

Inequalities in Mobility Patterns: Reconciling Access and Travel in American Cities

Talia Kaufmann^{*1}, Gabriel Agostini^{†2}, Trivik Verma^{‡3} and Daniel T. O'Brien^{§1}

¹School of Public Policy and Urban Affairs, Northeastern University

²Cornell Tech, Cornell University

³School for Policy Studies, University of Bristol

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Summary

Amenities and institutions provide essential services and facilitate social interactions within urban communities, contributing to residents' well-being. Therefore, the disparity in access to amenities across communities is one of the main contributors to urban inequality. This paper measures whether being close to an amenity reduces the distances traveled to reach such an amenity across amenity types and income groups, using high-resolution mobility data from SafeGraph all 162 metro areas in the USA. Results suggest that having easy access to essential amenities decreases traveled distances across all urban communities but that increased access to amenities is more valuable for low-income communities.

KEYWORDS: urban mobility, accessibility, income inequality, land use planning

1 Introduction

How far would one walk to a grocery store or a pharmacy? Drive to a gym? Take a subway to the park? Urban dwellers tend to perceive the quality of their neighborhood by the amount and variety of accessible amenities from their home (Buys and Miller 2012; Hur, Nasar, and Chun 2010), while their amenity needs and travel behavior is highly subjective varying by demographic characteristics like age, gender and income (Colabianchi et al. 2007; Farthing, Winter, and Coombes 1996; Coulton, Jennings, and Chan 2013; Saelens, Sallis, and Frank 2003; Lenormand et al. 2015; Sobolevsky et al. 2016). Spatial proximity to amenities and institutions is important for urban communities because these establishments provide essential services while also facilitating social interaction (Simmel 1971; Whyte 1980; Lund 2003; Hampton, Goulet, and Albanesius 2015).

^{*}kaufmann.t@northeastern.edu

[†]gsagostini@infosci.cornell.edu

[‡]trivik.verma@bristol.ac.uk

[§]d.obrien@northeastern.edu

These authors contributed equally: Talia Kaufmann, Gabriel Agostini

Research has also shown that the ability to travel far and wide from home diminishes as incomes shrink. Spatial accessibility to services weighs higher importance to low- and middle-income groups confined in their mobility while their immediate surroundings has a much larger affect on their quality of life (Ahlbrandt 1984; Fried 1986; Talen 1999). Amenities and institutions act as information and knowledge brokers within low income communities and thus enable people to access to social and job opportunities (Massey, Condran, and Denton 1987; Wilson 1987; Musterd and Ostendorf 2013; Allard and Small 2013; Small 2013; Klinenberg 2018), while also contributing to well-being and upward mobility in later stages of life (Sampson, Morenoff, and Gannon-Rowley 2002; Chetty and Hendren 2018).

However, urban planners responsible for allocating resources that shape urban environments do not take into account the social and spatial mechanism at play in cities which perpetuates urban inequality (Mouratidis 2018) while also lacking the metrics to measure accessibility at scale across cities to guide their decisions (Glaeser et al. 2018; Bettencourt and West 2010). To highlight motivation of travel choices, this paper measures travel distance to amenities at the census block level in 162 American cities by analyzing type of amenity visited in relation to distances to the closest accessible amenities. We build upon prior research showing that the distance traveled to amenities varies by demographic group and amenity type (Lenormand et al. 2015; Moro et al. 2021; Hilman, Iñiguez, and Karsai 2022) to study whether having nearby amenities influences access and travel choices. We focus on how the relationship between those two sets of distances differ in light of the type of amenity visited and by income level, while also highlighting how these patterns vary by local conditions of cities.

2 Data and Methods

We use SafeGraph Places and trip data to study mobility patterns across all US metropolitan areas during September 2019. Mobility patterns include the number of mobile phone devices that visit a POI (captured by latitude, longitude and type) aggregated by weeks, from their Census Block Group (CBG) home location. We corrected visitors data for sampling bias using the number of devices reported by SafeGraph as residing in the origin CBG, proportional to the CBG population reported by the US Census (American Community Survey 2018 5-Year Estimate). Overall, SafeGraph data covers roughly 10% of U.S. mobile devices estimated as 46.8 million devices. Sampling bias in SafeGraph data appears is small and consistent across American CBGs and demographic groups (Squire 2019).

Distances from home CBG to POI are calculated along the street network as collected from OpenStreetMap(OSM) using OSMnx in Python (Boeing 2017). We include commutes within 162 Functional Urban Areas (FUA) (OECD 2012), with a peripheral 10 km buffer. We compute distances for each realized commute and distances from each CBG to the 10 closest POIs in each category, as illustrated in Figure 1.



