TNC Integration and Subsidization as a Compliment to Public Transportation

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Regressions

Basic Regressions

Dependent Variables:	ridership		$\log(\text{ridership})$	ridership	log(ridership)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	2,616,962.7***				
treated \times time	(28,280.7) $-2,024,092.7$ $(2,447,533.6)$	67,348.2* (35,459.1)	-0.1077** (0.0436)	417,961.8*** (124,785.7)	-0.7074*** (0.1007)
Fixed-effects agency month		Yes Yes	Yes Yes	Yes	Yes
date				Yes	Yes
Fit statistics					
Observations	314,577	314,577	314,577	314,577	314,577
R^2 Within R^2	2.17×10^{-6}	$0.99407 \\ 3.99 \times 10^{-7}$	$0.73850 \\ 3.14 \times 10^{-7}$	$0.99413 \\ 1.54 \times 10^{-5}$	$0.76482 \\ 1.5 \times 10^{-5}$

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

The dataset for this one does not include dates after 03/01/20 (COVID)

Treatment Group

- Pinellas Suncoast Transit Authority
- Livermore/Amador Valley Transit Authority

• Research Triangle Regional Public Transportation Authority

Equations

- 1. $y_{it} = \beta D_{it}$, no fixed effects
- 2. $y_{it} = \beta D_{it} + \text{agency} + \text{month}$, month and agency fixed effects
- 3. $ln(y_{it}) = \beta D_{it} + agency + month$, fixed effects and taking log of ridership
- 4. $y_{it} = \beta D_{it} + \text{agency} + \text{date}$, changing month fixed effects to date fixed effects (month, year)
- 5. $ln(y_{it}) = \beta D_{it} + agency + date$, using log of ridership

Notes

- Adding date fixed effects increases magnitude and changes effect of ridership to negative. Why?
- Lose statistical significance for (3) and (4). Look into

Dependent Variables:	ride	rship	$\log(\text{ridership})$	ridership	log(ridership)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	2,450,385.1***				
	(24,938.7)				
$treated \times time$	-706,035.7	-1,098,683.5**	-0.4231***	-20,793.8	-0.8935***
	(493,190.8)	(486,809.3)	(0.0908)	(582, 936.9)	(0.1330)
Fixed-effects					
agency		Yes	Yes	Yes	Yes
month		Yes	Yes		
date				Yes	Yes
Fit statistics					
Observations	369,585	$369,\!585$	369,585	$369,\!585$	$369,\!585$
\mathbb{R}^2	5.55×10^{-6}	0.97232	0.70354	0.97308	0.73059
Within \mathbb{R}^2		0.00041	7.8×10^{-5}	1.48×10^{-7}	0.00038

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

Treatment Group

• Pinellas Suncoast Transit Authority

- Livermore/Amador Valley Transit Authority
- Research Triangle Regional Public Transportation Authority
- Dallas Area Rapid Transit
- Bi-State Development Agency of the Missouri-Illinois Metropolitan District

Notes

• Same equations as above, but data goes until 2023 (removing 2020)

Without New York City

Dependent Variables:	rider	ship	$\log(\text{ridership})$	ridership	$\log(\text{ridership})$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	1,697,670.2***				
	(8,512.2)				
$treated \times time$	-1,056,538.8	141,851.6***	0.3059^*	194,826.0***	-0.7862***
	(963,034.3)	(35,452.0)	(0.1842)	(52,477.5)	(0.2134)
Fixed-effects					
agency		Yes	Yes	Yes	Yes
month		Yes	Yes		
date				Yes	Yes
Fit statistics					
Observations	358,392	358,392	$358,\!392$	358,392	$358,\!392$
\mathbb{R}^2	3.36×10^{-6}	0.98796	0.66734	0.98825	0.72636
Within R ²		4.98×10^{-6}	9.64×10^{-7}	9.55×10^{-6}	7.68×10^{-6}

