Modeling the Efficacy of the 15-Minute City Using Large-Scale Mobility Data from the Perspective of Accessibility and User Choice: A Case Study on the Urban Food Environment

by

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Abstract

The growing popularity and adoption of the 15-minute city, a concept aimed at improving physical accessibility to services and amenities, indicates a global effort towards making cities more equitable and sustainable. However, at it's core, the 15-minute city implies that accessibility can be quantified by proximity, and that people are more likely to visit amenities that are physically closer to them. In this study, we investigate the relationship between choice and spatial proximity in the context of healthy food accessibility by modeling an individual's choice to visit their closest grocery store, and the extent to which certain sociodemographic variables contribute to their choice.

Using logistic regression models on $\sim 7M$ grocery store visits from $\sim 72,000$ people in the Greater Boston area, we show that proximity is not a good proxy for accessibility, and that peoples' behaviors differ widely by sociodemographic traits, time, and type of amenity. These results indicate that distance cannot be used as the primary basis of a holistic urban design or accessibility policy. Instead, effective policies will need to be tailored to specific communities and categories of amenities in order to promote sustainable and equitable cities.

Thesis Supervisor: Esteban Moro
Title: Visiting Professor

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Chapter 1

Introduction

The world is becoming increasingly urbanized and connected. By 2030, the United Nations projects that nearly 70% of the global population will be living in cities [2].As a result, efforts toward making cities more equitable and sustainable have become global priorities [1].

1.1 15-minute cities

A popular idea to make cities more inclusive is introduced by the "15-minute city" concept, which restructures cities by localizing neighborhood economies, thereby promoting socio-ecological welfare [22]. The concept addresses the well-established fact that accessibility is a major barrier to improved livelihoods. Low-income populations tend to be spatially concentrated and have less physical access to resources and opportunities [30]. The 15-minute city aims to improve physical accessibility by defining an ideal geography where most human needs can be reached within a travel distance of 15 minutes [31]. Forward-looking cities have already established plans inspired by this concept, from Paris' Ville du quart d'heure to Ottawa and Melbourne's 15/20-minute neighborhoods [3].

Theoretically, proximity to jobs, healthcare, food, housing, education, green spaces and more can save valuable time and improve accessibility. In reality, such a city can be a slippery ideal that depends on the needs to be provided within the area, the means of transport, which will determine the size of the area, and the population density, which will determine the economic feasibility [39]. Despite a lack of consistent criteria for defining its geographical boundaries, the 15-minute city at its core implies that urban access and equitable design can be quantified, whether by distance or time.

While this method will undoubtedly create hyper-local accessible neighborhoods, it is unclear whether citizens will actually make use of nearby amenities. The 15-minute city assumes the primacy of proximity over other factors such as quality or price in individual decision making. In short, it assumes that people are more likely to visit amenities that are physically closer to them. On the contrary, we hypothesize here that distance is not the primary consideration for a large number of people. Rather, their choices likely depend on a combination of the category or quality of amenities, sociodemographic traits, and other indescribable preferences. To distinguish such factors, we will investigate the relationship between choice and spatial proximity by studying venue choices made by individuals versus the closest venues available. By doing so, we hope to reveal the discrepancies between accessibility and choice amongst different sociodemographic groups and inform inclusive policy making towards the concept of 15-minute cities.

1.2 The case of food access

We test our hypothesis on a category of amenities essential to a 15-minute city, grocery stores. Food insecurity is a persistent global problem, and spatial inaccessibility serves to increase its prevalence in certain populations and geographies, particularly low income and non-white neighborhoods [40]. As a result, enhancing access to healthy food is near the top of the political agenda. The USDA defines low access to healthy food as being more than one mile from a supermarket, supercenter, or large grocery store [24]. These distance-based measures also assume that distance is a proxy for actual decisions. If that is the case, then opening more grocery stores in areas with low grocery store density should improve accessibility. However, researchers have found that despite an increase in the number of grocery stores, segregated, low-income

Figure 1-1: Choice and accessibility may not be commensurate for grocery store trips.

regions in low food access areas did not benefit, and some even experienced worse access [25]. Moreover, numerous studies have evidenced enormous diversity in food shopping behavior, particularly that shoppers often bypass grocery stores closest to their home for preferred stores further away [35, 16, 33].

The question then becomes: Do users actually go to their closest grocery stores? If so, who goes to the closest grocery stores, and what determines their choice? Given a handful of grocery stores around a person's home, the 15-minute city assumes that the person will visit a store within 15 minutes (or an arbitrary radius) of their home. However, the person could choose a store much further away, as illustrated by Figure 1-1, where the light blue dashed line represents the distance to the closest grocery store, and the dark blue solid line is the choice actually made.

Researchers have proposed various frameworks for conceptualizing food environments and different dimensions of measurement, among which are availability, accessibility, affordability, acceptability, and accommodation [15]. Most studies on healthy food environments employ the first two dimensions, which account for spatial interactions. They measure accessibility as a function of potential access to opportunity rather than retrospective records of those who actually accessed the opportunities. Few studies examine the remaining dimensions, which are more in line with determinants of individual food behaviors. The ones that do employ non-GIS based measures and are reliant on store audits or surveys to study personal preferences, which are often time-intensive, small-scale, and non-comprehensive [14].

Questions of human behavior and choices can be comprehensively answered by analyzing real mobility data. The widespread adoption and use of GPS-enabled smartphone technology has significantly enhanced scientific understanding of human mobility across vast spatial and temporal resolutions. Researchers have found that individual travel patterns are probabilistically distributed and highly predictable [14]. The application of mobility data analyses to support sustainable development and policy interventions offers insightful solutions to existing challenges, from modeling diseases to assessing income segregation [15, 16]. In the context of the 15-minute city, current research relies on the spatial arrangement of residences and amenities without considering actual behavior. Leveraging mobility data will allow us to validate such assumptions of accessibility by analyzing human choices. For instance, different socioeconomic groups exhibit different mobility patterns, which may result in one group preferring to visit grocery stores further away, and another group visiting stores closer to home.

This research presents a novel analysis of the efficacy of distance-based accessibility on different sociodemographic groups by leveraging mobility data to assess individual behavior concerning the use of opportunities rather than the potential of using them. By doing so, we hope to establish equity, in addition to access to services and amenities and the characteristics of the built environment, as a key dimension in planning the 15-minute cities of the future.

We employ a logistic regression model to investigate the probability that a person chooses their closest grocery store by distance, and to what extent certain sociodemographic variables contribute to their choice. While studies have shown that socioeconomic traits are good indicators of food access, the criteria used to select such factors vary widely [6]. However, it is well known that communities with fewer options to access healthy food tend to be predominantly racial minorities, high-poverty, and have low educational attainment rates [21]. In addition, grocery stores are more likely to be clustered in dense urban areas. Therefore, we choose race, poverty level, and population density as regression variables. Finally, we include commute time as it is often associated with obesity and lack of access to healthy food [42].

Our study aims to fill the literature gap by characterizing the relationship between choice, accessibility, and neighborhood-level sociodemographic traits using the case of healthy food access in Boston, Massachusetts. Moreover, by using large-scale mobility data, we place a greater emphasis on the degree of accessibility, preference, and choice that individuals actually experience.

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Chapter 2

Data

We acquire mobility data in partnership with Cuebiq, a privacy-compliant location intelligence company. The data consists of month-long records of de-identified and privacy-enhanced mobility data for academic research and humanitarian initiatives for 72,000 opted-in devices in the Great Boston Metropolitan area. The home area and income quantile of each individual is inferred at the census block group (CBG) level and "stays" that last longer than 5 minutes are extracted. The location data from these visits are matched with a collection of verified venues (POIs) obtained from Foursquare, giving us the category of each stay (Grocery Store, Coffee Shop, Park, Library, Office, etc.). Finally, residential location data is matched to CBG level demographic data obtained from the 2015 American Communities Survey (ASC).

