Supplementary Information

This file contains supplementary information for the following paper:

Banks, alternative institutions, and the spatial-temporal ecology of racial inequality

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1. Using Google Maps and Google Places API to find AFIs

In this section, we describe in greater detail the process through which we acquired data on conventional banks and alternative financial institutions (AFIs).

City selection

The following 19 cities were selected for analysis: Austin, Boston, Chicago, Columbus, Dallas, Detroit, El Paso, Fort Worth, Houston, Indianapolis, Jacksonville, Los Angeles, Memphis, New York, Philadelphia, Phoenix, San Antonio, San Diego, and San Jose. Each of these except Boston was one of the largest 20 places in the U.S. in 2015 per the U.S. census. We included Boston, then the 22st largest city, as it is the location of the researchers' home institutions, and allowed the examination of some face validity of some of the data based on local knowledge. The cities offer strong representation in the Northeast, Midwest, South, Southwest, and West, as well as cities with different political and economic contexts. Computational constraints precluded analysis of a much larger number of cities, but we believe that constraint will be reduced over time.

Data source

We used Google Maps and Google Places API. Google Maps collects large amounts of data on many kinds of commercial and non-commercial establishments, including conventional banks and alternative financial institutions, such as check cashing places, payday lenders, etc.

Our rationale for using Google data instead of alternatives was the comprehensiveness and high quality of the data. The establishment data is based on at least three sets of sources. First, Google uses publicly available administrative data sources from official and private sources. Second, as the volume and quality of its street imaging capacity have ballooned, Google has also developed advanced algorithms to detect places based on Google Street View imagery, which allow the detection and updating of establishments with high accuracy.[1,2,3] Google essentially reads signs from storefronts and shops about what an establishment is and feeds it to its database, through a process that, given the company's vast

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[1] Yu, Qian, Christian Szegedy, Martin C. Stumpe, Liron Yatziv, Vinay Shet, Julian Ibarz, and Sacha Arnoud. "Large scale business discovery from street level imagery." arXiv preprint arXiv:1512.05430 (2015). [Accessed July 2, 2020].

[2] Movshovitz-Attias, Yair, Qian Yu, Martin C. Stumpe, Vinay Shet, Sacha Arnoud, and Liron Yatziv. "Ontological supervision for fine grained classification of street view storefronts." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1693-1702. 2015.

[3] Wojna, Zbigniew, Alexander N. Gorban, Dar-Shyang Lee, Kevin Murphy, Qian Yu, Yeqing Li, and Julian Ibarz. "Attention-based extraction of structured information from street view imagery." In 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), vol. 1, pp. 844-850. IEEE, 2017.

amount of data, refined algorithms, and computational power, results in remarkable accuracy.[4] Third, Google employs crowdsourcing. Business owners can easily submit information on their establishment if their data are missing. Google also encourages "local guides," people who know their neighborhoods well, to independently post their own data on places.[5] At this juncture, anyone can propose the existence of an establishment: "[From] Local Guides, active Google users, and business owners via Google My Business, [Google] receives more than 20 million contributions from users every day."[6]

The sources, however, are not taken at face value. Each submission from individuals to add or correct information about an establishment is reviewed for accuracy before posting. In addition, automated data are also checked. Google has employed what has been described as "a small army of people to manually correct the information collected from these different sources."[7] Indeed, at this juncture, the process of improving establishment and place data at the local level has been "gamified," through a social media platform that rewards input and databased improvement through public recognitions, perks, and prizes for contributions. The Local Guides platform is, in fact, both for the submission and the continuous correction of site information.

The combination of administrative data, proprietary imagery, and crowdsourcing, all continuously updated and reviewed for accuracy, has meant that Google has produced an extraordinary database. We performed additional validations. Before conducting our analyses, we compared data on conventional banks and ATMs from Google Places to those from Microsoft Bing Maps in each of the 19 cities we studied.[8] In all but two cities, Google identified more existing locations.[9] We also examined the Google data against some known neighborhoods 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 labeled.

The Google data are ultimately the optimal source for our purposes. They are more accurate and appropriate than other sources that might appear better, such as an official list of banks or AFIs from a government source. While the latter have obvious advantages, they are already part of Google's database. More importantly, they have two disadvantages for our purposes. First, official data are typically released annually, rather than updated continuously. Since establishments are continuously either opening or going out of business, any yearly or semi-annual snapshot will inevitably be dated. Second, official records are often inaccurate. They are inaccurate not merely due to clerical errors but, more importantly, because they may not reflect reality as it is experienced—establishments may exist only on paper, constituting an address and a mailbox; be long dead but still on the

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[4] https://www.theatlantic.com/technology/archive/2012/09/how-google-builds-its-maps-and-what-it-means-for-the-future-of-everything/261913/ [Accessed July 3, 2020]

[5] https://maps.google.com/localguides [Accessed July 3, 2020]

[6] https://cloud.google.com/blog/products/maps-platform/beyond-the-map-how-we-build-the-maps-that-power-your-apps-and-business [Accessed July 3, 2020]

[7] Nahar, Anish. 2017. "Google Maps: The Most Expansive Data Machine." In *HBS Digital Initiative*. https://digital.hbs.edu/platform-digit/submission/google-maps-the-most-expansive-data-machine/ [Accessed July 3, 2020]

[8] We thank Markus Mobius for the acquisition and extraction of the Microsoft data.

[9] Depending on the city, there were between 5% and 721% more places in the Google data, with the starkest differences deriving from Google's effective identification of ATMs.

books; or be misclassified by malfeasant actors. The upshot of these possibilities is that, as in many areas of life, the government's record of an establishment may not match the reality that someone walking down the block on their neighborhood experiences. Our data come closest to approximating that experience, since it takes that official record, confirms it with a Street View car that has driven down the block and taken a picture of the building and signage at address, and re-confirms it with a crowdsourced platform wherein an individual, within a social media context of continuous evaluation for accuracy, reports that an establishment is in fact at that location. While no data source is perfect, ours comes closest to that ideal for the objectives of our analysis.

