NBER WORKING PAPER SERIES

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EVIDENCE FROM CELL PHONE DATA

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Working Paper 27072
http://www.nber.org/papers/w27072

NATIONAL BUREAU OF ECONOMIC RESEARCH
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May 2020

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May 2020
JEL No. R23

ABSTRACT

Traveling beyond the immediate surroundings of one's residence can lead to greater exposure to new ideas and information, jobs, and greater transmission of disease. In this paper, we document the geographic mobility of individuals in the U.S., and how this mobility varies across U.S. cities, regions, and income classes. Using geolocation data for ~1.7 million smartphone users over a 10-month period, we compute different measures of mobility, including the total distance traveled, the median daily distance traveled, the maximum distance traveled from one's home, and the number of unique haunts visited. We find large differences across cities and income groups. For example, people in New York travel 38% fewer total kilometers and visit 14% fewer block-sized areas than people in Atlanta. And, individuals in the bottom income quartile travel 12% less overall and visit 13% fewer total locations than the top income quartile.

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What is the geographic mobility of a typical American? Does geographic mobility vary across different cities and income groups? From an economic standpoint, mobility is important because it can lead to broader exposure to information about public goods, jobs, and alternative lifestyles. In fact, various social programs, like Moving to Opportunity for Fair Housing (MTO), Trips for Kids, and Open Outdoors for Kids, have been introduced specifically to encourage and support the mobility of individuals living in disadvantaged neighborhoods. Outside of economics, understanding geographic mobility is useful for the study of a variety of topics, including transmission of disease, privacy and predictability of movement, urban and traffic planning, trade, and the spread of ideas/norms.

Despite the importance of understanding geographic mobility, the overall level of mobility in the U.S. and the extent to which mobility differs across cities and socioeconomic groups is not clear. While anecdotes abound regarding kids from low-income families who have never seen the beach/lake/park despite living only a few kilometers away, systematic data to support these claims are rare. Commonly used data, such as census and tax records, provide evidence of year-to-year residential moving patterns and the importance of neighborhood of residence, but fail to capture hour-to-hour or even day-to-day movement that occurs.[1,2] Other studies have analyzed survey or travel diaries to characterize movement, but are often limited to a small group of individuals, a particular type of travel behavior (e.g. vacations, commuting), and/or a narrow geographic area/population.[3,4] More recently, several research teams have taken advantage of GPS data to better understand mobility. For example, researchers have tracked ~100k cell users when they receive a call/text to study models of travel trajectory,[5] ~36k users of the LifeLog App to understand "conserved quantity" of locations visited,[6] 440 Yelp users in New York City and their restaurant choices,[7] and ~400k Twitter users and the locations from where they tweet.[8] Relative to these innovative papers, the data used in our paper is unique in both its size (we track ~1.7 million smartphone users) and the types of mobility measured (we receive close to continuous geolocations as opposed to only a geotag when a call is received or a tweet is sent). Thus, our paper contributes to this literature by painting a broader picture of geographic mobility and how this mobility varies across cities and income groups.

Data and Methods

We use location data from Safegraph, a company that aggregates de-identified, geospatial data points of more than 10 million U.S. smartphones. Our data record the average latitude-longitude coordinates of a phone whenever it remains within a seven-digit geohash (a square with dimensions

153m×152m of a predetermined geocoding system that grids the entire globe) for at least 15 minutes in any clock-hour. Thus, we can track individuals as they move from one generalized location to another. All coordinates are located in the continental U.S.

We restrict the data to approximately 1.7 million smartphones that transmit latitude-longitude coordinates ("pings") consistently over a 10-month period from February to November of 2016 (see the Online Appendix A for a discussion of the restriction criteria and robustness to this criteria). For each of the 1.7 million smartphone users, we infer the census block and tract of the individual's home based on pings that occur during night and early morning hours. Using these home locations, we merge in information from the 2010 Decennial Census to obtain demographic information such as household income.

One limitation of our paper is that the sample is an imperfect representation of the U.S. population. While 77% of American adults currently use a smartphone,[9] our results cannot speak to the mobility of individuals in the U.S. who do not own a smartphone. Furthermore, because we restrict our sample to smartphones that are active and consistently transmitting geodata over our 10-month period, we are removing some individuals who (1) turn off their phones for extended periods of time, (2) do not allow location-tracking services on their phone, (3) regularly switch cell phones, (4) leave the country for an extended period of time, or (5) fail to pay their cell phone bill. All of these potential selection concerns may limit the generalizability of our findings. However, as we show in Online Appendix B, our sample is fairly representative of the U.S. as a whole with the key exception that it skews towards being wealthier—which is consistent with wealthier individuals being more likely to own a smartphone.

An additional limitation of our paper is that a cellphone's movement may not necessarily track the user's movement; phones may be left at home or used by more than one person. In the analysis that follows, we interpret the results as if each smartphone fully represents the movement of one person.

Overall Mobility in the U.S.

We begin by documenting overall mobility in the U.S. with four separate measures: a total 10-month distance chain, a daily distance chain, the maximum distance traveled from one's home, and unique haunts visited. The first mobility measure is a "distance-chain" of movements across a 10-month period of time: we linearly connect an individual's pings and compute the total length of the connected chain over 10-months. Panel A of Figure 1 provides the distribution for this mobility measure. The median American in our data travels approximately 19,579 kilometers with an interquartile range of 20,180 kilometers during the 10-months of our data. Also noteworthy is that about 15% of the individuals in our data travel more than 50,000 kilometers. These individuals appear to be a combination of heavy commuters (e.g. fly to work a couple of days a week), truck drivers, or local drivers (taxi, bus, etc.).

The second measure of mobility is the median distance traveled for each individual in a given day. Like the previous measure of mobility, we sum the linear distance between each ping for each person and day in the data. We then take the median of all days for each individual. This measure informs us about day-to-day movement and removes anomalous travel schedules, like a few days of long travel (e.g. vacations), which may skew the 10-month distance statistics. As Panel B of Figure 1 reveals, the median American in our data travels 33 kilometers on the median day with an interquartile range of 40 kilometers. There is a segment of the population that travels less than a kilometer on a median day (approximately 5%) and another group of individuals (approximately 10%) who travel more than 100 kilometers on a typical day. In the Online Appendix C, we break down this median daily movement for weekends and weekdays.

Our third measure of mobility (shown in Panel C of Figure 1) calculates the maximum distance that an individual traveled from their home during the 10-month span of our data. The median American travels 1,046 kilometers from his or her home with an interquartile range of 1,708 kilometers during our 10-month period. Around 2.5% of the individuals in our data did not travel beyond 50 kilometers of their home. Online Appendix D shows that of those who traveled no more than 50 kilometers from their home, most of these individuals traveled at least a few kilometers and less than 0.2% of individuals stayed within a kilometer of their home. The remaining distribution is fairly spread out with over 25% of the sample having traveled more than 2,000 kilometers from their home at some point during the sample period.

The fourth and final measure of mobility is a measure of the total land area that an individual inhabits. We define every geohash of length 7 where an individual stayed for at least 15 minutes to be a "haunt". For example, haunts would almost surely include an individual's home and other locations such as a workplace, friend's home, supermarkets, restaurants, museums, etc. For each individual, we calculate the total number of unique haunts visited during the 10 months and plot the distribution in Panel D of Figure 1. The median smartphone user in our sample visited 411 unique haunts with an interquartile range of 295.

How do these mobility measures correlate with each other in the overall sample? Using the individual-level data, we find that the 10-month distance chain is highly correlated with the median distance chain with a relationship of 0.93. It is also correlated—although more weakly—with how far a person travels from their home and the total number of unique haunts within 10 months (0.25 and 0.27 respectively). The other measures are correlated as well: R(Median Daily, Max Dist) = 0.18; R(Median Daily, Unique Haunts) = 0.23; R(Max Dist, Unique Haunts) = 0.32. Online Appendix E shows the correlation between these measures for the 50 most populous commuting zones at the commuting zone level (described in more detail below).

Differences across Geographic Regions

Figure 2 shows a map of the U.S. for each of the four mobility measures described above that can help illustrate the broad geographic patterns of mobility across the country. The geographic unit in each map is a commuting zone. Unlike counties which may reflect political boundaries, commuting zones are designed to reflect the local economy. These zones typically include not just a city, but the surrounding suburbs as well. Commuting zones tend to be more uniform in size than other geographic measures (e.g. counties) and they fully describe all areas of the U.S. (unlike, for example, dividing the data into MSAs which would leave out rural America).

Panels A and B of Figure 2 illustrate that people in the Midwest and the South travel longer total distances and day-to-day distances across the 10-month sample period. As evident in Panel C, people in the Mountain West, New England, and Florida on average travel the furthest distance from home. In part, this is mechanical because the largest possible distance one can travel in the continental U.S. from the center of the U.S. is smaller than for those living on the coasts. Lastly, individuals living in the Midwest and especially the South (e.g. Texas, Louisiana, and Mississippi) visit the most number of unique haunts (Panel D).

While Figure 2 illustrates the broad geographic patterns around the entire U.S., in Online Appendix F, we graph the mobility measures for the eight most populous commuting zones. Further, in Online Appendix G we provide a table that lists the mobility measures for the 50 largest commuting zones by population. The commuting zone with the highest median total distance traveled is Austin (22,306 kilometers) and the lowest is New York (12,890 kilometers). Grand Rapids has the highest median daily distance traveled with a median of 40 kilometers and New York has the lowest with 21 kilometers. Individuals living in Minneapolis have the highest median maximum distance traveled away from their home (1,731 kilometers) while those in Fresno have the lowest median maximum distance traveled from home (467 kilometers). Lastly, the city with the largest median haunts visited is Nashville (447 geohashes) and the lowest is Raleigh (348 geohashes).

Mobility Differences by Income Class

Figure 3 shows differences in our four mobility measures for individuals in the top and bottom income quartiles. The determination of income quartiles can be made in different ways. For example, the quartile cutoffs could be set using the full national sample, or cutoffs could be determined at the commuting zone level. We use cutoffs at the commuting zone level, which allows us to focus on income differences in mobility while controlling for geographic location in the US. In Online Appendix H, we show the results using national income quartile cutoffs (and find very similar effects to our primary results using commuting zone quartile cutoffs).

Panel A of Figure 3 shows that the median high-income individual travels 19% more kilometers during the 10-months in our sample than the median low-income individual (21,202 compared to 17,794 kilometers; $p<0.001$). Similarly in Panel B, the median high-income individuals travel 12% more day-to-day (33 compared to 29 kilometers; $p<0.001$). High-income individuals also travel a farther distance from their home than low-income individuals (Panel C). For example, 10% of low-income individuals in our data do not travel farther than 100 kilometers from their home while less than 5% of high-income individuals stay within 100 kilometers of their home. Lastly, the median high-income individual in our sample has approximately 15% more haunts than the median low-income individual in our data (441 compared to 385; $p<0.001$).

How do these mobility differences across income vary location by location around the U.S.? In Panels A-D of Figure 4, we plot a ratio for each mobility measure that compares the median low-income to high-income individual in that commuting zone. For example, a commuting zone that has a ratio of 0.75 on the first measure of mobility (total 10-month distance traveled) indicates that the median low-income individual traveled 25% less than the median high-income individual in that commuting zone. These figures do not show stark patterns, with the exception of the South being more equal (or in some cases low-income people are even more mobile than high-income individuals) in terms of the amount of mobility between across income groups.

In Online Appendix I, we graph the mobility measures by income quartile for the eight most populous commuting zones and the table in Online Appendix G provides inequality ratios for the 50 largest commuting zones by population. The commuting zone with the most inequality in total distance traveled is New York City (ratio of 0.54) and the least inequality is Las Vegas (ratio of 0.96).

Providence has the most inequality (ratio of 0.67) of median daily distance traveled compared to Atlanta where low-income individuals actually travel more on a day-to-day basis (ratio of 1.22). New York has the most inequality for the median maximum distance traveled away from their home (ratio of 0.23) while Seattle is the most equal (ratio of 0.81). Lastly, the commuting zone with the most inequality in the median number of unique haunts is Columbus (ratio of 0.76) and the one with the most equality is Las Vegas (ratio of 0.96).

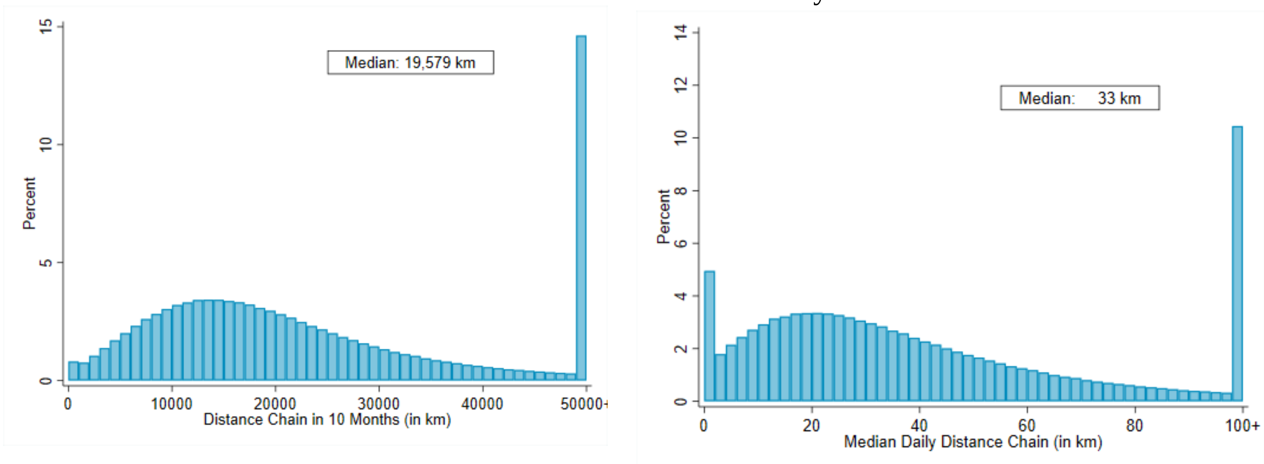
Conclusion

Our findings provide descriptive evidence of mobility patterns in the US. Importantly, we document large differences in mobility across cities and broader geographic areas. Looking within commuting zones, we find that high-income individuals almost always travel more and visit more locales than low-income individuals. The size of these differences can be large. For example, low-income individuals are more than twice as likely not to have gone farther than 100km from their home relative to high-income individuals. Future work will hopefully lead to additional insights into how mobility is changing over time and the impacts of mobility on life outcomes.