2.1 Study Area

The study is conducted in the Boston-Cambridge-Newton, MA-NH core based statistical areas (CBSA), which has a population of 4.8 million people and is composed of the municipality of Boston and its surrounding areas 2-1 [12]. The area comprises 1,130 census tracts and 3,418 block groups.

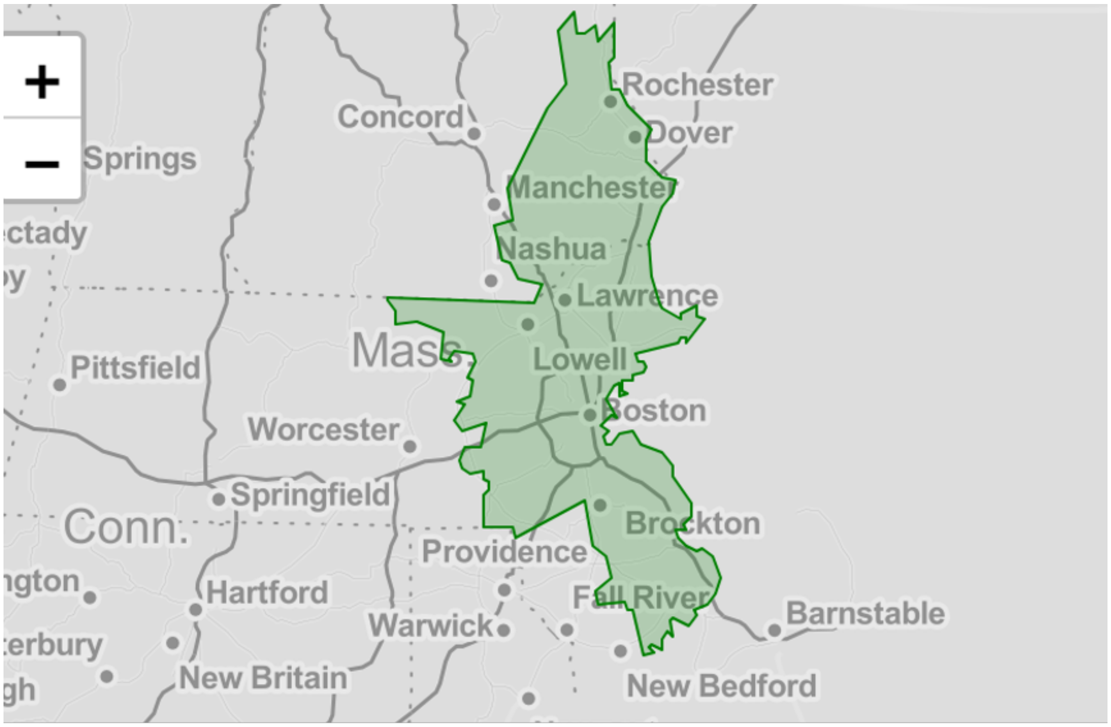

Figure 2-1: Outline of the Boston-Cambridge-Newton CBSA

2.2 Data Sources and Cleaning

2.2.1 Mobility Data

The set of stays data used in this research was acquired from Cuebiq, a location intelligence company that collates anonymized, privacy-enhanced GPS location signals from users that opt-in to data collection compliant with the GDPR and California Privacy Act framework. This data was obtained by the Human Dynamics Lab under contract through Cuebiq's Data for Good program, which allowed access to privacy-enhanced mobility data for academic research and humanitarian initiatives only.

The primary dataset consists of GPS location pings from mobile devices between October 2016 and March 2017 with 11 CBSAs. Only devices with more than 2000 pings were included in the filtering criteria. The size of the final data set includes 67.0 billion pings and 4.5 million unique de-identified smartphones.

2.2.2 Home and visits extraction

The Hariharan and Toyama algorithm was run on the extract stops from the, producing a set of clustered locations, times, and duration of stays for each individual. This was followed by a nearest-neighbor search to identify the closest venue to each cluster. We further discard visits that last for under 5 minutes or more than 1 day, and clusters that do not have a venue within a 200-meter radius. The home CBG of each individual was inferred using the 2017 5-year American Community Survey (ACS) as the device's most common location between the hours of 10:00pm and 6:00am. The CBG's median household income is then used as a proxy for assigning each individual's income quartile. Finally, users that spend less than 10 nights in their inferred home CBG are discarded from the dataset, resulting in a set of 976 million stays from 3.6 million individuals. From this primary dataset, we filtered for stays within the Boston-Cambridge-Newton CBSA for this study.

We noticed that over 30% of the visits have home origins and POI destinations located within the same CBG, implying that the destination is close to the home. To avoid miscounting a user's home as a visit, we filtered for visits where the destination was more than 50 meters from the user's home, and where the visit time was less than 1.5 hours. This resulted in a dataset of 7.1 million visits from 72,834 unique users.

2.2.3 Data Filtering

We found that the Foursquare categorization of "Grocery Stores" and "Markets" are not in line with conventional definitions of grocery stores. For example, Seven-Eleven's "7-11", along with liquor stores and other convenience stores were classified as grocery stores. Thus, we extracted the list of all grocery-related categories (Supermarket, Grocery Store, Market, Farmer's Market, Convenience Store, Fruit & Vegetable Store, Butcher, Fish Market, Organic Grocery) in the dataset and manually labeled each POI as either a full-service or non-full-service store. The criteria used to define a store as full-service included whether it was a supermarket, whether it displayed a variety of fresh meats, vegetables, and frozen or shelved pantry items. Finally, to

Table 2.1: Distribution of distance from home to POI (km)

	Grocery Stores	Post Offices
n	241,168	30,832
Mean	8.66	11.72
STD	11.77	13.46
Min	0.05	0.05
25%	1.93	2.11
50%	4.30	6.77
75%	10.14	16.75
Max	159.43	137.09

ensure the validity of POIs, we filtered for those stores that were either verified or had at least 5 check-ins on Foursquare. After the selection process, we found 628 full-service grocery stores corresponding to 241,168 stays from 35,782 unique users in the data.

For the placebo category, Post Offices, we followed a similar filtering criterion without a manual labeling process, which resulted in 30,832 stays from 9,484 unique users. A descriptive summary of the Euclidean distance from users' homes to their POIs of choice in the two categories are shown in Table 2.1.

2.2.4 Demographic Variables

We extracted demographic data on Massachusetts CBGs using the 2015 American Community Survey. CBGs consist of clusters of blocks within the same census tract that are generally defined to contain between 600 and 3,000 people [11]. The granularity of such data is between the level of census tracts and census blocks. A description of the variables and their specific source table can be found in Table 2.2.

Table 2.2: Description and source of demographic regression variables

Name	Description	Source
wht	White alone as a proportion of the total home CBG population	U.S. Census Bureau (2017). 2015 American Community Survey 5-year estimate. Table B03002.
blk	Black or African American alone as a proportion of the total home CBG population	U.S. Census Bureau (2017). 2015 American Community Survey 5-year estimate. Table B03002.
pov_quant	Proportion of people in home CBG whose income in the past 12 months is below poverty level	U.S. Census Bureau (2017). 2015 American Community Survey 5-year estimate. Table B03002.
pop_density	Population of home CBG / area of land	U.S. Census Bureau (2017). 2015 American Community Survey 5-year estimate. Table B03002.
edu	Proportion of people 25 years and over with Bachelor's degree or higher in home CBG	U.S. Census Bureau (2017). 2015 American Community Survey 5-year estimate. Table B15003.
commute	Proportion of people in home CBG whose commute is less than 20 minutes	U.S. Census Bureau (2017). 2015 American Community Survey 5-year estimate. Table B08303.