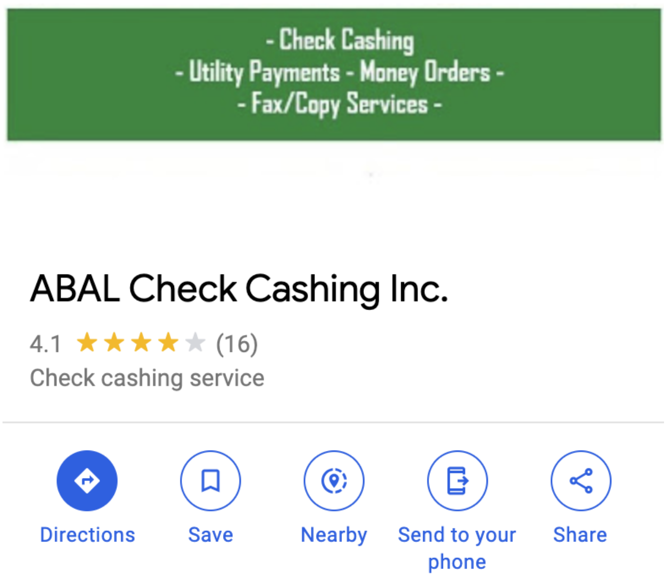
Extraction
Each of the establishments in Google Maps' database is stored as an "object" with a set of attributes. Google's Places API "is a service that returns information about places using HTTP requests. Places are defined within this API as establishments, geographic locations, or prominent points of interest."[10] Through Google Places API, one can access the Google Maps data directly. The data returned from the Google APIs are stored as JSON "objects," which we collected and then parsed into our own database for original analysis.

The current paper was part of a larger study for which we collected data on a large number of establishments. We collected establishment data using the Google Places API from December 2016 to January 2017 in 19 of the largest cities in the U.S. We split the area of each city into grids and used the "nearby" function of the Places API to collect any places in every grid. If a search returned more than 60 (i.e., the maximum number of places that can be returned from a single request) places, we split the grid into four equal smaller grids and searched again in each of the sub-grids. The algorithm stopped whenever a search returned less than 60 places and moved on to the next grid. The codes and algorithms can be found here: https://github.com/urbaninformaticsandresiliencelab/gmaps_scraper.[11] All place data collected from a city were stored in a combined .json file.

Of particular importance to our analysis was the place attribute "type," which describes the function of the establishment (see https://developers.google.com/places/supported_types). On Google Places API, conventional banks are assigned the "type" *bank*. By accessing the Google Maps database through the Places API, we were able to simply and efficiently retrieve data that identified conventional banks in the 19 major cities in our analysis. However, not all Google Maps data are available through the Places API; some must be retrieved using a web browser. For example, searching for an establishment on Google Maps using a web browser or mobile phone returns data such as hours of operation that are not retrievable from the Places API. Similarly, while banks are easily accessible through the Places API, alternative financial institutions are not, because there is currently no Places API "type" for AFIs.

[10] Google Maps Platform (2019). Overview: Places API. Available online at https://developers.google.com/places/web-service/intro. [Accessed June 26, 2020]
[11] Updated June 29, 2020. The data were collected using a previous version of Google Places APIs, and at the time collecting the data was free of charge. Google has updated its Place API since, and one can now incur a high cost by using the "nearby" function.

Still, AFIs are indeed readily identifiable through a simple Google Maps search using a web browser. Doing so requires deciding on search terms. For example, while there is no Places API "type" for "check cashing establishment," a browser search on Google Maps for the term "check cashing" retrieves the data from the same database used by the Places API, and lists the full results, including the "name," "rating," and "vicinity" attributes from each place "object." In fact, the results also include a line indicating that the establishment is of the "Check cashing service" category (see below). This establishment category as indicated on the web browser is not one of the Places API listed "types."



On a browser, it is possible to find AFIs under different searches, and a particular AFI may be listed under different categories in different searches. For example, since many payday lenders cash checks, the same establishment may be listed as a "Loan agency" in one search and as a "Check cashing service" in another. However, some categories are broader than others. While payday lenders are rather consistently categorized under check cashing services, the reverse is not necessarily the case, as many places where one could cash a check for a fee do not offer loans.

We used the term "check cashing" to identify check cashing service categories, which is appropriate given the ubiquity of cashing checks as a basic service across a large swath of different AFIs, including not only check cashing establishments but also payday lenders and currency exchanges. Indeed, in some cities where payday lenders are not legally allowed, alternative financial institutions are simply known as "check cashing stores." While our approach is appropriately comprehensive, it nonetheless excludes some alternative institutions, such as pawn shops that do not cash checks or are otherwise not classified as doing so. It also does not include most auto title lenders. Thus, our data contain robust coverage of check cashers and payday lenders, but likely undercounts some classes of AFIs. If so, then unless institutions such as pawnshops are especially likely in predominantly white neighborhoods, our results would likely understate the extent of racial inequality.

To create an intermediate dataset of AFIs, we first used Google Maps to identify all available establishments marked "Check cashing service." We then matched these establishments to the "name" for each location in the Places API, and extracted the place "objects" and all related attributes. This process provided AFI data that are as rich as the data we had collected on conventional banks. To scrape the AFI data, we programmed a Python script to open a Firefox browser, navigate to the Google Maps URL, click on the search box, type in "check cashing," and click on the search button. From there, we processed through the results, storing the names of all places categorized as "Check cashing service." The script then matched the names to the place "object" from our dataset built from the Places API.

We experimented with four ways to collect these data with Google Maps on a web browser. Using http://www.google.com/maps/ as the base URL, we tried each of the following:

1. Using coordinates, in latitude/longitude format, and passing the coordinates to the search end point with a search query. For example, to access Chicago: http://www.google.com/maps/search/<search query, e.g. check cashing>/@40.7274826,-74.0902511,11z
2. Using the place endpoint and navigating to city, e.g., Chicago, using the URI of `https://www.google.com/maps/place/Chicago,+IL/` and then clicking on the element for NEARBY search `section-action-button-icon maps-sprite-pane-action-ic-searchnearby` and search for `check cashing`
3. Searching for the place with the search endpoint, meaning first using, e.g., Chicago to search for Chicago, which returns the place endpoint, and continuing with the steps above.
4. Combining the two searches and searching, e.g., for `Chicago,+IL+check+cashing`

The script we settled on uses the fourth method to search. It goes through the list of results, paginating and matching names between the browser-based Google Maps and the Places API. This process, for Chicago alone, returned 254 places we then added to our database. We then made additional rounds of browser scraping with different zooming scales, and looked at the rate of finding additional places as a determining factor to stop the operations. We were able to scrape the rest of the places that the first round did not return by making a loop/iterator for a zoom/drag operation with randomized values for zoom levels and drag directions, ensuring the completeness of our data.

