# Assessing the Impact of Public Transit-Rideshare Partnerships

Charlie Berman

Advised by Professor Kyle Coombs

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# Introduction

In 1958, the Transportation Act of 1958 was passed in order to strengthen the national transit system. This passage represented the most important development towards the Federal Transit system used today (*History of the NTD and Transit in the United States* 2017). Over half a century later, the transit system in the United States finds itself in need of strengthening once again, despite the advantages in sustainability, affordability, and safety public transportation enjoys over other modes of transit (*Public Transportation Facts* 2024). Since 2012, bus ridership and rail ridership have fallen 15% and 3%, respectively (Erhardt et al. 2022). The COVID-19 pandemic has not helped matters, with ridership cratering during the lockdowns and having yet to recover.

In order to address this, some transit agencies have contracted rideshare companies (otherwise known as transit network companies or TNCs)[1], like Uber and Lyft, to help them boost ridership. By offering discounted rides within an urbanized area (UZA), transit agencies hope to boost ridership by increasing accessibility. While there are studies that evaluate the effect of TNC emergence in an area on transit ridership, there is little literature on what the impact of this sort of partnership is.

This paper is the first to empirically examine the efficacy of increasing public tran-

[1] The names rideshare company and TNCs are used interchangeably throughout the paper.

sit ridership through a partnership with TNCs. I use a two-way fixed effect model on ridership data from the National Transit Database and demographic data from the American Community Survey from 2014 to 2019. By examining monthly ridership numbers from different transit agencies, I account for what the average treatment effect the partnership has in general, as well as for each agency that contracted a TNC. I find that ridership per capita increases anywhere from 4% to 11%, depending on the agency, and an average treatment effect of 4.7% as a result of partnership.

## Transit Network Companies and Public Transit

On its face, the decision for agencies to partner with TNCs is a curious one. Intuition would suggest that TNCs could act as a substitute to public transportation, and research reinforces this, finding that ride-hailing is the single biggest driver of ridership decline (Erhardt et al. 2022). News outlets have also reported on the threat of TNC competition to public transportation, claiming "cities would grind to a halt" if these companies captured a large enough market share (McFarland 2019).

There are alternative perspectives, however. TNCs can offer easier access to rail and bus stops and have been shown to serve as a compliment, increasing ridership on average, especially in large cities or areas with smaller transit agencies (Hall, Palsson, and Price 2018). The heterogeneity of effect uncovered in Hall, et al. is consistent across other literature. Using monocentric city model, Zhao finds that the effect on ridership is dependent on the quality of the transit agency, with high quality transit systems seeing a boost, while low quality systems find their ridership poached by TNCs (Zhao 2019). Extending the monocentric city model to account to account for multiple transportation modes suggests that whether rideshare companies are a substitute or compliment is dependent on policy choices and subsidizing them in order to provide last-mile service increases ridership more than regulation or taxation (Agrawal and Zhao 2023).

## Types of Partnerships

There are several types of partnerships that transit agencies can engage in, but they can broadly be divided into a few different categories, drawn from Schwieterman, et al. in their review on public transit partnerships (Schwieterman, Livingston, and Slot 2018). Generally speaking, there are subsidized rides, app integration, and paratransit support/other specialty programs.

This paper focuses on the first type of program: direct subsidies. In this partnership, the goal is to incentives public transit ridership via financial incentives. These programs occur as discounts for any rides that take place within a UZA's borders, discounts for rides specifically to transit stops, or discounts for specific trips during off-peak hours. Programs like St. Petersburg's Direct Connect fall into this category. This program discounts rides that are taken to one of twenty-six designated locations within the city.

Agencies have also contracted TNCs to integrate their apps with the agency's app. This sort of partnership allows users to hail a ride directly from the same app that they manage their transit tickets from. Programs that allow users to see transit schedules and manage trips from a TNC app also fall under this category. An example of this program is Dallas's GoPass app, which allows riders to hail an Uber from in app. This represents a cheap way of promoting transit services alongside TNCs.

