$9^{th}$ International Conference on Computational Social Science $IC^2S^2$
July 17-20, 2023, Copenhagen, Denmark

# Mobility Connectedness: Uncovering socioeconomic bias and connectivity in urban mobility

*Keywords: human mobility, income segregation, socioeconomic mixing, urban mobility*

## Extended Abstract

Socioeconomic segregation and mixing patterns in urban mobility indicate economic inequality in cities [1, 2]. Socioeconomic mixing patterns are examined with the segregation and diversity indices [3] but the studies are mainly based on residential segregation or visiting patterns [4, 5]. Accounting individuals' selective movements to integrate both socioeconomic factors and geographical constraints will increase our analytic understanding of socioeconomic inequality. Here we develop a new measure, *Mobility Connectedness*, to uncover people's mobile propensity towards economic status by comparing the surrounding places' composition to the actual visiting patterns. Our findings show policy implications for better socioeconomic integration.

We construct urban mobility networks in 384 Metropolitan Statistical Areas (MSAs) using the SafeGraph dataset [6]. The mobility data consist of the number of visitors to points of interest (POIs) with the information on visitors' home census block groups (CBGs). To analyze the relationship between the income levels of CBGs and POIs, we divide them into two groups based on their median income; above the city median as a high-income group $H$ and below the city median as a low-income group $L$.

Mobility connectedness measures how much visitors prefer to visit areas in the income group compared to the given geographical proportion. A single CBG $i$'s mobility connectedness toward income group $G$ ($G \in \{H, L\}$) is defined as $MC_{i,G} = t_G/n_G$, where $t_G$ is the proportion of traffic to group $G$ areas ($t_G = \sum_{j \in G} T_{ij} / \sum_j T_{ij}$) and $n_G$ is the proportion of the number of POIs in income group $G$ areas ($n_G = N_G/N$). Fig. 1a shows an example of measuring mobility connectedness toward high-income areas.

The mobility connectedness illustrates the entire landscape of connections between high- and low-income areas. We obtain county-level mobility connectedness by aggregating all the CBGs' mobility connectedness in a county. For instance, a county's low-to-high mobility connectedness ($MC_{L,H}$) is computed by averaging all low-income CBGs' mobility connectedness to high-income areas in the county. Fig. 1b illustrates the low-to-high and high-to-low mobility connectedness ($MC_{H,L}$) of all counties across 384 MSAs. The mobility connectedness varies across counties even in similar geographical locations, and it reflects very localized preferences in choosing where to visit.

Although both $MC_{L,H}$ and $MC_{H,L}$ values may indicate socioeconomic connectivity and mixing, the connection between low-income CBGs and high-income POIs is negatively correlated with the high-income CBGs to low-income POIs connection (Fig. 1c). This pattern can be explained by the combined effects of traffic differences by travel distance and income segregation. Intra-city movements are mostly dominated by short-distance travel and neighboring areas tend to have a similar economic status due to income segregation. Therefore, more visits to neighboring areas inherently affect mobility connectedness given the segregated landscape. The strong relationship between $MC_{L,H}$ and $MC_{H,L}$ and the county's median income supports this distance and segregation effect. The low-to-high connection is generally higher in higher-income areas while the high-to-low connection is the opposite.

To address the distance effect in more depth, we measure mobility connectedness for several travel distance bins. Figure 2 demonstrates the changes in the POI proportion ($n_G$), the traffic proportion ($t_G$), and mobility connectedness by travel distance and home CBG's income level. Due to residential segregation, the proportions of POIs in high-income areas and traffic visiting those POIs from high-income origins both decrease with travel distance (red curves in Fig. 2a,b) and a similar pattern is observed for visits from low-income CBGs to low-income areas (blue curves in Fig. 2d,e). However, the individuals' mobility propensity toward identical or different economic status areas from their own is not significantly influenced by travel distance (Fig. 2c,f).