A note on credit unions

Our study focuses on the time difference in access to traditional banks vs AFIs. It does not focus on credit unions. Credit unions account for roughly 15% of the overall banking market, and while some credit unions were captured by our data collection process, we did not seek to create a comprehensive set of credit union locations. We encourage future researchers to examine credit unions, their spatial distribution, and their role in financial decisions vis-à-vis AFIs to greater extent.

Still, we believe that including credit unions under our category of conventional banking institutions would likely not have altered our substantive conclusions. We conducted a small-scale comparison. We extracted data from our purchased Google API, examined the number of credit unions in all block groups in four cities from across the country—Boston, Chicago, Dallas, and Los Angeles—and compared the demographic characteristics of neighborhoods with and without credit unions. In all four cities, the overwhelming majority of block groups—well over 90%—had no credit unions. Very few had more than one. The table below compares the proportion poor, proportion black, and proportion Latino/a in block groups with no credit unions to those with any credit unions.

Demographic characteristics of block groups with and without credit unions

	No credit unions			Any credit unions		
	% poor	% black	% Latino/a	% poor	% black	% Latino/a
Boston	21.2%	23.3%	17.7%	20.0%	10.4%	14.5%
Chicago	22.6%	36.3%	26.3%	22.3%	29.3%	16.6%
Dallas	22.1%	22.4%	39.4%	21.1%	20.2%	33.2%
Los Angeles	20.5%	10.1%	45.1%	14.6%	7.8%	30.1%

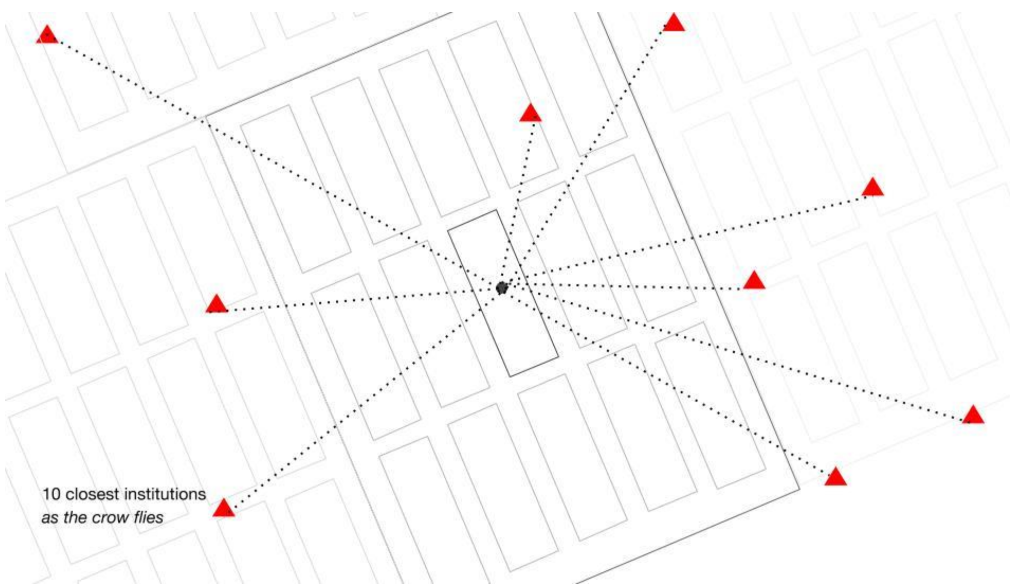
The table shows that neighborhoods with credit unions have consistently lower proportions of minorities. The pattern holds across all cities in spite of their dramatic differences in racial composition. Credit unions are not especially likely in minority areas, and in fact are especially unlikely to be there. Thus, including credit unions would not likely alter our basic finding that conventional banking is harder in minority neighborhoods. Nonetheless, the particular spatial dynamics of credit unions vis-à-vis banks deserves future scrutiny.

2. Calculating access

An important contribution of this paper is our improvement in the measurement of access in the literature on the spatial distribution of conventional banks versus alternative financial institutions. In this section, we describe the process we used to calculate access in our analysis.

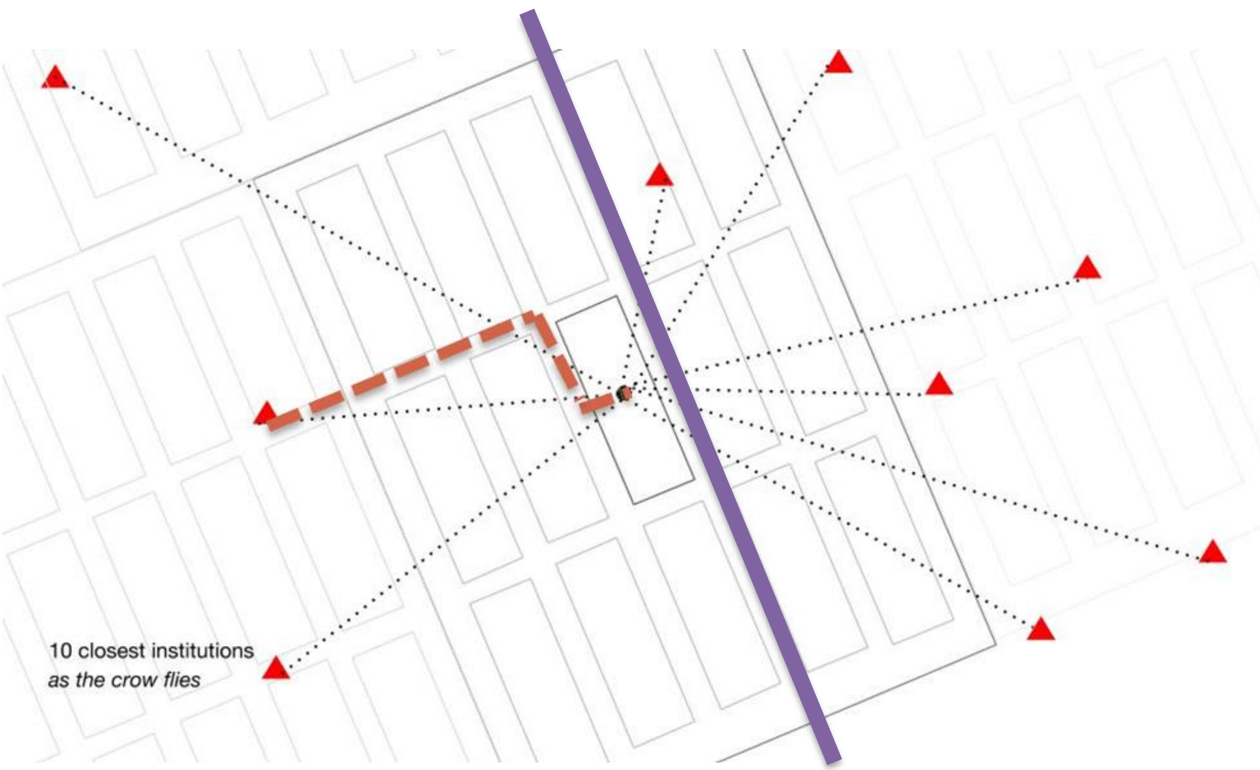
To minimize spatial aggregation error associated with accessibility measure calculations, we calculated our measures at the most granular census geography available: census blocks. We then summarized the block-level data at the block-group level when performing our analysis in relation to other socio-demographic attributes from census data.

