Quantifying the Effect of Rapid Transit on Drunk Driving

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Abstract

This paper estimates the causal effect of rapid transit systems on drunk driving. Many rapid public transit systems in the U.S. were developed over the past 40 years. Among the benefits of such systems is the potential for them to offer an alternative to driving under the influence of alcohol. In this paper I take advantage of the gradual build out of rapid transit systems to estimate the causal effect of increasing the size and scope of such networks on the incidence of drunk driving in those cities. Using a fixed effects difference-in-differences methodology I estimate the effect of the number of lines, stations and the interconnectedness of the systems' lines on the number of fatal alcohol-related auto accidents and DUI/DWI arrests. I find that adding additional transit line and stations significantly reduces fatal accidents and drunk driving arrests.

1 Introduction

Rapid public transit systems have the potential to alleviate a number of negative outcomes, from road congestion and parking availability to air pollution from automobiles. These systems also have the potential to reduce the incidence of drunk driving if they provide a convenient alternative to self-driving for people who plan to consume alcohol. This last effect is important due to the high prevalence of drunk driving in the United States. Driving under the influence of alcohol causes over 11,000 deaths and 300,000 injuries in the U.S. each year. The monetary cost of these accidents ranges from $49 to $200 billion annually. This high cost makes quantifying the effects of rapid transit on drunk driving rates an essential tool for policymakers tasked with weighing the costs and benefits of developing or expanding rapid transit systems.

Little research exists looking at the effects of building rapid transit systems on drunk driving. Jackson and Owens (2011) estimate the impact of Washington DC extending the operating hours of its subway system in the late 1990s and early 2000s. They find that while there is no measurable effect on drunk driving deaths or arrests city-wide, they do find localized reductions in DUI arrests in areas with both a large number of drinking establishments as well as subway access. In this paper I exploit a more potent source of potential drunk driving reduction, the presence of rapid transit rather than just the operating hours.

Most of the research on drunk driving prevention has focused on either punishment and enforcement or restricting access to alcohol. While these studies find these strategies effective in some cases (Kenkel (1993)) these types of policies can carry significant public costs with little external benefit beyond drunk driving prevention. Rapid transit systems have the potential to reduce drunk driving while simultaneously providing other important benefits to cities such as reduced road congestion and lower traffic pollution.

In this paper I use the gradual build out of rapid transit systems in U.S. cities since the 1970s to identify the causal effect of these systems on fatal alcohol-related auto accidents and DUI/DWI arrests. I gathered data on every line and station opening for sixteen U.S. cities with rapid transit systems (heavy rail, light rail, and/or rapid buses) and combined that with data on all fatal alcohol-related auto accidents and drunk driving arrests from 1975 through 2014.[1] This sample includes all cities with heavy rail (i.e. subways) and a selection of cities with only light rail and rapid bus transit. These non-heavy rail cities were selected because they developed their systems during the sample period. Using a fixed effects difference-in-differences methodology I find that adding an additional rapid transit line reduces fatal drunk driving accidents by 11.5% to 13.2%. Alternatively, I find that adding an additional station reduces fatal accidents by 1% to 1.2%. For DUI/DWI arrests I find similar reductions of 12.7% to 14.4% in fatal alcohol-related accident for each additional rapid transit line and

[1] The sixteen cities are: Washington DC, Los Angeles, New York, Chicago, Philadelphia, Boston, Atlanta, Miami, Baltimore, Cleveland, San Francisco, Denver, Houston, Buffalo, Charlotte, and Dallas.

alternatively a 1.4% to 1.8% reduction per additional rapid transit station. Density and interconnectedness of rapid transit systems, measured by the number of stations per line and the number of connections between lines, have little effect on either drunk driving outcome.

The remainder of the paper proceeds as follows. Section 2 provides background on the use of rapid transit systems in the U.S. as well as the problem of drunk driving. Section 3 provides an analytical framework for the decision process behind drunk driving and the potential effects of rapid transit. Section 4 describes the data sources I use. Section 5 presents the empirical methodology. Section 6 presents the results of my analysis. Section 7 tests the robustness of these estimates. Finally, Section 8 concludes.

2 Background

2.a Rapid Transit in the United States

The development of rapid transit systems in the United States varied substantially from city to city. Early adopters such as New York City and Chicago developed their systems in the late 19th and early 20th centuries, with the systems remaining largely fixed since then.[2] Rapid transit systems consist of some combination of heavy rail (subways and elevated trains), light rail (smaller, slower trains which sometimes share roadways with cars), street-

[2]Some early adoption cities such as Boston have since added rapid bus and/or light rail services.

cars (similar to light rail but with more frequent shared roadways) and rapid buses. Rapid buses are distinguished from standard buses by their limited stops and dedicated right-of-way for substantial portions of their routes. This allows them to move passengers much more quickly than traditional buses and thus are included as part of the rapid transit system.

Cities across the U.S. have developed rapid transit systems of different types at various times over the last 150 years. Cities like Boston, New York, Chicago, Philadelphia, and Cleveland all built rail transit systems in the late 19th and early 20th centuries and continue to operate them today. Other cities have built their systems much more recently, with places like Washington DC, Los Angeles, Baltimore, Dallas, and Denver developing systems between the 1970s and the present. The scale of each of these systems varies substantially. New York City's rapid transit system contains 27 lines and over 450 individual stations while Atlanta has only four lines with 38 stations. The growth of these systems beginning in the 1970's was also substantial. Figure 1 shows the change in the number of rapid transit lines in each city from 1975 through 2014.[3]

[Figure 1 about here.]

[3] New York City is omitted since it is far higher than any other city. It had a constant 27 rapid transit lines over this period.

2.b Drunk Driving in the U.S.