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Chapter 3

Methodology

For each visit, we calculate the nearest POI of the same category to the user's home using the RANN package, which finds the k nearest neighbors for every point in a given dataset in $O(N \log N)$ time based on Euclidean distance. We choose the RANN package because it is based off of the Approximate Nearest Neighbors library, which is known to be highly efficient for identifying both exact and approximate nearest neighbors in high dimensional data [7].

3.1 Regression Variables

After finding the closest POI, we merge the user's home CBG with corresponding demographic data for each stay. We only take into account CBGs with a population of over 400 people in order to exclude sparsely populated areas for which we have little data.

We calculate the ratio of black and white people as a proportion of the home CBG population (wht, blk). The poverty ratio variable, $poverty\_quant$, is split into quartiles to avoid skew since there are very few CBGs with extremely high poverty ratios, but many with moderately high ratios. To control for the differences between urban and rural areas, we include the population density of each CBG as a variable by calculating the ratio of its population to its land area ($pop\_density$). The education variable, edu, is derived from the proportion of people 25 years old and over who have a Bachelor's degree or above (Master's, Professional school, or Doctorate). The commute time variable, $commute\_lt20$, is calculated from the proportion of people in the CBG who commute less than 20 minutes to work. All variables, other than the poverty ratio quartile are then transformed to align to a normal distribution.

We also considered the interaction between the proportion of white people and the income quartile. The income quartile was determined by splitting the median income of a CBG into quartiles. We did not include it as an independent variable in the regression because it was highly correlated to the poverty ratio. However, it is relevant as part of an interaction variable as there are known disparities in opportunities and behavior amongst poor and nonpoor white neighborhoods [41].

3.2 Logistic Regression

The goal of our model is to infer the probability that an individual visits their closest grocery store, and how that probability varies based on the variables described above. Our hypothesis are as follows:

$H1$: Most people do not visit their closest grocery stores.

$H2$: Certain demographic groups travel further for groceries than others.

To test these hypotheses, we run logistic regressions on the demographic variables above (wht, blk, $poverty\_quant$, $wht : quant$, $pop\_density$, edu, $commute\_lt20$) using the `statsmodels` package in Python. Our aim is to characterize the probability that a user goes to their closest POI. Thus, for each stay, we assign a label of 1 if the user went to their closest POI, and 0 otherwise.

3.2.1 Defining the Closest POI

In addition to the USDA's Food Access Research Atlas, researchers have proposed food access metrics using various transit modes, travel time estimations, and network distance [43, 23, 8, 37]. Studies have found that there is a significant positive correlation between Euclidean and street-network distances [8]. Moreover, Euclidean distance-based measures demonstrate the same relative patterns of food access as network distances, even in varying population densities, and serve as reasonable proxies for travel time [36, 32]. Among these measures, using buffer distances or proximity to the nearest food store are perhaps most prevalent to operationalizing food access research [15].

In many cases, there are multiple POIs of the same category that are approximately the same distance from the users' home. To increase robustness, we define a visit to the "closest" POI as a visit where the difference between the choice POI and actual closest POI is less than the maximum of either 120% of the closest distance or one kilometer.

We include both distance parameters in order to account for the differences in the spatial distribution of POIs. For example, there tends to be a higher concentration of grocery stores in urban areas compared to suburban or rural areas, which makes the distance to the closest grocery store from an urban resident's home much smaller than that of a suburban resident. To assuage this, we adopt an extra 20% distance radius. At the same time, the high density of grocery stores in urban areas makes it hard to distinguish the closest store. For example, if the closest store to a resident's home is 100 meters and the user chose a store 200 meters away, their choice would not fall under the 20% radius even though the difference is trivially walkable. Hence the rationale for choosing a 1km tolerance. Additionally, 1km is roughly the metric for a walkable 15-minute city [20].

A more formal characterization for modeling the probability that an individual i visits a place α (of a particular category) that is closest to their home is expressed by equation (1), where $d_{h_i \to \alpha}$ is the distance from an individual i's home (h_i) to the place α that was actually visited by i and $d_{h_i \to \alpha^*}$ is the distance from i's home to the closest place α^* of the same category.

$$\phi_i = \begin{cases} 1 \text{ if} & d_{h_i \to \alpha} \leq max(1.2 d_{h_i \to \alpha^*}, 1km) \\ 0 \text{ otherwise} & \end{cases} \tag{3.1}$$

We use the `corrplot` library to generate the correlation heatmap between regression variables, and `statsmodels` to calculate the variance inflation factor. Finally, we use `stargazer` to visualize the regressions, and `seaborn` to plot visual representations. Graphs are created using OpenStreetMap and the leaflet plugin. A detailed implementation can be found in the project Github repository.[1]

[1] https://github.com/tyl21938/accessibility_choice_groceries

Chapter 4

Results

Between the two categories, approximately 30.44% of grocery store visits were to the user's closest grocery store (or within the tolerance limit) while 29.61% of post office visits were to the closest post office from the user's home. However, the spatial distribution of these two categories is very different, as are users' preferences towards them.

4.1 Distance from home to POIs

Figure 4-1 shows the Euclidean distance distributions of the visits to grocery stores and post offices, segmented by users' income quartiles where Q1 corresponds to the

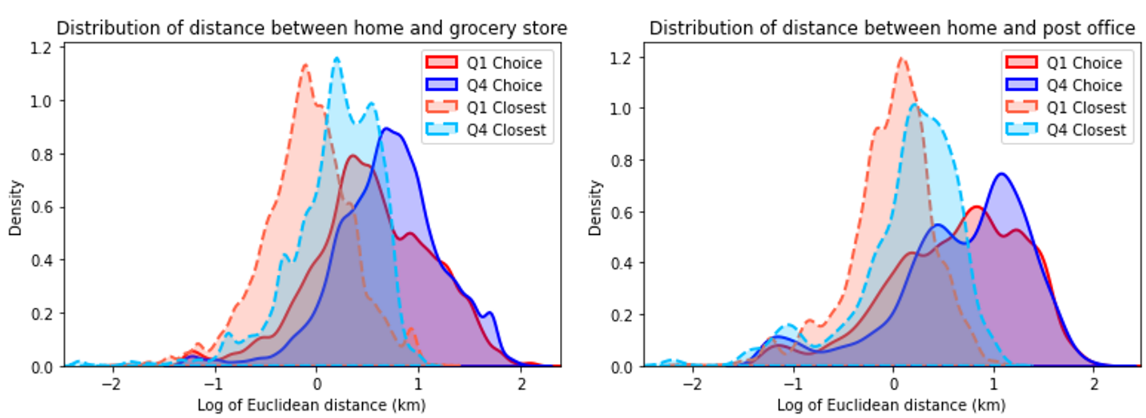

Figure 4-1: Distribution of distance between users' home and POIs of choice compared to the closest POI

lowest income and Q4 is the highest income. The distance distributions of users' closest POIs are shown in dashed lines for reference. For both categories, users choose to visit POIs further away from ones that are closest to their home. Compared to Q4, Q1 users are located closer to grocery stores and also travel a shorter distance to grocery stores. This is in line with our expectations as Q1 users likely live in more dense areas where both post offices and grocery stores are in closer proximity [4]. Similarly for post offices, we see that Q1 users live closer to post offices than Q4 users; however, there is no marked difference in the distances they travel to visit post offices as opposed to Q4.