Calculating travel times for all possible combinations of blocks and amenities is not computationally feasible. We instead limited our calculations to the ten closest amenities (conventional banks and AFIs) based on their linear ("as the crow flies") distance to each individual block's centroid. We performed the calculation for every block in each of our cities. We calculated linear distances using Postgres/PostGIS database's ST_Distance_Sphere function.



We then used open-source commercial routing engine Graphhopper to estimate the driving and walking times from each block centroid to the ten closest amenities. We repeated this process for all 19 cities in our analysis. We used OTP (Open Trip Planner) to calculate travel times for public transportation. We repeated this process for 18 of the 19 cities in our analysis. Public transportation data were not available for Memphis at the time of our analysis, and thus this city was excluded from public transit calculations.

We then selected the closest amenity based on the time-duration measure, separately for each mode of transit. Because of physical barriers, public transit routes, and other factors, the closest amenity by time was often not the closest as the crow flies. Though a person is naturally not limited to the closest institution, identifying the closest permits the comparative analysis posed in the paper.



Finally, we calculated the value separately for each block in the block group, and produced the block-group's average. Each block group had a separate average time for each mode of transportation.

By design, our approach conceives of access based on the presumed place of residence. It does not include the full range of possible locations that an individual may encounter over the course of a given day, on the way to work, during regular commuting, or during routine shopping. Alternative conceptualizations of access might explore the full range of such locations. For the sake of making tractable the task of identifying differences across neighborhoods of different racial composition on a large scale, we have chosen a narrow conception of access. Future work could examine in finer detail how access is affected by daily activities, commutes, and everyday mobility.

3 Estimating adjusted time to nearest AFI vs. nearest bank

To determine whether the adjusted time to the block group's nearest AFI was closer than the nearest bank, we estimated random effects models with a binary dependent variable. The model was essentially a two-level hierarchical generalized linear model for block group *i* in city *j* predicting the log of the odds of that the nearest AFI was closer. The link function was, $\eta_{ij} = \log\left(\frac{\varphi_{ij}}{1-\varphi_{ij}}\right)$, where φ= 1 if time to nearest AFI < time to nearest bank and 0 otherwise. The model takes the following form:

Level 1

$$\eta_{ij} = \pi_{0j} + \sum_{p=1}^{P} \pi_p X_{pij} + e_{ij}$$

where

η_{ij} is the expected log odds that the AFI is closer for block group *i* in city *j*
π_{0j} is the average rate at which the AFI is closer in city *j*
π_p are coefficients associated with the block-group-level variables
X_{pij} are the independent variables
e_{ij} is the specific variation associated with a given block group

Level 2

$$\pi_{0j} = \beta_{00} + r_{0jk}$$

where

β_{00} is the average rate at which AFI is closer
r_{0j} is the random "city effect," or variation associated with a given city

After simple substitution,

$$\eta_{ij} = \beta_{00} + \sum_{p=1}^{P} \pi_p X_{pij} + e_{ij} + r_{0jk}$$

The model was estimated in Stata. In Stata, melogit estimates the equation above. However, we used xtlogit, as it produces nearly identical results and allows for more straightforward production of Figures 1 and 2. For code, see https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/tree/master/scripts/stata

4 Variables

Name	Description	Source	Alternative field names
cityname	City name.		CITYNAME
wht15	White alone as proportion of total population.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B03002. (July 2019)	WHT15
blc15	Black or African American alone as proportion of total population.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B03002. (July 2019)	BLC15
lat15	Hispanic or Latino/a American alone as proportion of total population.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B03002. (July 2019)	LAT15
asi15	Asian alone as proportion of total population.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B03002. (July 2019)	ASIA15
oth15	Other as proportion of total population.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B03002. (July 2019)	
pov15	Income in the Past 12 Months Below Poverty Level as proportion of total population for whom poverty status Is determined.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B17021. (July 2019)	POV15
frn15	Foreign born as proportion of total population.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B99051. (July 2019)	FRN15
ump15	Employment rate as civilian labor force employed as proportion of total civilian labor force population.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B23025. (July 2019)	UMP15
edu15	Education level as proportion of population 25 years and over with doctorate degree.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B15003. (July 2019)	EDU15
own15	Home owner ship as proportion of population in owner occupied housing, from the total population living in occupied housing units.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B25008. (July 2019)	OWN15
blb00	Built before 2000 as proportion of total housing units built before 2000.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B25036. (July 2019)	BLB00
hu15	Housing units.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B25001. (July 2019)	HU15
hu15sqk	Housing units per square kilometer.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B25001. (July 2019)	
vacrat15	Proportion of housing units not occupied.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Tables B25004, B25001 . (July 2019)	VACRAT15
ppdnl15	Population density; Total population, expressed as natural log.	U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B03002. (July 2019)	POPDEN_NATLOG15
cmdnpcpt	Commercial density; Number of commercial establishments per 1,000 total population of occupied housings.	Google Places API, U.S. Census Bureau (2016). 2015-2011 American Community Survey 5 year estimate. Table B03002. (July 2019)	COMDENPERCAPT

5 Regression coefficients

A. Coefficients, standard errors, and odds ratios for Figures 1 and 2

Table 1a. Coefficients predicting log odds that nearest AFI will be closer than nearest bank, **car travel**