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

Dependent Variables:	ride	rship	$\log(\text{ridership})$	ridership	$\log(\text{ridership})$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	1,593,889.3***				
	(7,559.0)				
$treated \times time$	$150,\!460.2$	-1,068,664.2**	-0.2535	$-321,\!695.4$	-1.162***
	(157,956.7)	(484,729.5)	(0.1929)	(509, 198.4)	(0.2225)
Fixed-effects					
agency		Yes	Yes	Yes	Yes
month		Yes	Yes		
date				Yes	Yes
Fit statistics					
Observations	$412,\!644$	412,644	412,644	$412,\!644$	412,644
\mathbb{R}^2	2.2×10^{-6}	0.95427	0.63756	0.95749	0.69914
Within R ²		0.00209	1.71×10^{-5}	0.00020	0.00043

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

These two regressions are the same as the two tables above (pre-COVID and during COVID) but New York City is removed from the sample. We see that this has basically no effect on the regression table.

UZA ridership vs Agency Ridership

Dependent Variables: Model:	ridership (1)	log(ridership) (2)	total_ridership (3)	$\log(\text{total_ridership}) $ (4)
Variables				
$treated \times time$	417,961.8***	-0.7074***	17,474,872.4***	-0.2273***
	(124,785.7)	(0.1007)	(2,172,347.0)	(0.0685)
Fixed-effects				
agency	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	$314,\!577$	$314,\!577$	$314,\!577$	$314,\!577$
\mathbb{R}^2	0.99413	0.76482	0.99391	0.86024
Within \mathbb{R}^2	1.54×10^{-5}	1.5×10^{-5}	5.49×10^{-5}	3.11×10^{-6}

Clustered (agency) standard-errors in parentheses

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

Notes

Regressions (3) and (4) use the pre-COVID treatment group (only 3) and regress treatment \times time on the total ridership in a UZA. Note that the increase in ridership is much larger, which makes sense given this accounts for a whole UZA. However, the decrease in the log is a lot smaller. Still using agency and date fixed effects.

Population Controls: Agency and UZA ridership

Dependent Variables:	total_ridership		$\log(\text{total}_{-}$	ridership)	
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
${\rm treated}\times{\rm time}$	14,953,608.9***	-0.0048	-0.0797	0.0067	-0.0049
	(2,396,557.7)	(0.0335)	(0.2149)	(0.0315)	(0.0335)
Fixed-effects					
agency	Yes	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes	Yes
pop	Yes	Yes			
$\operatorname{med}_{\operatorname{-}\!age}$			Yes		
white				Yes	
med_house_income					Yes
Fit statistics					
Observations	288,762	288,762	288,762	287,283	288,762
\mathbb{R}^2	0.99619	0.98996	0.89878	0.99039	0.98995
Within R ²	5.16×10^{-5}	2.05×10^{-8}	5.98×10^{-7}	4.23×10^{-8}	2.13×10^{-8}

Clustered (agency) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Dependent Variables:	ridership	log(ridership)			
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
${\rm treated}\times{\rm time}$	$308,\!656.7^{**}$	-0.2131	-0.5351^*	-0.2020	-0.2131
	(129,140.2)	(0.1944)	(0.2752)	(0.1941)	(0.1944)
Fixed-effects					_
agency	Yes	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes	Yes
pop	Yes	Yes			
$\operatorname{med}_{\operatorname{-}\!age}$			Yes		
white				Yes	
med_house_income					Yes
Fit statistics					
Observations	288,762	288,762	288,762	$287,\!283$	288,762
\mathbb{R}^2	0.99439	0.87122	0.78617	0.87117	0.87122
Within R ²	7×10^{-6}	2.33×10^{-6}	9.43×10^{-6}	2.1×10^{-6}	2.33×10^{-6}

Clustered (agency) standard-errors in parentheses

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

Data

I am using the pre-COVID dataset. Since I have statistically significant results and COVID data has a large negative effect, I will just use pre-COVID for right now.

Notes

We see that there is no statistical significance attributed to population/ACS controls that I currently have access too. Changing from UZA ridership to Agency ridership had no effect on significance when using log. The exception is for median age in agency ridership, which had some statistical significance but I am not convinced it adds to the model. Based on this, it seems that population controls are unnecessary or not useful. Perhaps different variables need to be used?

