University of Toronto
Department of Economics

Working Paper 585

Is Uber a substitute or complement for public transit?

By Jonathan D. Hall, Craig Palsson and Joseph Price

July 04, 2017

Is Uber a substitute or complement for public transit?*

Jonathan D. Hall
University of Toronto

Craig Palsson
Naval Postgraduate School

Joseph Price
Brigham Young University and NBER

July 3, 2017

Abstract

How Uber affects public transit ridership is a relevant policy question facing cities worldwide. Theoretically, Uber's effect on transit is ambiguous: while Uber is an alternative mode of travel, it can also increase the reach and flexibility of transit's fixed-route, fixed-schedule service. We use a difference-in-differences design to measure the effect of Uber on public transit ridership. The design exploits variation across U.S. metropolitan areas in both the intensity of Uber penetration (as measured using data from Google Trends) and the timing of Uber entry. We find that Uber is a complement for the average transit agency. This average effect masks considerable heterogeneity, with Uber being more of a complement in larger cities and for smaller transit agencies. Comparing the effect across modes, we find that Uber's impact on bus ridership follows the same pattern as for total ridership, though for rail ridership, it is a complement for larger agencies.

*We are grateful for helpful feedback from Jonathan V. Hall, who works for Uber and should not be confused with one of the authors of this paper, Will Strange, Rob McMillan, Peter Morrow, Morley Gunderson, Jessica Peck, and seminar audiences at the University of Toronto, Washington University in St. Louis, ETH Zurich, International Transport Economics Association, University of Toronto/University of British Columbia Summer Conference, Urban Economics Association, and the Canadian Political Science Association. This research was supported by the Social Sciences and Humanities Research Council of Canada. We received excellent research assistance from Michael Gmeiner, Matthew Walshe, Marc-Antoine Schmidt, Tanner Eastmond, and Mona Balesh Abadi. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

1 Introduction

Uber, Lyft, and other ride-hailing companies have transformed the transportation marketplace in over 606 cities around the world. While their entry into cities has been controversial, they have been credited with providing a reliable and affordable transportation option, serving neglected areas of cities, and providing meaningful employment. Against these benefits, they have been accused of being unsafe, creating congestion, destroying stable jobs, and flouting the law. Cities have struggled to decide how to regulate these companies, in part because of a poor understanding of the actual economic effects of ride-hailing companies.

Economists are quickly trying to understand Uber's general economic effects and especially its influence on other modes of transportation. Uber's direct benefits appear to be large. Using Uber's individual-level data and its unique surge pricing, Cohen et al. (2016) estimate that UberX created $6.8 billion of consumer surplus in 2015. The indirect effects are less clear: recent evidence shows that Uber could benefit public health by reducing drunk driving accidents and fatalities (Greenwood and Wattal 2017; Peck 2017; Dills and Mulholland 2016), though other work finds that it has not affected traffic fatalities in any way (Brazil and Kirk 2016). However, an important part of understanding the future of Uber and similar services involves measuring its effect on other modes of transportation. In terms of taxis, Nie (2017) finds Uber has reduced taxi ridership, though Cramer (2016) finds this has not decreased the wages of taxi drivers and chauffeurs.

This paper's contribution is to measure the effect of Uber on public transit. There are three reasons Uber's effect on public transit is important, and all three depend on whether Uber complements public transit. First, Uber could have important effects on public transit's social efficiency. Transit fares are typically above social marginal cost (though below average cost) due to economies of scale and density, implying transit ridership is inefficiently low.[1] Uber increasing (decreasing) transit ridership would then increase (decrease) its efficiency. Second, Uber's effect on public transit directly affects city and state budgets. Ride-hailing services already face fierce political opposition from taxi services, and its effect on

[1] Proost and Dender (2008), Parry and Small (2009), and Basso and Silva (2014) show that increasing transit subsidies, and so increasing transit ridership, increases social welfare given the existing set of transportation policies.

government budgets could tip the political balance.[2] Third, the interaction between Uber and public transit affects congestion and pollution. Regardless of whether Uber is a complement or substitute for public transit, Uber can increase congestion and pollution simply by increasing the number of trips taken. However, its effect on congestion and pollution will be larger if it is a net substitute for transit.

It is not immediately clear whether Uber is a net substitute or a net complement to public transit. On the one hand, Uber is an alternative mode of travel, and many policy makers and experts have speculated whether the introduction of Uber is behind recent declines in transit ridership.[3] Furthermore, Rayle et al. (2016) found that 33 percent of those using a ride-hailing app in San Francisco said their next best alternative for their current trip was using public transit. On the other hand, as we discuss in more detail in Section 2, Uber could complement public transit by increasing the reach and flexibility of transit's fixed-route, fixed-schedule service. Consistent with this possibility, Murphy and Feigon (2016) found that 25 percent of those who use ride-hailing apps, car-sharing, or bike-sharing report that they drive less, and 15 percent report that they ride public transit more. Uber has reported that in several cities 25-40 percent of all Uber pick-ups and drop-offs are near a public transit station; however, they acknowledge that it is impossible to tell whether someone is using Uber to get to a transit stop or to get to a destination that happens to be near a transit stop (Smith 2015). Consistent with either possibility, a 2016 Pew survey found that 56 percent of those who use Uber each week also use public transit each week. This means the same set of people use Uber and public transit, and suggests we will find some effect.

We estimate Uber's net effect on public transit using a difference-in-differences approach across all Metropolitan Statistical Areas (MSAs) in the United States with public transit. We exploit two sources of variation across MSAs. The first is variation in when Uber entered each market, and the second is variation in the intensity of Uber penetration, as measured using the relative number of Google searches for "Uber" in each MSA. This measure is strongly correlated with the

[2]See Spicer and Eidelman (2017) for a review of the political opposition to Uber.