	(1)		(2)		(3)		(4)		(5)	
	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds
blc15	0.0273***	1.028***	0.0247***	1.025***	0.0246***	1.025***	0.0163***	1.016***	0.0162***	1.016***
	(0.00228)		(0.00212)		(0.00213)		(0.00278)		(0.00278)	
lat15	0.0207***	1.021***	0.0176***	1.018***	0.0177***	1.018***	0.00731	1.007	0.00727	1.007
	(0.00273)		(0.00277)		(0.00401)		(0.00417)		(0.00413)	
asi15	-0.00451	0.995	-0.00573	0.994	-0.00466	0.995	-0.00534	0.995	-0.00532	0.995
	(0.00996)		(0.00953)		(0.0104)		(0.0105)		(0.0105)	
oth15	0.0176	1.018	0.0147	1.015	0.0145	1.015	0.00809	1.008	0.00805	1.008
	(0.0147)		(0.0147)		(0.0145)		(0.0153)		(0.0152)	
pov15			0.00880***	1.009***	0.00832***	1.008***	0.00758*	1.008*	0.00762*	1.008*
			(0.00253)		(0.00245)		(0.00331)		(0.00332)	
frn15					0.00105	1.001	0.000116	1.000	0.000104	1.000
					(0.00667)		(0.00573)		(0.00573)	
ppdnl15					-0.176*	0.838*	-0.0696	0.933	-0.0745	0.928
					(0.0897)		(0.0857)		(0.0867)	
edu15							-0.0211***	0.979***	-0.0211***	0.979***
							(0.00634)		(0.00633)	
ump15							-0.00306	0.997	-0.00307	0.997
							(0.00386)		(0.00387)	
own15							0.00239	1.002	0.00233	1.002
							(0.00255)		(0.00254)	
hu15sqk							-0.000120***	1.000***	-0.000122***	1.000***
							(0.0000251)		(0.0000249)	
vacrat15							0.00738	1.007	0.00688	1.007
							(0.00382)		(0.00403)	
blb00							-0.00321	0.997	-0.00322	0.997
							(0.00332)		(0.00331)	
cmdnpcpt									-1.110	0.329
									(1.855)	
_cons	-4.671***		-4.696***		-3.451***		-2.830***		-2.774***	
	(0.263)		(0.264)		(0.658)		(0.716)		(0.721)	
lnsig2u	-0.293	0.746	-0.318	0.728	-0.295	0.744	-0.586	0.557	-0.588	0.555
	(0.307)		(0.313)		(0.336)		(0.319)		(0.320)	
N	21852		21824		21824		21800		21800	

Models behind Figures 1 and 2, car travel. To create the figures, we include proportion white and suppress the constant. This modification does not alter the results but eases production of marginal effects. In each model, left column presents logit coefficients with standard errors in parentheses; right column presents odds ratios.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1b. Coefficients predicting log odds that nearest AFI will be closer than nearest bank, **foot travel**.

	(1)		(2)		(3)		(4)		(5)	
	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds
blc15	0.0253***	1.026***	0.0231***	1.023***	0.0229***	1.023***	0.0172***	1.017***	0.0171***	1.017***
	(0.00169)		(0.00139)		(0.00138)		(0.00181)		(0.00178)	
lat15	0.0259***	1.026***	0.0231***	1.023***	0.0220***	1.022***	0.0147***	1.015***	0.0146***	1.015***
	(0.00136)		(0.00150)		(0.00231)		(0.00295)		(0.00294)	
asi15	0.00145	1.001	0.000147	1.000	-0.00186	0.998	-0.00300	0.997	-0.00298	0.997
	(0.00408)		(0.00391)		(0.00279)		(0.00307)		(0.00306)	
oth15	0.0128*	1.013*	0.0112*	1.011*	0.0105**	1.011**	0.00769	1.008	0.00765	1.008
	(0.00504)		(0.00470)		(0.00400)		(0.00451)		(0.00450)	
pov15			0.00815***	1.008***	0.00809***	1.008***	0.00539***	1.005***	0.00546***	1.005***
			(0.00125)		(0.00117)		(0.00108)		(0.00106)	
frn15					0.00471	1.005	0.00248	1.002	0.00246	1.002
					(0.00602)		(0.00349)		(0.00350)	
ppdnl15					-0.171**	0.843**	-0.0744	0.928	-0.0842	0.919
					(0.0664)		(0.0855)		(0.0858)	
edu15							-0.0141***	0.986***	-0.0141***	0.986***
							(0.00332)		(0.00332)	
ump15							-0.00131	0.999	-0.00130	0.999
							(0.00317)		(0.00317)	
own15							0.000191	1.000	0.0000984	1.000
							(0.00117)		(0.00116)	
hu15sqk							-0.0000151	1.000	-0.0000162	1.000
							(0.0000389)		(0.0000389)	
vacrat15							0.00396	1.004	0.00283	1.003
							(0.00230)		(0.00215)	
blb00							0.00763***	1.008***	0.00760***	1.008***
							(0.00167)		(0.00167)	
cmdnpcpt									-1.885*	0.152*
									(0.861)	
_cons	-2.989***		-3.025***		-1.838*		-2.371**		-2.264**	
	(0.318)		(0.313)		(0.724)		(0.855)		(0.855)	
lnsig2u	-1.343*	0.261*	-1.482*	0.227*	-1.425*	0.241*	-1.607*	0.200*	-1.610*	0.200*
	(0.628)		(0.669)		(0.689)		(0.629)		(0.629)	
N	21852		21824		21824		21800		21800	

Models behind Figures 1 and 2, car travel. To create the figures, we include proportion white and suppress the constant. This modification does not alter the results but eases production of marginal effects. In each model, left column presents logit coefficients with standard errors in parentheses; right column presents odds ratios.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1c. Coefficients predicting log odds that nearest AFI will be closer than nearest bank, **public transit travel**.