Figure 1: **The CBG-POI mobility network model.** Example of Manhattan, NY. The bottom map shows all census block groups (CBGs), demonstrating three CBGs as trip origins. The top map show the POIs, the amenities the are visited by residents. Solid lines represents the traveled distances to amenities which are the weekly visitation patterns and dotted lines represents the accessible distances to amenities in close proximity to home. In three-dimensional representation, diagonal lines capture long distances while straight lines capture short distances.

2.1 Hierarchical Linear Models

We explore the relationship between traveled and accessible distances using hierarchical linear models that nest CBGs within FUAs. Such models permit simultaneously testing the effects of CBG and FUA-level features using all data while accounting for notable differences across FUAs. We run a separate model for each POI category considered.

Model Specification Our dependent variable ($y_{j,k}$) is the median traveled distance to POIs of a given category for each CBG j , nested within FUA k . Our main independent variable ($x_{j,k}$) at the CBG level is the median accessible distance for POIs of that category. We use a logarithm transformation in the distances, expressed in kilometers. We standardize the accessible distance independently for each FUA. We model FUA-level effects due to population and POI density in both the intercept ($\beta_{0,k}$) and the accessible distance coefficient ($\beta_{1,k}$). We include a binary indicator of the CBG income, $C_{j,k}$, which takes value $C_{j,k} = 1$ if the CBG is high-income and 0 otherwise, and its interaction with the accessible distance predictor. The basic model can thus be expressed

in the following form:

$$\log y_{j,k} = [\beta_{0,k} + \beta_2 \cdot C_{j,k}] + [\beta_{1,k} + \beta_3 \cdot C_{j,k}] \cdot \log x_{j,k} + \eta_{j,k} \quad (\text{CBG-level}) \quad (1)$$

$$\beta_{0,k} = \beta_0 + \gamma_{0,1} \cdot \text{population}_k + \gamma_{0,2} \cdot \text{POI_density}_k + \varepsilon_{0,k} \quad (\text{intercept, FUA-level}) \quad (2)$$

$$\beta_{1,k} = \beta_1 + \gamma_{1,1} \cdot \text{population}_k + \gamma_{1,2} \cdot \text{POI_density}_k + \varepsilon_{1,k} \quad (\text{distance coeff., FUA-level}) \quad (3)$$

Models Considering Driving Behavior. We also introduce models taking into account the propensity for driving in a CBG ($d_{j,k}$), standardized within-FUA. Such models the following CBG-level equation:

$$\log y_{j,k} = [\beta_{0,k} + \beta_2 \cdot C_{j,k}] + [\beta_{1,k} + \beta_3 \cdot C_{j,k}] \cdot \log x_{j,k} + \beta_4 \cdot d_{j,k} + \beta_5 \cdot d_{j,k} \cdot \log x_{j,k} + \eta_{j,k} \quad (4)$$

3 Results

We first look at the distributions of traveled and accessible distances, finding that on average the distance to the closest amenities is far smaller than traveled distances across all cities and amenity types (Figure 2). Then, we use our models to examine the effects of income and FUA-level mechanisms on the relationship between visitation and accessibility.

3.1 Income Inequalities Reveal Disparities in Travel Radii

We compare travel patterns between high- and low-income residents, with results summarized in Figure 3. A CBG is classified as low-income if at least 30% of the CBG residents live below the poverty line. We observe inequalities in the data and verify that these inequalities do not vanish when controlling for FUA-varying levels of accessibility; in fact, even characteristics such as preference for driving are not sufficient to eliminate the disparate travel patterns of high- and low-income CBG residents.

The population-weighted traveled and accessible distances suggest that residents from high-income CBGs travel farther than residents from low-income CBGs, yet also experience comparatively lower accessibility. However, when we use a model to control for the average within-FUA accessible distance to POIs, the discrepancy in traveled distances remains directionally the same in all categories except grocery stores. These disparities are higher in POI categories which represent leisure or recurrent trips: high-income residents travel more than low-income residents on average to day cares (18.7% more), parks and museums (13.7%), and religious organizations (7.5%). None of these disparities vanishes when accounting for the capacity to drive (Figure 3b). We find that the capacity to drive reduces significance of the disparities in traveled distances to restaurants and gyms (significant at the $p = 10^{-13}$ level before accounting for driving, only significant at the $p = 0.3$ level afterwards). These trips are often chained with trips to work or entail social activities. Conversely, propensity to drive *heightens* disparities in distances traveled to schools—perhaps explained by school zoning and other American urban policies. Interestingly, income disparities in traveled distances to grocery stores directionally disagree with all other categories: residents of high-income CBGs travel about 7.5% *less* to grocery stores than residents of low-income CBGs after adjustments, whether accounting or not for driving capacity.

