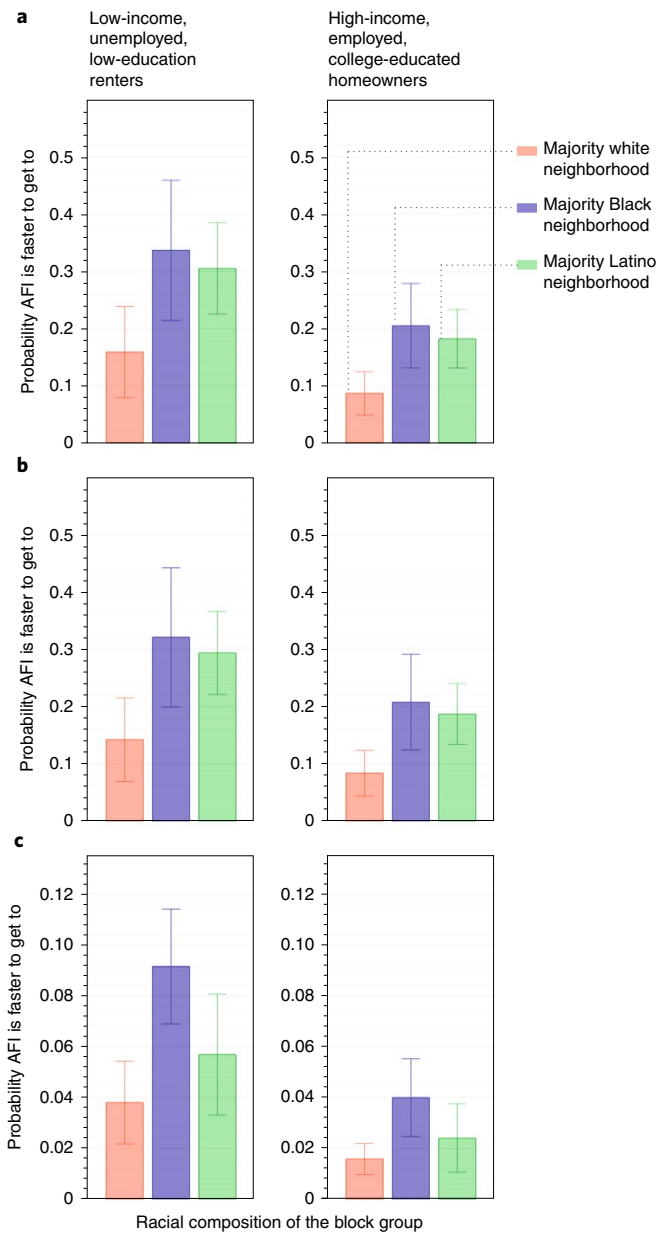


Fig. 2 | Could race differences in demand account for the pattern? Banks are still harder to get to in low-poverty, college-educated, minority homeowner neighbourhoods than high-poverty, low-education, white renter neighbourhoods. a–c, Adjusted probability that an AFI is faster to get to by foot (**a**), public transport (**b**) and car (**c**), based on model behind Fig. 1 (Supplementary Table 1a–c). All variables are set at the grand means except as follows: the bars on the left show the probability that an AFI is closer for neighbourhoods with 50% low income with unemployment at the 75th percentile (14% unemployed) of the total distribution, proportion college educated at the 25th percentile (11%) and proportion homeowner at the 25th percentile (25%); the bars on the right, for neighbourhoods with 10% low income with unemployment at the 25th percentile (5% unemployed), proportion college educated at the 75th percentile (47%) and proportion homeowner at the 75th percentile (71%). Error bars represent 95% confidence intervals. Number of observations: 21,852 for travel by car, 21,313 by public transport, 21,800 by foot.