	(1)		(2)		(3)		(4)		(5)	
	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds
blc15	0.0251***	1.025***	0.0233***	1.024***	0.0231***	1.023***	0.0180***	1.018***	0.0179***	1.018***
	(0.00159)		(0.00144)		(0.00138)		(0.00175)		(0.00175)	
lat15	0.0256***	1.026***	0.0233***	1.024***	0.0226***	1.023***	0.0157***	1.016***	0.0157***	1.016***
	(0.00144)		(0.00154)		(0.00257)		(0.00318)		(0.00318)	
asi15	0.000359	1.000	-0.000793	0.999	-0.00194	0.998	-0.00306	0.997	-0.00304	0.997
	(0.00403)		(0.00391)		(0.00309)		(0.00325)		(0.00324)	
oth15	0.0104	1.010	0.00917	1.009	0.00878	1.009	0.00626	1.006	0.00622	1.006
	(0.00563)		(0.00553)		(0.00495)		(0.00542)		(0.00541)	
pov15			0.00684***	1.007***	0.00679***	1.007***	0.00615***	1.006***	0.00622***	1.006***
			(0.00132)		(0.00132)		(0.00120)		(0.00118)	
frn15					0.00296	1.003	0.00130	1.001	0.00126	1.001
					(0.00583)		(0.00370)		(0.00371)	
ppdnl15					-0.122*	0.885*	-0.0523	0.949	-0.0622	0.940
					(0.0548)		(0.0678)		(0.0688)	
edu15							-0.0136***	0.987***	-0.0135***	0.987***
							(0.00303)		(0.00302)	
ump15							-0.00325	0.997	-0.00323	0.997
							(0.00326)		(0.00326)	
own15							0.00219	1.002	0.00210	1.002
							(0.00122)		(0.00121)	
hu15sqk							-0.00000702	1.000	-0.00000811	1.000
							(0.0000343)		(0.0000343)	
vacrat15							0.00261	1.003	0.00141	1.001
							(0.00184)		(0.00202)	
blb00							0.00440*	1.004*	0.00437*	1.004*
							(0.00188)		(0.00188)	
cmdnpcpt									-1.970**	0.139**
									(0.741)	
_cons	-3.003***		-3.031***		-2.186***		-2.400**		-2.291**	
	(0.337)		(0.336)		(0.634)		(0.759)		(0.776)	
lnsig2u	-1.664*	0.189*	-1.802*	0.165*	-1.760*	0.172*	-1.983**	0.138**	-1.991**	0.137**
	(0.758)		(0.828)		(0.842)		(0.716)		(0.722)	
N	21362		21336		21336		21313		21313	

Models behind Figures 1 and 2, car travel. To create the figures, we include proportion white and suppress the constant. This modification does not alter the results but eases production of marginal effects. In each model, left column presents logit coefficients with standard errors in parentheses; right column presents odds ratios.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B. Supplementary analyses—travel time to nearest AFI, and travel time to nearest bank

Table 2a. Coefficients predicting travel time to **nearest AFI**, by form of travel.

	Car				Foot				Public Transit			
	(1)		(2)		(1)		(2)		(1)		(2)	
	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds
blc15	-0.0149***	0.985***	-0.0124***	0.988***	-0.160***	0.852***	-0.137***	0.872***	-0.142***	0.867***	-0.119***	0.888***
	(0.000550)		(0.000690)		(0.00660)		(0.00830)		(0.00647)		(0.00815)	
lat15	-0.0247***	0.976***	-0.0164***	0.984***	-0.274***	0.760***	-0.191***	0.826***	-0.237***	0.789***	-0.172***	0.842***
	(0.000581)		(0.000882)		(0.00697)		(0.0106)		(0.00671)		(0.0103)	
asi15	-0.00441***	0.996***	0.00157	1.002	-0.0383**	0.962**	0.00924	1.009	-0.0689***	0.933***	-0.0471**	0.954**
	(0.00116)		(0.00136)		(0.0139)		(0.0164)		(0.0134)		(0.0159)	
oth15	-0.0115**	0.989**	-0.0110**	0.989**	-0.0969*	0.908*	-0.102*	0.903*	-0.134**	0.875**	-0.147***	0.863***
	(0.00353)		(0.00334)		(0.0422)		(0.0400)		(0.0407)		(0.0389)	
pov15			-0.00621***	0.994***			-0.0777***	0.925***			-0.0700***	0.932***
			(0.00113)				(0.0136)				(0.0133)	
frn15			-0.0115***	0.989***			-0.102***	0.903***			-0.0568***	0.945***
			(0.00122)				(0.0147)				(0.0143)	
ppdnl15			0.369***	1.446***			3.768***	43.28***			3.375***	29.23***
			(0.0274)				(0.329)				(0.322)	
edu15			-0.00369***	0.996***			-0.0468***	0.954***			-0.0371***	0.964***
			(0.000931)				(0.0112)				(0.0109)	
ump15			0.00578**	1.006**			0.0782***	1.081***			0.0667**	1.069**
			(0.00182)				(0.0219)				(0.0216)	
own15			0.0156***	1.016***			0.170***	1.186***			0.144***	1.155***
			(0.000603)				(0.00724)				(0.00706)	
hu15sqk			-0.0000366***	1.000***			-0.000451***	1.000***			-0.000204***	1.000***
			(0.00000406)				(0.0000488)				(0.0000474)	
vacrat15			0.00204	1.002			0.0187	1.019			-0.00807	0.992
			(0.00156)				(0.0187)				(0.0185)	
blb00			-0.0248***	0.976***			-0.318***	0.728***			-0.308***	0.735***
			(0.000891)				(0.0107)				(0.0104)	
cmdnpcpt			-1.105**	0.331**			-12.94*	0.00000240*			-18.21***	1.24e-08***
			(0.429)				(5.149)				(5.024)	
_cons	4.301***		3.132***		43.55***		37.25***		39.05***		35.48***	
	(0.260)		(0.324)		(3.190)		(3.976)		(3.362)		(4.180)	
sigma_u												
_cons	1.121***		0.888***		13.79***		11.21***		14.16***		12.51***	
	(0.183)		(0.145)		(2.247)		(1.831)		(2.369)		(2.095)	
sigma_e												
_cons	1.979***		1.860***		23.75***		22.35***		22.84***		21.69***	
	(0.00949)		(0.00893)		(0.114)		(0.107)		(0.111)		(0.105)	
N	21760		21711		21756		21707		21362		21313	

In each model, left column presents logit coefficients with standard errors in parentheses; right column presents odds ratios. After controls, race differences in travel times to nearest AFI remain.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2b. Coefficients predicting travel time to **nearest bank**, by form of travel.