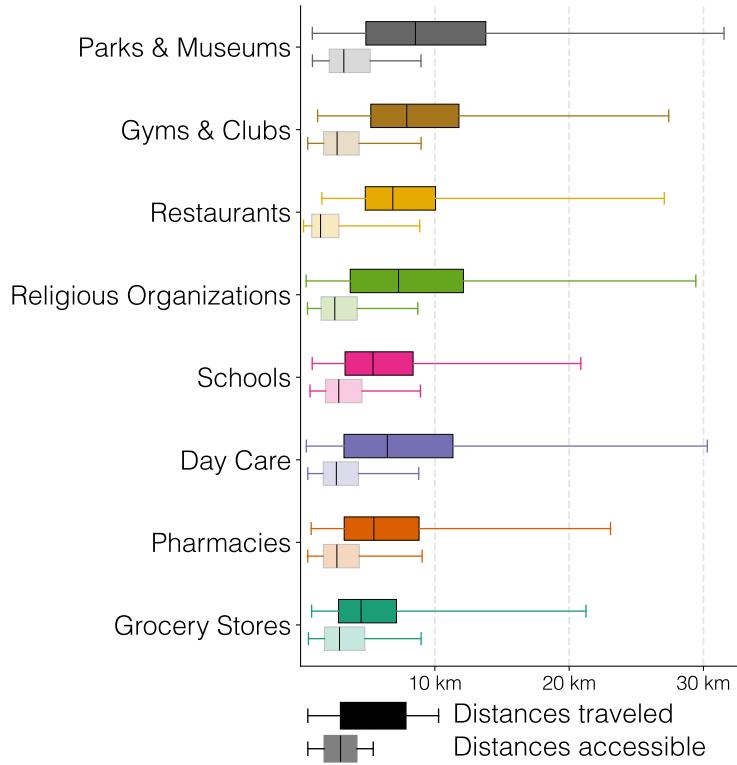
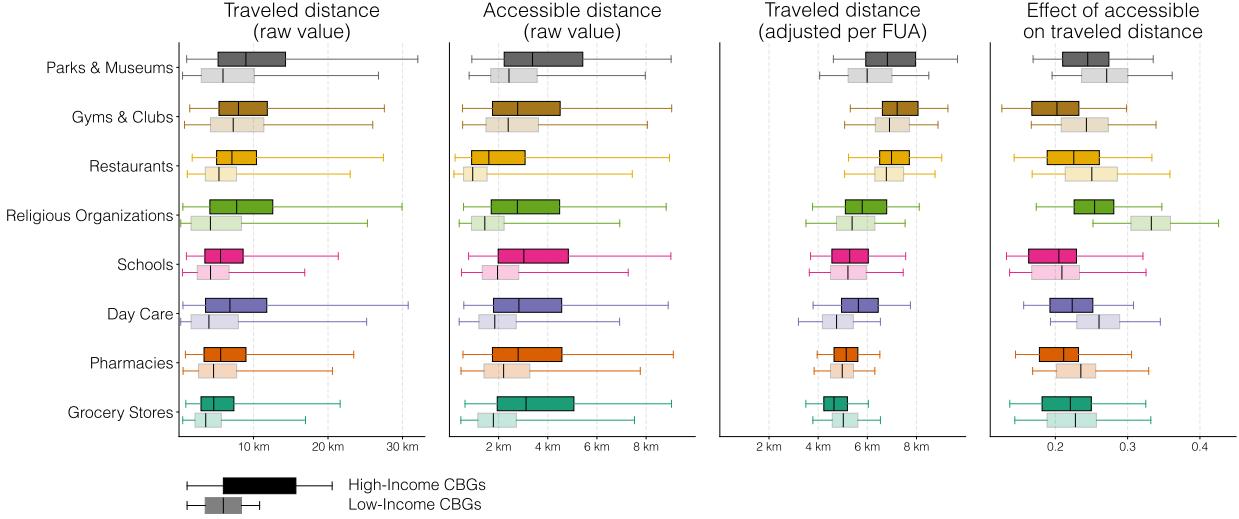
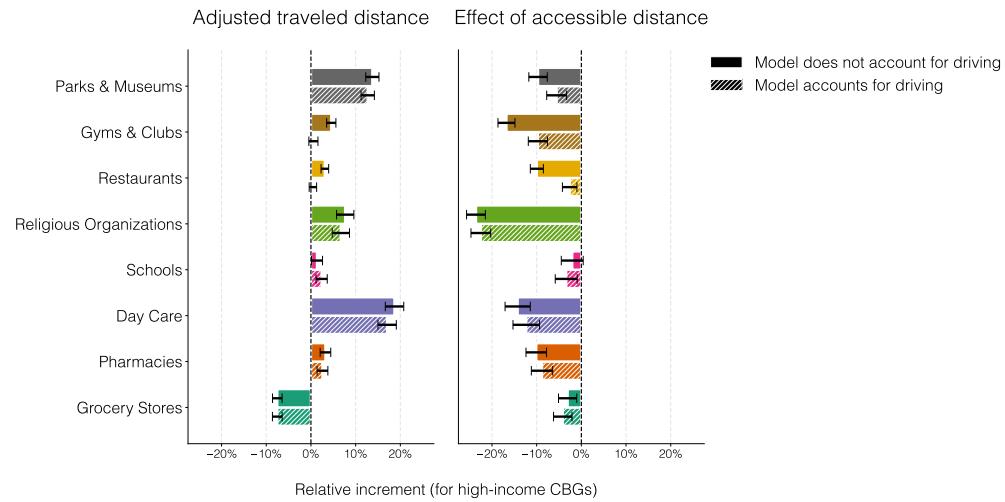