The specialty programs tend to be less popular. While these can be similar to subsidized programs, they generally only apply to transit users that qualify for existing paratransit services. These riders can qualify for discounted trips using specific Uber/Lyft cars that can accommodate people with disabilities. While this is an important service, the scope is narrow enough that this partnership is not considered in the analysis.

# Data

Most of the data used comes from the National Transit Database (NTD), which is maintained by the Federal Transit Authority and reports on a monthly basis for several transit related variables. These include Vehicle Revenue Miles (VRM), Vehicle Revenue Hours (VRH), Passenger Miles Traveled (PMT), Unlinked Passenger Trips (UPT), and Operating Expenses (OE) for every transit agency that receives federal funding. UPT is a metric of how many people board an individual vehicle, and is used in this paper to determine transit performance. While there are other variables that indicate improved transit performance (e.g. less delays, increased service hours, cleaner conditions, etc.), ridership is the only performance variable that will be directly effected by a TNC partnership and is used as an outcome variable. I use VRH, which is a measure of how many hours transit vehicles are accepting customers, in my analysis as a placebo outcome in order to help establish parallel trends.

While the data exists from 2002-Present, it is subsetted to 2014-2019 as that is when UberX had become widespread, entering 65 cities. UberX was a service that lowered the price of calling a ride and is far more similar to the ride-hailing services used today[2]. The data after 2019 is removed in order to avoid contamination of the result due to COVID-19. Treatment is determined using the list provided by the Chaddick Institute (Schwieterman, Livingston, and Slot 2018) and is coded in manually.

[2]While I include all TNC partnerships in my analysis, Uber has such a massive market share that several of my decisions are driven by their actions.

| Variable | N | Mean | Std. Dev. | Min | Pctl. 25 | Pctl. 75 | Max |
|---|---|---|---|---|---|---|---|
| Ridership | 35208 | 1676969 | 13576543 | 1 | 40455 | 473923 | 322725962 |
| Ridership per capita | 35208 | 0.74 | 1.3 | 0.000000052 | 0.032 | 0.91 | 17 |
| Vehicle Revenue Hours | 35208 | 45222 | 166603 | 0 | 4759 | 25452 | 3262509 |
| Mode | 35208 | | | | | | |
| ... Bus | 30960 | 88% | | | | | |
| ... Rail | 1932 | 5% | | | | | |
| ... Ferry | 1210 | 3% | | | | | |
| ... Other | 1106 | 3% | | | | | |
| Agencies | 492 | | | | | | |
| ... Treated | 9 | | | | | | |
| ... Control | 483 | | | | | | |
| UZAs | 262 | | | | | | |
| States | 49 | | | | | | |

Table 1: Summary statistics for NTD data

A brief examination of ridership per capita over the years illustrates the clear decline of ridership over time, which is consistent with previous literature (Erhardt et al. 2022).

| Year | N | Mean | Std. Dev. | Min | Pctl. 25 | Median | Pctl. 75 | Max |
|---|---|---|---|---|---|---|---|---|
| 2014 | 5832 | 0.7843 | 1.3700 | 0.0000 | 0.0272 | 0.3503 | 0.9719 | 17.1029 |
| 2015 | 5856 | 0.7757 | 1.3783 | 0.0000 | 0.0313 | 0.3394 | 0.9452426 | 16.8476 |
| 2016 | 5892 | 0.7484 | 1.3275 | 0.0000 | 0.03254 | 0.3290 | 0.9218 | 16.3226 |
| 2017 | 5868 | 0.7181 | 1.2841 | 0.0000 | 0.03174 | 0.3100 | 0.8932 | 16.7465 |
| 2018 | 5880 | 0.7134 | 1.2783 | 0.0000 | 0.03193 | 0.3080 | 0.8750 | 16.87828 |
| 2019 | 5880 | 0.7077 | 1.2808 | 0.0000 | 0.0335 | 0.3091 | 0.8484145 | 17.0671 |

Table 2: Ridership per capita by year

Filtering by treated and control groups show similar movement for both over time, with the treated group having increased ridership post 2017.