Figure 1. Distribution of the 4 Main Mobility Measures

a. Distance Chain

b. Median Daily Distance Chain



c. Maximum Distance from Home

d. Unique Haunts

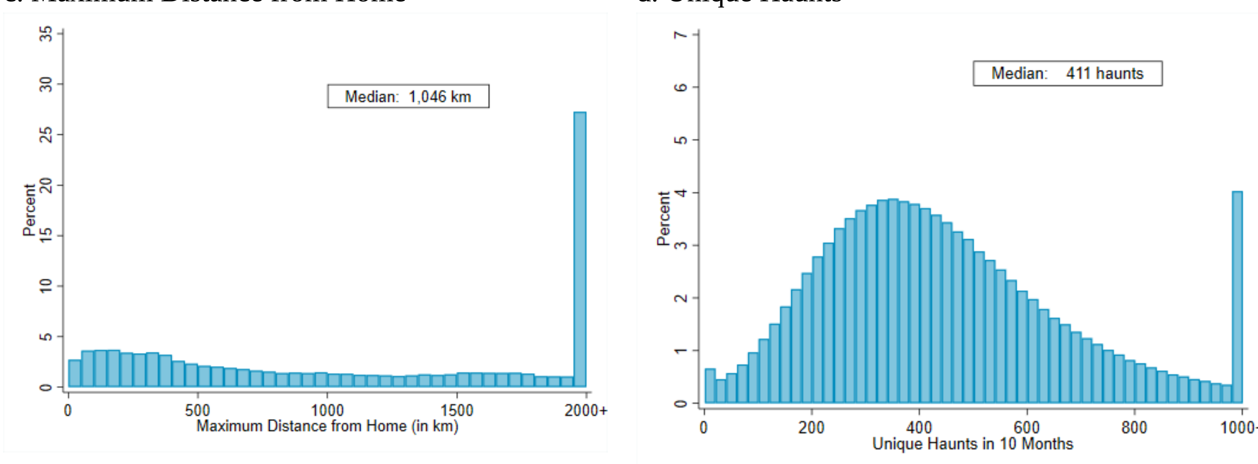


Figure 2. Mobility Measures Across CZs

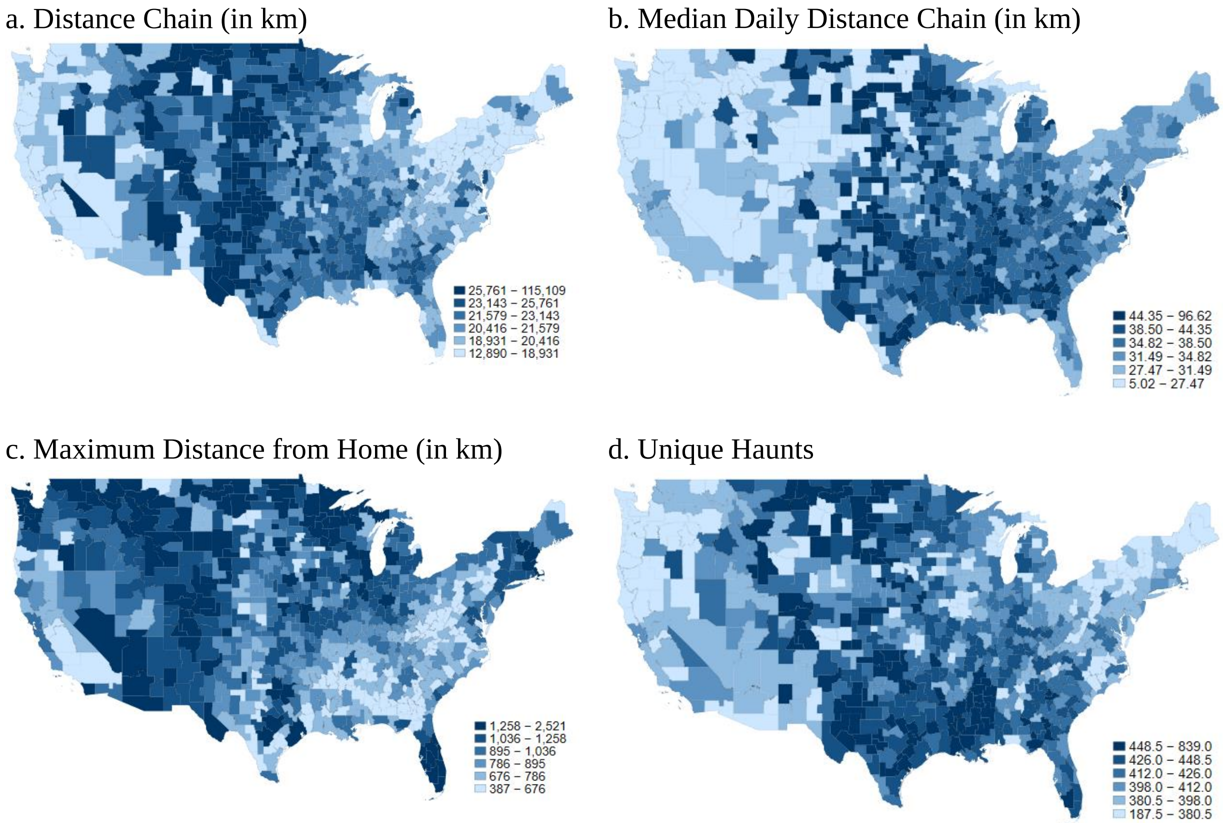


Figure 3. Distributions of Mobility Measures by Top and Bottom CZ Income Quartiles

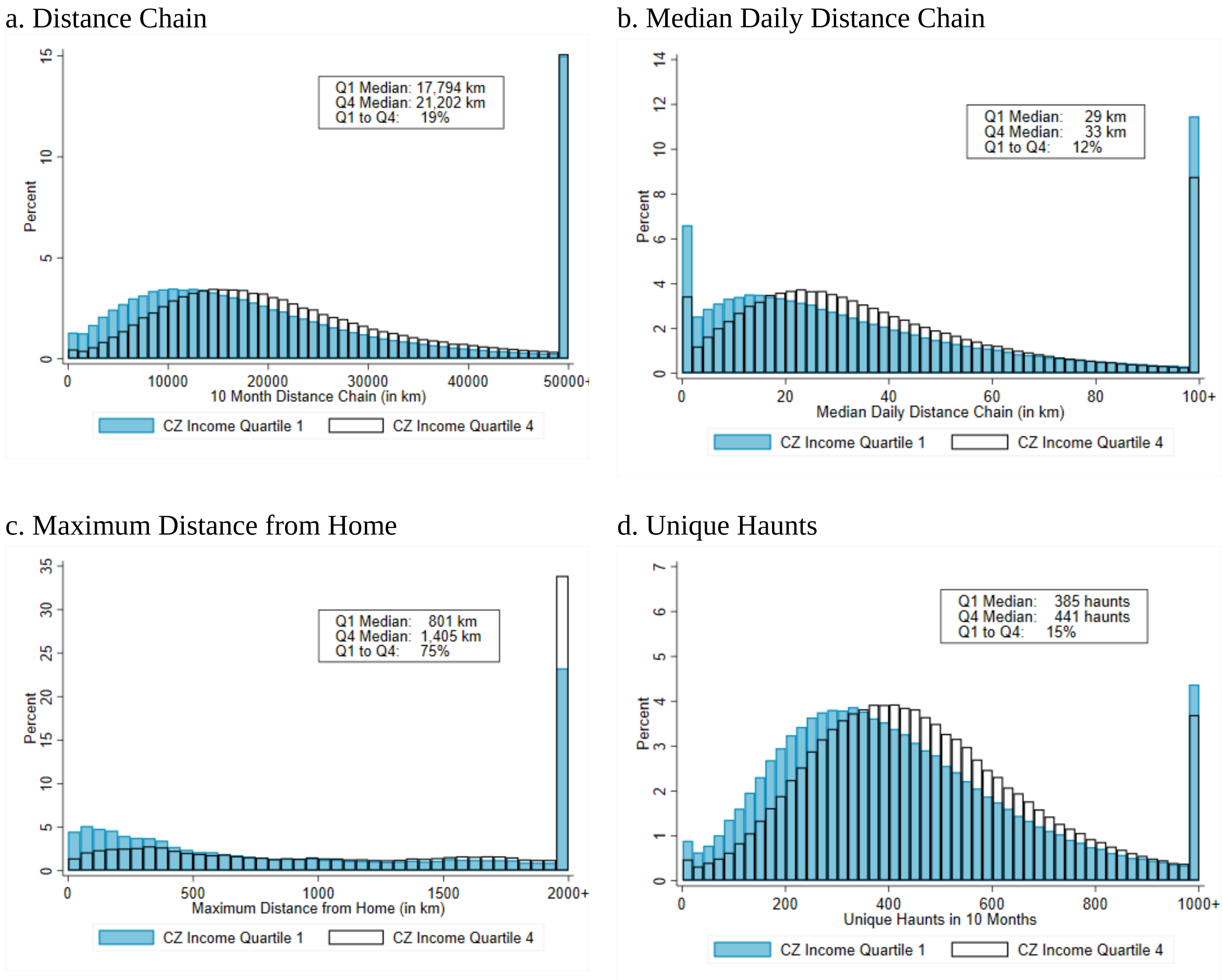
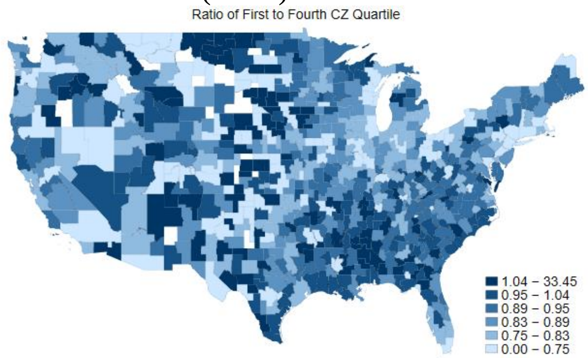
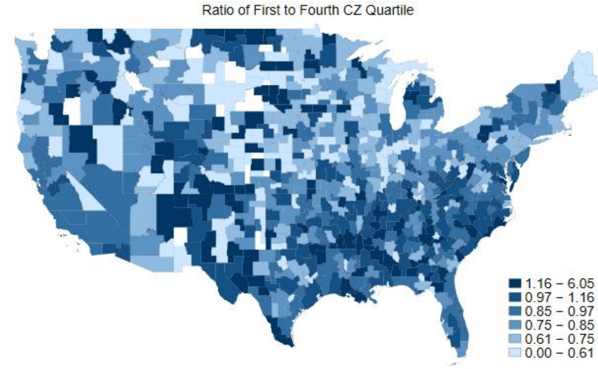


Figure 4. Ratio of the First to Fourth Income Quartile Mobility Measures Across CZs

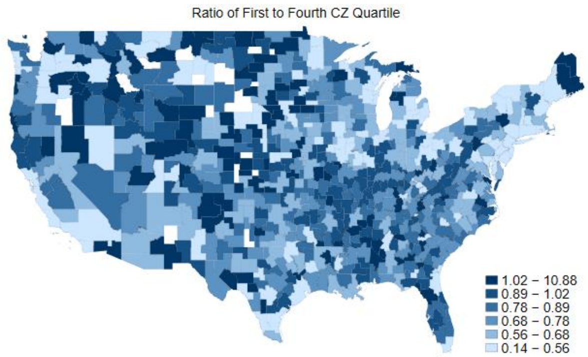
a. Distance Chain (in km)



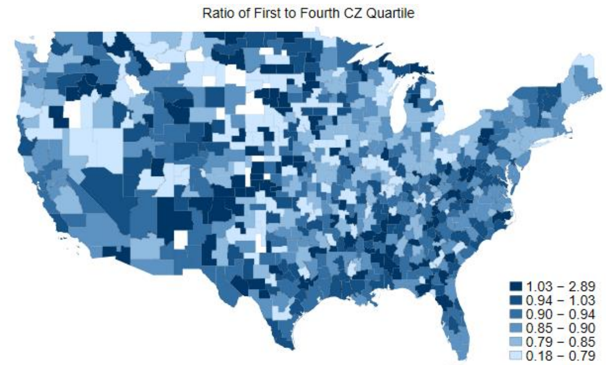
b. Median Daily Distance Chain (in km)



c. Maximum Distance from Home (in km)

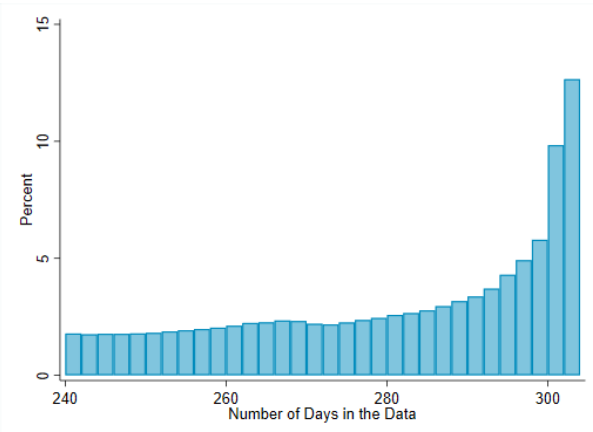


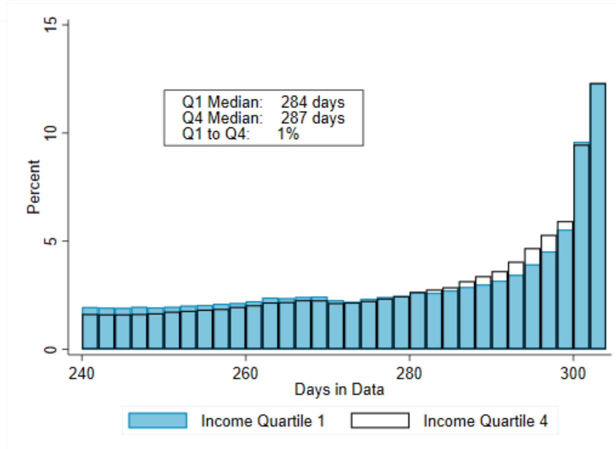
d. Unique Haunts



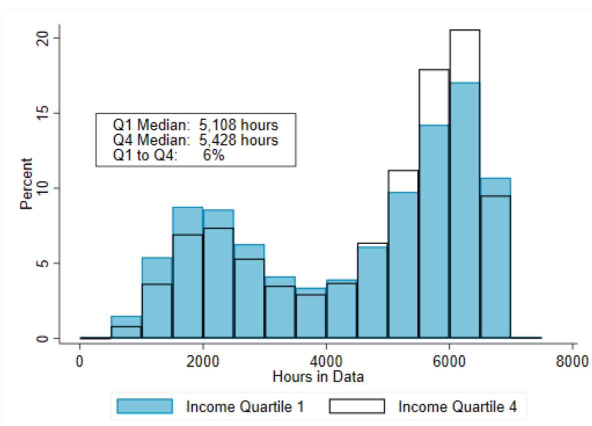
Online Appendix A. Sample Restriction

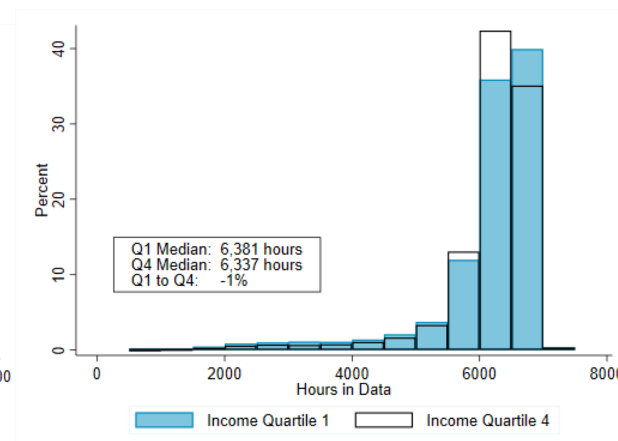
Of individuals in the data for whom we were able to obtain a home location, we restricted our final sample to those who had appeared at least 240 days in the dataset. The first figure below illustrates the distribution of the total days in the data. The second figure breaks this down by the top and bottom CZ income quartile. As shown in the second figure, the median wealthy individual appears 3 days more (or 1% more) than the median low-income individual.





Over 20% of individuals in our final sample have at least 300 of the total 304 days; note that the top and bottom income quartile are equally represented within this range. The left figure below breaks down the distribution of total hours in the full sample by the top and bottom income quartile. The right figure below features the same distribution but is restricted to those with at least 300 days in the data.

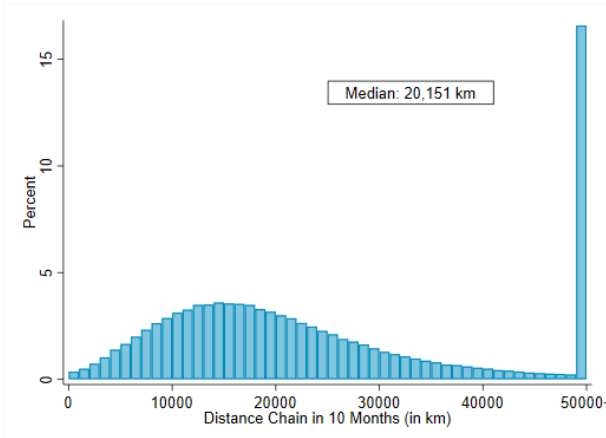




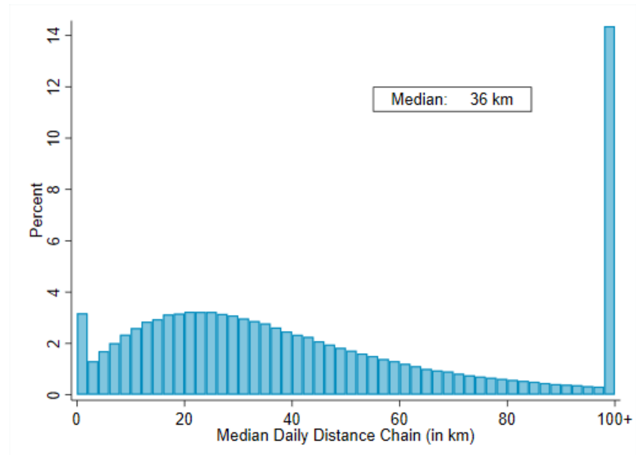
As evident in the figures, the top quartile in our full sample spends about 6% more hours in the data than the bottom quartile. In the restricted sample, the top quartile has about 1% fewer hours in the data. To check for robustness, we restrict the data to individuals that pinged for at least 300 days and replicate the main figures (Figures 1-4) with this smaller sample. We find similar results as our main results.