	Car				Foot				Public Transit			
	(1)		(2)		(1)		(2)		(1)		(2)	
	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds	β (SE)	Odds
blc15	0.00222***	1.002***	-0.0000978	1.000	0.0299***	1.030***	0.00137	1.001	0.0153***	1.015***	-0.00609	0.994
	(0.000356)		(0.000453)		(0.00336)		(0.00419)		(0.00323)		(0.00403)	
lat15	-0.00196***	0.998***	-0.00235***	0.998***	-0.00770*	0.992*	-0.0185***	0.982***	-0.0204***	0.980***	-0.0288***	0.972***
	(0.000376)		(0.000578)		(0.00355)		(0.00535)		(0.00335)		(0.00510)	
asi15	-0.00407***	0.996***	-0.00216*	0.998*	-0.0358***	0.965***	-0.0170*	0.983*	-0.0312***	0.969***	-0.0189*	0.981*
	(0.000750)		(0.000894)		(0.00708)		(0.00827)		(0.00668)		(0.00787)	
oth15	-0.000577	0.999	-0.000482	1.000	-0.00993	0.990	-0.0128	0.987	-0.0152	0.985	-0.0215	0.979
	(0.00228)		(0.00218)		(0.0215)		(0.0202)		(0.0203)		(0.0193)	
pov15			-0.000365	1.000			0.000866	1.001			-0.00722	0.993
			(0.000742)				(0.00687)				(0.00660)	
frn15			-0.00657***	0.993***			-0.0644***	0.938***			-0.0477***	0.953***
			(0.000801)				(0.00741)				(0.00706)	
ppdnl15			0.170***	1.185***			1.374***	3.950***			1.160***	3.191***
			(0.0179)				(0.166)				(0.159)	
edu15			-0.00928***	0.991***			-0.101***	0.903***			-0.0838***	0.920***
			(0.000611)				(0.00565)				(0.00541)	
ump15			0.00244*	1.002*			0.0271*	1.027*			0.0212*	1.021*
			(0.00120)				(0.0111)				(0.0107)	
own15			0.0104***	1.010***			0.102***	1.108***			0.0823***	1.086***
			(0.000394)				(0.00365)				(0.00350)	
hu15sqk			-0.0000111***	1.000***			-0.0000583*	1.000*			-0.0000438	1.000
			(0.00000267)				(0.0000247)				(0.0000235)	
vacrat15			0.00108	1.001			0.00938	1.009			-0.00488	0.995
			(0.00102)				(0.00947)				(0.00917)	
blb00			-0.0119***	0.988***			-0.122***	0.885***			-0.114***	0.893***
			(0.000582)				(0.00539)				(0.00516)	
cmdnpcpt			-1.695***	0.184***			-15.79***	0.0000001***			-14.47***	0.0000005***
			(0.281)				(2.604)				(2.488)	
_cons	2.103***		1.849***		17.24***		17.72***		16.06***		17.73***	
	(0.153)		(0.203)		(1.590)		(1.989)		(1.534)		(1.930)	
sigma_u												
_cons	0.659***		0.515***		6.868***		5.539***		6.449***		5.325***	
	(0.108)		(0.0843)		(1.119)		(0.905)		(1.080)		(0.894)	
sigma_e												
_cons	1.284***		1.223***		12.12***		11.32***		11.42***		10.74***	
	(0.00615)		(0.00586)		(0.0580)		(0.0542)		(0.0553)		(0.0520)	
N	21852		21800		21852		21800		21362		21313	

In each model, left column presents logit coefficients with standard errors in parentheses; right column presents odds ratios. After controls, black-white differences in travel times to nearest bank disappear; some of the other race differences remain.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C. Supplementary analyses—Effects of specific covariates

Table 3a. Coefficients predicting log odds that AFI is closer **by foot**, previously unpacked covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foot							
blc15	**0.0167*** **	**0.0226*** **	**0.0227*** **	**0.0223*** **	**0.0226*** **	**0.0226*** **	**0.0171*** **
	(0.00181)	**(0.00153)**	**(0.00136)**	**(0.00172)**	**(0.00137)**	**(0.00135)**	**(0.00178)**
lat15	**0.0141*** **	**0.0219*** **	**0.0218*** **	**0.0217*** **	**0.0219*** **	**0.0215*** **	**0.0146*** **
	(0.00282)	**(0.00216)**	**(0.00227)**	**(0.00169)**	**(0.00231)**	**(0.00241)**	**(0.00294)**
asi15	-0.00368	-0.00186	-0.00190	-0.00206	-0.00192	-0.00120	-0.00298
	(0.00278)	(0.00278)	(0.00269)	(0.00274)	(0.00276)	(0.00257)	(0.00306)
oth15	0.00664	0.0104*	0.0106**	0.00977*	0.0104**	0.0114**	0.00765
	(0.00429)	(0.00415)	(0.00401)	(0.00459)	(0.00396)	(0.00401)	(0.00450)
pov15	0.00498**	0.00764***	0.00919***	0.00860***	0.00794***	0.00800***	0.00546***
	(0.00156)	(0.00152)	(0.00158)	(0.000927)	(0.00116)	(0.00105)	(0.00106)
frn15	0.00325	0.00477	0.00488	0.00455	0.00468	0.00398	0.00246
	(0.00528)	(0.00578)	(0.00540)	(0.00432)	(0.00592)	(0.00623)	(0.00350)
ppndnl15	-0.163*	-0.169*	-0.173*	-0.162	-0.171*	-0.125*	-0.0842
	(0.0665)	(0.0665)	(0.0719)	(0.0946)	(0.0687)	(0.0543)	(0.0858)
cmdnpcpt	-2.292**	-2.311**	-2.341**	-2.468**	-1.995*	-2.177**	-1.885*
	(0.860)	(0.815)	(0.822)	(0.853)	(0.816)	(0.842)	(0.861)
edu15	**-0.0155*** **						**-0.0141*** **
	(0.00264)						**(0.00332)**
ump15		**0.00214**					**-0.00130**
		(0.00343)					**(0.00317)**
own15			**0.00136**				**0.0000984**
			(0.00256)				**(0.00116)**
hu15sqk				**-0.0000262**			**-0.0000162**
				(0.0000399)			**(0.0000389)**
vacrat15					**0.00186**		**0.00283**
					(0.00204)		**(0.00215)**
blb00						**0.00842*** **	**0.00760*** **
						(0.00185)	**(0.00167)**
_cons	-0.941	-1.843*	-1.895*	-1.840*	-1.830*	-2.883***	-2.264**
	(0.735)	(0.722)	(0.845)	(0.772)	(0.752)	(0.608)	(0.855)
/							
lnsig2u	-1.592*	-1.433*	-1.457*	-1.505*	-1.451*	-1.402*	-1.610*
	(0.668)	(0.693)	(0.687)	(0.636)	(0.691)	(0.693)	(0.629)
N	21822	21815	21824	21824	21811	21811	21800