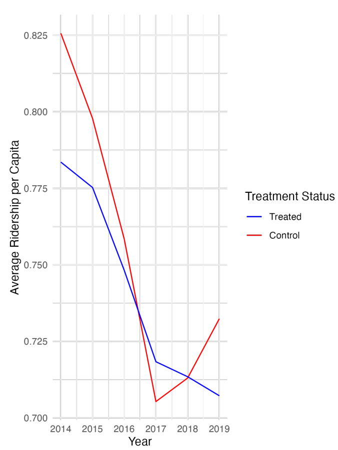


Figure 1: Ridership over Time

Demographic variables are also used, and are obtained from The American Community Survey (ACS). The ACS is maintained by the US Census Bureau and records annual demographic data on hundreds of different variables for different levels (e.g. state, county, urbanized area, etc). I use population, median age, racial composition, and median household income, all on the UZA level. Population and median household income are used in the regression, as a higher population correlates with higher ridership and families with lower median income are more likely to use public transit (Wang and Woo 2017). The variables relating to race and age are used to illustrate the similarities between the treated agencies and the UZAs they serve to the broader control group. The data is subsetted to the same years as the NTD data, and merged by the UZA.

| Variable | N | Mean | Std. Dev. | Min | Pctl. 25 | Pctl. 75 | Max |
|---|---|---|---|---|---|---|---|
| Median Age | 35208 | 37 | 4.1 | 23 | 35 | 39 | 58 |
| Population | 35208 | 3076829 | 5080259 | 62112 | 215650 | 3468694 | 19094455 |
| Perc. White | 35040 | 0.7 | 0.13 | 0.17 | 0.58 | 0.8 | 0.97 |
| Perc. Black | 35040 | 0.13 | 0.11 | 0.001 | 0.058 | 0.18 | 0.65 |
| Perc. Asian | 35040 | 0.065 | 0.058 | 0.001 | 0.026 | 0.083 | 0.44 |
| Perc. Hispanic | 35208 | 0.12 | 0.16 | 0 | 0 | 0.21 | 0.99 |
| Median Household Income | 35208 | 294088 | 499848 | 1990 | 23852 | 279635 | 2008329 |

Table 3: Summary statistics of ACS variables

# Methods

I find the effect of TNC partnership on ridership per capita using a two-way fixed effects (TWFE) regression of the following form.

$$Y_{it} = \beta X_{jt} + \alpha_i + \delta_t + \sum_{t}^{T} \mu_\ell D_{it} \times 1(t - \tau) + \epsilon_{it}$$

where $Y_{it}$ is the ridership per capita of agency $i$ at calendar time $t$; $X_{jt}$ is a vector of socioeconomic and demographic covariates of the UZA the agency is based in; $\alpha_i$ and $\delta_t$ are agency and calendar time fixed effects; $\mu_\ell$ is the effect of the treatment at relative time $\ell = t - \tau$, where $\tau$ is the time treatment was implemented; $D_{it}$ is 1 when the partnership is in effect and 0 when the partnership is not.

In order to provide more robust estimates of the treatment effect, I rely on Sun and Abraham's work on estimating dynamic treatment effects (Sun and Abraham 2021). They create an interaction weighted (IW) estimator to consistently estimate the weighted average of the cohort average treated effect (CATT), where a cohort is units that were treated at the same time. This IW estimator also has the advantage of being robust to contamination from earlier and later treated groups, as well as treatment effect heterogeneity, whereas the base TWFE model is not. This is important because the different makeups of the UZAs and transit agencies mean that the agencies are likely to experience differing effects. I aggregate $\text{CATT}_{e,\ell}$ for all $\ell$ to find $\text{CATT}_e$, which describes the average treatment effect (ATT) of the cohort. I aggregate $\text{CATT}_e$ to find the ATT of all TNC-Transit partnerships as well, in order to determine the average effect across cohorts. All of this is done as described by Sun and Abraham (2021).

The main assumption is parallel trends between treated and control agencies, which I address in the next section. I make the assumption for absorbing treatments as well. While several of the treated groups only have subsidized rides for shorter periods, the change in transportation habits that this treatment could cause has some likelihood of persisting even after the program has ended. I also assume no anticipation of treatment, as the population tends to be notified via press release on the day of launch (Newspapers 2017).