4.2 Types of grocery stores frequented by lower- and upper-income groups

Table 4.1 shows the top 15 grocery stores visited by both Q1 and Q4 groups in the data, and table 4.2 shows the closest grocery stores to each quartile. The first three columns represent the closest grocery stores to users in the data. For each user, we find all grocery stores within the "closest" range defined above. We assign each grocery store a weight based on the number of times it appears as a proportion of the total number of "closest" grocery stores. We then order the top 15 grocery stores for each income quartile, Q1 and Q4, by relative weight to the closest stores to for all income quartiles. The choice grocery stores are ordered according to the relative percentage of visits made by each quartile (e.g. 34.4% of all Q1 visits were to Market Basket).

We see that there is significant overlap between the grocery stores closest to each quartile, and the grocery stores of choice. Specifically, large brand supermarkets such as Stop & Shop, Market Basket, and Shaw's are located "close" to all quartiles, because of the abundance of stores. At the same time, these supermarkets are frequented by both Q1 and Q4 users, because shoppers prefer supermarkets. The difference between their choice exists at the relative weights of each grocery store. For example, while

Table 4.1: Top 15 choice grocery stores by income quartile

	Q1	Q4	All Quartiles
1	Market Basket (0.344)	Market Basket (0.288)	Market Basket (0.324)
2	Stop & Shop (0.170)	Stop & Shop (0.171)	Stop & Shop (0.172)
3	Hannaford (0.086)	Whole Foods (0.108)	Shaw's (0.088)
4	Shaw's (0.074)	Shaw's (0.077)	Hannaford (0.080)
5	Whole Foods (0.042)	Roche Bros (0.046)	Whole Foods Market (0.067)
6	Star Market (0.039)	Hannaford (0.045)	Star Market (0.038)
7	Wegmans (0.017)	Star Market (0.034)	Wegmans (0.024)
8	Price Rite (0.015)	Wegmans (0.033)	Roche Bros (0.021)
9	America's Food Basket (0.012)	Sudbury Farms (0.019)	Big Y (0.013)
10	Roche Bros (0.011)	Donelan's Market (0.016)	Price Rite (0.007)
11	Tendercrop Farm (0.010)	Big Y (0.015)	Sudbury Farms (0.007)
12	Save-A-Lot (0.009)	Franklin Farmers Market (0.009)	McKinnon's Butcher Shop (0.006)
13	Big Y (0.009)	Wilson Farm (0.009)	Trader Joe's (0.005)
14	Vicente's Tropical (0.008)	Russo's (0.009)	Aldi (0.005)
15	Aldi (0.007)	Marblehead Farmers Market (0.006)	America's Food Basket (0.005)

Whole Foods, a brand known to sell healthy and higher-priced items, is visited by both quartiles, it comprises 10.8% of Q4 visits but only 4.2% of Q1 visits. For stores in close proximity, the difference exists in the type of non-branded stores. For example, Q4 residents are located closer to boutique stores (e.g. Water Fresh Farms, Wilson Farm, Strawberry Hill Farm), which are generally more expensive, while Q1 residents are closer to larger supermarkets (e.g. Seabra, Vicente's, Tesoro). Moreover, we see that Q4 people also choose to visit more boutique markets, which are smaller, gourmet, and generally non-chain stores, than Q1. These results reveal that people of different income quartiles have different preferences for, and are also surrounded by, different types of supermarkets.

4.3 Choice of closest grocery store varies by user demographics and day of week

Results from the logistic regressions on demographic variables demonstrate that the choice of going to the nearest grocery store is not uniform (Figure 4-2) across socio-

Table 4.2: Top 15 closest grocery stores by income quartile

	Q1	Q4	All Quartiles
1	Seabra (0.936)	Water Fresh Farms (0.928)	Stop & Shop (0.143)
2	Vicente's Tropical (0.761)	Wilson Farm (0.901)	Market Basket (0.128)
3	New Angkor Thom (0.718)	Strawberry Hill Farm (0.877)	Shaw's (0.091)
4	Tesoro (0.718)	Brothers Marketplace (0.720)	Hannaford (0.065)
5	Save-A-Lot (0.691)	Crosby's Marketplace (0.646)	Whole Foods Market (0.057)
6	America's Food Basket (0.674)	Indian Basket (0.620)	Star Market (0.026)
7	Haverhill Farmer's Market (0.559)	Stillman's Farm (0.586)	Roche Bros (0.023)
8	McKinnon's Butcher Shop (0.319)	Wegmans' (0.556)	Aldi (0.012)
9	Market Basket (0.303)	Sudbury Farms (0.532)	McKinnon's Butcher Shop (0.012)
10	Hannaford (0.269)	Roche Bros (0.486)	Big Y (0.008)
11	Stop & Shop (0.267)	Whole Foods (0.393)	Sudbury Farms (0.008)
12	Shaw's (0.240)	Star Market (0.278)	America's Food Basket (0.007)
13	Star Market (0.214)	Big Y (0.268)	Wegman's (0.006)
14	Aldi (0.203)	Shaw's (0.238)	Crosby's Marketplace (0.006)
15	Whole Foods (0.158)	Stop & Shop (0.188)	Stillman's Farm (0.006)

demographic groups. Instead, it varies significantly by the socio-demographic profile of the user's home CBG. We see that people living in areas with larger Black populations are less likely to choose the closest grocery store. However, the proportion of white population in the area does not play a significant role on users' choices. More specifically, a one standard deviation increase in the proportion of Blacks in a CBG results in a 13.4% decrease in the odds of visiting the closest grocery store. Conversely, people living in higher poverty areas are more likely to visit their closest grocery store (5.1% odds increase). A similar positive effect of 4.1% is seen for people living in areas with higher population density, and 7.9% for those in areas with commute times less than 20 minutes. In contrast, people in areas with higher education levels are less likely to visit their closest grocery store (7.5% odds decrease). Finally, the interaction variable tells us that for a constant proportion of white population in an area, people from higher income quartiles are more likely to visit the closest store (9.2% odds increase). In summary, people from areas with higher poverty quartile, higher proportion of high-income white population, higher population density, and shorter commute times are more likely to visit groceries stores nearby. These results show the multidimensional variability of the decision made by different groups

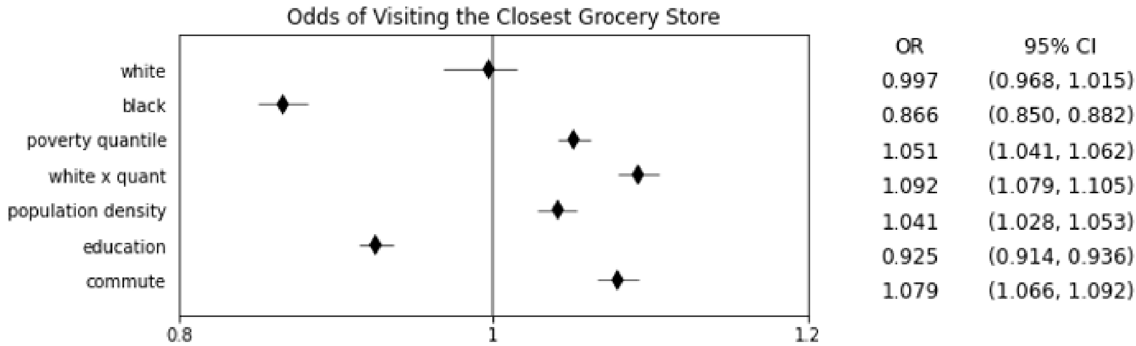

Figure 4-2: Forest plot of the odds of visiting the closest grocery store for each regression variable, with 95% confidence interval shown

to choose the nearest supermarket, with each group having different motives beyond distance.

Given the drastic spatiotemporal variation inherent to human mobility behavior, we thought it important to separate the time of grocery store visits between weekdays and weekends. It is likely that people stop for groceries on the way to or from work on weekdays, or on the way to and from leisure activities on the weekends. To better control for these temporal effects, we conducted separate regressions between weekday (Monday - Friday) and weekend (Saturday - Sunday) grocery trips (Figure 4-3).