Black or Latino and at the grand mean for all other variables except as follows: for predominantly white neighbourhoods, the poverty rate is set at 50%, the proportion unemployed is set at the 75th percentile (14%) of the total distribution, the proportion college educated at the 25th percentile (11%) and the proportion homeowner at the 25th percentile (25%); for predominantly Black or Latino neighbourhoods, the poverty rate is set at only 10% and the respective percentiles are reversed, that is, 25th (5% unemployed), 75th (47% college educated) and 75th (71% homeowners). Thus, we compare neighbourhoods of low-income, unemployed, not college educated, white renters with those of high-income, working, college-educated, minority homeowners.

Figure 2 presents the results. The sets of bars on the left show the adjusted probability that AFIs are easier to get to among high-poverty, low-education, high-unemployment, primarily renter-occupied neighbourhoods, and those on the right, among low-poverty, college-educated, high-employment, primarily owner-occupied neighbourhoods. Reason would suggest that AFIs should be easier to get to for bars on the left than the right, as they do.

The bars' colours (red, blue or green) represent neighbourhoods that are 70% white, Black or Latino, respectively. Comparing red bars on the left with blue and green ones on the right reveals a striking result: regardless of mode of transportation, the predicted probabilities that AFIs are closer are higher in affluent homeowner Black neighbourhoods than in highly disadvantaged renter white neighbourhoods, whether by foot (mean 0.205, s.e. 0.038, $Z=5.43$, $P<0.001$, 95% CI 0.131–0.279 versus mean 0.159, s.e. 0.041, $Z=3.90$, $P<0.001$, 95% CI 0.079–0.238), public transport (mean 0.208, s.e. 0.043, $Z=4.88$, $P<0.001$, 95% CI 0.124–0.292 versus mean 0.142, s.e. 0.037, $Z=3.81$, $P<0.001$, 95% CI 0.069–0.215) or car (mean 0.040, s.e. 0.008, $Z=5.10$, $P<0.001$, 95% CI 0.025–0.055 versus mean 0.038, s.e. 0.008, $Z=4.57$, $P<0.001$, 95% CI 0.022–0.054). They are also higher in affluent homeowner Latino neighbourhoods by foot (mean 0.1819, s.e. 0.0261, $Z=6.96$, $P<0.001$, 95% CI 0.1307–0.2332) or public transport (mean 0.187, s.e. 0.027, $Z=6.88$, $P<0.001$, 95% CI 0.134–0.241) but not by car (mean 0.024, s.e. 0.007, $Z=3.48$, $P<0.001$, 95% CI 0.010, 0.037).

The differences vary, and are around 5 percentage points, though confidence intervals are large and call for caution. Still, for simple race/ethnicity differences in preferences for AFIs to account for these spatial patterns, it would need to be the case that affluent, highly educated, minority homeowners (even though most would have had to apply for college and mortgage loans) somehow still preferred that conventional banks be harder to get to. No research currently supports that idea, and most research is consistent with the opposite, that income and education differences account for much of the person-level variance in conventional banking[43]. To be clear, the discussion above does not constitute a formal analysis of preferences. Moreover, higher-income African Americans have been found to prefer integrated or predominantly Black neighbourhoods at higher rates than white people[44–46]. Nevertheless, none of the differences that have been documented on these issues are large enough to account for the dramatic race gradient we report.

Discussion

Banking conventionally is more difficult in richer minority neighbourhoods than higher-poverty white ones. The differences cannot be accounted for by a robust slate of demographic, educational, economic, commercial or structural characteristics and are large enough among groups at opposite ends of the banked–unbanked spectrum that race or ethnic differences in preferences alone would seem to be an implausible explanation.

Our results reveal the remarkable primacy of race over class in the distribution of financial services across neighbourhoods. Residential segregation dramatically undermines the advantages that would be expected of affluent, highly educated, homeowner racial/ethnic minority neighbourhoods[46–51]. As an extensive literature on banking, institutional discrimination and redlining demonstrates, financial institutions have played an important role in racial

disparities in wealth[40–42,52]. Our results suggest that the unequal distribution of their accessibility across the city may be an important mechanism behind such differences.