Table 3b. Coefficients predicting log odds that AFI is closer by **public transit**, unpacked covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Publ. transit							
blc15	**0.0173*****	**0.0230*****	**0.0229*****	**0.0226*****	**0.0230*****	**0.0229*****	**0.0179*****
	(0.00176)	**(0.00156)**	**(0.00136)**	**(0.00164)**	**(0.00138)**	**(0.00137)**	**(0.00175)**
lat15	**0.0152*****	**0.0226*****	**0.0224*****	**0.0224*****	**0.0226*****	**0.0223*****	**0.0157*****
	(0.00298)	**(0.00244)**	**(0.00264)**	**(0.00192)**	**(0.00259)**	**(0.00266)**	**(0.00318)**
asi15	-0.00358	-0.00188	-0.00204	-0.00218	-0.00194	-0.00142	-0.00304
	(0.00302)	(0.00313)	(0.00304)	(0.00305)	(0.00305)	(0.00291)	(0.00324)
oth15	0.00518	0.00882	0.00905	0.00809	0.00868	0.00934	0.00622
	(0.00535)	(0.00506)	(0.00503)	(0.00542)	(0.00490)	(0.00482)	(0.00541)
pov15	0.00391**	0.00668***	0.00938***	0.00732***	0.00670***	0.00655***	0.00622***
	(0.00140)	(0.00150)	(0.00174)	(0.00141)	(0.00128)	(0.00132)	(0.00118)
frn15	0.00164	0.00283	0.00341	0.00281	0.00299	0.00248	0.00126
	(0.00520)	(0.00557)	(0.00535)	(0.00427)	(0.00580)	(0.00597)	(0.00371)
ppdnl15	-0.116*	-0.120*	-0.117*	-0.111	-0.128*	-0.0883	-0.0622
	(0.0547)	(0.0544)	(0.0593)	(0.0786)	(0.0546)	(0.0475)	(0.0688)
cmdnpcpt	-2.080**	-2.085**	-2.153**	-2.271***	-2.159**	-2.158**	-1.970**
	(0.703)	(0.675)	(0.699)	(0.677)	(0.814)	(0.706)	(0.741)
edu15	**-0.0145*****						**-0.0135*****
	(0.00235)						**(0.00302)**
ump15		**0.000300**					**-0.00323**
		(0.00351)					**(0.00326)**
own15			**0.00315**				**0.00210**
			(0.00189)				**(0.00121)**
hu15sqk				**-0.0000265**			**-0.00000811**
				(0.0000337)			**(0.0000343)**
vacrat15					**0.000140**		**0.00141**
					(0.00212)		**(0.00202)**
blb00						**0.00548*****	**0.00437***
						(0.00163)	**(0.00188)**
_cons	-1.333*	-2.180***	-2.423***	-2.196**	-2.116**	-2.876***	-2.291**
	(0.641)	(0.637)	(0.704)	(0.683)	(0.659)	(0.600)	(0.776)
/							
lnsig2u	-1.963*	-1.778*	-1.835*	-1.880**	-1.773*	-1.717*	-1.991**
	(0.815)	(0.858)	(0.820)	(0.720)	(0.840)	(0.845)	(0.722)
N	21334	21327	21336	21336	21324	21324	21313

Table 3c. Coefficients predicting log odds that AFI is closer **by car**, previously unpacked covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Car							
blc15	**0.0160*** **	**0.0245*** **	**0.0244*** **	**0.0237*** **	**0.0241*** **	**0.0244*** **	**0.0162*** **
	(0.00271)	**(0.00219)**	**(0.00216)**	**(0.00202)**	**(0.00221)**	**(0.00216)**	**(0.00278)**
lat15	**0.00639**	**0.0179*** **	**0.0172*** **	**0.0172*** **	**0.0177*** **	**0.0178*** **	**0.00727**
	(0.00458)	**(0.00399)**	**(0.00382)**	**(0.00387)**	**(0.00397)**	**(0.00405)**	**(0.00413)**
asi15	-0.00550	-0.00396	-0.00472	-0.00467	-0.00481	-0.00514	-0.00532
	(0.0104)	(0.0105)	(0.0103)	(0.0104)	(0.0104)	(0.0106)	(0.0105)
oth15	0.00862	0.0149	0.0152	0.0129	0.0140	0.0139	0.00805
	(0.0149)	(0.0147)	(0.0144)	(0.0151)	(0.0145)	(0.0140)	(0.0152)
pov15	0.00428	0.00837**	0.0111***	0.00992***	0.00756***	0.00854***	0.00762*
	(0.00263)	(0.00298)	(0.00322)	(0.00243)	(0.00216)	(0.00235)	(0.00332)
frn15	-0.0000538	0.000332	0.00214	0.00147	0.000757	0.00112	0.000104
	(0.00638)	(0.00670)	(0.00651)	(0.00604)	(0.00672)	(0.00674)	(0.00573)
ppdnl15	-0.150	-0.155	-0.168	-0.137	-0.139	-0.207**	-0.0745
	(0.0895)	(0.100)	(0.0881)	(0.0917)	(0.0971)	(0.0721)	(0.0867)
cmdnpcpt	-1.571	-1.731	-1.782	-2.396	-0.775	-1.505	-1.110
	(1.990)	(2.007)	(2.061)	(2.054)	(1.874)	(1.944)	(1.855)
edu15	**-0.0221*** **						**-0.0211*** **
	(0.00638)						**(0.00633)**
ump15		**0.000520**					**-0.00307**
		(0.00436)					**(0.00387)**
own15			**0.00368**				**0.00233**
			(0.00237)				**(0.00254)**
hu15sqk				**-0.000163*** **			**-0.000122*** **
				(0.0000267)			**(0.0000249)**
vacrat15					**0.00627**		**0.00688**
					(0.00426)		**(0.00403)**
blb00						**-0.00300**	**-0.00322**
						(0.00342)	**(0.00331)**
_cons	-2.352**	-3.593***	-3.750***	-3.535***	-3.752***	-2.952***	-2.774***
	(0.748)	(0.737)	(0.614)	(0.686)	(0.753)	(0.486)	(0.721)
/							
lnsig2u	-0.314	-0.303	-0.316	-0.586	-0.323	-0.318	-0.588
	(0.330)	(0.341)	(0.336)	(0.328)	(0.337)	(0.334)	(0.320)
N	21822	21815	21824	21824	21811	21811	21800

6 Data and replication code links

Dataset S1 (external link): Data and Replication Code for Calculating Access

https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/tree/master/scripts/python

Dataset S2 (external link): Data and Replication Code for the Random Effects Analysis of Time-Based Proximities to Banks and AFIs

https://github.com/urbaninformaticsandresiliencelab/bnk_afi_si/tree/master/scripts/stata