A.Figure 1. Distribution of the Four Main Mobility Measures

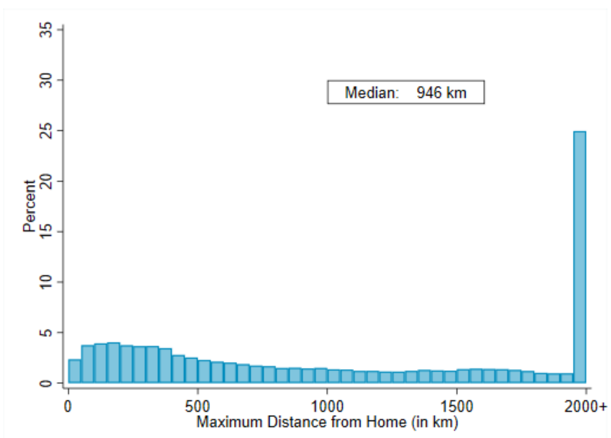
a. Distance Chain



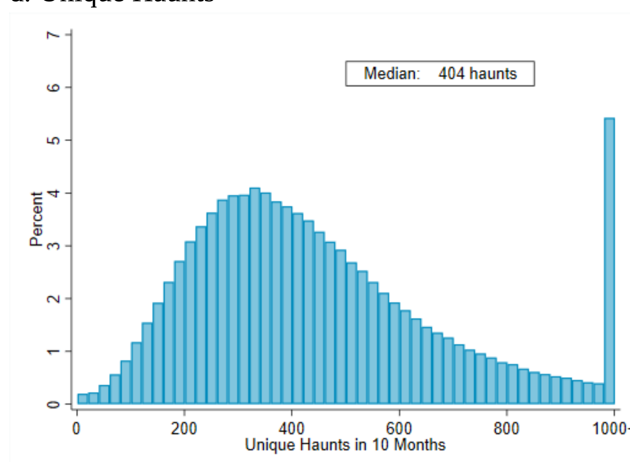
b. Median Daily Distance Chain



c. Maximum Distance from Home

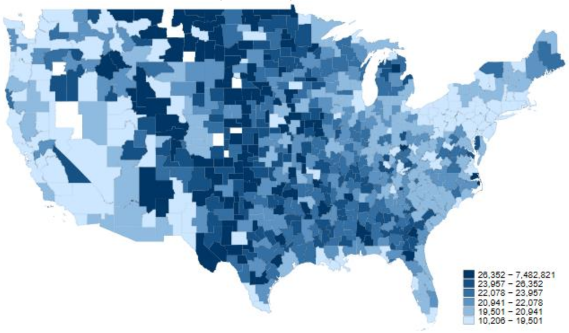


d. Unique Haunts

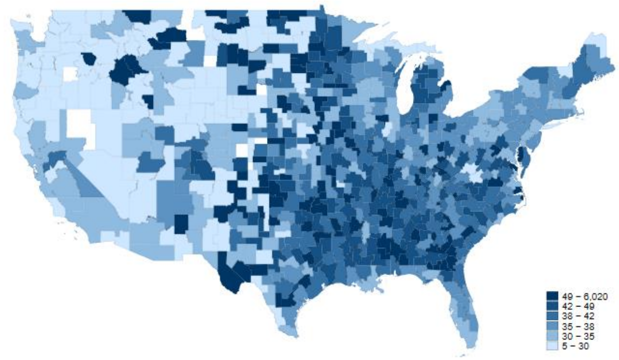


A.Figure 2. Mobility Measures Across CZs

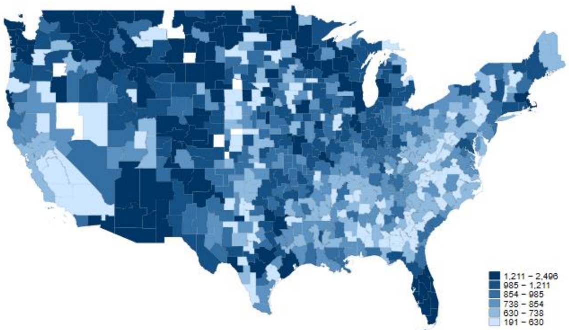
a. Distance Chain (in km)



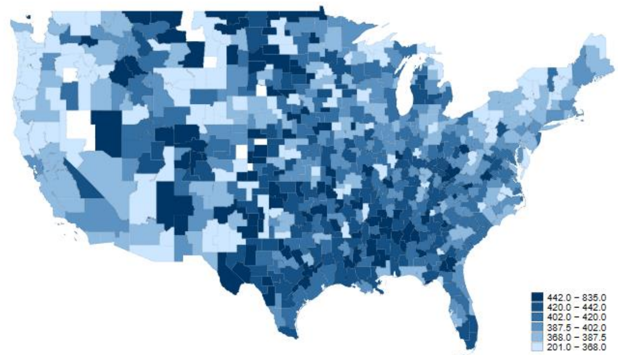
b. Median Daily Distance Chain (in km)



c. Maximum Distance from Home (in km)

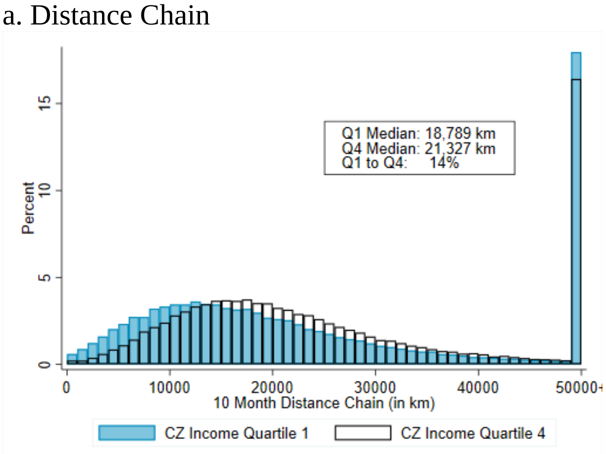


d. Unique Haunts

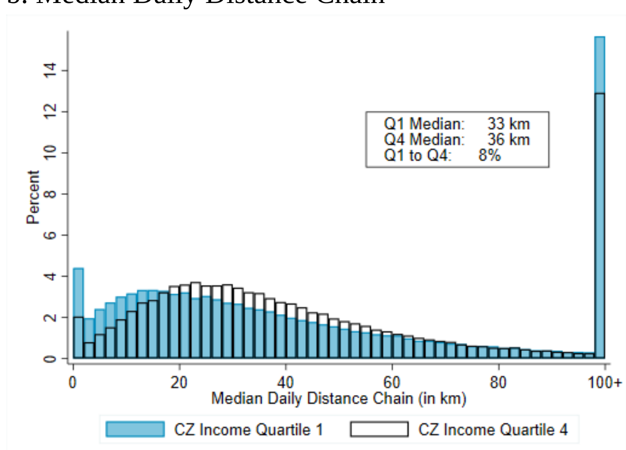


A.Figure 3. Distribution of Mobility Measures by Top and Bottom CZ Income Quartiles

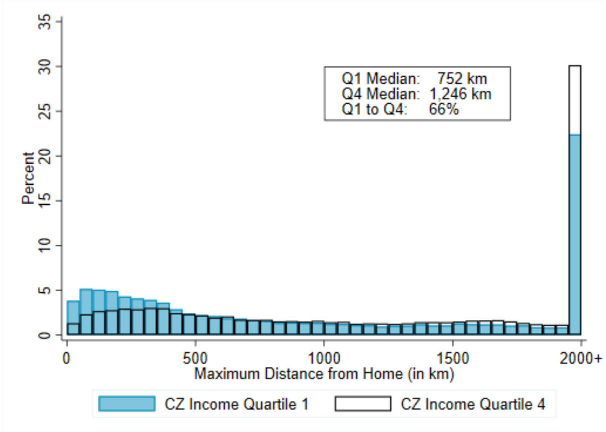
a. Distance Chain



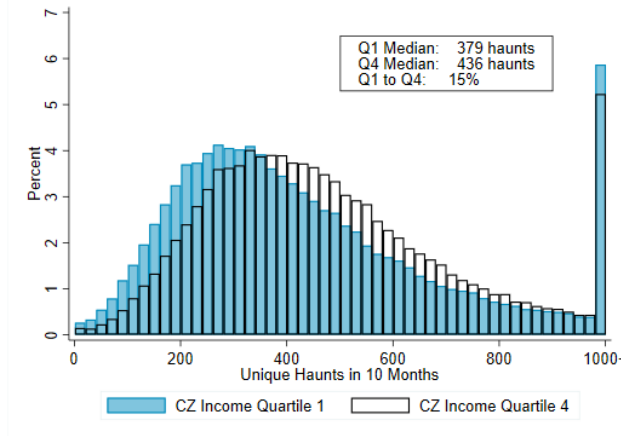
b. Median Daily Distance Chain



c. Maximum Distance from Home

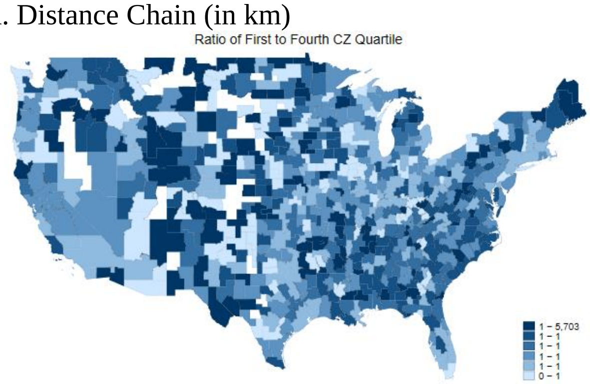


d. Unique Haunts

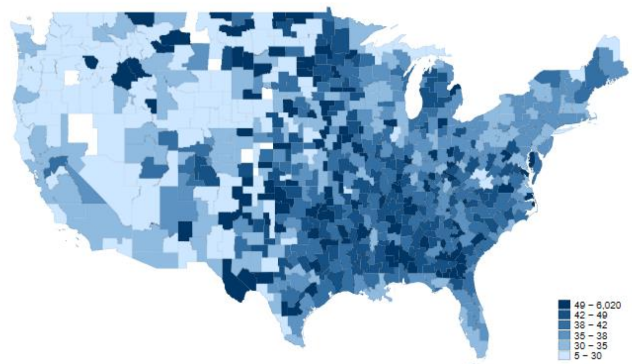


A.Figure 4. Ratio of the First to Fourth Income Quartile Mobility Measures Across CZs

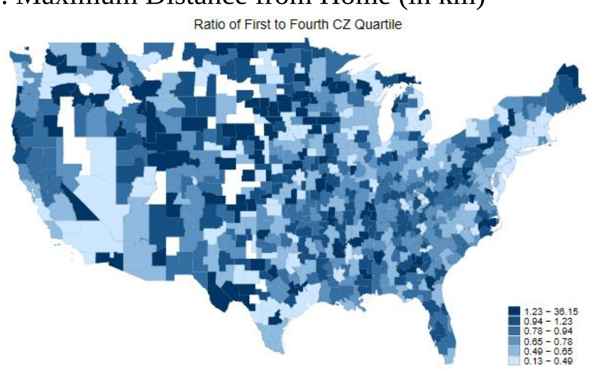
a. Distance Chain (in km)



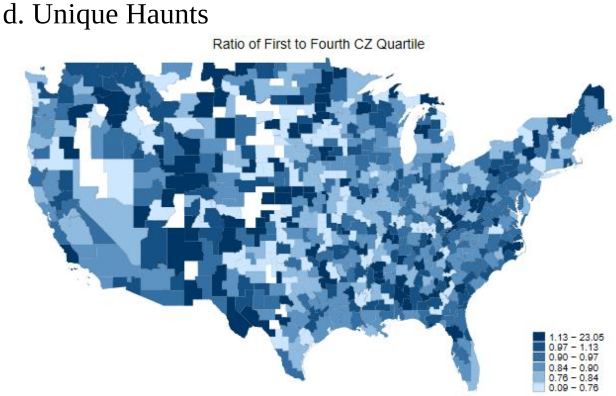
b. Median Daily Distance Chain (in km)



c. Maximum Distance from Home (in km)

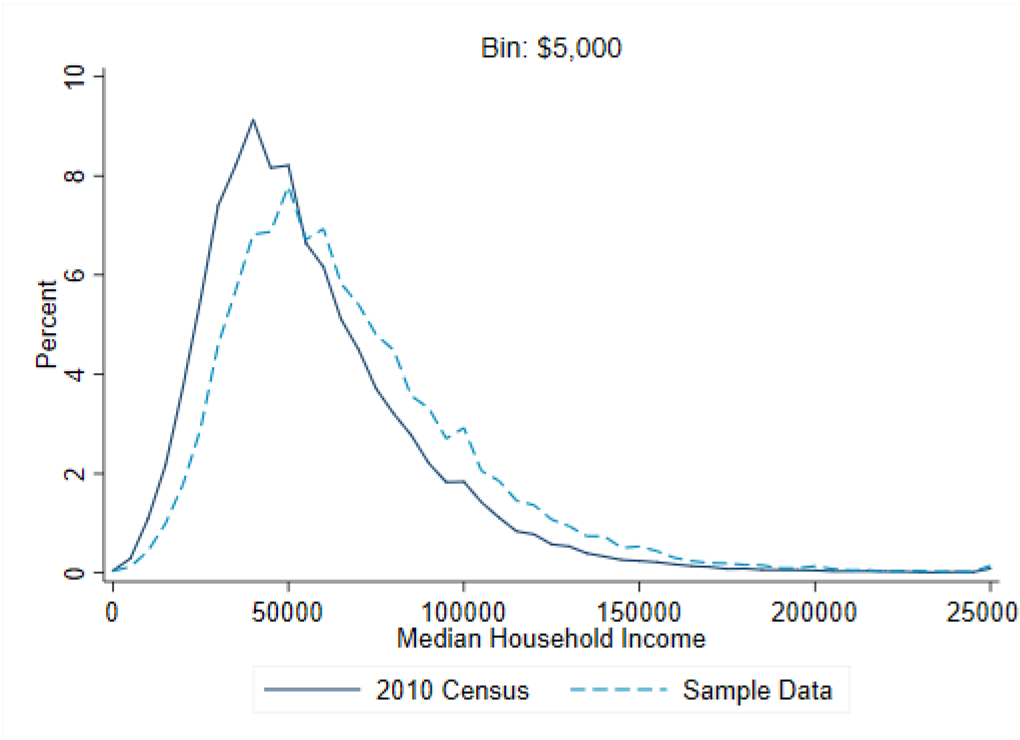


d. Unique Haunts

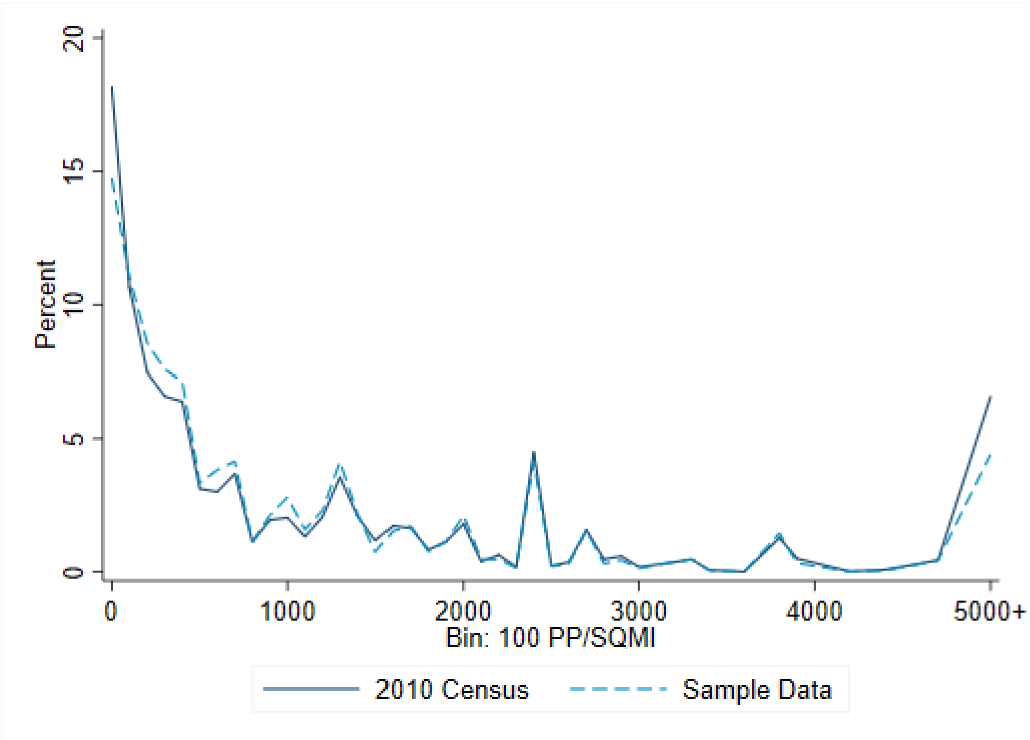


Online Appendix B. Sample Representativeness

B.Figure 1. Distribution of Median Household Income by Census Block Groups in the 2010 Census vs. Sample Data