Figure 2: Travel distances are much larger than accessible distances. Comparing the distribution of the population-weighted median traveled distances (top box-plots) to the median accessible distances (bottom box-plots) for each amenity reveals a consistent gap. In the case of amenities visited frequently like grocery stores and pharmacies the gap between accessible to traveled distances is smaller, ranging just a couple kilometers. In comparison, amenities like parks and restaurants which are visited based on resident’s personal preferences, their quality and type of service they offer as well as the causal way in which they are visited show longer traveled distances and a larger gap from accessible amenities.

There is, overall, a positive association between traveled and accessible distances: residents are more likely to travel further if there are less POIs of a given category accessible to them. Disparities due to income are remarkably consistent: in high-income CBGs, the association between distances is *weaker*, implying that the travel patterns of high-income residents are less elastic than those of low-income CBGs. Higher-income residents change their travel habits less as their accessibility changes, which also means that the impact of accessibility is *stronger for low-income CBGs*. We observe the strongest discrepancy in the effect of accessibility (22.5% lower for high-income CBGs) in trips to religious organizations, which could be revealing that lower-income residents factor in proximity even alongside faith and personal beliefs when choosing places of worship.



(a) Population-weighted traveled ($y_{j,k}$) and accessible ($x_{j,k}$) distances, alongside regression estimates for the adjusted traveled distance (income-varying intercepts β_0 or $\beta_0 + \beta_2$, exponentiated) and for the association between traveled and accessible distances (income-varying coefficients β_1 and $\beta_1 + \beta_3$). Bars show 95% confidence intervals.



(b) Discrepancies (β_2 and β_3) in regression estimates due to income in models that account and do not account for driving behavior. Positive values imply that the estimate is *higher* for high-income CBGs.

Figure 3: Data and model coefficients reveal inequality in visitation patterns according to income. (a) Stratifying Census Block Groups by income shows consistent inequality patterns across categories: residents from high-income CBGs travel more than residents from low-income CBGs, before and after controlling for the accessible distance within FUAs in all categories except grocery stores, yet experience a lower effect of the accessible distance in their travel habits. (b) Almost all of these discrepancies are significant at the 0.05 level, and do not vanish even if we use a model which accounts for driving preference (Eq. 4).