Results from these regressions demonstrate differences in user behavior. The data indicates that, ceteris paribu, users from higher proportion black CBGs are significantly less likely to visit their closest grocery stores on both weekdays and weekends. On the other hand, we see drastic differences between the impact of the poverty quartile and education on weekdays and weekends. The effect of the poverty quantile is almost eliminated over the weekend, indicating that the poverty level of an individual is not a factor in choosing the nearest grocery store on weekends. The effect of the education variable is more pronounced on the weekend than on weekdays. On weekends, being more educated indicates a significantly lower chance of visiting the closest grocery store. It appears then that people are more constrained by time on the weekdays given the nature of the work, and thus choose to visit the nearest grocery store with a higher probability than on the weekends, particularly residents of high poverty CBGs. This same trend does not appear to be true for residents of CBGs

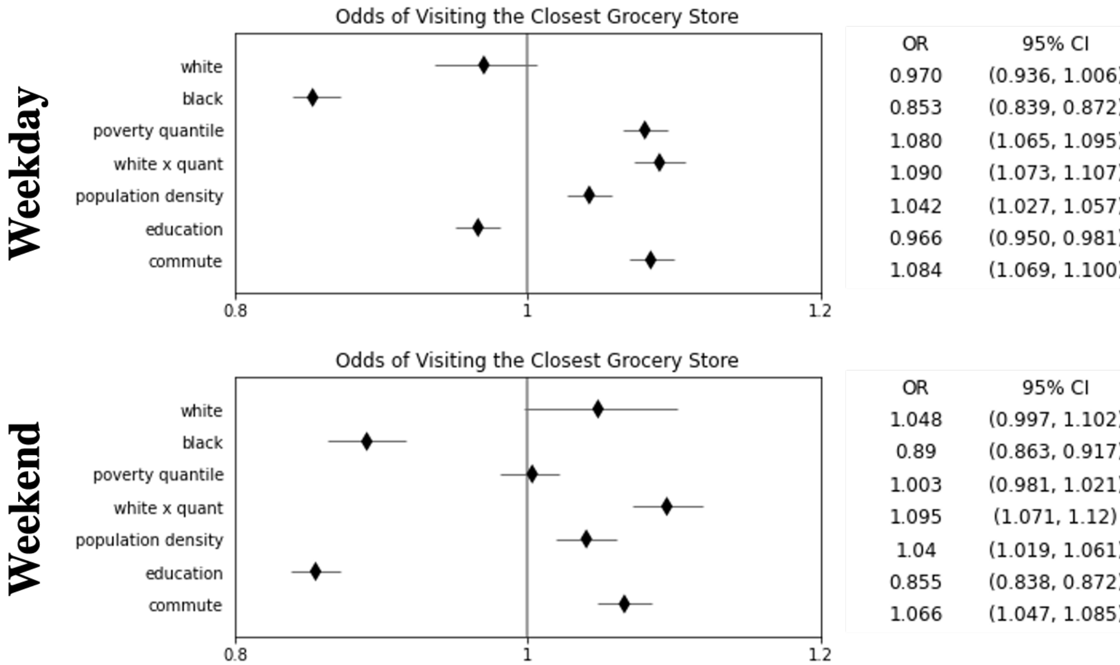

Figure 4-3: Odds of choosing the nearest Grocery Store, separated by weekdays and weekends

with high population density, likely because there are more grocery store options in more densely populated areas. The same trend is observed for residents from white and high income CBGs, perhaps because they prefer the quality of stores closer to their home. Again these results show that choice of different shopping venues is not only influence by distance, but by other temporal factors which could be due to trip bundling, more free time, etc.

4.4 Comparing Grocery Store Visits to Post Office Visits

We compare the regression coefficients of Grocery Stores against that of Post Offices between Weekdays and Weekends in Figure 4-4. We note that standard errors are larger for Post Offices, likely because the sample size of Post Office visits are a quarter that of Grocery Store visits. However, both sample sizes are in the thousands, and thus the model is unlikely to overfit on either given the number of parameters. We see that on the weekdays, the odds of visiting the closest Post Office increases significantly for rich white users, users from high-density areas, users who are more educated, and users with lower commute times. The same effect is seen on the weekends, but less pronounced.

Meanwhile, the effects of the demographic variables on Grocery Store visits are much lower. This is likely because there exists a lot more nuance when choosing to visit a grocery store compared to visiting a post office which cannot be characterized by demographics alone. We see that Black people travel further for groceries on both weekends and weekdays, while they are more likely to visit the closest post office. Rich white people travel closer to Grocery Stores and Post Offices on both time periods. The effects of poverty are insignificant on a user's decision to visit their closest Post Office, but it has a positive impact on visiting the closest Grocery Store on the weekdays. We see similar effects from the population density and commute variables between Grocery Stores and Post Offices. However, the education variable has opposing effects between the two categories. A higher education level indicates a lower chance of visiting the closest grocery store but a higher chance of visiting the closest post office. Overall, we see that most demographic variable effects in choosing the closest grocery store are dampened on the weekends, save for education. This indicates that non-demographic variables may play a larger role on the choice of grocery stores on the weekends while demographic variables explain the choice based on spatial accessibility better on the weekdays.

4.5 Effects are robust across changes in definitions of "closest" POI

There are many contending metrics found in literature and policy around the definition of a 15-minute accessible city, from modes of transport to distance and time. We decided to test the sensitivity of our model to varying distance metrics and definitions of “closest” POI and find that our model is robust to such changes.

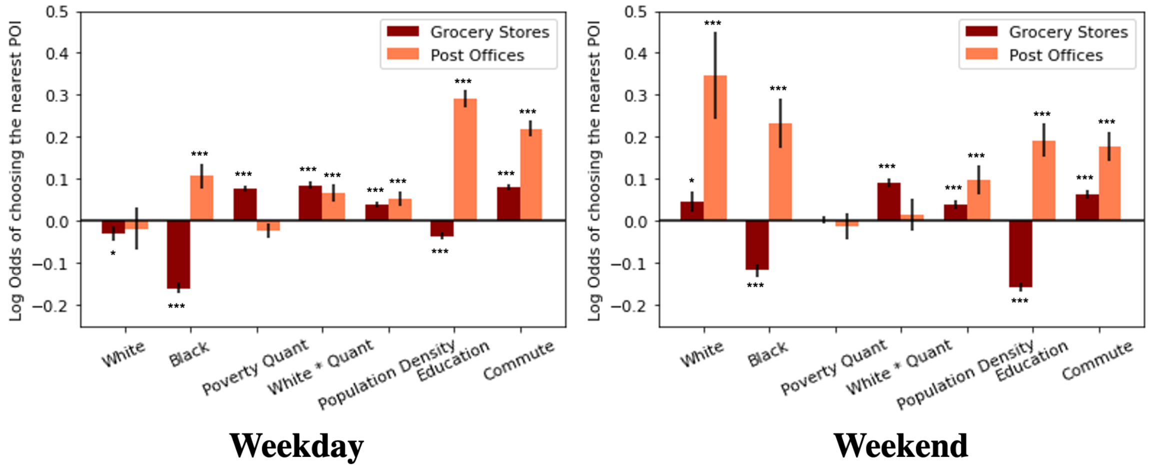

Figure 4-4: Logistic regression coefficients of the log odds of visiting the nearest POI

4.5.1 Choosing a POI within 15 minutes (5km)

A travel time of 15 minutes varies based on travel mode. It is approximately 1.2 kilometers by foot and 5 kilometers by bike, and much further by car depending on road networks [20]. However, the concept of a 15-minute city places a heavy focus on accessibility by foot or bike. Thus, we use the upper threshold of 5 kilometers to define "closest" POI and find that 55.2% Grocery Store visits and 42.8% of Post Office visits fall within this threshold. Figure 4-5 shows that people from high poverty quartiles in areas of high population density, higher education, and lower commute times are more likely to visit POIs within 5 kilometers than other demographics. The impacts of these variables are more pronounced from the previous coefficients in Figure 4-4, but display the same general trends.