[3]For example, see Fitzsimmons, Emma. 2017. "Subway Ridership Declines in New York. Is Uber to Blame?." *New York Times.* 24 February 2017; Nelson, Laura and Dan Weikel. 2016. "Billions spent, but fewer people are using public transportation in Southern California." *Los Angeles Times.* 27 January 2016; Curry, Bill. 2016. "Where have all the transit riders gone." *The Globe and Mail.* 27 May 2016; or Lazo, Luz. 2016. "Ripple effect of Metro's troubles: plummeting bus ridership across the region." *The Washington Post.* 20 February 2016.

number of drivers per capita in each market (Cramer 2016).

A major threat to identification is whether Uber chooses to enter based on something correlated with transit ridership, we estimate Uber's entry decision. We find Uber largely entered MSAs in population rank order. We also allow each MSA to have its own linear time trend, and use an Autor (2003)-style Granger-causality test to show there are no pre-trends in transit ridership.

Using public transit data from the National Transit Database, we show that the average transit agency's ridership increased with Uber's entrance and search intensity. We find this effect grows slowly over time, with Uber increasing transit ridership by five percent after two years. However, this average effect masks considerable heterogeneity in Uber's effect on public transit. We find that Uber is more of a complement in larger cities and for transit agencies with lower ridership prior to Uber's existence. Comparing the effect across modes, we find that Uber's effect on bus ridership follows the same pattern of increasing average ridership, and of having a larger effect on larger cities and with smaller bus agencies; in contrast, we find Uber is more of a complement for larger rail agencies compared to smaller rail agencies.

2 Why Uber could be either a complement or substitute for public transit

Our goal is to measure the net impact of Uber on public transit, to establish whether it is a net substitute or a net complement for public transit. It is easy to make a case that Uber could take riders away from public transit: while Uber fares are typically higher than public transit fares, riders will substitute Uber for public transit if Uber is fast enough and convenient enough to outweigh its additional cost.

The case for Uber complementing public transit comes from the fact that most public transit systems use fixed routes with fixed schedules. Uber makes it cheaper and easier to travel to places, and at times, that public transit serves poorly. Uber can help riders to travel between work or home and the transit stop. These first and last portions of a trip on public transit typically account for a small share of the distance travelled but a large share of the travel time. Greenwood and Wattal

(2017) show that UberX provides a 20 to 30 percent reduction in prices relative to traditional taxis. By lowering the cost of getting to the transit stop, Uber could make riding a train or express bus more appealing. This can make it feasible to not own a car, or for a family to own only one car, and instead use public transit and Uber.

Furthermore, Uber helps deal with the risks of relying on fixed-schedule public transit. Some people might be happy to use public transit if it provided the same flexibility as personal driving but choose not to do so because the schedule cannot respond to personal emergencies or changes in work schedules. The ability to use Uber if you need to get home because a child is sick or do not want to wait for the bus in the rain could make riding public transit more appealing, increasing transit ridership. For instance, the research on Uber's effect on drunk driving suggests that people might take transit to an activity that involves drinking and then take Uber home.

As the strength of these mechanisms differ for different types of trips, we expect to find that Uber has heterogeneous effects on transit. In particular, Uber is likely to have a stronger effect, either positive or negative, in larger cities where transit riders tend to be wealthier and thus able to pay Uber fares.[4] In addition, smaller transit agencies will tend to have less complete coverage, both over space and time. This could mean that their service is so bad that Uber will be a strong substitute, or that Uber's ability to fill holes in their coverage is all the more valuable so that Uber will be a strong complement.

3 Data

To estimate the effect of Uber on public transit, we collect data on transit ridership, Uber entry and exit, and a variety of controls for 2004–2015.

Our data on transit ridership come from the National Transit Database (NTD). This database contains monthly ridership for essentially all transit agencies which receive federal funding, separated by mode (bus, train, etc.).[5] Specifically, they

[4] That is, in suburban and rural areas, the only people who ride transit are those who cannot afford to drive. These "captive riders" are unlikely to switch to Uber.

[5] Any agency receiving funds from a Federal Transit Administration (FTA) formula program must submit reports to the NTD. These programs account for seventy percent of all FTA funding. To the best of our knowledge, the only other source of federal funding for public transit is Department

report the number of times a rider steps onto a transit vehicle, and so a trip that uses multiple transit vehicles counts as multiple rides. The National Transit Database also contains data on important supply-side variables: fares, capital expenditures, and several measures of the quantity of service provided.[6]

We recorded when each Uber service entered, and exited, the 386 Metropolitan Statistical Areas of the United States of America.[7] This gives us 196 MSAs where Uber has had a presence. Entry and exit were determined based on newspaper articles as well as Uber's press releases, blog posts, and social media posts.

We follow Cramer (2016) in using Google Trends to get the number of Google searches for "Uber" relative to other Google searches as an MSA-level measure of the intensity of treatment.[8] Cramer (2016) uses data on the number of Uber drivers in 18 MSAs from Hall and Krueger (2015) to show that Google searches for "Uber" are strongly correlated with the number of drivers per capita in each market. Figure 1 shows how search intensity grows after Uber entered the eleven largest MSAs. As expected, search intensity starts climbing when Uber enters; it grows slowest in Uber's earliest markets, San Francisco and New York; and grows fastest in their newest markets, Miami and Houston, both of which match up with what actually happened in these markets. Google Trends data is available for 147 of the 196 MSAs Uber has entered.

We also use data from a variety of sources as controls. We use data on MSA population, income, age, and education from the 2008–2012 American Community Survey 5-year estimates, data on monthly MSA total employment and unemployment rates from the Bureau of Labor Statistics, and annual MSA population estimates from the U.S. Census Bureau. Finally, we obtain monthly regional gas price data from the U.S. Energy Information Administration. Table 1 reports summary statistics.

---

of Homeland Security funding for security improvements. Transit systems with no trains and no more than 30 vehicles in operation at any time are not required to report monthly ridership.