Robustness Checks

Dependent Variables: Model:	ridership (1)	$\frac{\log(\text{ridership})}{(2)}$
$Variables$ treated \times time	248,769.5*** (94,966.1)	-0.7765*** (0.1115)
Fixed-effects agency date	Yes Yes	Yes Yes
Fit statistics Observations R ² Within R ²	$275,055 \\ 0.99435 \\ 8.5 \times 10^{-6}$	$275,055 \\ 0.79700 \\ 3.95 \times 10^{-5}$

Clustered (agency) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

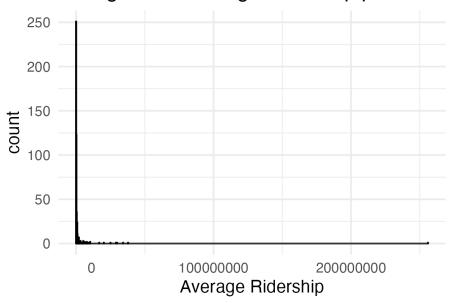
Notes

Treatment group is Hillsborough Area Regional Transit Authority, The Eastern Contra Costa Transit Authority and the Town of Chapel Hill. These all border the original pre-COVID treatment group and do not have Uber voucher programs—though some go on to create a program after the dataset ends.

Using this check, we can subtract this coefficient from the original coefficient to find that $\beta_{1,\text{treated}} - \beta_{1,\text{placebo}} - 0.7074 - (-0.7765) = 0.0691$. I exponentiate this coefficient to find that the effect on ridership is 1.07, or a 7% increase in transit ridership.

Charts

Histogram of Average Ridership per Month



Histogram of Average Ridership per Month

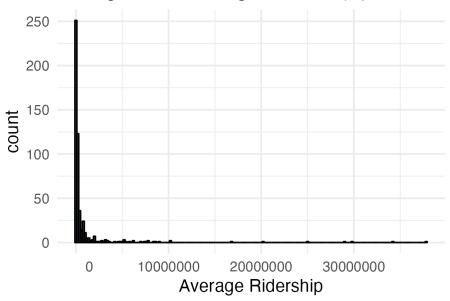


Figure 1: Average rides per month (bin of 200,000). Bottom histogram does not include NYC $\,$

Transit Agencies per UZA 200 -150 **-**Frequency 001 50 **-**

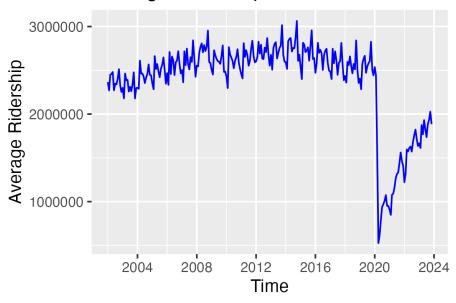
Figure 2: Average number of agencies per UZA