Then, which socioeconomic and geographic factors are associated with mobility connectedness? We use regression models to describe the mobility connectedness with multiple variables of demography, traffic, social capital, industry categories, and urban indicators. Figure 3 shows that the median income and some visiting categories have the opposite influences on $MC_{L,H}$ and $MC_{H,L}$, while both high $MC_{L,H}$ and $MC_{H,L}$ have less income segregation. As shown in Fig. 1d and Fig. 3, the correlation between mobility connectedness and the fraction of traffic to POIs in a certain industry category varies greatly across the categories and the visiting proportion to retail trade and health care & social assistance POIs are associated with $MC_{L,H}$ and $MC_{H,L}$.

The mobility connectedness measure not only captures the individuals' movement propensity but also highlights the connections across different income-level areas within cities. Our research has the potential to improve our understanding of the intricate relationship between mobility, segregation, and equity in urban environments. Also, the efforts of increasing mobility connectedness between two different income groups i.e. policies to promote mixed-income neighborhoods or considering industries of high determinants for mobility connectedness can promote greater social integration.

# References

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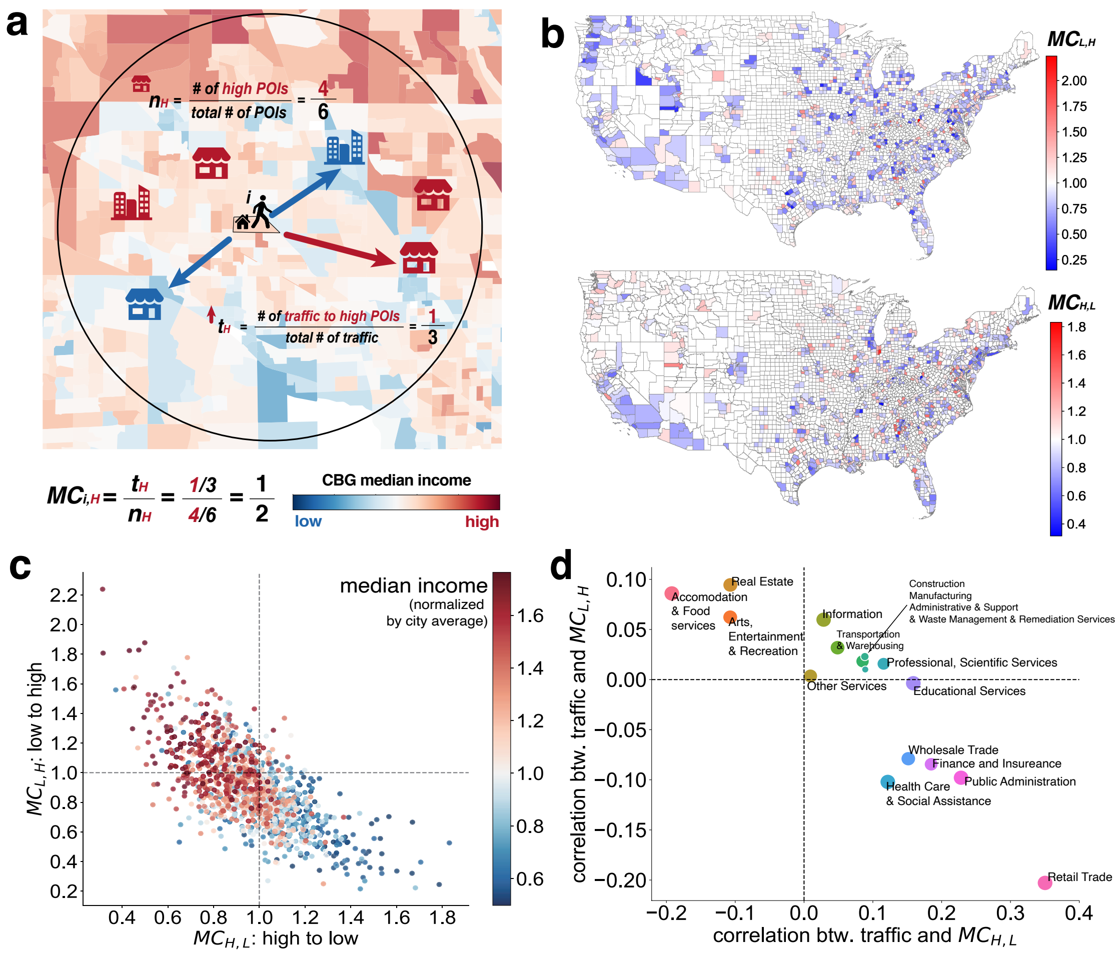