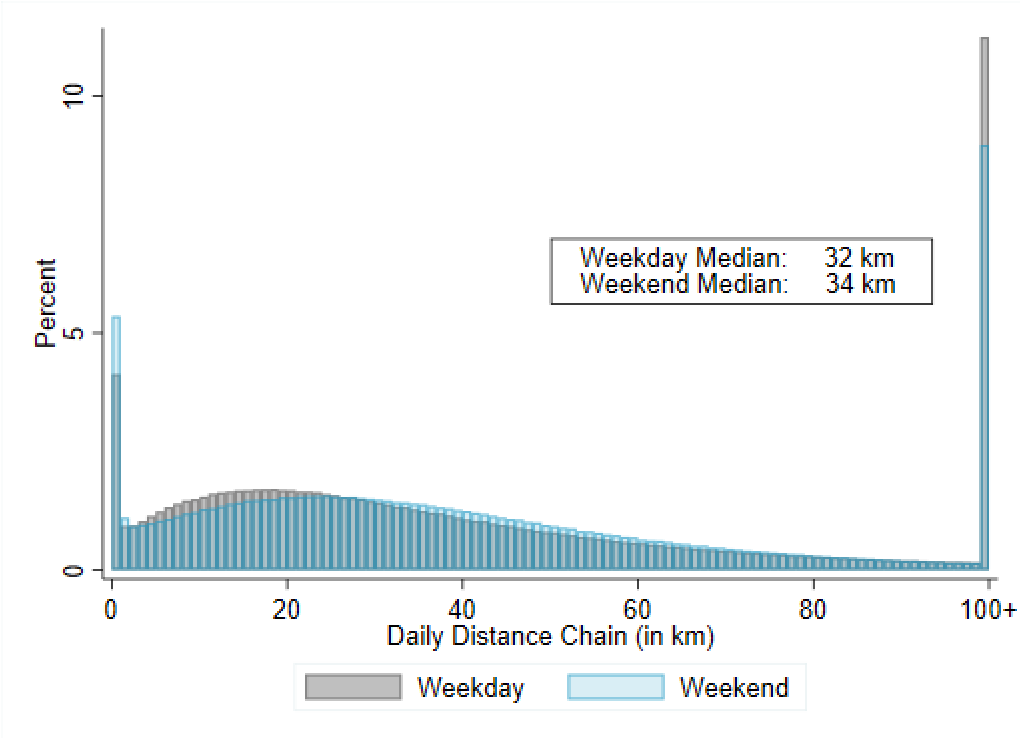


B.Figure 2. Distribution of Population Density Per Square Mile by County in the 2010 Census vs. Sample Data

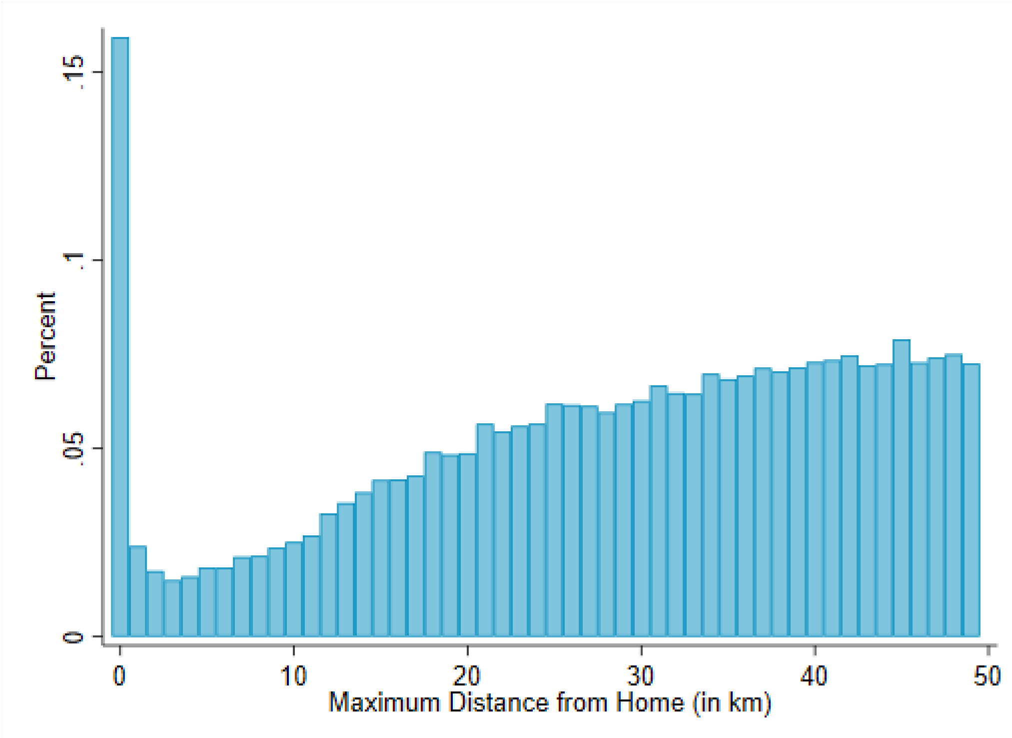


B.Figure 3. Percent of Total Population by State in the 2010 Census vs. Sample Data

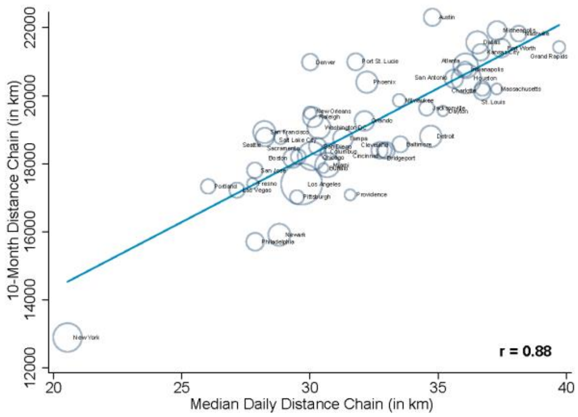
Online Appendix C. Daily Distance Chain by Weekday and Weekend

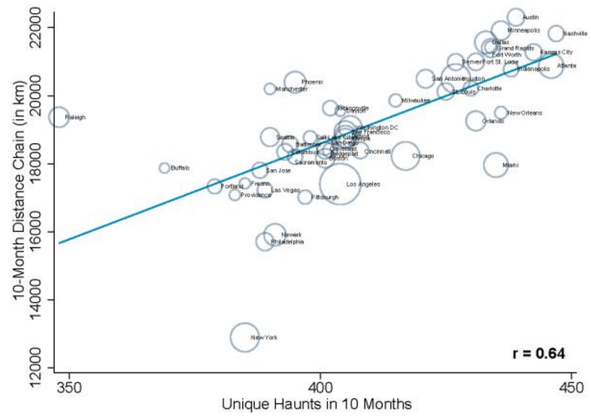


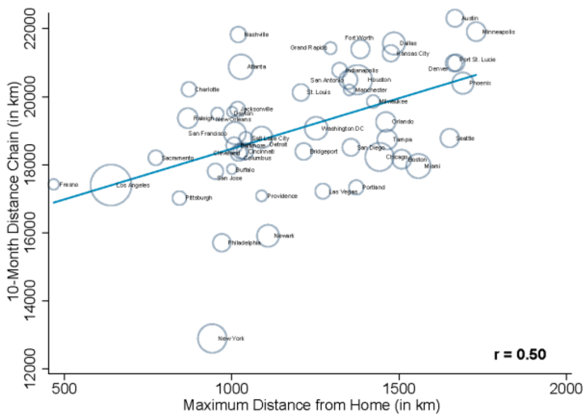
Online Appendix D. Distribution of Maximum Distance Traveled from Home (<50 km)

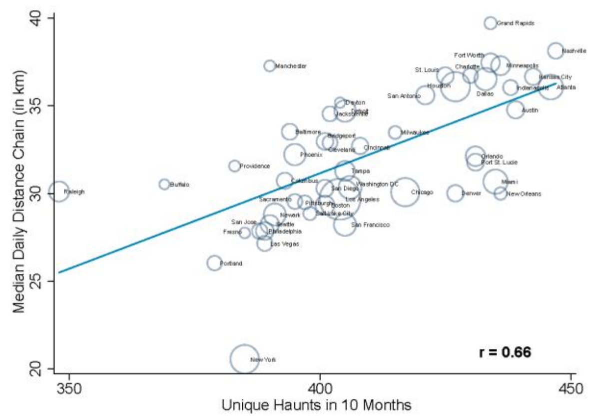


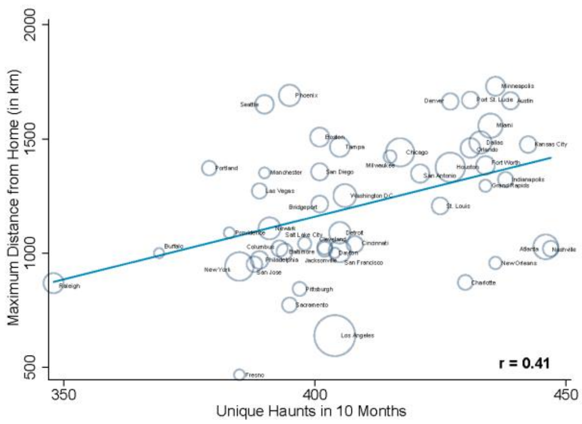
Online Appendix E. Top 50 CZ Correlation Graphs

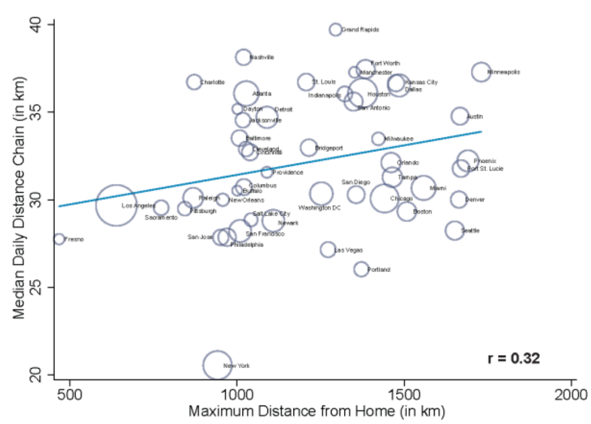








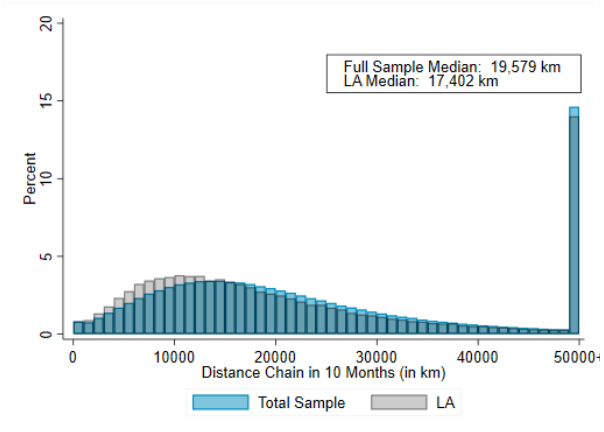




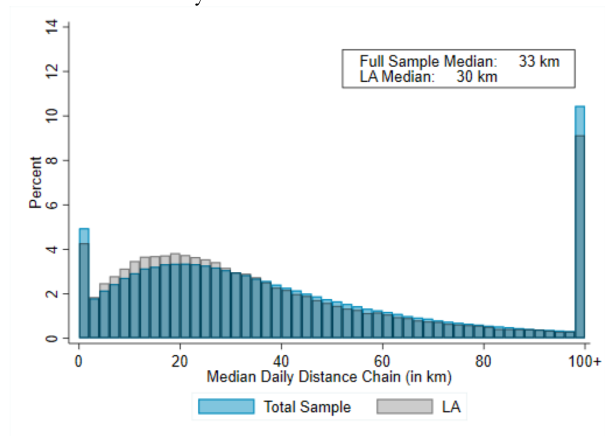
Online Appendix F. Mobility Measures for the 8 Most Populous CZ