0

10 20 Number of Transit Agencies

30

Average Ridership Over Time



Log Average Ridership Over Time

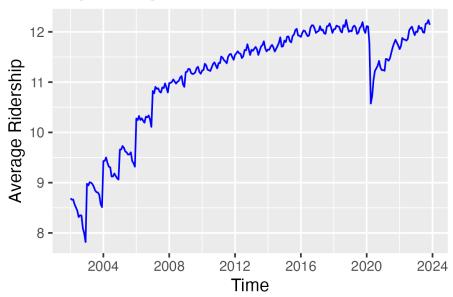


Figure 3: Ridership over time

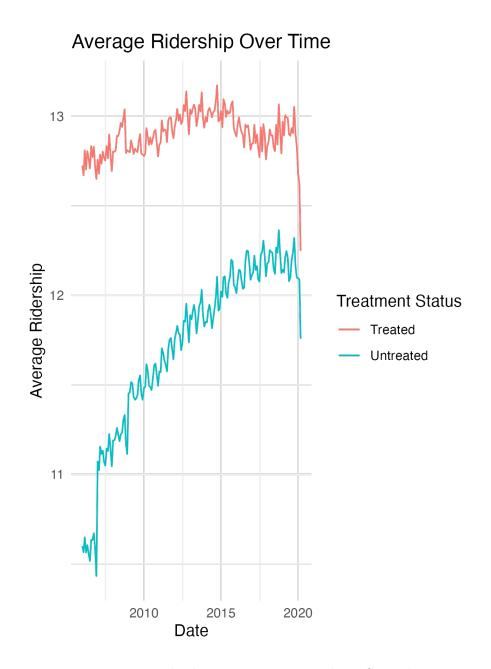


Figure 4: Ridership over time, Treated vs. Control

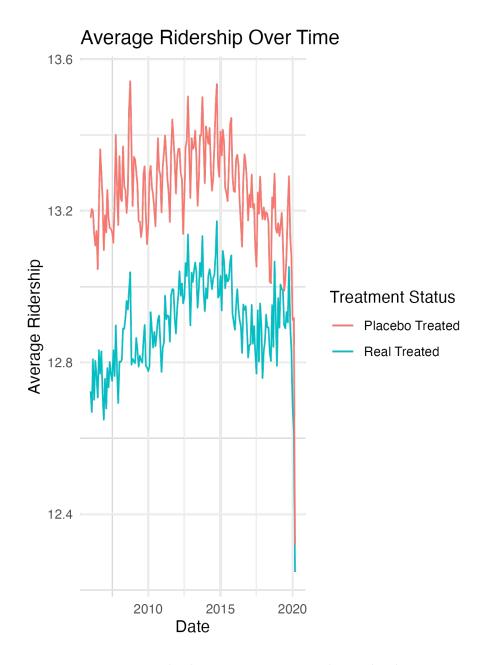


Figure 5: Ridership over time, Treated vs. Placebo

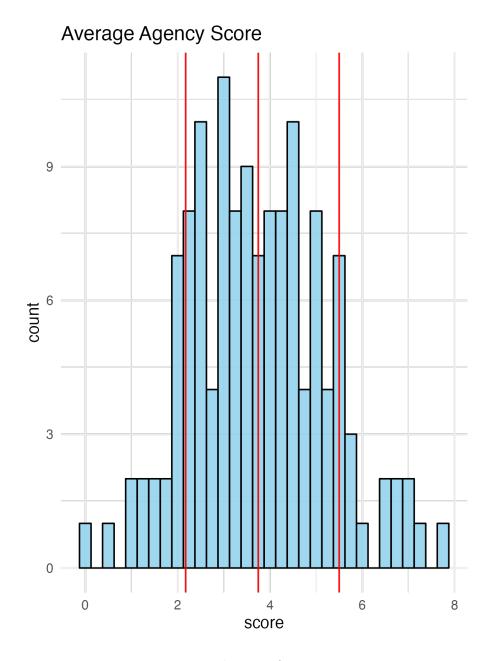


Figure 6: Distribution of agency scores

Notes According to AllTransit (through email correspondence), a score of 7+ is a "good" transit system by US standards. This is done at UZA level, not agency level so should be used with total ridership, not agency ridership

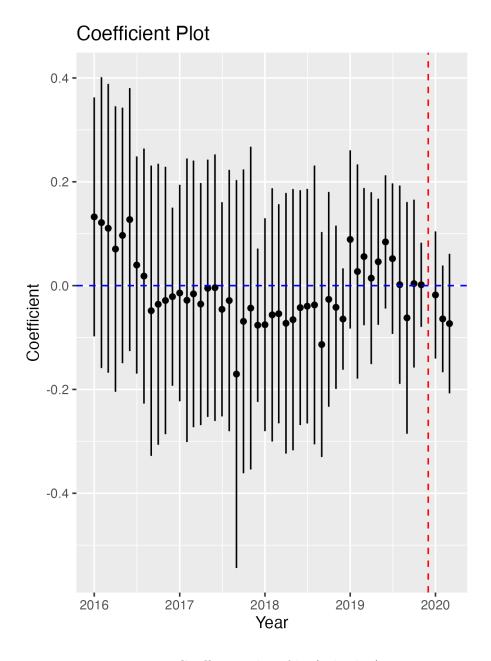


Figure 7: Coefficient plot of log(ridership)

Notes From 2016-01-01 to 2020-03-01