[6]Such as the maximum number of vehicles in service, the number of vehicle-hours of service, and the number of vehicle-miles of service.

[7]We use the 2009 definitions of MSAs throughout this paper.

[8]Other papers to use Google Trends data include Stephens-Davidowitz (2014), who uses Google Trends to proxy for racial animus, and Hoopes et al. (2015), who use Google Trends to measure searches for information about taxes.

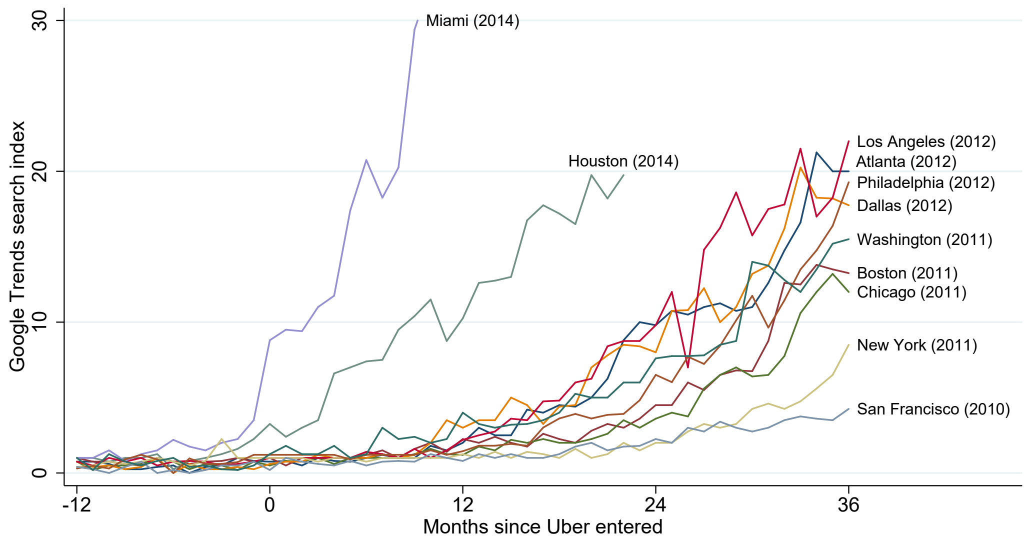

Figure 1: Relative frequency of Google searches for "Uber" by months since any Uber service entered

Notes: Google Trends search index normalized so it is 100 in San Francisco the week starting January 29th, 2017 (not shown). The entry dates in this figure are for *any* Uber service, not just UberX. Year of entry in parenthesis.

Table 1: Summary statistics

	Mean	Median	Std. dev.
Average bus fare	1.31	0.75	4.45
Average rail fare	4.94	2.00	11.0
Average fare	1.77	0.91	4.13
Bus vehicles operating in maximum service	108.1	30	283.8
Rail vehicles operating in maximum service	274.5	51	725.3
Vehicles operating in maximum service	185.2	48	590.1
Bus vehicle revenue hours (1,000)	27.8	6.90	79.1
Rail vehicle revenue hours (1,000)	76.5	11.9	231.2
Vehicle revenue hours (1,000)	40.4	8.70	158.9
Bus vehicle revenue miles (1,000)	345.6	100.4	813.7
Rail vehicle revenue miles (1,000)	1672.0	231.1	4556.6
Vehicle revenue miles (1,000)	616.5	135.2	2326.7
Bus ridership (100,000)	9.53	1.32	41.3
Rail ridership (100,000)	63.5	7.90	263.8
Total ridership (100,000)	15.6	1.21	124.7
Population (100,000)	32.9	8.37	50.9
Employment (100,000)	15.4	3.90	23.6
Gas price	2.98	2.97	0.65
Google search intensity for "Uber"	2.71	1	5.01
Uber in MSA	0.12	0	0.33
Observations	76213		

Notes: Transit ridership measures the number of times someone steps onto a transit vehicle, and so a trip that uses multiple transit vehicles counts as multiple rides.

4 Method

We estimate the effect of Uber on public transit ridership using a differences-in-difference approach. We compare how transit ridership changes in cities when Uber enters relative to changes in cities where Uber has not entered yet. While Uber offers several services, including a black car service, we focus on the entry of UberX, which accounts for the vast majority of their ridership.

Our estimates are based on the following regression:

$$Y_{it} = \beta D_{c(i),t} + \boldsymbol{x}_{it}'\boldsymbol{\eta} + \gamma_i + \delta_t + \theta_{im} + \zeta_{c(i)} \cdot t + \epsilon_{it}.$$

where Y_{it} is log transit ridership on transit agency i in year-month t; $D_{c(i)t}$ is 1 if UberX is active in the MSA $c(i)$ in year-month t and 0 otherwise; $\mathbf{x}_{it}'$ is a vector of controls for transit agency i, such as MSA population and total employment, measures of the quantity of service the transit agency provides, and average fares, in year-month t; γ_i is a transit agency specific fixed effect; δ_t is a year-month specific fixed effect; θ_{im} is a transit agency-month of year fixed effect; and $\zeta_{c(i)}$ is an MSA specific time trend. In all of our analysis, we cluster the standard errors at the MSA level.

We also use the Google Trends data to measure the level of penetration of Uber. We use the same empirical framework as before, but now $D_{c(i)t}$ is the standardized Google Trends search index in MSA $c(i)$. This second measure allows us to exploit variation within the set of treated cities in their intensity of treatment. This captures Uber's market penetration across all their services.

The Google Trends data is not the ideal measure of intensity of treatment, as the frequency of searches for "Uber" is an equilibrium outcome rather than a measure of exogenous differences in supply. However, as previously noted there is strong correlation between the number of Google searches and the number of Uber drivers per capita, indicating that the Google Trends data is a valid proxy for intensity of treatment.