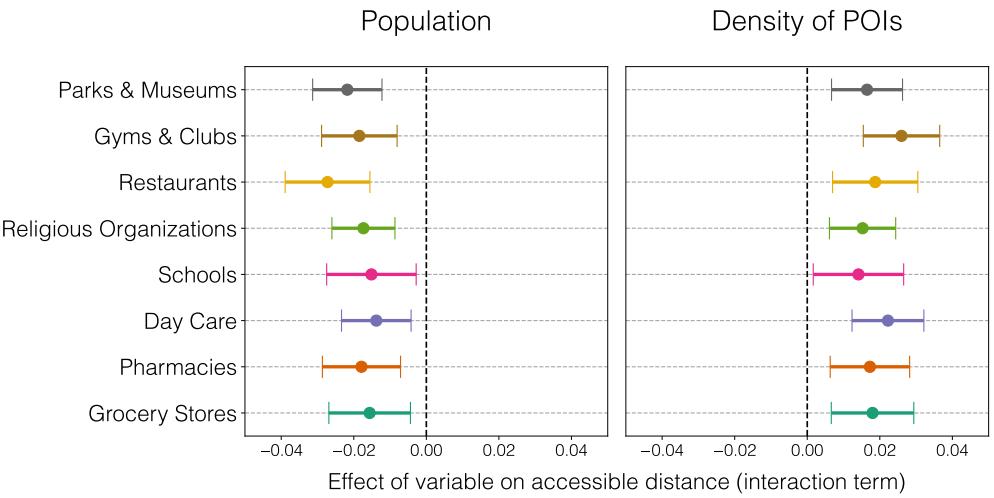
3.2 FUA-level Dynamics Provide Additional Insights into Distances Traveled

We now explore FUA-level mechanisms in the relationship between traveled and accessible distance (Figure 4). We find that accessibility explains less of the visitation in more populous FUAs, but more of it in FUAs with higher POI density (Figure 4a). After controlling for those two features, regression residuals for most FUAs directionally agree across categories (Figure 4b), suggesting that the unexplained relationship between accessible and traveled distances varies according to FUA-level mechanisms. Accounting for driving yields similar results.

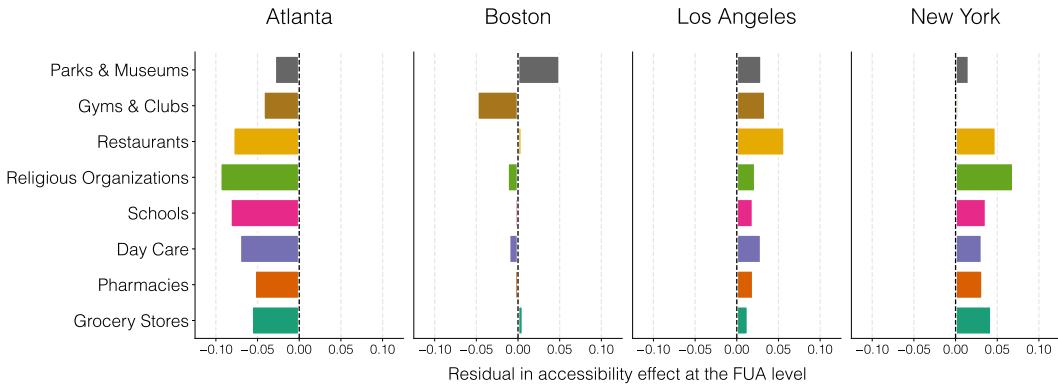
Thinking about potential intra-FUA geographies, we study trips to restaurants in New York (Figure 5). We find that core-periphery dynamics within the FUA explains much of the prediction error: after accounting for income and accessibility, residents in the periphery tend to travel more than average and residents in the FUA core tend to travel less. Geographies of home and work locations could explain this discrepancy, as most work opportunities are located near the FUA core. This finding exemplifies the importance of understanding factors beyond residence to effectively plan the distribution of urban amenities.

4 Discussion

Our analysis highlights that true understanding of spatial access to amenities arises from studying accessibility in light of resident travel choices. Access impacts visitation differently depending on city-level variables and amenity type. While considering these factors is crucial—accessing amenities that constitute daily necessities is more important for urban communities than those used for leisure—, we find that access consistently carries more weight for low-income urban communities.



(a) Regression coefficients for the interaction between accessibility and FUA population ($\gamma_{1,1}$) or POI density ($\gamma_{1,2}$), with 95% confidence intervals. Both predictors were standardized.



(b) Residuals $\varepsilon_{1,k}$ in the FUA-level regression of the accessible distance coefficient $\beta_{1,k}$.

Figure 4: Mechanisms beyond accessibility influence travel patterns at the Functional Urban Area-level, consistently changing the relationship between accessibility and visitation across categories. (a) The population size and POI density in an FUA interact consistently with accessibility in our models: accessibility is more important to visitation in less populous yet more POI-dense FUAs. (b) Regression residuals for the FUA-level associations between traveled and accessible distances also tend to directionally agree across categories, revealing that dynamics at the FUA-level, rather than POI-level, might impact visitation patterns once we control for accessibility.