F.Figure 1. Los Angeles

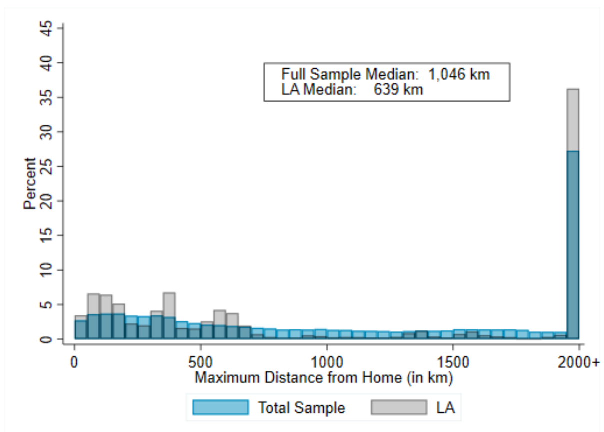
a. Distance Chain



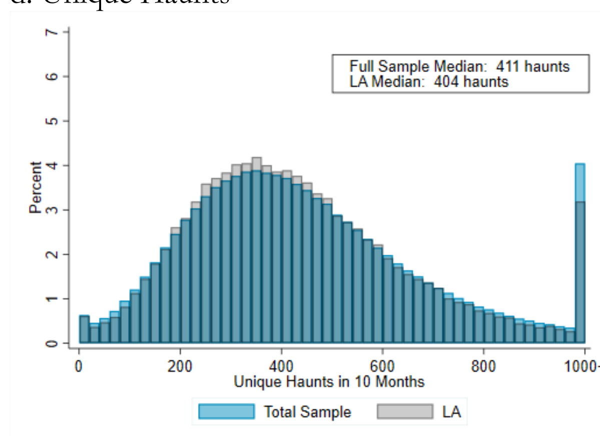
b. Median Daily Distance Chain



c. Maximum Distance from Home

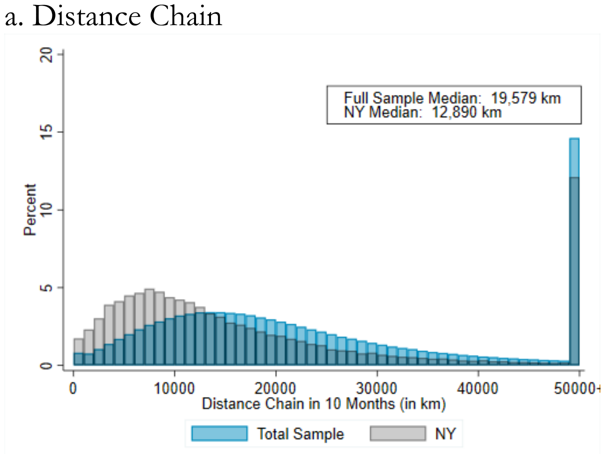


d. Unique Haunts

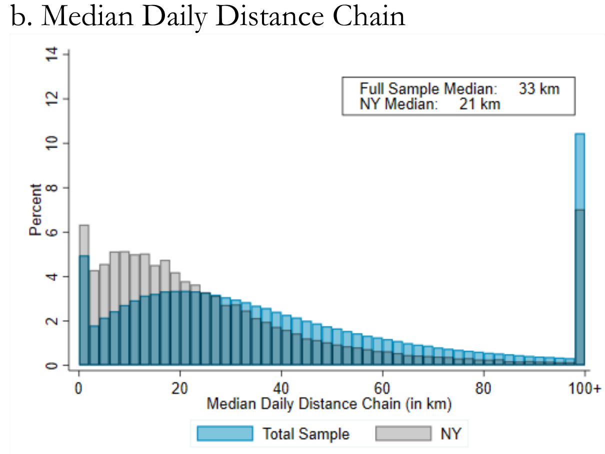


F.Figure 2. New York

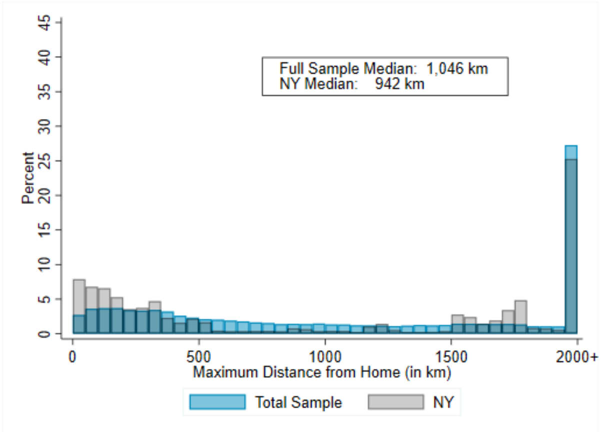
a. Distance Chain



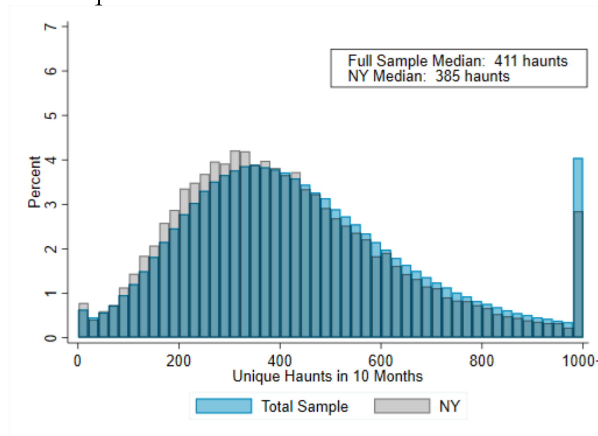
b. Median Daily Distance Chain



c. Maximum Distance from Home

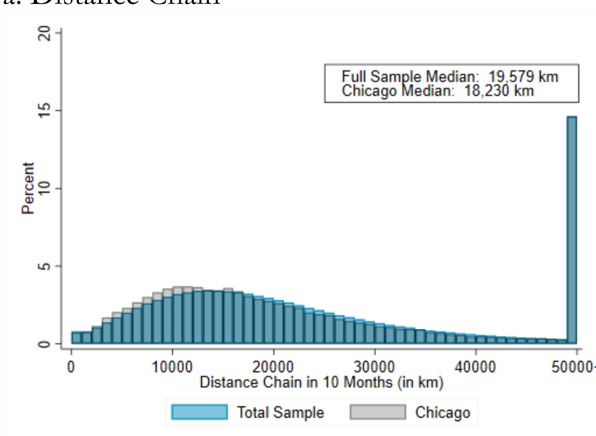


d. Unique Haunts

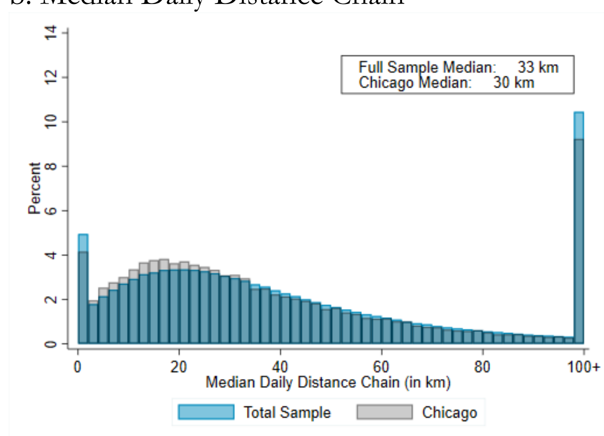


F.Figure 3. Chicago

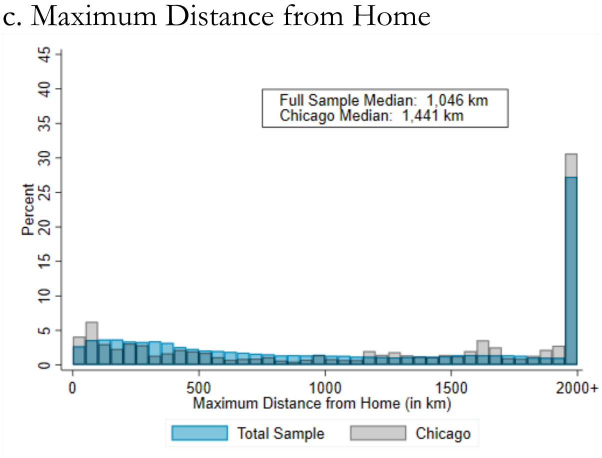
a. Distance Chain



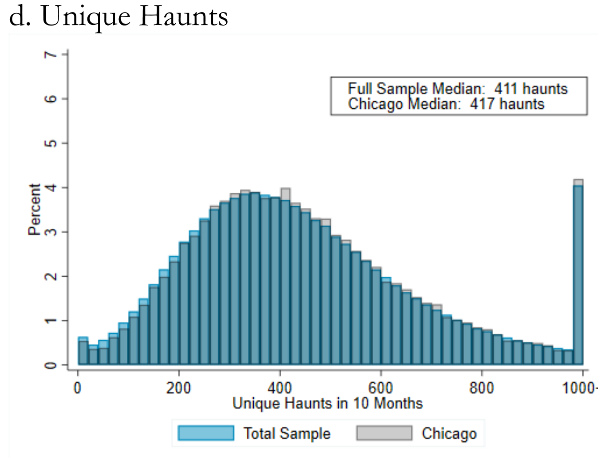
b. Median Daily Distance Chain



c. Maximum Distance from Home

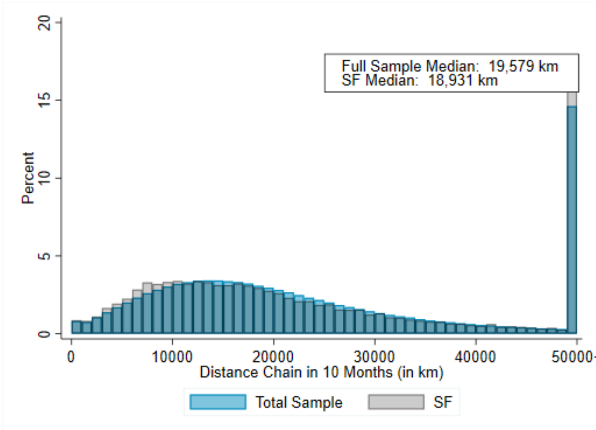


d. Unique Haunts

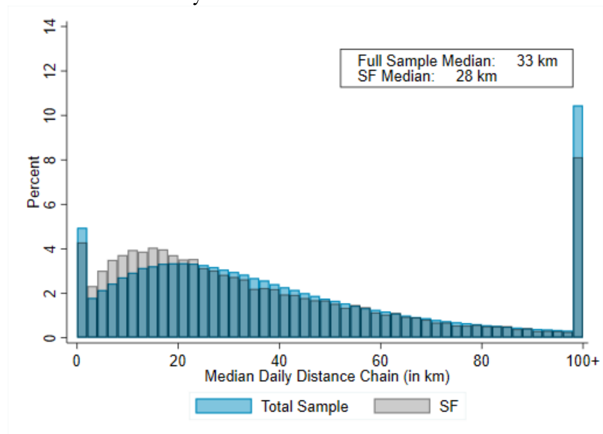


F.Figure 4. San Francisco

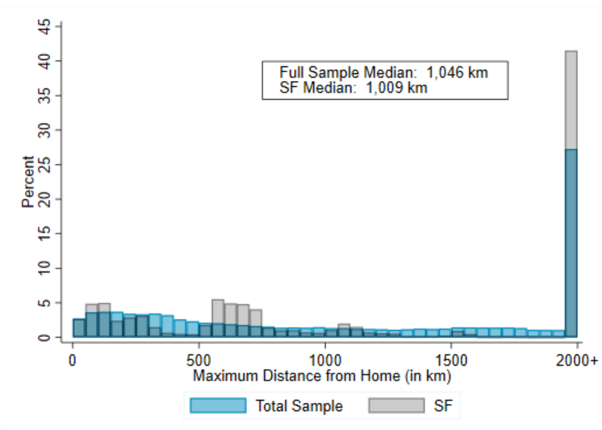
a. Distance Chain



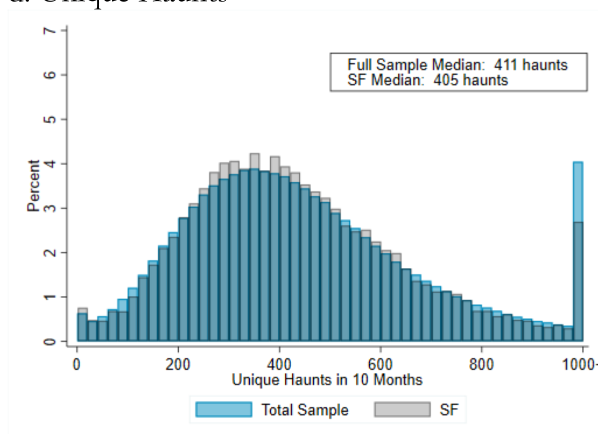
b. Median Daily Distance Chain



c. Maximum Distance from Home

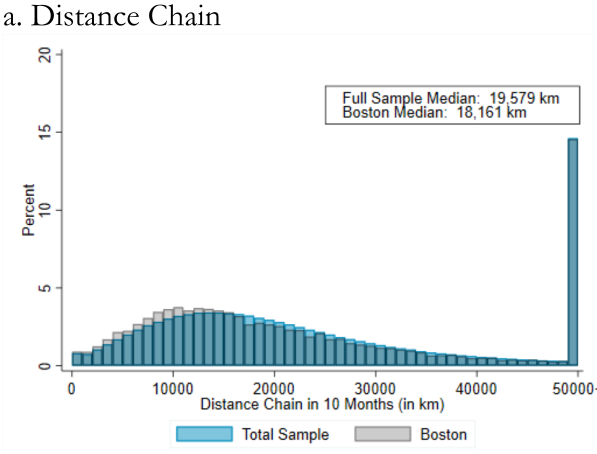


d. Unique Haunts

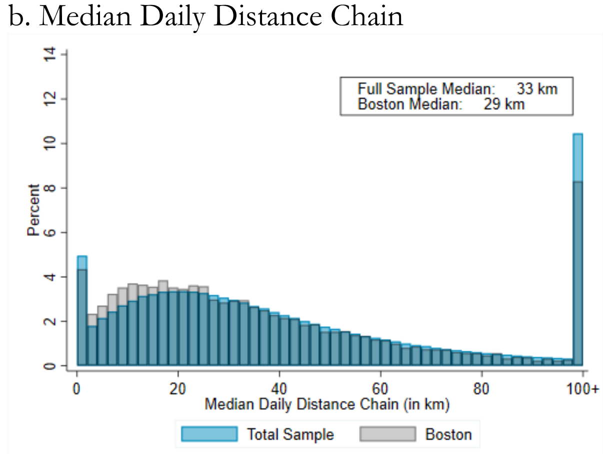


F.Figure 5. Boston

a. Distance Chain

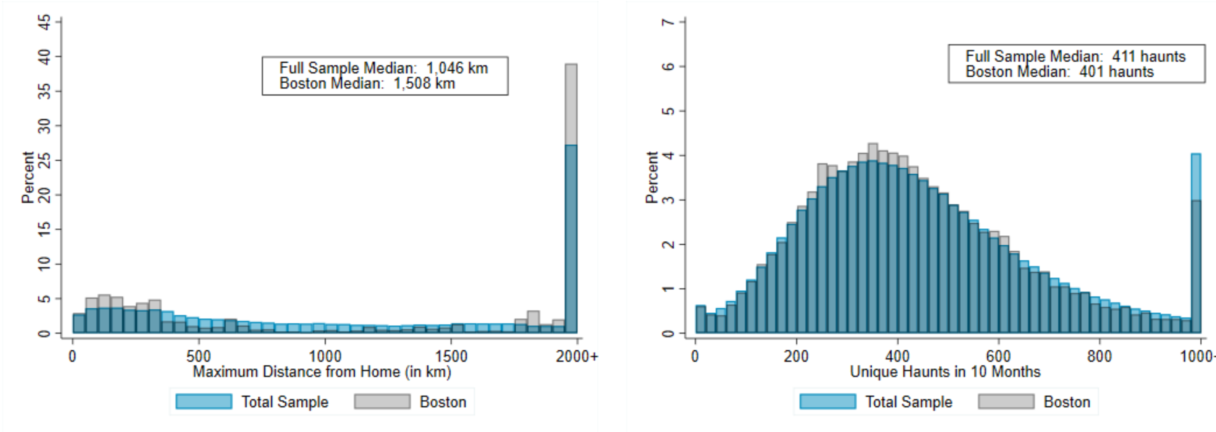


b. Median Daily Distance Chain



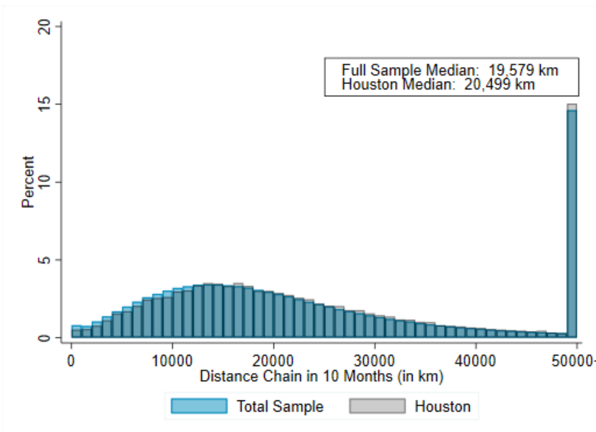
c. Maximum Distance from Home

d. Unique Haunts

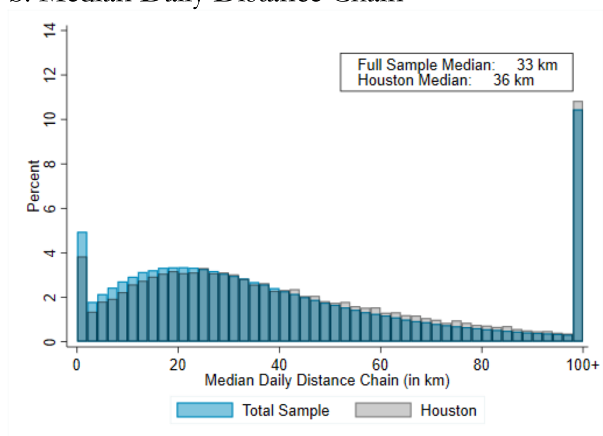


F.Figure 6. Houston

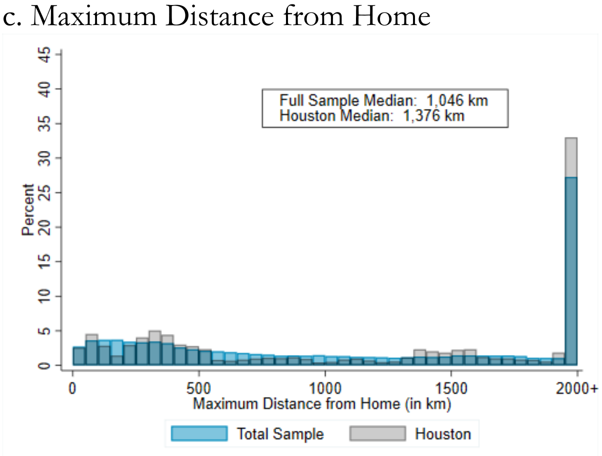
a. Distance Chain



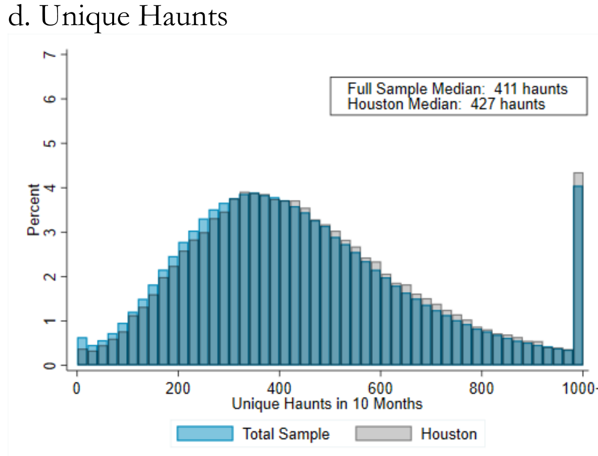
b. Median Daily Distance Chain



c. Maximum Distance from Home

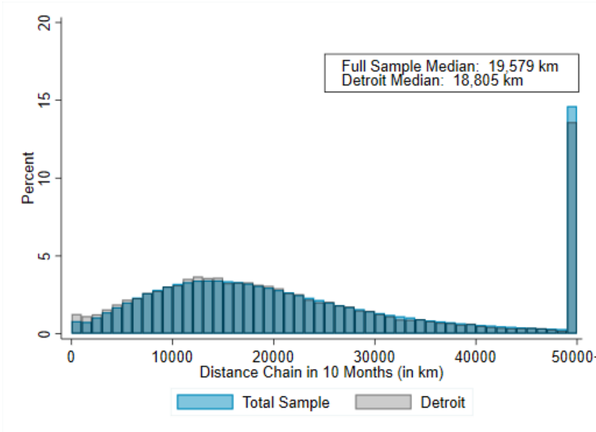


d. Unique Haunts

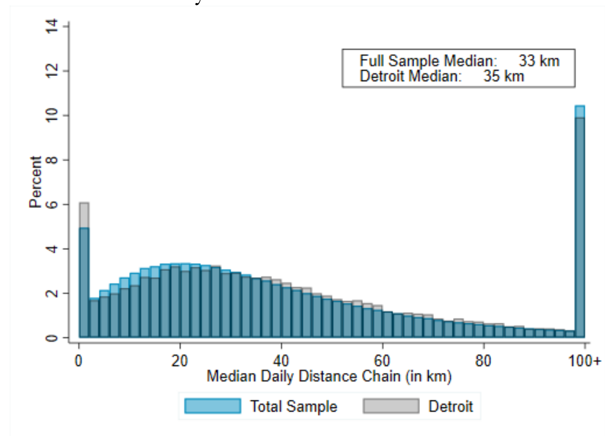


F.Figure 7. Detroit

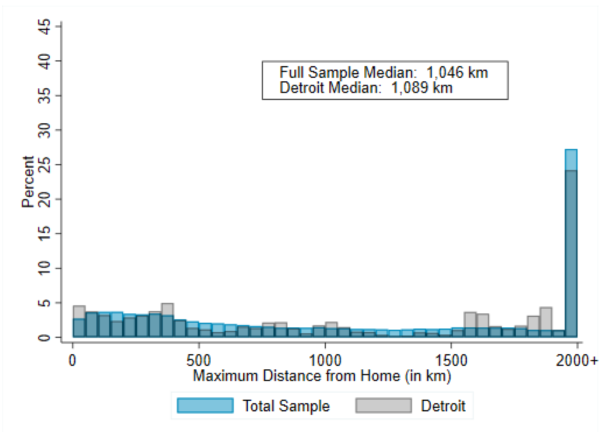
a. Distance Chain



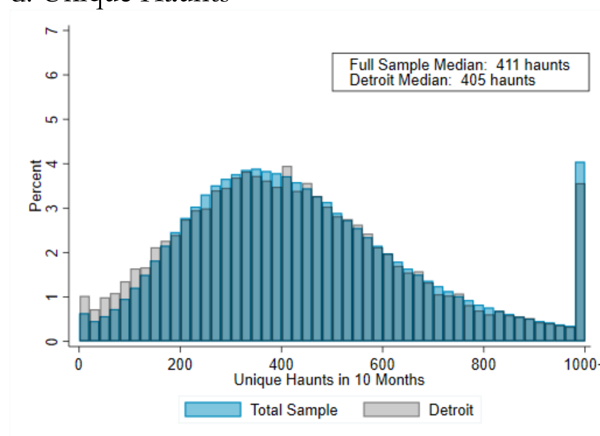
b. Median Daily Distance Chain



c. Maximum Distance from Home

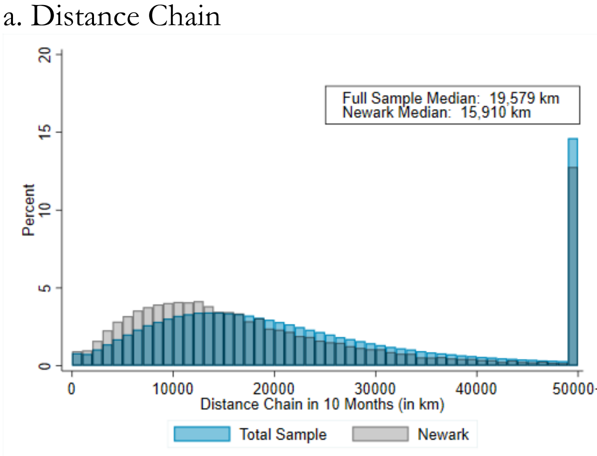


d. Unique Haunts

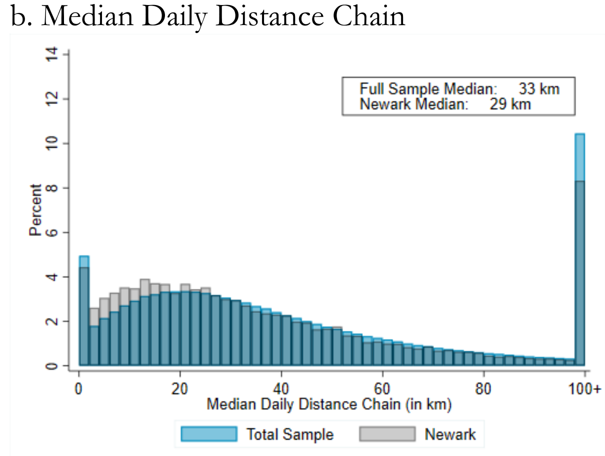


F.Figure 8. Newark

a. Distance Chain

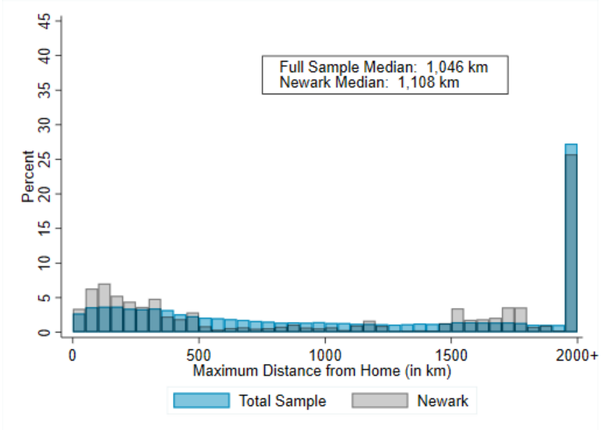


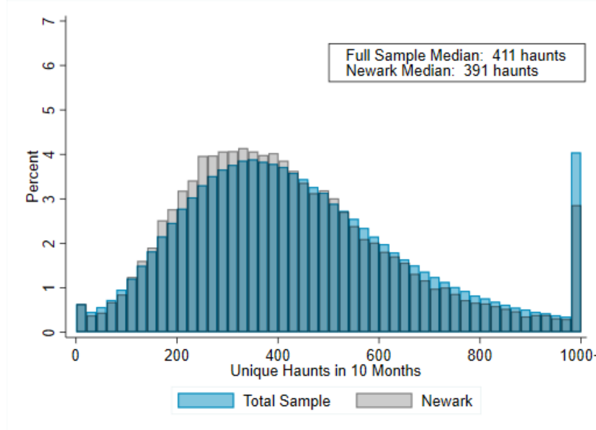
b. Median Daily Distance Chain



c. Maximum Distance from Home

d. Unique Haunts


Full Sample Median: 1,046 km
Newark Median: 1,108 km
Percent
Maximum Distance from Home (in km)
Total Sample
Newark


Full Sample Median: 411 haunts
Newark Median: 391 haunts
Percent
Unique Haunts in 10 Months
Total Sample
Newark

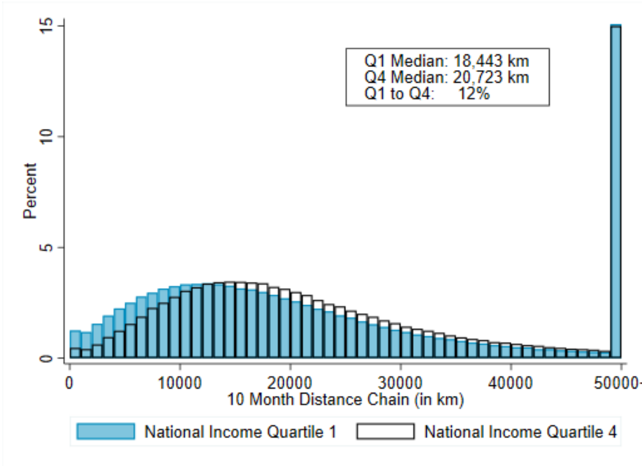
Online Appendix G. Top 50 Commuting Zones Mobility Measures

	Median of Mobility Measures				Ratio of CZ Quartile 1 : Quartile 4			
	Distance Chain (km)		Max. Dist. From Home (km)	Median Unique Haunts	Distance Chain		Max. Dist. From Home	Median Unique Haunts