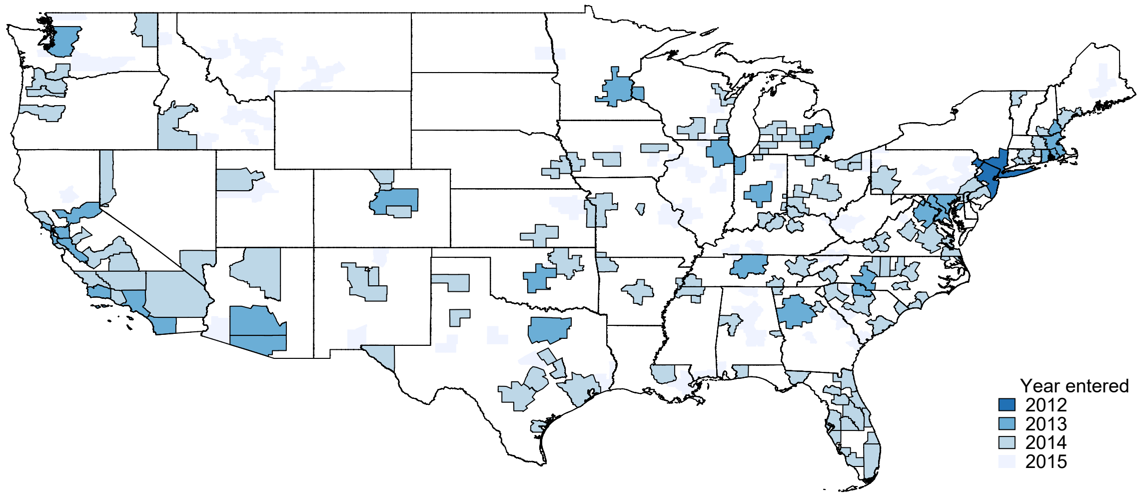

Figure 2: Map of when Uber entered each MSA

5 Estimating Uber's entry decision

The greatest threat to identification comes from whether Uber chooses to enter based on something that is correlated with transit ridership. To address this issue, in this section we provide some insight about Uber's entry decision, concluding Uber largely entered markets based on population, working from large to small.

Figure 2 shows when Uber first entered each MSA, and Figure 3 shows Uber was introduced to cities essentially in population rank order. Kendall's rank correlation between population and entry date is $-.37$ and for any two MSAs Uber has entered, the probability Uber was available in the larger MSA first is 68 percent.

The first column in Table 2 reports the results of a linear regression predicting when Uber enters an MSA. The independent variables are measured in standard deviation units to facilitate comparison of the magnitudes of the coefficients. We find that population is the strongest predictor of when Uber enters an MSA, with an effect 50 percent larger than that of any other predictor. These results increase our confidence that Uber enters markets largely in order of their population rank.

Population and education levels are also the best predictor of *whether* Uber enters an MSA. The second column of Table 2 reports the result from a linear regression predicting whether Uber has entered an MSA. Once again, population is the strongest predictor of whether Uber enters an MSA: the coefficient on

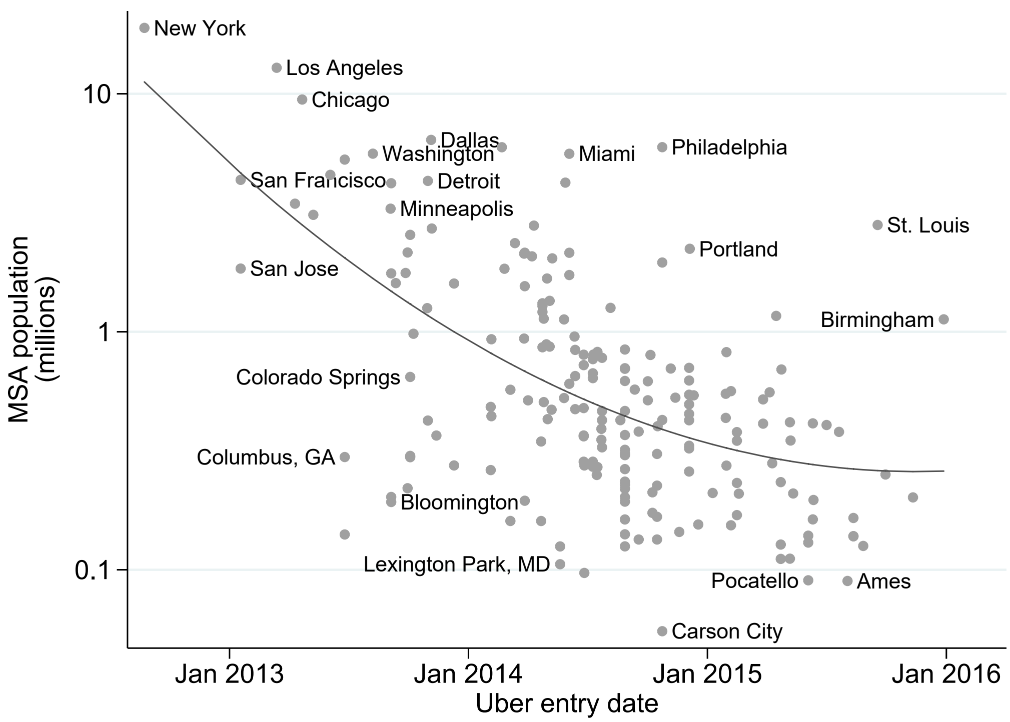

Figure 3: Uber entry date by MSA population

Notes: Data on population from the 2008–2012 American Community Survey 5-year estimates. Data on when Uber entered each MSA collected by the authors. The fitted line is from a quadratic regression of log population on date of entry.