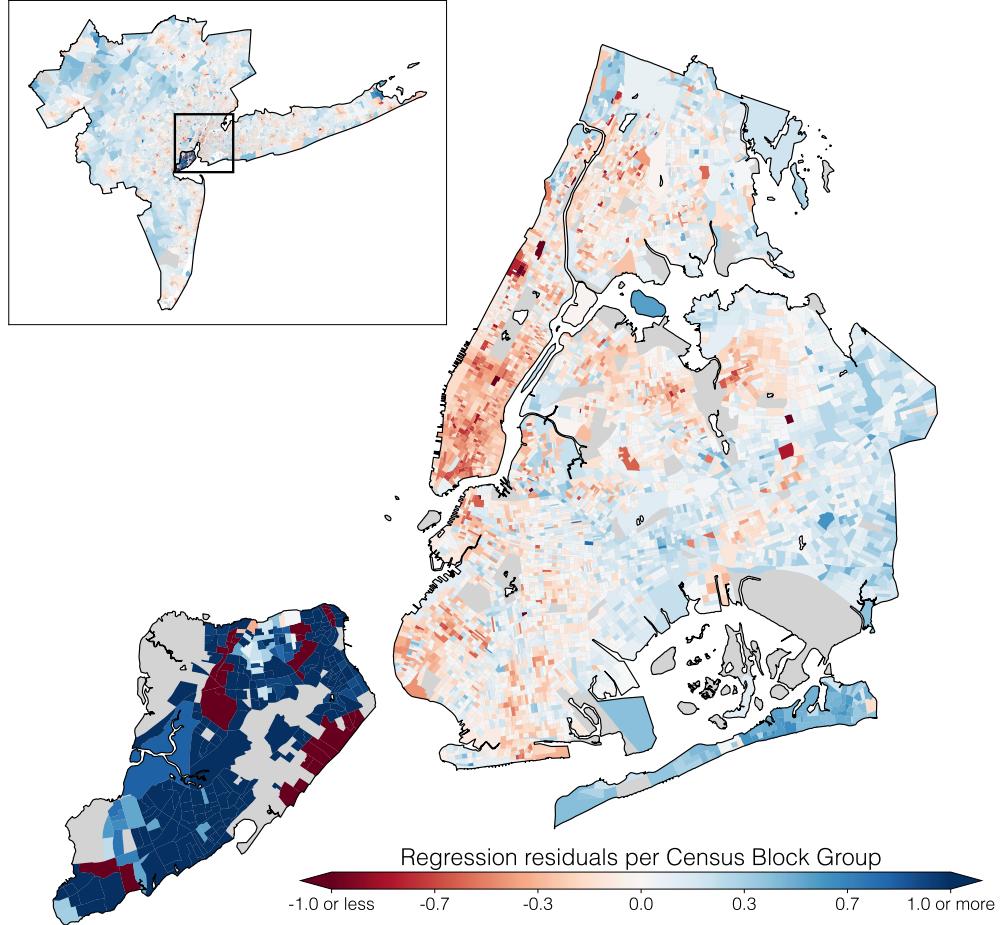


Figure 5: Regression residuals illustrate core-periphery dynamics in the greater New York Functional Urban Area. Residuals $\eta_{i,k}$ in the CBG-level regression New York City. Positive residuals correspond to under-predictions of the traveled distance, and negative residuals to over-predictions. The FUA map (upper left) shows predominantly under-prediction, while the FUA core (main map) shows predominantly over-prediction.

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Biographies

Talia Kaufmann is a Postdoctoral Associate at the Jerusalem Center for Urban Innovation at the Hebrew University of Jerusalem, where she leads the Algorithmic City Planning Lab. In her research, she collaborates with International organizations, municipal governments and industry partners to develop data-driven tools for decision-makers in city planning.

Gabriel Agostini is a 3rd-year PhD student in Information Science at Cornell Tech, Cornell University. He works with spatial data analysis, leveraging statistics and machine learning methods for more equitable urban planning. He is particularly interested in spatial problems relying on sparse or biased data.

Trivik Verma is an Associate Professor at the Bristol Future's Institute. His research focuses on tackling challenges of urbanisation in an equitable and just manner. Specifically, he is using methods in spatial data science, complex network analyses and participatory mapping to develop computational tools for advancing the theories and practices of urban science.

Daniel O'Brien is a professor of Public Policy and Urban Affairs and Criminology and Criminal Justice at Northeastern University and Director of the Boston Area Research Initiative (BARI). His research focuses on equity in urban neighborhoods, including crime, environmental justice, and more.