Figure 1: **a**. Mobility connectedness for given CBG $i$ to high-income group $H$ is calculated by dividing the visitation proportion by the number of POIs located in high-income areas. **b**. County-level low-to-high and high-to-low mobility connectedness landscape in 384 MSAs across the USA. **c**. Correlation between low-to-high and high-to-low connectedness value. The color displays each county's median income normalized by the city average. **d**. Correlation between the proportion of out-traffic to specific POI categories and $MC_{L,H}$ and $MC_{H,L}$. The POI's categories are assigned by the standard North American Industry Classification System (NACIS) code.

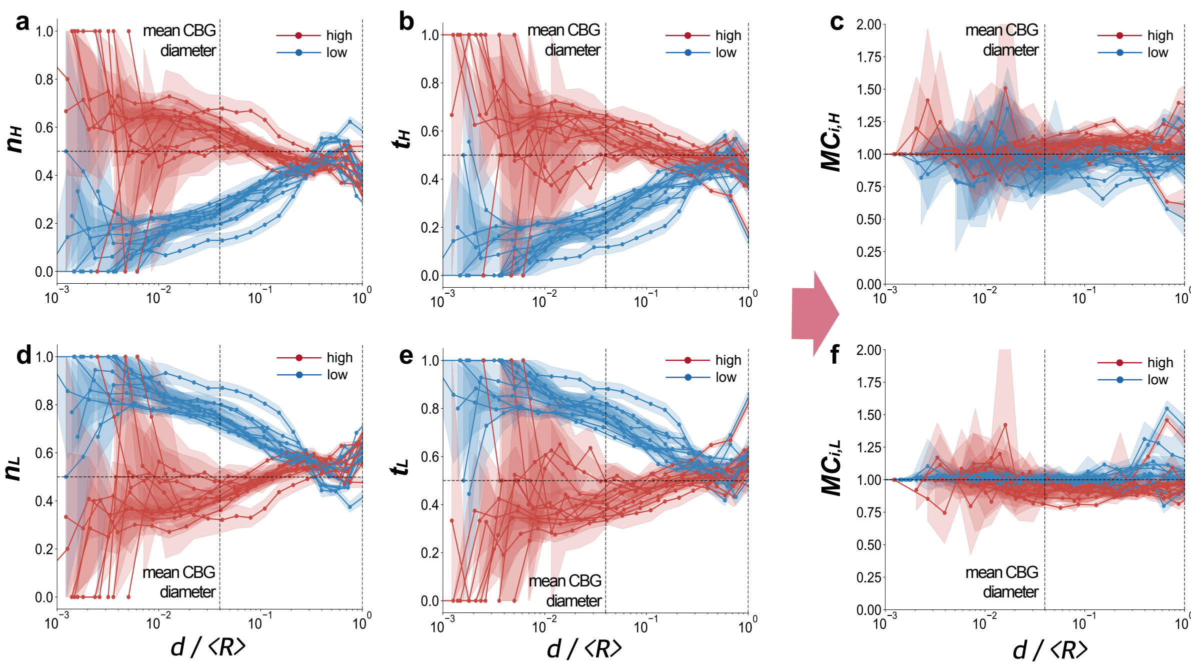


Figure 2: The average POI proportion (**a**), traffic proportion (**b**), and the mobility connectedness (**c**) toward high-income areas by travel distance and toward low-income areas (**d**, **e**, **f**). The distance in the x-axis is normalized by the city's radius $R$ which is estimated as the half value of the square root of the land area. The sample of 10 randomly chosen cities with more than 500 CBGs is shown in the figure. The trend is robust for sampling.

