TNC Integration and Subsidization as a Compliment to Public Transportation

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March 19, 2024

Methods

In order to estimate the effect that an Uber voucher program can have on public transit ridership, I compare ridership for agencies where an Uber voucher program is in place to agencies with no such program. The dependent variable is the monthly unlinked passenger trips every month for a specific agency. The ridership variable is not city wide, so it is technically possible for ridership to increase for an agency, yet remain unchanged for a city if that city has multiple transit agencies.

To estimate this effect, I use a difference in difference model, as shown below.

$$Y_{i,t} = \beta_0 + \beta_1 D_{i,t} + \gamma_i + \delta_t + \epsilon$$

Y_{it} represents the log of agency ridership, and is regressed on D_{it}, which is whether a city has an Uber voucher program during that specified month/year. Given the outliers that exist in public transit ridership (e.g. New York City, Chicago, etc.), transforming the dependent variable to the log of ridership will yield more accurate results. I believe that this interaction will have a positive effect on Y_{it}.

I also include month/year and agency fixed effects to account for changes in transit culture and weather across the data. Since ridership is reported on the 1st of every month, the date variable suffices for month/year fixed effects. Agency fixed effects should account for variation in demand and demographics among UZAs, rendering specific population and socioeconomic controls unnecessary. They will also likely account for differences in transit system quality. The full list of variables, along with the variable names used in the code, can be found in Table 1 below.

Variable	**Codebook Name**	**Explanation**
Y_{it}	log(ridership)	Unlinked passenger trips (UTP) per month for transit agency
D_{it}	treated $\times$ time	1 if transit agency i is partnered with Uber in month t, 0 otherwise
γ_i	agency	Fixed effects for the transit agency i is located
δ_t	date	Fixed effects for month, year. In the format $YYYY-MM-01$ (always recorded on 1st of every month)

Table 1: Explanation of Variables

Key assumptions are that the agencies in the treatment and control are experiencing parallel growth prior to the intervention of Uber vouchers, and that agencies are facing the same issues. If an agency is experiencing booming growth, they would be unlikely to implement different policies. Additionally, I assume that each agency in the untreated group choose either to do nothing or enact the same policies instead of creating an Uber voucher program.