Table 2: Linear regressions predicting when and whether Uber enters an MSA

	(1) Date UberX entry	(2) Did UberX enter
Log(population) (σ)	-88.91***	0.262***
	(14.35)	(0.0227)
Percent with bachelors degree (σ)	-59.32***	0.160***
	(17.54)	(0.0321)
Median age (σ)	25.07	-0.0613***
	(15.74)	(0.0210)
Median income (σ)	-28.03*	-0.000865
	(15.27)	(0.0317)
Unemployment rate (σ)	-56.26**	0.0297
	(23.87)	(0.0270)
Percent work trips transit (σ)	17.21	-0.0665
	(22.74)	(0.0443)
Capital expenditures on public transit (σ)	-31.27**	-0.0165
	(14.67)	(0.0360)
Dist from Uber HQ (σ)	9.284	0.0145
	(13.90)	(0.0228)
Observations	196	386
Adjusted R^2	0.402	0.409

Notes: Data on when Uber entered each MSA collected by the authors. Data on population, income, age, and education from the 2008–2012 American Community Survey 5-year estimates. Data on unemployment from Bureau of Labor Statistics and is for 2012. Capital expenditures on public transit is the total between 2008–2012 and is from the National Transit Database. All independent variables are measured in standard deviation units. Standard errors are in parenthesis.
**p*<.10; ***p*<.05; ****p*<.01

population is more than 60 percent larger than the next largest. The three largest MSAs without Uber are all in New York, as Uber has been banned in upstate New York. Kendall's rank correlation between population and whether Uber has ever entered is .49, and if Uber is available in one MSA but not another, then the probability that Uber is available in the larger MSA is 85 percent.

These results suggest that Uber has focused on entering larger cities first, and gives us confidence that their entry decision is uncorrelated with other trends in public transit ridership.

6 Estimating Uber's effect on transit

We start with a visual summary of the transit ridership data in Figure 4. This figure plots the difference in log transit ridership for transit agencies who had Uber in their MSA relative to those who did not, using a 24 month-window before and after Uber's entry. The difference in log transit ridership the month before Uber enters is normalized to zero. Figure 4 shows no significant pre-trend, suggesting that, given our set of controls and MSA-specific-linear-time-trends, the parallel trends assumption holds.

Additionally, Figure 4 shows that transit ridership increases slowly after Uber enters an MSA, until two years after Uber's entry transit ridership is 5–8 percent higher than it would have otherwise been. While only one of the month-specific estimates is statistically significant at the 5 percent level, we can reject the joint hypothesis that all of the month-specific estimates after Uber's entry are zero.

Table 3 reports our estimates for the effect of Uber on overall transit ridership. Our outcome variables are all measured in logs so the coefficients represent the percent increase in public transit rider that accompanies the arrival or increased penetration of Uber. Column 1 confirms what Figure 4 shows, that when Uber arrives in an MSA, transit ridership does not change much. However, the results in Column 5 indicate that as Uber becomes more commonly used in the MSA, there is an increase in public transit use, with a standard deviation increase in Uber penetration increasing public transit ridership by 1.4 percent. This is consistent with the slowly growing effect of Uber on transit ridership shown in Figure 4.

One reason Uber is a complement rather than a substitute for the average transit agency may be that transit is still much cheaper to use. The median minimum

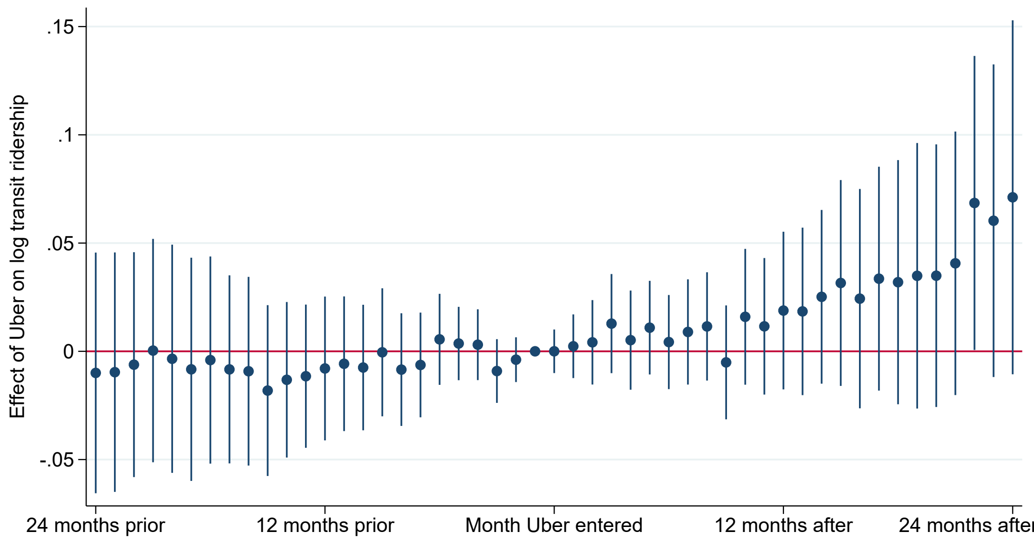

Figure 4: Effect of Uber on log transit ridership before and after entry

Notes: This figure plots the coefficients from a Autor (2003)-style regression of log transit ridership on leads and lags of Uber entry, as well as the controls and fixed effects in our base specification. The omitted indicator is the month before Uber enters. Bars denote 95 percent confidence intervals.