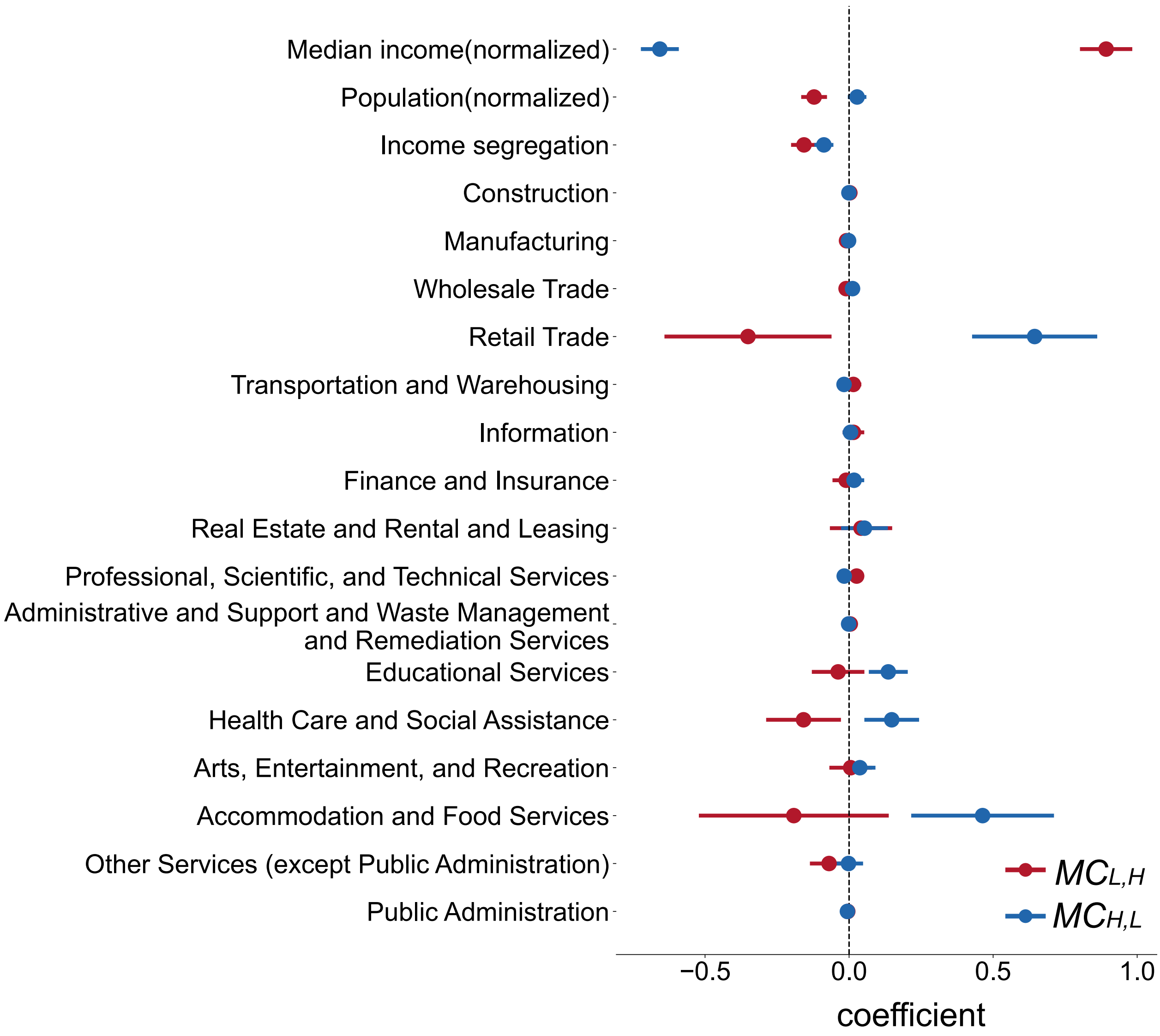


Figure 3: The estimate and 95% confidence interval of the coefficient of regression model for $MC_{L,H}$ and $MC_{H,L}$ after controlling the estimated city's radius, total population, and median income.