We vary the above threshold between 1km and 5km, and see that coefficients converge towards lower magnitudes as the distance increases. This is likely because the effects of demographic variables become negligible for larger distances. In a densely populated metropolitan area, a 5km radius would encompass a myriad of demographic traits, as discussed below.

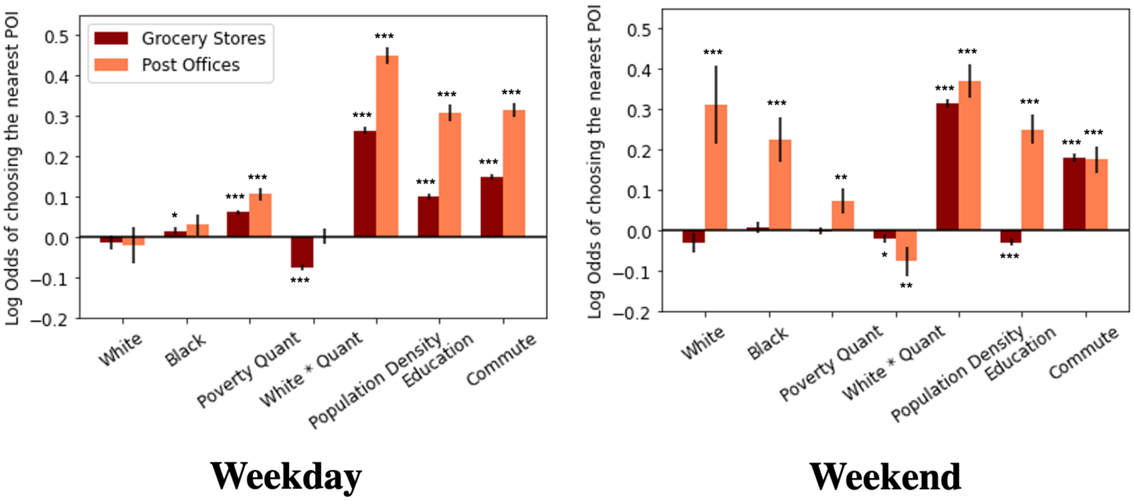

Figure 4-5: Logistic regression coefficients of the log odds of visiting a POI within 5km of home

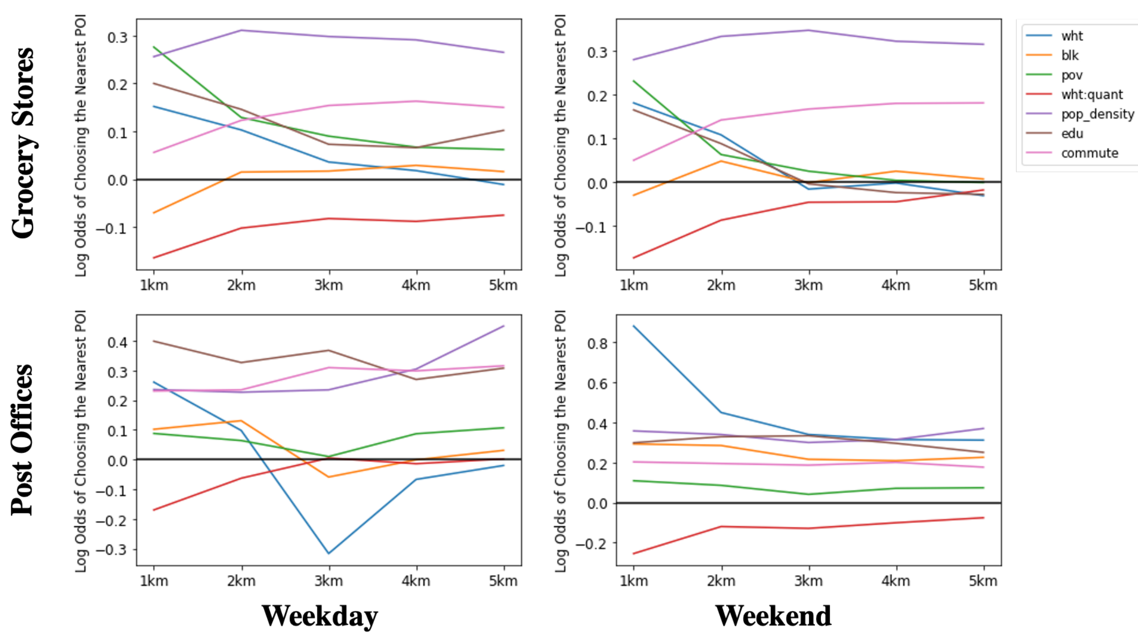

Figure 4-6: Line plot of variable coefficients at different distance thresholds

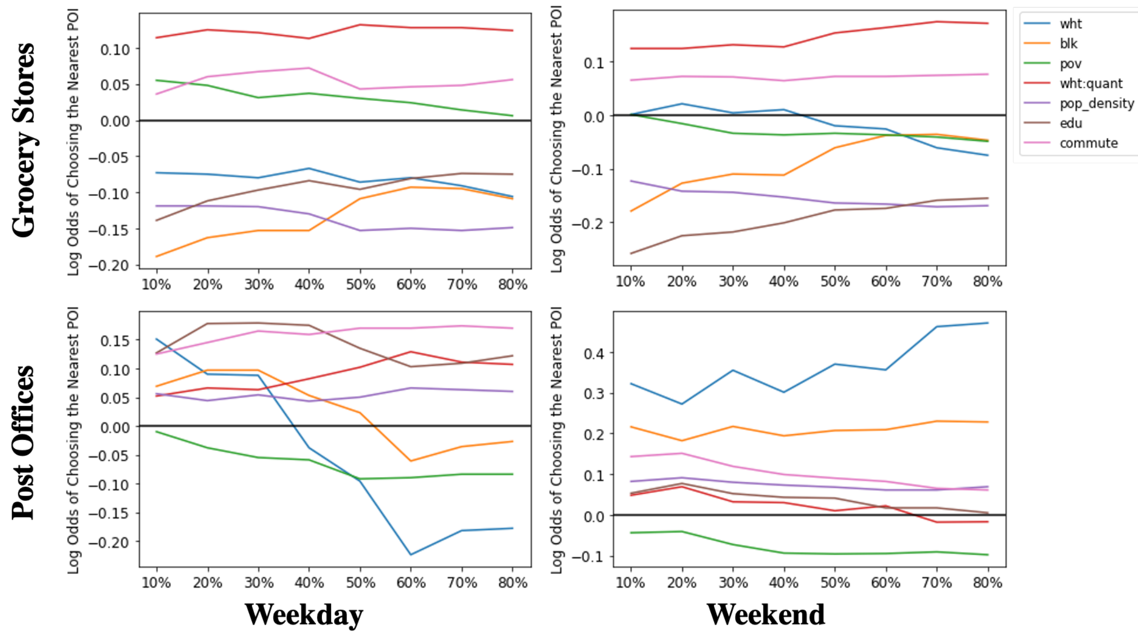

Figure 4-7: Logistic model coefficients at various percentage thresholds

4.5.2 Varying the threshold deviation of "closest" POI definition

An absolute distance-based threshold is not robust to neighborhoods with different spatial geographies and impediments. For example, a radius of 5km in downtown Boston likely includes the majority of Cambridge, Beacon Hill, South Boston, and Back Bay neighborhoods, which have many grocery store and post office offerings in addition to a diverse sociodemographic population, while the same 5km radius in Milton may include only a few. Therefore, using percentage deviations from the absolute closest POI may prove to be a more robust sensitivity measure. We define the “closest” POI as any POI within x percentage of the distance of the absolute closest POI from home. For example, if a grocery store is 1km from a user’s home, any grocery store within 1.1km of the home would fall under a 10% threshold.