## TNC-Transit Partnership Effect on Vehicle Revenue Hours

In order to establish parallel trends, I use the placebo outcome of VRH. VRH should remain unaffected, as these partnerships do not increase the frequency of trips, or the number of hours transit is used. Using the regression specification above on the outcome variable of VRH, I find that while the effect is nonzero, it is entirely inconsistent. This suggests that while shocks might occur to impact VRH, changes in this variable are not correlated with the consistent ridership increases seen via these partnerships.

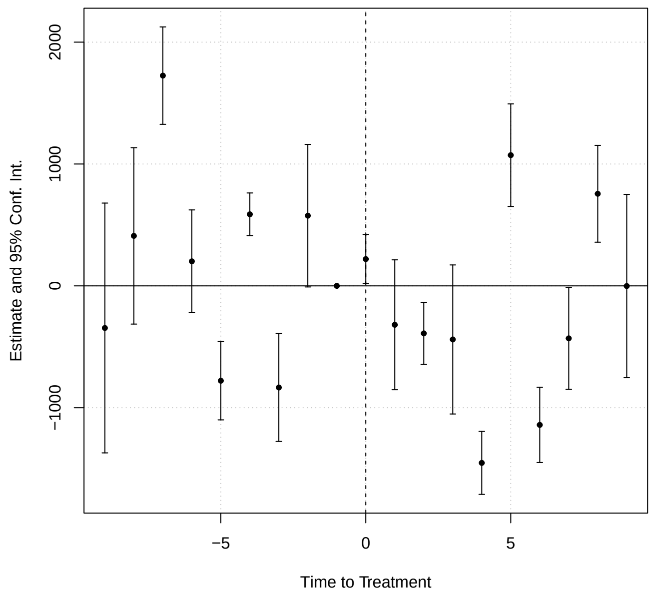


Figure 2: Treatment effect on VRH pre and post treatment

# Results

The results of this regression shown in Table 4 illustrate the effect of population on ridership per capita is statistically insignificant, suggesting that as population increases, ridership per capita remains fixed. This means ridership expands as population does, as ridership per capita would remain unchanged under this condition. Median household income is shown to negatively effect ridership per capita, with a higher household income lowering the outcome variable. The ATT is observed to yield a statistically significant increase to ridership per capita, at around 4.7%. In examining the event study plot in Figure 3, there are significant results prior to the treatment, suggesting the presence of exogenous shocks to ridership that are not accounted for by this model. The point estimates after the treatment are largely positive and significant, however, which indicates that there is a possible increase in the outcome variable.

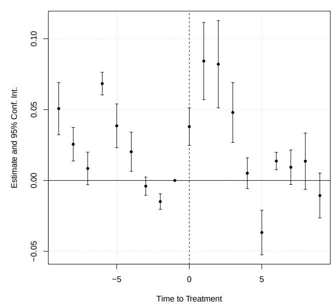


Figure 3: Event study plot of TNC-transit partnership

| | Ridership/Pop. |
|---|---|
| Population (in 100,000s) | 0.0010 |
| | (0.0045) |
| Med. Household Income (in 10,000s) | -0.0028*** |
| | (0.0008) |
| Average Treatment Effect | 0.0471*** |
| | (0.0058) |
| Pinellas Suncoast Transit Authority | -0.0142 |
| | (0.0123) |
| Livermore/Amador Valley Transit Authority | 0.0620*** |
| | (0.0139) |
| Orange County Transportation Authority | 0.0815*** |
| | (0.0191) |
| Solano County Transit | 0.1117*** |
| | (0.0124) |
| Greater Dayton Regional Transit Authority | -0.0066 |
| | (0.0172) |
| City of Charlotte North Carolina | 0.0514*** |
| | (0.0079) |
| Pierce County Transportation Benefit Area Authority | 0.0585*** |
| City of Detroit | (0.0141) |
| Research Triangle Regional Public Transportation Authority | 0.0378*** |
| | (0.0136) |
| *Fixed-effects* | |
| agency | Yes |
| date | Yes |
| Observations | 24,990 |
| $R^2$ | 0.9270 |
| Within $R^2$ | 0.0014 |

*Clustered (agency) standard-errors in parentheses*

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Effect of TNC-transit partnership on ridership per capita

The effect on the cohorts is mostly significant, with agencies seeing anywhere from a 3.8% to an 11.2% increase. This is a fairly wide spread around the ATT of 4.7% and demonstrates that not all cohorts experience the same effect, supporting the assumption that there is treatment heterogeneity. Some agencies experiencing insignificant results, which I attribute to the noise around transit ridership numbers. The effects can be observed in Figure 4 below.