Commuting Zone	10-Month	Daily			10-Month	Daily		
Atlanta, GA	20,880	36	1,028	446	0.94	1.22	0.79	0.90
Austin, TX	22,306	35	1,667	439	0.86	0.97	0.68	0.93
Baltimore, MD	18,571	34	1,007	394	0.72	0.77	0.46	0.86
Boston, MA	18,161	29	1,508	401	0.75	0.74	0.58	0.87
Bridgeport, CT	18,390	33	1,215	401	0.74	0.79	0.36	0.80
Buffalo, NY	17,873	31	1,000	369	0.82	0.79	0.64	0.87
Charlotte, NC	20,215	37	872	430	0.87	1.12	0.72	0.89
Chicago, IL	18,230	30	1,441	417	0.72	0.90	0.63	0.86
Cincinnati, OH	18,396	33	1,039	408	0.79	0.80	0.67	0.81
Cleveland, OH	18,392	33	1,027	402	0.75	0.78	0.57	0.81
Columbus, OH	18,350	31	1,020	393	0.74	0.82	0.52	0.76
Dallas, TX	21,567	37	1,485	433	0.80	1.09	0.50	0.85
Dayton, OH	19,552	35	1,001	404	0.83	0.84	0.65	0.84
Denver, CO	20,988	30	1,664	427	0.78	0.87	0.68	0.87
Detroit, MI	18,805	35	1,089	405	0.76	0.82	0.49	0.78
Fort Worth, TX	21,399	37	1,384	434	0.83	1.00	0.58	0.86
Fresno, CA	17,422	28	467	385	0.88	0.93	0.78	0.83
Grand Rapids, MI	21,427	40	1,295	434	0.86	0.92	0.59	0.81
Houston, TX	20,499	36	1,376	427	0.83	1.05	0.44	0.90
Indianapolis, IN	20,780	36	1,322	438	0.76	0.93	0.66	0.82
Jacksonville, FL	19,634	35	1,017	402	0.87	0.92	0.54	0.89
Kansas City, MO	21,278	37	1,475	443	0.79	0.97	0.63	0.80
Las Vegas, NV	17,222	27	1,272	389	0.96	0.86	0.81	0.96
Los Angeles, CA	17,402	30	639	404	0.75	0.87	0.31	0.87
Manchester, NH	20,199	37	1,351	390	0.88	0.88	0.40	0.88

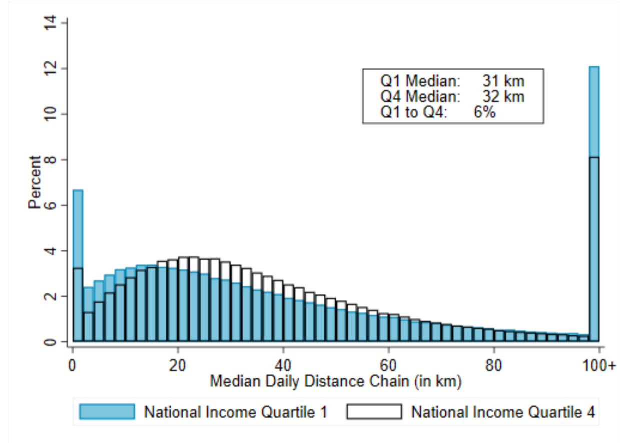
Miami, FL	17,961	31	1,558	435	0.70	0.85	0.55	0.87
Milwaukee, WI	19,861	33	1,423	415	0.76	0.73	0.68	0.84
Minneapolis, MN	21,914	37	1,731	436	0.81	0.84	0.73	0.84
Nashville, TN	21,828	38	1,020	447	0.87	1.04	0.76	0.86
New Orleans, LA	19,499	30	957	436	0.85	0.95	0.64	0.90
New York, NY	12,890	21	942	385	0.54	0.71	0.23	0.77
Newark, NJ	15,910	29	1,108	391	0.66	0.74	0.29	0.82
Orlando, FL	19,260	32	1,461	431	0.85	0.92	0.79	0.90
Philadelphia, PA	15,705	28	970	389	0.67	0.68	0.33	0.84
Phoenix, AZ	20,399	32	1,691	395	0.80	0.85	0.60	0.85
Pittsburgh, PA	17,019	29	843	397	0.77	0.79	0.52	0.83
Port St. Lucie, FL	20,997	32	1,670	431	0.78	0.91	0.78	0.86
Portland, OR	17,332	26	1,372	379	0.75	0.91	0.76	0.86
Providence, RI	17,085	32	1,089	383	0.77	0.67	0.36	0.87
Raleigh, NC	19,369	30	869	348	0.90	1.10	0.62	0.88
Sacramento, CA	18,205	30	773	395	0.84	0.89	0.69	0.90
Salt Lake City, UT	18,771	29	1,042	398	0.82	0.85	0.63	0.85
San Antonio, TX	20,498	36	1,349	421	0.75	0.78	0.37	0.86
San Diego, CA	18,511	30	1,356	401	0.76	0.94	0.32	0.88
San Francisco, CA	18,931	28	1,009	405	0.82	0.93	0.34	0.90
San Jose, CA	17,806	28	951	388	0.82	0.95	0.27	0.93
Seattle, WA	18,783	28	1,652	390	0.83	0.98	0.81	0.89
St. Louis, MO	20,125	37	1,207	425	0.83	0.97	0.68	0.82
Tampa, FL	18,740	31	1,465	405	0.83	0.87	0.80	0.91
Washington DC	19,070	30	1,252	406	0.84	0.97	0.61	0.93