Figure 4-7 shows the model’s coefficients at different percentage tolerance levels. Results indicate that the impact of most demographic variables converges as the threshold increases, especially on the weekends, which is in line with previous results.

Table 4.3: Proportion of trips to the closest POI

TABLE 4: Proportion of trips to the closest POI

	Grocery Stores		Post Offices	
	Urban	Rural	Urban	Rural
Total	27.39%	38.97%	29.37%	30.15%
Weekdays	26.63%	37.33%	27.83%	28.70%
Weekends	28.80%	42.03%	36.25%	36.05%

4.6 Effects of Differentiating Urban and Rural CBGs

While the 15-minute city concept is meant to apply to urban areas, it may serve to exacerbate inequalities between urban and rural communities if it is not inclusive. Rural areas generally have less population density and less amenities within close proximity. Using the same 20% threshold that avoids spatial variations, we test the impacts of the variables on rural and urban CBGs. We define a CBG to be urban if it has a population density of over 1000 people per square mile, in line with US Census definitions [13]. All other CBGs are classified as rural.

Using our definition of nearest, we find that a larger percentage of those in Rural areas choose their closest POIs in both categories 4.3. However, this difference is much more pronounced in the case of Grocery Stores, where the percentage of those choosing the closest store in rural areas is more than 10% higher than in urban areas. We also see a difference in the two groups' behaviors between the weekday and weekends. In general, more people tend to visit their closest grocery stores on weekends rather than weekdays; however, this difference is much larger for post offices.

We ran the logistic model separately for visits in urban and rural CBGs, removing the population density variable, and show the model coefficients in Figure 4-8. We see a drastic difference between the behavior of urban and rural populations. There are four notable differences. First, the impact of demographic variables on the decision to visit the closest grocery store or post office are much more pronounced in rural areas than in urban areas. This is particularly true for the proportion of black people in a residential area. It appears that holding all else constant, black people in rural areas travel further for their groceries and postal services on both weekends and weekdays.

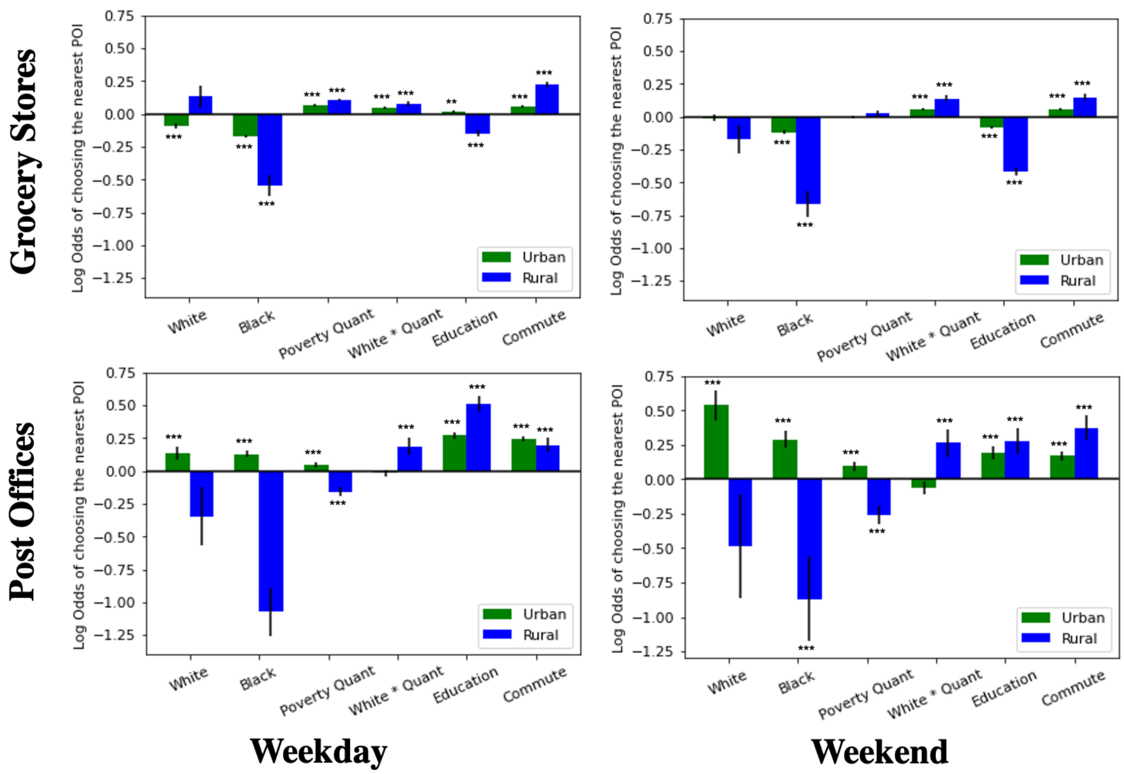

Figure 4-8: Logistic regression coefficients for urban and rural CBGs, segmented by category and time of week

Second, more educated people in rural areas are less likely to visit their closest grocery store, but more likely to visit their closest post office. Third, the opposite is true for high-poverty areas. People from high-poverty rural CBGs are more likely to visit their closest grocery store, but less likely to visit their closest post office. Lastly, the effect of the white proportion and income quartile interaction variable is highly significant for grocery stores and rural post office visits, but not for urban post office visits.

Chapter 5

Discussion

As the world emerges from the COVID-19 pandemic, the 15-minute city concept has gained increasing attention as an avenue to building more accessible, sustainable, and resilient communities. The social inequities laid bare by the pandemic reveal that residents of disadvantaged sociodemographic groups were most adversely impacted by stay-at-home orders, especially in the context of food insecurity [26, 17]. The 15-minute city asserts the proximity of services and opportunities as an accessibility metric for urban planning. With this backdrop, this study presents two important contributions towards understanding the relationship between proximity and accessibility. First, our approach leverages large-scale, granular mobility data to assess actual visits made by individuals. We find that distance is not a good proxy for accessibility, or whether an individual will actually visit a place. Second, by modeling the choice of visiting an amenity based on either proximity, we show how peoples' behavior differs by sociodemographic traits, time, and type of service or amenity.

These results warn that urban planning policies based on metrics such as distance or travel time will not achieve the goals they are designed to. This is not because such metrics are not important or informative, but more so because individuals value different things beyond distance and time, and organize their lives accordingly. The assumption that "if you build it, people will come" is wholly misguided. The reasons behind their decisions cannot be explained by distance or time alone. Rather, they are constrained by income, mobility, and time to differing degrees, each of which limit the range of destinations within reach and the choices available to them.

This demonstrates that in regards to the 15-minute city, we cannot frame a holistic accessibility policy through the narrow lens of proximity. Instead, further studies need to be conducted as to the contexts of why social groups value proximity differently. From there, policies should be tailored to specific categories of amenities at various time-points and demographic groups. For instance, our case study results showed that on average, people are more likely to visit their nearest grocery stores on weekdays as opposed to weekends. This suggests that the metrics used to define a 15-minute city should be more stringent on weekdays than on weekends, as people appear to be more time constrained.