Table 3: Effect of Uber on log transit ridership

	Uber entry				Uber penetration			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UberX	0.00293	-0.0573*	0.0604**	0.000623	0.0138***	-0.00483	0.0328***	0.00758
	(0.0143)	(0.0297)	(0.0236)	(0.0367)	(0.00515)	(0.00527)	(0.00652)	(0.00677)
Above median population		0.0650**		0.0644**		0.0228***		0.0343***
× UberX		(0.0296)		(0.0308)		(0.00716)		(0.00796)
Above median ridership			-0.0816***	-0.0815***			-0.0281***	-0.0323***
× UberX			(0.0292)	(0.0292)			(0.00977)	(0.0100)
Obs.	71386	71386	71386	71386	58015	58015	58015	58015
Clusters	309	309	309	309	227	227	227	227

Notes: Controls are the log of the following: average fare, the maximum number of vehicles in service during the month, vehicle-hours of service, vehicle-miles of service, regional gas prices, employment, and population. Includes a linear MSA time-trend, and fixed effects for each month-year, transit agency, and transit agency-month of year pair. Median population is calculated among the set of MSAs with public transportation. Median ridership calculated based on mean ridership before Uber existed. Uber penetration measured using Google Trends and reported in standard deviation units. Standard errors are reported in parentheses and clustered at the MSA level.
*p<.1;**p<.05; ***p<.01

Table 4: Examples of transit agencies by ridership and MSA size

Ridership	Population: Small	Population: Big
Small	County of Lebanon Transit (PA)	McAllen Express Transit (TX)
Small	Springfield City Area Transit (OH)	MTA (Manchester, NH)
Small	Mid-Ohio Valley Transit (Parkersburg, WV)	East Chicago Transit (IL)
Big	CyRide (Ames, IA)	MTA (New York, NY)
Big	Tompkins Consolidated Area Transit (Ithaca, NY)	MTA (Nashville, TN)
Big	Cache Valley Transit District (Logan, UT)	Green Bay Metro (WI)

Notes: Big and small are defined relative to the median.

Uber fare is \$5, while transit fares average just \$1. Undiscounted fares for bus or light rail are never above \$3, and for those with a monthly pass the marginal fare is zero. Transit is enough cheaper that Uber's role in adding flexibility to the transit system is more important than its ability to substitute for riding transit.

This average treatment effect masks considerable heterogeneity in the effect of Uber on transit. We expand our analysis to examine how the effect of Uber differs based on the population of the MSA and the number of riders that were using public transit before Uber arrived. For both of these measures, we split the sample based on whether an observation is above or below our sample median and include each of these binary variables as an interaction term with our Uber measures. The median population is 280,000 (Duluth, MN) and median monthly ridership is 82,000 (Sioux Area Metro in Sioux Falls, SD). Table 4 reports example of transit agencies with each possible combination of our dummy variables for ridership and population. The big transit agencies in small cities are almost always university towns, while small agencies in big cities are a mix of suburban agencies and cities with limited public transit.

Our results indicate that Uber reduces transit ridership in smaller MSAs while increasing ridership in larger cities. In fact, the coefficients in Table 3 indicate that the arrival of Uber in smaller cities decreases public transit ridership by 5.7 percent while increasing public transit ridership by 0.8 percent in the larger cities. Our estimates based on the Uber penetration rates indicate that a standard deviation increase in Uber use lowers public transit ridership in smaller cities by 0.5 percent while increasing ridership in larger cities by 1.8 percent.

In contrast, we find that Uber actually had the largest effects for transit agencies that had smaller levels of initial ridership prior to Uber's founding. For the transit agencies that had below median public transit ridership, the arrival of Uber increased public transit use by 5.8 percent while for the transit agencies with above median ridership, it decreased public transit use by 2 percent. All of these estimates are roughly the same whether or not we simultaneously control for population and pre-Uber public transit ridership.

Uber most strongly complements small transit agencies in large cities. This is likely because small transit agency in a large city provides the least flexible service in terms of when and where they travel, and so Uber's ability to add flexibility for these agencies is valuable to riders. In addition, transit riders in larger cities tend to be wealthier, and so there is greater overlap between those who ride transit and can afford to take Uber.

Table 5 reports the result of estimating the effect of Uber on bus ridership and train ridership. It shows that we find similar results for bus ridership and for total ridership. The point estimates are of the same sign, though we have less power, so they are typically less statistically significant. However, Uber's effect on rail ridership is different than its effect on bus and overall ridership. In particular, Uber now helps larger agencies relative to smaller agencies.

In the appendix we conduct four robustness tests. Appendix Table 6 shows our results are robust to leaving out New York City and leaving out our controls. Appendix Table 7 shows our results are robust to calculating standard errors by block bootstrapping, and passes a placebo test where we randomly assign treatment status and treatment date. We conduct this placebo test under two different assumptions about the data generating process. In the first we randomly re-assign the observed treatment variables at the MSA-month level, while in the second we randomly assign which cities Uber enters and when. For this second test using the penetration data, we assign treated cities a penetration history from an MSA which was actually treated and adjust the timing to match the placebo treatment date. For untreated cities, we randomly assign a penetration history from an MSA which was not treated. We then calculate p-values by comparing the t-statistic from our main results to those generated by two thousand placebo treatments.

Table 5: Effect of Uber on log bus ridership and log rail ridership

	Bus				Rail			
	Uber entry		Uber penetration		Uber entry		Uber penetration	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UberX	0.0192	0.0193	0.0153***	0.00243	-0.0312	-0.103*	0.00370	-0.0274
	(0.0166)	(0.0329)	(0.00456)	(0.00592)	(0.0194)	(0.0533)	(0.0179)	(0.0245)
Above median population		0.0362		0.0272***		0.0365		0.0199
× UberX		(0.0303)		(0.00891)		(0.0583)		(0.0207)
Above median ridership		-0.0469**		-0.0131		0.0771**		0.0215
× UberX		(0.0222)		(0.00845)		(0.0363)		(0.0152)
Obs.	53295	53295	42673	42673	7427	7427	7360	7360
Clusters	294	294	216	216	45	45	43	43

Notes: Controls are the log of the following: average fare, the maximum number of vehicles in service during the month, vehicle-hours of service, vehicle-miles of service, regional gas prices, employment, and population. Includes a linear MSA time-trend, and fixed effects for each month-year, transit agency, and transit agency-month of year pair. Median population is calculated among the set of MSAs with the given mode of public transportation. Median ridership calculated based on mean ridership before Uber existed and among the set of agencies with the given mode of public transportation. Uber penetration measured using Google Trends and reported in standard deviation units. Standard errors are reported in parentheses and clustered at the MSA level.
*p<.1;**p<.05; ***p<.01