Online Appendix H. Mobility Measures by the Top and Bottom National Income Quartiles

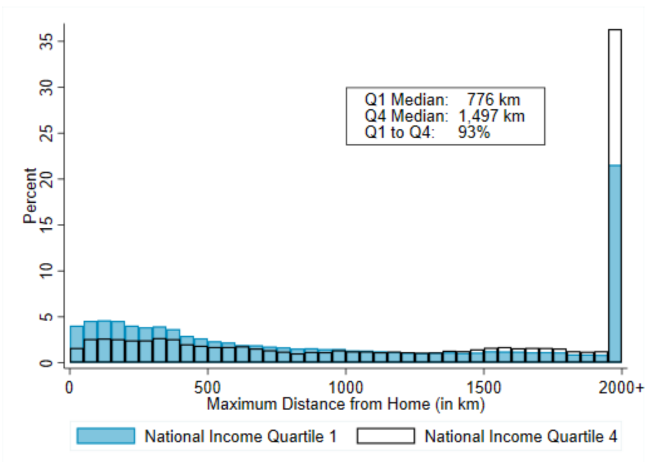
a. Distance Chain



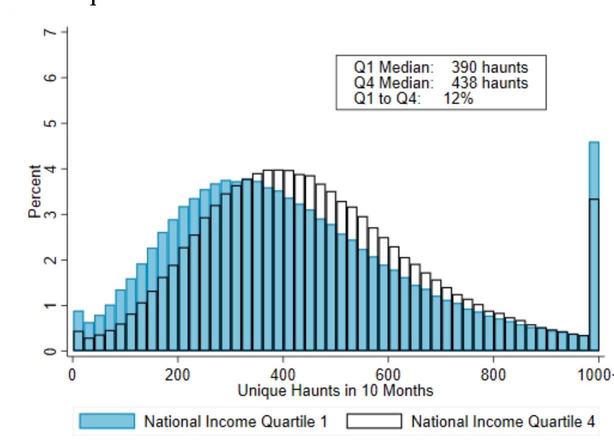
b. Median Daily Distance Chain



c. Maximum Distance from Home



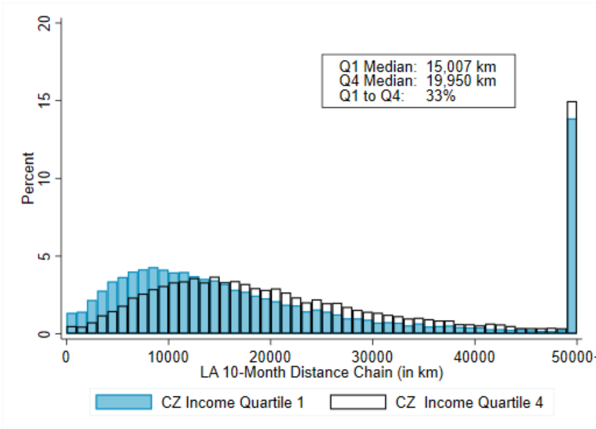
d. Unique Haunts



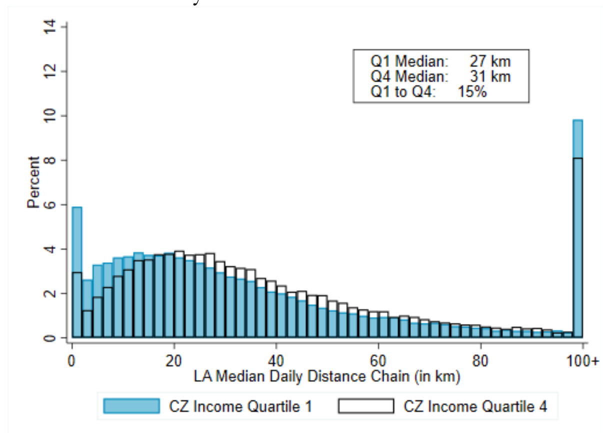
Online Appendix I. Mobility Measures of the 8 Most Populous CZs by the Top and Bottom CZ Income Quartile