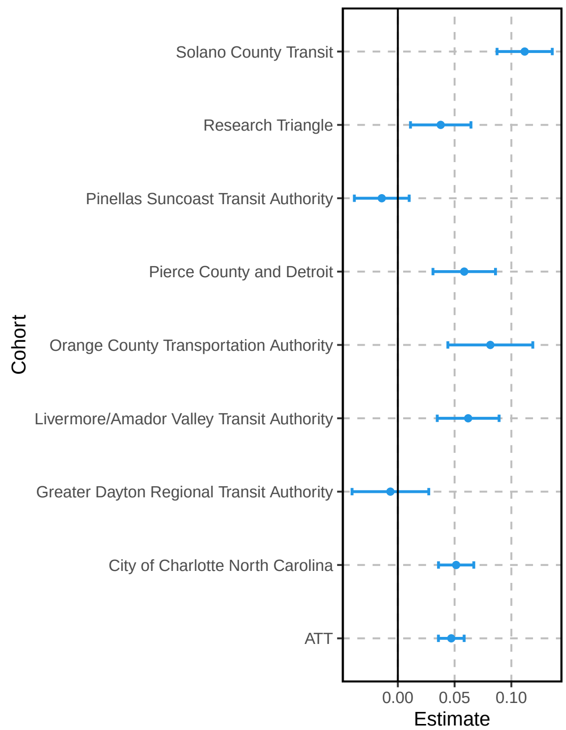


Figure 4: Cohort average effects of TNC-transit partnership

To get a sense of how representative the treated agencies are of transit agencies nationwide, I plot the distribution of population, ridership, percentage white, median age, and median household income of both the treated and the control groups. Figure 5 illustrates that the distribution of the treated group is similar to the broader control group in almost all categories, with the peak of the distribution at a similar point. The treated agencies tend to be slightly wealthier, and serve slightly larger populations, but otherwise, there is good reason to believe that the results of this treatment could be applicable to other agencies.


Figure 5: Distribution of demographic traits between treated and control

# Conclusion

The introduction of transit agency subsidized TNC rides represents a possible policy option when governments and agencies are considering ways to increase accessibility. Increases of 4%-10% in ridership suggest that more riders are able to access transit stops, without the need to build new stops or employ more workers. Prior to the COVID-19 Pandemic, it was predicted that more agencies would roll out partnerships (Schwieterman, Livingston, and Slot 2018), and indeed, going into 2020, several more agencies had announced collaborations with Uber and Lyft (*Transit and TNC Partnerships* 2024).

However, the changing landscape of transit and TNCs post-COVID make recommending this policy approach more difficult. Conversations with an Uber project manager suggest that these partnerships have shifted from some agencies reaching out to Uber and vice-versa, to being driven by Uber in areas with low market share. This could change the nature of the treatment and render the results unreliable. Prices of TNCs have also risen dramatically. When Uber was slashing prices , with fares as low as $11 in 2015 (Lee 2015), offering a $5 voucher made sense. But prices are on the rise, with fares seeing an increase of 83% between 2019 and 2022 (Sherman 2023). These factors, in addition to the increasing number of controversies that Uber has found themselves have embroiled in (Davies et al. 2022) make partnering with any TNC a less attractive proposition to government transit agencies.

## Further Research

Rerunning this design on data from post-COVID to the present on the most recently formed partnerships could give empirical evidence as to the effectiveness of this program currently. Ridership data from the bus/rail stop level could reduce noise and the number of assumptions needing to be made. For example, stops from two neighboring counties, one with a partnership and one without, could be compared as a case study. A more carefully considered control group could also reduce the noise in the dataset, yielding cleaner results. The literature around staggered difference-in-difference designs is also still in flux, so a different specification might help to eliminate bias.

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