7 Conclusion

Uber and other ride-hailing companies have changed how people get around in cities worldwide. How this has impacted public transit matters both for assessing the welfare effects of Uber and for cities deciding how to regulate Uber. However, Uber's effect on transit is theoretically ambiguous: while Uber is an alternative mode of travel, it can also increase the reach and flexibility of transit's fixed-route, fixed-schedule service. The results in this paper employ a difference-in-differences design that exploits variation across U.S. metropolitan areas in both the intensity of Uber penetration and the timing of Uber entry. We find that the entry of Uber increases public transit use for the average transit agency. This average effect masks considerable heterogeneity, with Uber having the great impact in larger cities and smaller transit agencies. Comparing the effect across modes, we find that Uber's effect on bus ridership follows the same pattern as for total ridership, though for rail ridership Uber has the largest positive effect in cities with large public transit systems already in place.

The results from this paper provide further evidence that Uber increases welfare, though more work needs to be done before drawing definitive conclusions. Results from previous work indicated that Uber increases welfare at little cost; it increases consumer surplus Cohen et al. (2016) without lowering wages for taxi drivers Cramer (2016). This paper's results indicate that Uber has an additional effect on social welfare through encouraging use of public transit. In fact, Uber has the biggest complementary effects on the public transit systems that had the lowest ridership before Uber's entry. However, Uber seems to be decreasing ridership on larger systems, and the effect on these systems could counteract the increase on smaller systems. Whether we care about this net impact on total transit use depends on the questions we ask. Furthermore, while increasing public transit use would decrease congestion, Uber could still have a net increase on congestion by either increasing the total trips taken or by flooding the streets with Uber drivers looking for a fare. Exploring Uber's impact on urban transit and traffic warrants more attention.

The results also warn against making broad policy prescriptions regarding Uber. Uber's effect in a city varies based on the state of public transit. Thus the optimal policy response may also vary across cities.

Beyond contributing to our understanding of the effect of Uber on cities and the factors affecting transit use,[9] this paper also provides preliminary insight into the economic impact of autonomous vehicles. While there is much speculation about how autonomous vehicles may change cities, no empirical estimates exist to date because the technology is so new. However, if autonomous vehicles make transportation more convenient, accessible and affordable relative to existing services, Uber may serve as an appropriate proxy for the estimation of such effects. Thus our results provide suggestive evidence that autonomous vehicles may complement public transit, and that this effect will likely vary across cities.

References

Autor, David H. (2003) "Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing," *Journal of Labor Economics*, Vol. 21, pp. 1–42.

Basso, Leonardo J. and Hugo E. Silva (2014) "Efficiency and Substitutability of Transit Subsidies and Other Urban Transport Policies," *American Economic Journal: Economic Policy*, Vol. 6, pp. 1–33.

Brazil, Noli and David S. Kirk (2016) "Uber and Metropolitan Traffic Fatalities in the United States," *American Journal of Epidemiology*, Vol. 184, pp. 192–198.

Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe (2016) "Using Big Data to Estimate Consumer Surplus: The Case of Uber," Working Paper 22627, National Bureau of Economic Research.

Cramer, Judd (2016) "The Effect of Uber on the Wages of Taxi and Limousine Drivers," *Working Paper*.

Dills, Angela K. and Sean E. Mulholland (2016) "Ride-Sharing, Fatal Crashes, and Crime," SSRN Scholarly Paper ID 2783797, Social Science Research Network, Rochester, NY.

[9]Taylor et al. (2009) find that transit use is strongly correlated with the population of an urban area. Goetzke (2008) finds that key determinants in transit use include car access and network effects, where less access to a car increases transit use and network effects (where more people using transit makes transit more attractive) increase transit use as well.

Goetzke, Frank (2008) "Network Effects in Public Transit Use: Evidence from a Spatially Autoregressive Mode Choice Model for New York," *Urban Studies*, Vol. 45, pp. 407–417.

Greenwood, Brad N. and Sunil Wattal (2017) "Show Me the Way to Go Home: An Empirical Investigation of Ride Sharing and Alcohol Related Motor Vehicle Homicide," *MIS Quarterly*, Vol. 41, pp. 163–188.

Hall, Jonathan V. and Alan B. Krueger (2015) "An Analysis of the Labor Market for Uber's Driver-Partners in the United States," *Princeton University Working Papers*.

Hoopes, Jeffrey L., Daniel H. Reck, and Joel Slemrod (2015) "Taxpayer Search for Information: Implications for Rational Attention," *American Economic Journal: Economic Policy*, Vol. 7, pp. 177–208.

Murphy, Colin and Sharon Feigon (2016) "Shared Mobility and the Transformation of Public Transit,"Technical Report TCRP J-11/TASK 21, American Public Transportation Association, Washington, DC.

Nie, Yu (Marco) (2017) "How Can the Taxi Industry Survive the Tide of Ridesourcing? Evidence from Shenzhen, China," *Transportation Research Part C: Emerging Technologies*, Vol. 79, pp. 242–256.

Parry, Ian W. H. and Kenneth A. Small (2009) "Should Urban Transit Subsidies Be Reduced?" *American Economic Review*, Vol. 99, pp. 700–724.

Peck, Jessica Lynn (2017) "New York City Drunk Driving After Uber," *Working Paper*.

Proost, Stef and Kurt Van Dender (2008) "Optimal Urban Transport Pricing in the Presence of Congestion, Economies of Density and Costly Public Funds," *Transportation Research Part A: Policy and Practice*, Vol. 42, pp. 1220–1230.

Rayle, Lisa, Danielle Dai, Nelson Chan, Robert Cervero, and Susan Shaheen (2016) "Just a Better Taxi? A Survey-Based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco," *Transport Policy*, Vol. 45, pp. 168–178.

Smith, Amy (2015) "Using Open Data and Uber Data to Understand How Ridesharing Complements Public Transportation," Washington, D.C.