If neighbourhoods play a role in the use of conventional banking, then relative distances, particularly among neighbourhoods with high proportions of African Americans, may be an important part of the reason why. Given the important implications for racial inequality, future work should examine location decisions among alternative financial services and the extent to which local regulations are effective. Indeed, our results suggest that policy interventions may work. Since the difference was driven more by the prevalence of AFIs in minority areas than the absence of banks there, policies such as the Community Reinvestment Act that incentivize banks to locate in such areas may have worked. Conversely, restrictions on AFI location of the kind imposed by many localities may be worth exploration by policy-makers. From a scholarly perspective, the large number of localities with AFI regulations and the changes over time in the timing of those rules represent a potentially fruitful area to examine the causal effect of such interventions.

In addition, researchers should consider how decision-making with respect to banking, and other issues central to social inequality, are affected by the potential trade-offs between quality and proximity in establishment location. Our approach necessarily simplified both the choice set and the assumed process, by comparing the nearest bank with the nearest AFI. In practice, individuals are not restricted to either one, and additional factors, such as hours, fees, marketing and even the daily commute to work (and the resources available throughout those spaces) will affect how individuals living in a particular neighbourhood make financial decisions. Still, the large literature on the impact of proximity, added to the robustness of our descriptive findings, should prompt more detailed work on the intersection between decision-making and spatial conditions.

Methods

Our location data were collected and filtered from establishment data, called 'Places', from Google Maps, an especially rich and comprehensive resource. Using the Google Places API, we retrieved banks from the database based on 'types', the property that describes what kind of establishment a location is. Since a location can have multiple types, we restricted our filter to exclude other establishments. We also excluded ATMs located in places other than banks, such as grocery stores and liquor stores, for two reasons: first, ATMs require an individual to already have a bank account and card, and second, a stand-alone ATM outside of a bank has limited features and does not provide the financial services of a brick-and-mortar bank or AFI.

Our focus among conventional financial services was banks. Though our approach captured some credit unions, it can only speak to the relative presence of banks versus AFIs, and we encourage future scholars to probe credit unions. Still, our preliminary analysis suggests that the inclusion of credit unions is unlikely to alter our substantive conclusions (Supplementary Sect. 1).

To capture AFIs, we adopted 'check cashing' store as a general category, as it captures a broad array of AFIs. Although Google Places reports check-cashing places, its APIs do not support a query for check-cashing places types. To retrieve these data, we wrote a program to open a Google Maps website on a web browser that iteratively searched for such places in each city, using different zoom levels and map extents, until no more new places were found, and then recorded the results. We then matched the names of the recorded places with our Google Places database and extracted the place's data. We examined the resulting data against some known neighbourhoods in our local city, Boston, and found a high degree of accuracy, with known establishments present in the data and none of the establishments incorrectly labelled. The accuracy reflects the fact that in recent years Google has invested dramatically in the quality of these data, with the use of official sources, self-submission by establishments, Street View imagery, crowd-sourcing and multiple validation procedures. While our dataset successfully captured check-cashing places, payday lenders and other AFIs marked with the 'check cashing' label, this process did not collect exhaustive data on all types of AFIs. For example, our dataset includes some but not many car title lenders, and it does not include pawnbrokers. If these uncaptured AFIs are disproportionately located in disadvantaged neighbourhoods, then the results we provide here are likely a conservative estimate of the race disparity identified. For full details on our data, methods, code and replication data package, see https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si.