IFigure 1. Los Angeles

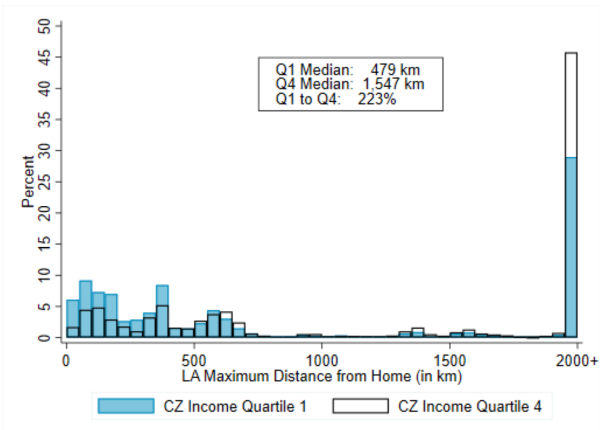
a. Distance Chain



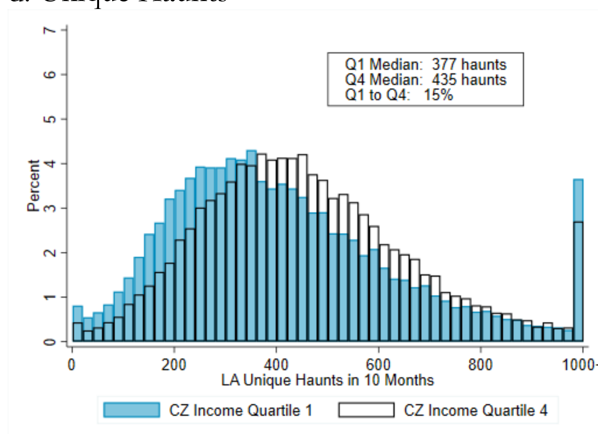
b. Median Daily Distance Chain



c. Maximum Distance from Home



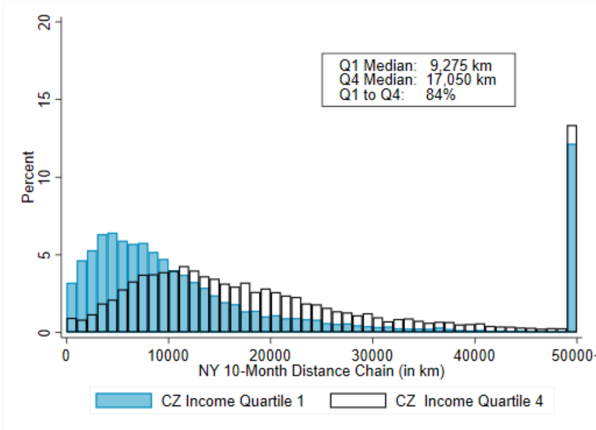
d. Unique Haunts

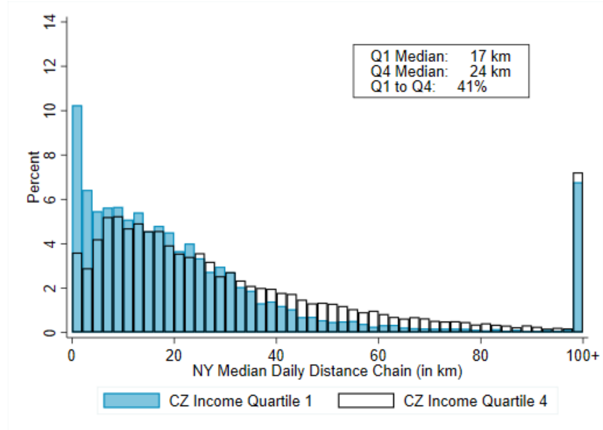


IFigure 2. New York

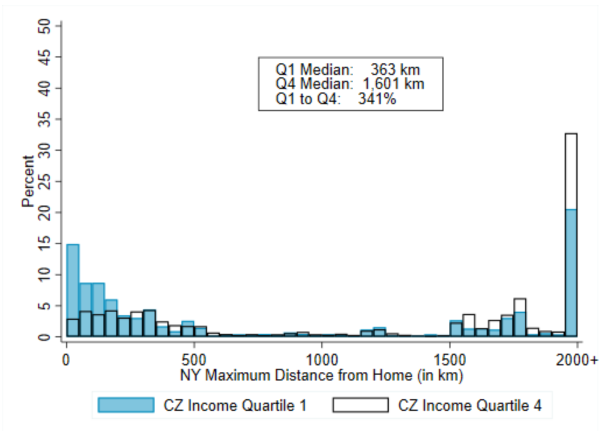
a. Distance Chain

b. Median Daily Distance Chain

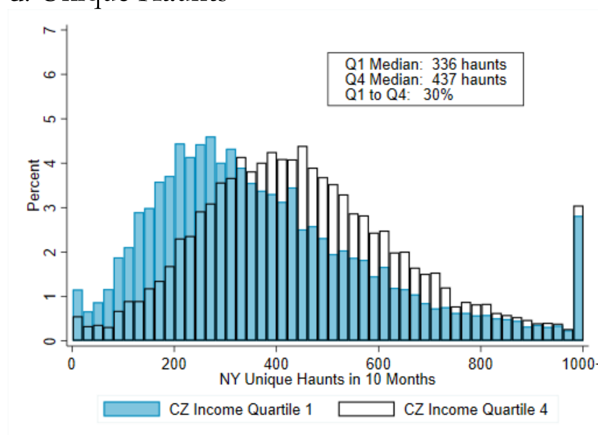




c. Maximum Distance from Home

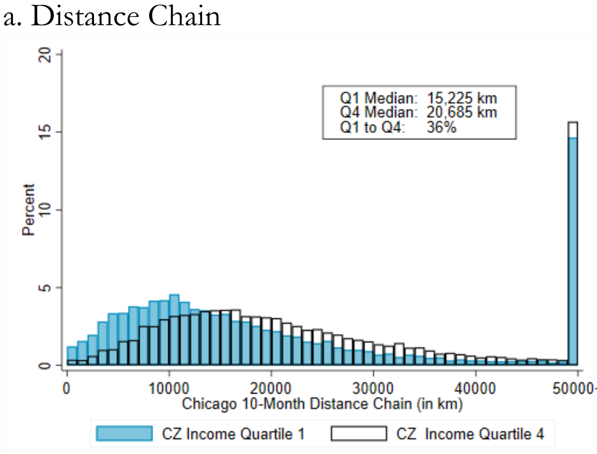


d. Unique Haunts

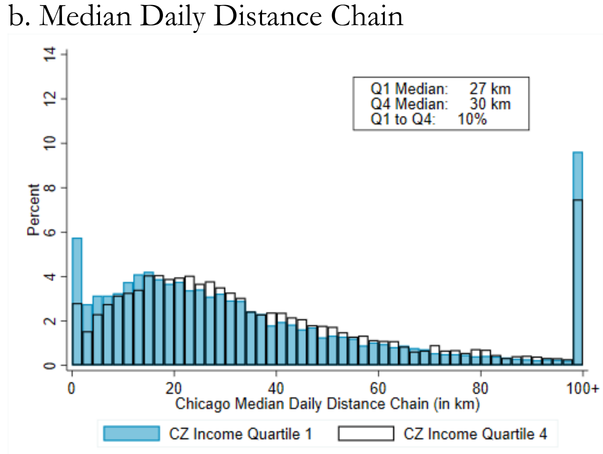


I.Figure 3. Chicago

a. Distance Chain

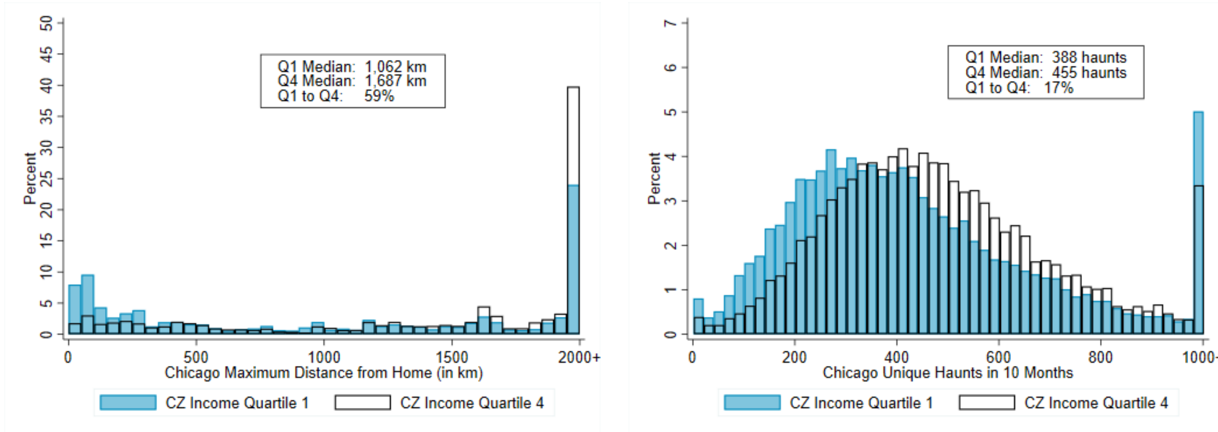


b. Median Daily Distance Chain



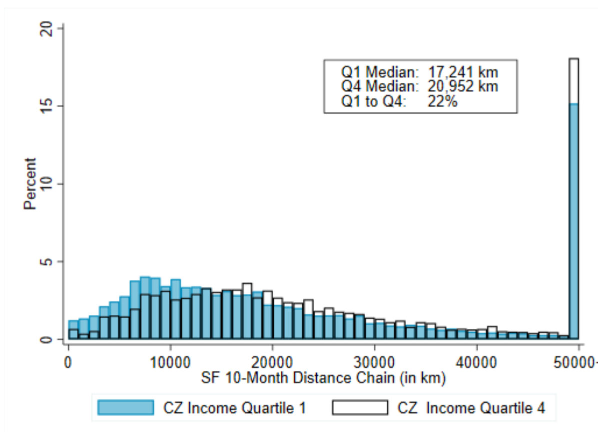
c. Maximum Distance from Home

d. Unique Haunts

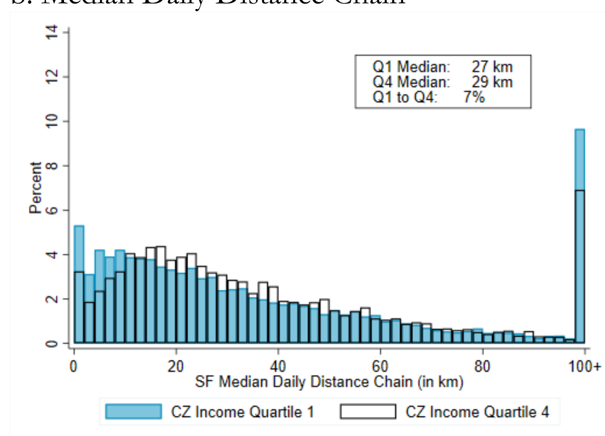


I.Figure 4. San Francisco

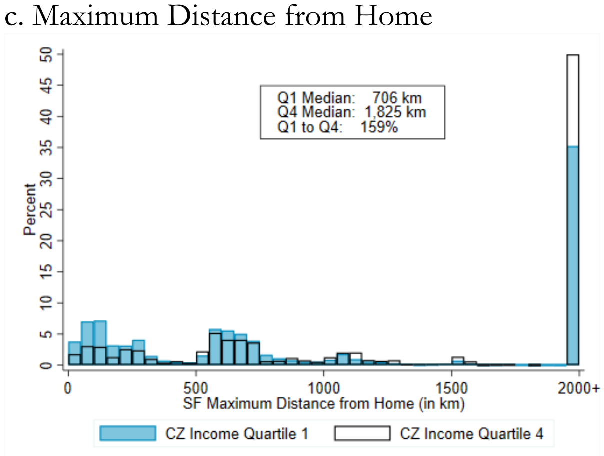
a. Distance Chain



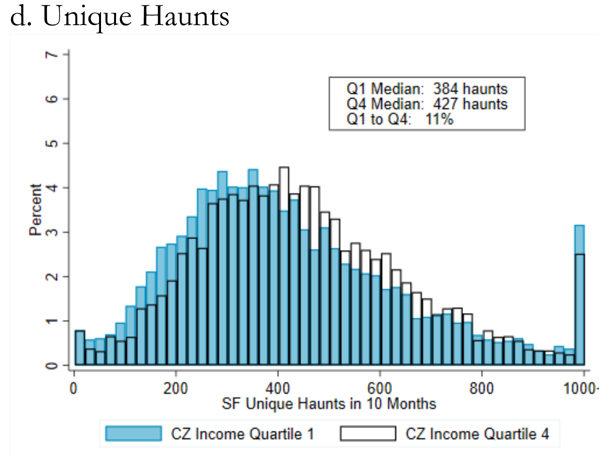
b. Median Daily Distance Chain



c. Maximum Distance from Home

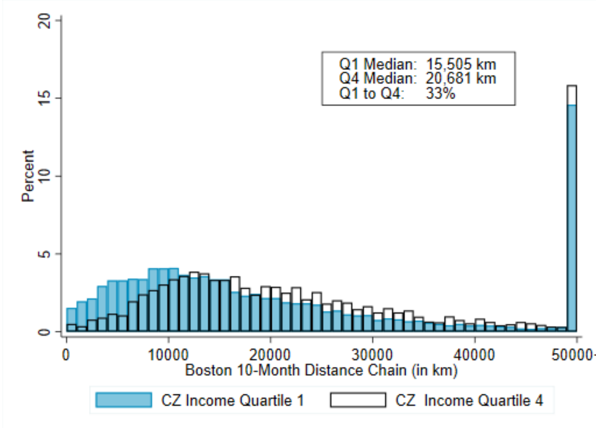


d. Unique Haunts

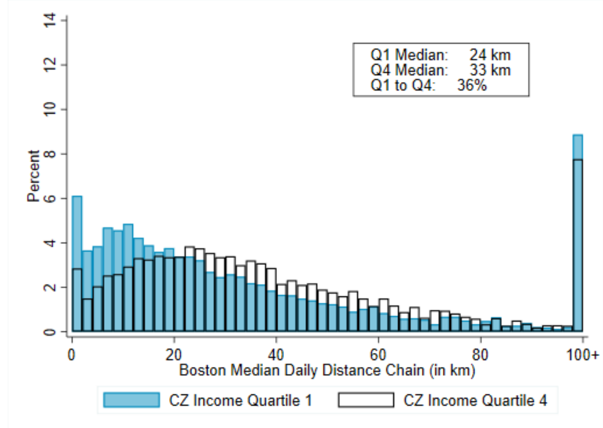


I.Figure 5. Boston

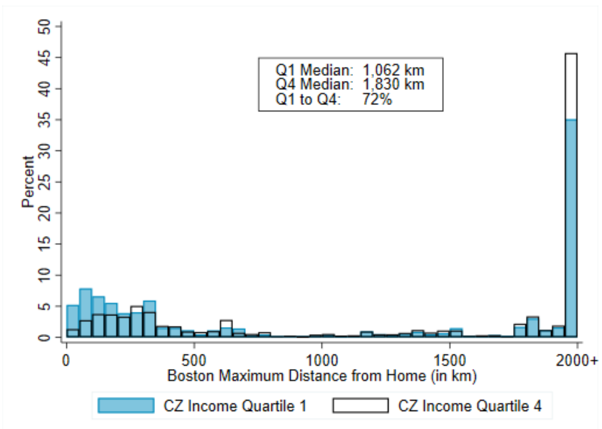
a. Distance Chain



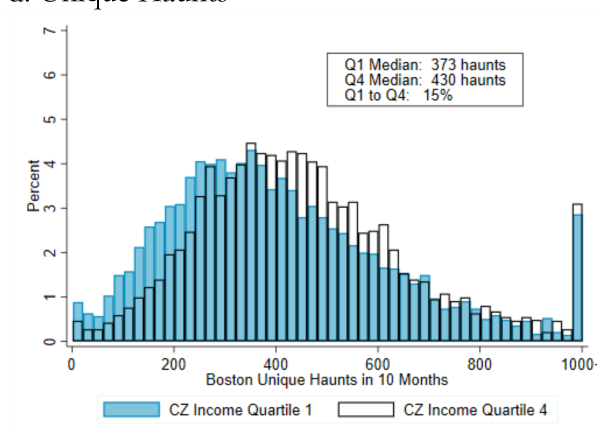
b. Median Daily Distance Chain



c. Maximum Distance from Home

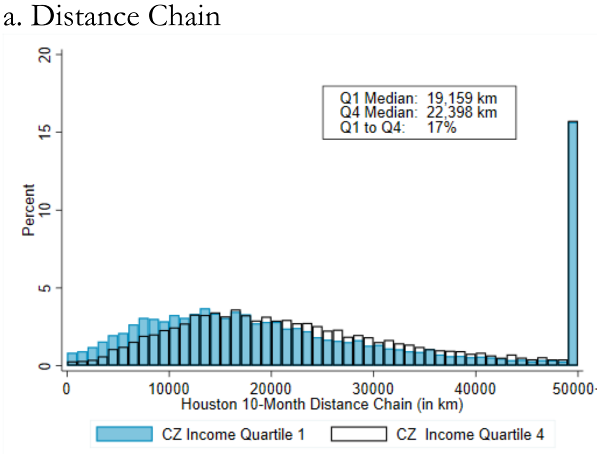


d. Unique Haunts

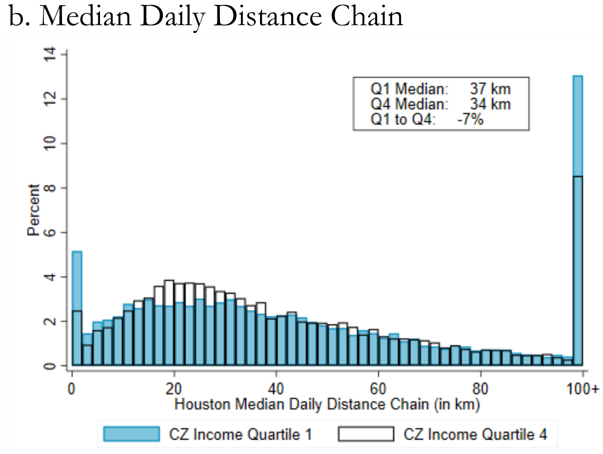


I.Figure 6. Houston

a. Distance Chain

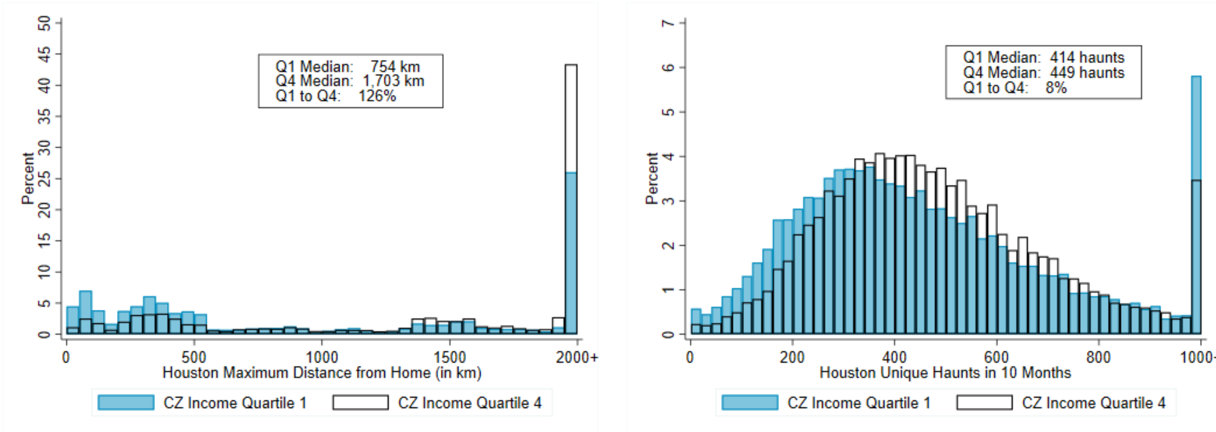


b. Median Daily Distance Chain



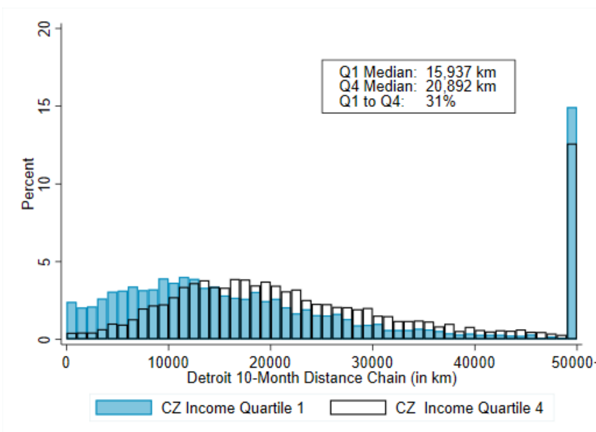
c. Maximum Distance from Home

d. Unique Haunts

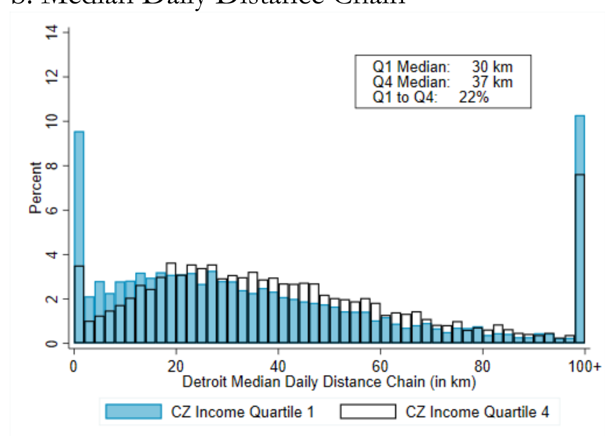


I.Figure 7. Detroit

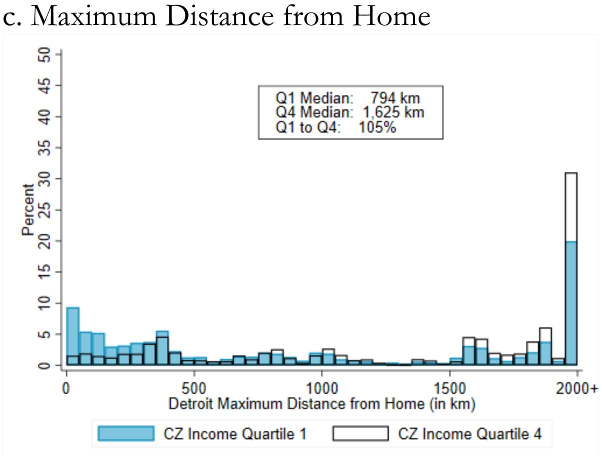
a. Distance Chain



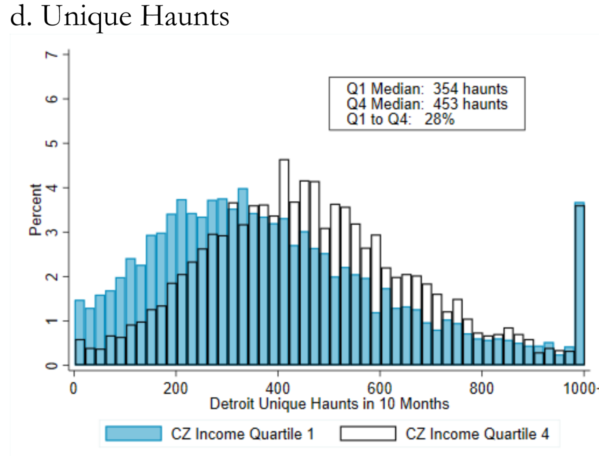
b. Median Daily Distance Chain



c. Maximum Distance from Home

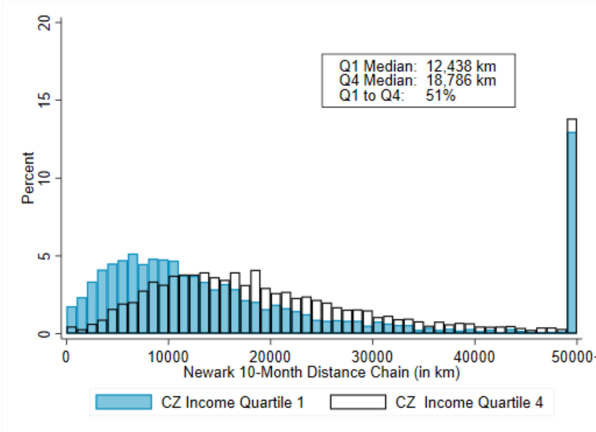


d. Unique Haunts

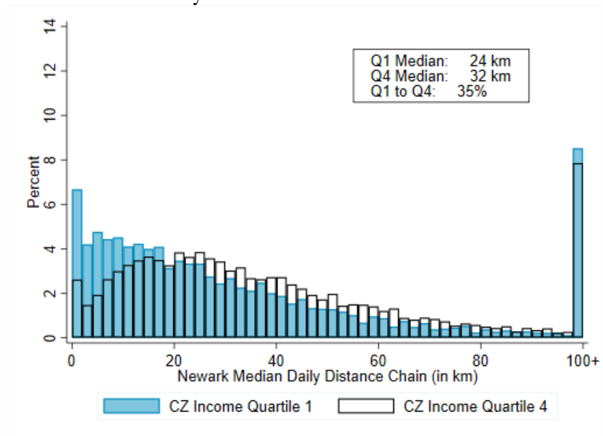


I.Figure 8. Newark

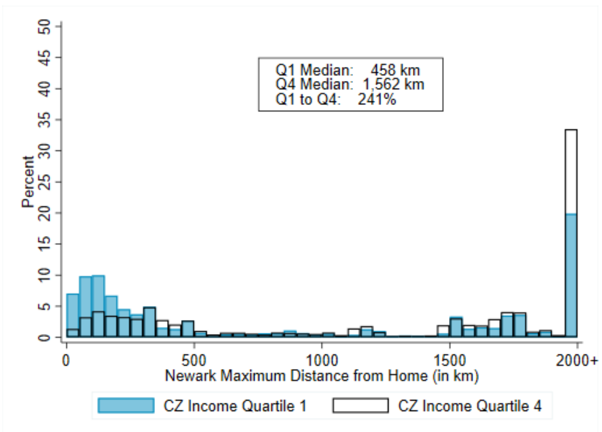
a. Distance Chain



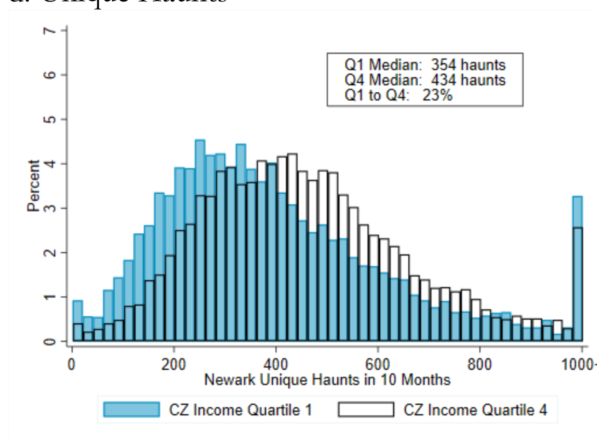
b. Median Daily Distance Chain



c. Maximum Distance from Home



d. Unique Haunts



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