Spicer, Zachary and Gabriel Eidelman (2017) "Global Cities, Local Disruption: Uber's Road to Regulatory Approval in Ten North American Cities," *Working Paper*.

Stephens-Davidowitz, Seth (2014) "The Cost of Racial Animus on a Black Candidate: Evidence Using Google Search Data," *Journal of Public Economics*, Vol. 118, pp. 26–40.

Taylor, Brian D., Douglas Miller, Hiroyuki Iseki, and Camille Fink (2009) "Nature and/or Nurture? Analyzing the Determinants of Transit Ridership across US Urbanized Areas," *Transportation Research Part A: Policy and Practice*, Vol. 43, pp. 60–77.

A Alternate specifications

This appendix contains a few alternate specifications, and shows that our results are robust to these other specifications.

Table 6: Alternate specifications for the effect of Uber on log public transit ridership

	Total				Bus				Rail			
	Uber entry		Uber penetration		Uber entry		Uber penetration		Uber entry		Uber penetration	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Panel A: Leaving out New York City						
UberX	-0.00241	0.00716	0.0133**	0.0107	0.0189	0.0282	0.0143***	0.00445	-0.0325	-0.0856*	0.00215	-0.0214
	(0.0158)	(0.0382)	(0.00547)	(0.00657)	(0.0186)	(0.0342)	(0.00479)	(0.00620)	(0.0225)	(0.0459)	(0.0158)	(0.0235)
Above median population		0.0593*		0.0346***		0.0340		0.0305***		0.0346		0.0136
× UberX		(0.0307)		(0.00864)		(0.0308)		(0.0106)		(0.0463)		(0.0185)
Above median ridership		-0.0909***		-0.0376***		-0.0547**		-0.0197*		0.0538		0.0198
× UberX		(0.0323)		(0.0105)		(0.0275)		(0.0103)		(0.0435)		(0.0173)
Obs.	66757	66757	53386	53386	49500	49500	38878	38878	6569	6569	6502	6502
Clusters	308	308	226	226	293	293	215	215	44	44	42	42
						Panel B: No controls						
UberX	0.0215	0.0465	0.0160**	0.00792	0.0219	0.00694	0.0117*	-0.000468	-0.0518*	-0.120*	0.00780	-0.00692
	(0.0189)	(0.0522)	(0.00655)	(0.00895)	(0.0211)	(0.0546)	(0.00595)	(0.00881)	(0.0273)	(0.0647)	(0.0185)	(0.0290)
Above median population		0.0849**		0.0502***		0.0991**		0.0438***		0.0762		0.0206
× UberX		(0.0404)		(0.0109)		(0.0434)		(0.0113)		(0.0773)		(0.0250)
Above median ridership		-0.148***		-0.0515***		-0.106**		-0.0363***		0.0185		-0.00578
× UberX		(0.0463)		(0.0135)		(0.0420)		(0.0136)		(0.0691)		(0.0220)
Obs.	75860	75860	61532	61532	65615	65615	52317	52317	8449	8449	8359	8359
Clusters	316	316	229	229	311	311	226	226	46	46	44	44

Notes: Panel A leaves out all observations from the New York City MSA, while Panel B omits the controls. All other controls as in Table 3. *p<.1;**p<.05; ***p<.01

Table 7: Alternate methods of statistical inference for the effect of Uber on log public transit ridership

	Total				Bus				Rail			
	Uber entry		Uber penetration		Uber entry		Uber penetration		Uber entry		Uber penetration	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Block bootstrap												
UberX	0.00293	0.000623	0.0138**	0.00758	0.0192	0.0193	0.0153***	0.00243	-0.0312	-0.103*	0.00370	-0.0274
	(0.0148)	(0.0383)	(0.00538)	(0.00664)	(0.0167)	(0.0339)	(0.00471)	(0.00634)	(0.0212)	(0.0549)	(0.0184)	(0.0254)
Above median population × UberX		0.0644**		0.0343***		0.0362		0.0272***		0.0365		0.0199
		(0.0321)		(0.00792)		(0.0315)		(0.00949)		(0.0593)		(0.0214)
Above median ridership × UberX		-0.0815***		-0.0323***		-0.0469**		-0.0131		0.0771*		0.0215
		(0.0304)		(0.0103)		(0.0238)		(0.00920)		(0.0410)		(0.0171)
Panel B: p-values from placebo test of randomly assigning treatment at MSA-month level												
UberX	0.8465	0.9890	0.0075	0.2750	0.2640	0.7020	p<0.0005	0.7950	0.1375	0.0730	0.8575	0.2860
Above median population × UberX		0.0350		p<0.0005		0.2730		0.0010		0.5750		0.3720
Above median ridership × UberX		0.0085		0.0005		0.0305		0.1375		0.0695		0.2115
Panel C: p-values from placebo test of randomly assigning entry date												
UberX	0.8580	0.9920	0.0065	0.2625	0.2910	0.7160	0.0020	0.7655	0.1425	0.0835	0.8305	0.3395
Above median population × UberX		0.0365		0.0005		0.3035		0.0255		0.5380		0.3710
Above median ridership × UberX		0.0450		0.0320		0.1895		0.321		0.0320		0.2085

Notes: Panel A calculates standard errors using block bootstrapping at the MSA level (with two thousand draws), while Panels B and C report p-values from a placebo test. In Panel B we randomly re-assign the observed treatment variables at the MSA-month level. In Panel C we randomly assign which cities Uber enters and when. For the penetration data in Panel C, we assign treated cities a penetration history from an MSA which was actually treated and adjust the timing to match the placebo treatment date. For untreated cities, we randomly assign a penetration history from an MSA which was not treated. We then calculate p-values by comparing the t-statistic from our main results to those generated by two thousand placebo treatments. All other controls as in Table 3.
*p<.1;**p<.05; ***p<.01