We believe that the data we use and the way we operationalize the measurement of proximity provides a practical framework for future studies that can further explore what traits or behavioral factors motivate an individual's mobility patterns. Moreover, the methodologies used in this study can be applied to policy interventions beyond the 15-minute city.

5.1 The 15-minute city concept applied to food access

In our analysis of food access, there is no clear pattern of grocery store access between different demographic groups. Instead, the behaviors can be quite contradictory. One takeaway is that residents of high proportion white and high-income areas are also more likely to visit their nearest grocery stores. This could be because privileged households have higher quality offerings in close proximity. However, at the same time, people who live in areas of higher educational attainment choose to travel further for groceries. This might be because they have more particular preferences or stringent commute schedules. While both groups exhibit the same trend, the reasons behind their choices are likely different.

Another contradiction we find, perhaps more relevant to policy interventions, is that while residents of higher poverty neighborhoods tend to go to their nearest grocery stores, those in black neighborhoods choose to travel further for their groceries. It is historically true that racial minority populations are lower-income and higher-poverty [28]. This behavioral pattern may be indicative of higher-level structural inequities, which is revealed in several contradictory reasons found in literature.

Firstly, high-poverty households have lower vehicle ownership rates and are more dependent on public transit or walking, which limits their access to faraway stores [5]. This is in line with previous research suggesting that food access problems are not so much the product of geographical distance as they are the social or welfare networks that allow people to access private transport [18, 16].

Secondly, black households are generally multi-person, and multi-person households prefer to shop at bulk or discount stores which are often located further away [29]. This may also be indicative of a "food mirage", where what appears to be adequate neighborhood food access actually obscures social exclusion [9]. In these areas, minority residents and those with less education and income tend to encounter grocery stores which are too expensive or culturally alien. This phenomenon extends beyond the food environment to the rest of the burgeoning retail sector, where studies unveiled general feelings of "racial resentment and exclusion" by Black residents [38].

The diversity of speculations found in literature is due to differences in methodologies and study populations. Most studies are survey based, which limits the number of samples and is likely to be biased towards the sub-populations participating [16]. They are also spatially concentrated in different cities, and even specific neighborhoods [10, 9]. Additionally, there are differences in definitions of healthy food, which includes corner convenience stores, farmers markets, and supermarkets, and in definitions of accessibility, which includes modes of transit, proximity, and choice [34]. Our results remove survey bias by using real mobility data that represents an entire metropolitan area and only include full-service grocery stores.

These divergent results make clear that food shopping patterns are multilevel and complex. It also suggests that urban planning and policy interventions for improving equitable access should be localized to their target demographic. For example, in the context of high-poverty communities that lack efficient transportation, it may be more effective to improve transit options between these neighborhoods and their preferred grocery stores. In communities where grocery offerings are pricey, we should increase efforts to add stable jobs and increase wages. And in areas with cultural barriers, we need to encourage more community organization and integration efforts.

Ultimately, food access is a critical component to any 15-minute city. However, it is clear that simply increasing the number of grocery stores in residential areas will not necessarily improve food access. Instead, we need to implement parallel initiatives to improve quality, lower prices, and ameliorate cultural barriers to inclusion.

5.2 Extensions to other contexts

Our results have shown that the 15-minute city accessibility metric need to be tailored for each sociodemographic groups, which thus suggests different approaches to designing such a city. This can and should be extended to other amenity categories, such as parks, libraries, entertainment, schools, hospitals, and transit hubs. We hypothesize that different people value proximity to these categories differently.

Such analysis can also be employed in commercial contexts, as sustainability planning and economic development go hand-in-hand. Local store owners deciding where to open a new business can consider the trade-offs between local accessibility and demand by assessing mobility patterns [27, 19]. Currently, local businesses largely rely on labor-intensive surveys to inform their decision making. It can also inform businesses of the sociodemographic traits of their visitors and the times at which they prefer to visit. This can help businesses tailor their hours and services to target customer groups.

5.3 Limitations

Our study has several limitations. From a data perspective, we only select individuals for whom we could infer a home location, therefore excluding those who do not have a stable residence or have non-normative work shifts. Similarly, only POIs identified via Foursquare were included. Moreover, we infer user demographic traits from their home CBG census demographics, the aggregation of which may not be a comprehensive or accurate measure of individuals.

We also make several simplifying assumptions. First, we assume that POI visits originate from users' homes. This is common among many distance and time-based accessibility measures, which focus on people's residences as the single point of access to amenities. However, a significant number of trips do not originate at home; instead, people can buy groceries near work, on their commutes, or at other locations. Therefore, developing trip chaining methods that bundle errands together would shed more insights into the relationship between choice and spatial convenience.

While Euclidean distances are suitable measures for walking accessibility, they do not account for spatial variations in the built environment or capture the opportunity cost of travel. The time is takes to travel between places is often constrained by changing urban infrastructure and disparate mobility resources. Therefore, it may be more informative to analyze access to opportunities and services as a function of network distance or travel time. Additionally, it would be interesting to perform this study on different travel modes, such as walking, biking, public transit, and driving to different cities depending on their urban density and embedded transit preferences. For example, driving is more prevalent amongst American cities while walking, biking, and public transit may be more popular in Asian and certain European cities.

Finally, caution should be taken when extending the data of our study to areas with low smartphone usage or contexts where the movement of smartphones may not be a good indicator of the movement of a population.

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Chapter 6

Conclusions

This paper proposes a mobility data approach to measuring the relationship between choice, accessibility, and sociodemographic traits, and applies it to healthy food offerings within the Boston area. In particular, we extract users' grocery stores of choice in addition to the closest stores to their home and model the probability that an individual visits their closest grocery store based on sociodemographic factors of their home neighborhoods. Results show that the nearest store alone, even at varied spatial thresholds, fails to reflect the multidimensional nature of healthy food accessibility. To our knowledge, this is the first study to use large-scale micro-mobility data to examine choice and accessibility in the healthy food environment.

Spatial planning is one of the most important social policy tools for mitigating food deserts by designing infrastructure for the supply, distribution, and access of healthy, affordable food at the neighborhood level. The methods demonstrated in this study should offer deeper insights into the healthy food landscape and provide more nuanced understanding of the importance of non-physical variables in urban planning.

6.1 Future Work

In addition to enhancing study designs that would allow us to overcome the limitations described in the previous section, there are opportunities to expand this work to better understand contemporary contexts. We acknowledge the extent to which work-from-home during the COVID-19 pandemic has changed people's daily mobility patterns and encourage further investigation. Correspondingly, the way we choose to navigate the food environment is also changing rapidly. During the COVID-19 pandemic, a significant number of Americans ordered groceries online or through delivery services, which has the potential to increase and diversify food access. Further exploring this phenomenon could help policy makers keep pace with the technologically evolving food environment.

Further demographic segmentation is another avenue of exploration. In this study, we take into account the interaction variable between white population proportion and income. Another population to potentially be aware of is students. Boston is notoriously known for being a college town, and student comprise a significantly portion of its population. The CBGs in which students reside are likely to be reported as low-income and high education levels in the census data. Thus, the temporal nature of students' income levels and food behaviors may be very different from those who are low-income have low educational attainment.

Alone the lines of food access, it would be interesting to repeat the experiment using data on visits to corner stores and convenience stores, which often have less healthy food selections. A common theory maintains that those who live in food deserts are forced to shop at local convenience stores. Studying the sociodemographics of those who choose corner stores over full-service grocery stores, and the spatiotemporal distribution of their choices, can inform future health interventions.

Finally, researchers have also identified existing social inequities in other categories core to the 15-minute city, such as public parks [39]. It would be interesting to test our methodology on other such categories, from healthcare to commerce. These findings could help urban planners and policy makers better define what a 15-minute city is, and the best operational model for each category and each social group.

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