Next, we calculated access. We developed an algorithm that first calculated the physical distance from the centre of the block to the ten nearest establishments. It then calculated the actual travel time – separately for each mode of travel – taking into account roads, obstacles, railways, etc., to each of the ten, and extracted the fastest as the block's recorded travel time. Results were then aggregated to the block group level. There are 21,864 block groups in our 19 cities. We repeated the process for every block, for every city and for travel by foot car, and public transport. For public transport, we used the General Transit Feed Specification data obtained from each city's local transport agencies (see details in data package). Due to missing data for Memphis at the time of our extraction, our public transport results are based on 18 cities only. Note that the relationship between calculated and actual travel times for car or public transport and actual travel times will be sensitive to traffic conditions. However, that between calculated travel time by foot and actual time will not. Thus, to the degree traffic conditions matter, the actual accessibility by car and public transport will approximate that by foot.

For neighbourhood characteristics, we used data from the US Census Bureau 2015 American Community Survey 5-year estimate at the block group level. For race/ethnicity, we used estimates of the proportion of the population identified as non-Hispanic white, non-Hispanic Black, Hispanic or Latino, non-Hispanic Asian or non-Hispanic other. We note that our analysis does not cover the full intersection of race and ethnicity, as racial/ethnic groups are not mutually exclusive in practice. (Following convention in the literature, we use the term 'racial inequality' to refer broadly to race or ethnic inequities.) Our main indicator of class is the proportion of the population living below the poverty line (but including additional indicators such as education level and homeownership rates). Full details on the variables used in this study are included in Supplementary Sect. 4.

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The Google Places establishment data were collected using a Google Maps API Premium Plan. The licence precludes publicly sharing the Places location data. Instead, we provide the travel times by foot, car and public transport from the centroid of each block, aggregated to the block group. These travel times are available at https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/tree/master/_all_data. The 2015 American Community Survey 5-year data files were collected from Census Bureau file transfer protocol (FTP) server (https://www.census.gov/data/developers/data-sets/acs-5year.2015.html). Full details on the variables used are included in Supplementary Discussion, Section 4. The street grid and associated variables were obtained from OpenStreetMap data (https://www.openstreetmap.org). The public transport schedules and associated data were obtained from each city's General Transit Feed Specification, via the Transitland platform (https://www.transit.land/). The minimum dataset needed for replicating our full set of results is available at https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/tree/master/modeling_data_cleaned. Source data are provided with this paper.

Code availability

The travel times were calculated with the open-source GraphHopper routing engine and OpenTripPlanner, using OpenStreetMap data. The main results were produced using STATA. The replication code for processing travel times is available at https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/tree/master/scripts/python. The replication code for the empirical analysis is available at https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/tree/master/scripts/stata. Source data are provided with this paper.

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Author contributions

M.L.S. designed research, performed research, analysed data and drafted paper. A.A. created dataset and visualizations, analysed data, produced replication package and edited paper. M.T. performed research and edited paper. Q.W. co-created dataset, performed research and edited paper.

Competing interests

The authors declare no competing interests.

Additional information

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Data were extracted from Google Places, from the U.S. Census, and from the General Transit Feed Specification.
Data analysis	Python and Stata were used for data extraction and analysis: https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si

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The Google Places establishment data were collected using a Google Maps API Premium Plan. The license precludes publicly sharing the Places location data. Instead, we provide the travel durations, by foot, car, and public transit, from the centroid of each block, aggregated to the block group. These durations, the procedures for calculating them, and the rest of the data used in our analysis are available at https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/.

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Study description	Based on more than 6 million queries, we compute the difference in the time required to walk, drive, or take public transit to the nearest bank vs. the nearest alternative financial institution from the middle of every block in each of 19 of the nation's largest cities. We examine differences across neighborhoods of different racial/ethnic composition.
Research sample	We examine all blocks, aggregated to the block group, in 19 of the largest cities in the U.S.
Sampling strategy	Every block was selected.
Data collection	Establishment data were obtained from Google Places; demographic, economic, and neighborhood structural data were obtained from the U.S. census; transit data were obtained from the General Transit Feed Specification. We extracted data from the three sources.
Timing	We extracted Google API data from December 2016 to January 2017; we extracted census data current to 2015; we extracted GFTS data in November 2017.
Data exclusions	No data were excluded; all available data were presented.
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