Drunk driving is a serious and persistent public safety issue in the U.S.. While there have been significant reductions in the number of drunk driving deaths over the past few decades drunk driving still kills around 10,000 people each year and injures hundreds of thousands. The National Highway Traffic Safety Administration (NHTSA) puts the annual direct economic cost of drunk driving at $49 billion and the total societal cost at almost $200 billion.[4] In 2012 there were approximately 121 million self-reported instances of drunk driving.[5] That same year over 1.2 million drivers were arrested for driving under the influence.[6]

Almost all research into drunk driving has focused on factors affecting the expected cost of driving drunk or policies that affect the amount of alcohol consumption. Deterrence through increasing the probability of detection or increasing the severity of the punishment has been a primary focus. Eisenberg (2003) examines the impact of laws regulating legal blood alcohol content (BAC) when driving as well as other non-enforcement policies such as graduated licensing[7]. Schultz et al (2001) look into more direct enforcement

[4]National Highway Traffic Safety Administration. "The Economic and Societal Impact Of Motor Vehicle Crashes, 2010." National Highway Traffic Safety Administration, May 2014, DOT HS 812 013. http://www-nrd.nhtsa.dot.gov/Pubs/812013.pdf

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[6]Federal Bureau of Investigation, "Crime in the United States: 2013." Web. 26 May 2015.

[7]Graduated licensing is the practice of providing new drivers with restricted licenses which become progressively less restrictive as the driver ages.

mechanisms, finding significant reductions in fatal alcohol-related accidents due to the use of sobriety checkpoints.

Recently, some studies have begun looking at the impact of alternative transportation availability on drunk driving outcomes. Jackson and Owens (2011) find that extending the operating hours of the Washington DC subway resulted in localized reductions in DUI arrests, though little city-wide effect. Greenwood and Wattal (2015) and Dills and Mulholland (2016) find reductions in drunk driving measures after introduction of ridesharing services such as Uber and Lyft. My paper expands on this growing literature by exploring the impacts of not just the operating hours of public transit systems, but their initial introduction. Public transit has many purposes beyond drunk driving prevention, such as relieving traffic congestion, reducing pollution, and easing parking constraints. When deciding to build or expand transit systems policymakers need to have a solid understanding of both the costs and potential benefits, along all dimensions, of these services. This paper helps to quantify the benefit of rapid transit in terms of drunk driving prevention.

3 Analytic Framework

In this section I present a simple model of the decision process faced by an individual who plans to consume alcohol. In the model, an individual faces three decisions: whether to consume alcohol inside their home ($H = 1$) or outside their home ($H = 0$), if they go out whether to self-drive ($S = 1$) or take alternative transportation ($S = 0$), and finally how much alcohol to consume (D). The individual will select the values of these variables which solve the utility maximization problem in Equation 1.

$$\begin{aligned} \underset{H,S,D}{\text{maximize}} \quad & H \cdot U_H(D, \beta_{i,H}) + (1 - H) \cdot S \cdot U_{NH,S}(D, P_S, \delta_{i,S}, \beta_{i,NH}) \\ & + (1 - H) \cdot (1 - S) \cdot U_{NH,NS}(D, P_{NS}, \delta_{i,NS}, \beta_{i,NH}) \end{aligned} \tag{1}$$

In this equation, P_S represents the price of self-driving and P_{NS} is the price of taking alternative transportation. These prices take into account the convenience of each mode of transportation as well. β represents idiosyncratic factors affecting the utility of consuming alcohol outside versus inside the home and δ are idiosyncratic factors affecting the utility of self-driving versus taking alternative transportation. $U_{NH,NS}(.)$ represents the utility received from drinking outside the home and taking the individual's most-preferred form of alternative transportation.

Prior to rapid transit introduction, drunk drivers are those individuals who optimally select to drink outside the home ($H = 0$), self-drive ($S = 1$), and consume more alcohol than legally allowed when driving ($D^* > \bar{D}$). Within the utility maximization framework I present here, drunk drivers are those for whom:

$$
\begin{aligned}
&U_{NH,S}(D_i^*, P_S, \delta_{i,S}, \beta_{i,NH}) > U_H(D_i^*, \beta_{i,H}) \\
&U_{NH,S}(D_i^*, P_S, \delta_{i,S}, \beta_{i,NH}) > U_{NH,NS}(D_i^*, P_{NS}, \delta_{i,NS}, \beta_{i,NH}) \\
&D_i^* > \bar{D}
\end{aligned}
\tag{2}
$$

The introduction or expansion of rapid transit services affects this decision problem through the price of alternative transportation (P_{NS}). For some individuals, the convenience and cost of rapid transit will now make it their most preferred form of alternative transportation. For a subset of these people, going out using rapid transit will now give them the highest utility. Not all of those who choose to use rapid transit would have driven drunk in its absence, some would have stayed home, others would have used some other form of alternative transportation, and still others would have self-driven but restricted their alcohol consumption to a level at which they could drive legally. The substitution that this study will measure does not include any of these groups. The substitution I measure is for people who would have driven drunk prior to rapid transit introduction (those who satisfy conditions in (2) above) but who now optimally choose to take rapid transit instead. If there is significant substitution of this type it should have an estimable impact on drunk driving outcomes.

4 Data

Estimating the effect of rapid transit on drunk driving requires data on both the availability of rapid transit and data on drunk driving outcomes for cities around the U.S.. I have gathered the following data for 16 U.S. cities with rapid transit systems covering 1975 through 2014.

4.a Alcohol-Related Traffic Fatalities

Since 1975 the National Highway Traffic Safety Administration (NHTSA) collects data on every fatal auto accident in the U.S. through their Fatality Analysis Reporting System (FARS). These data include information about the vehicles, their occupants, the time and location of the accident, and importantly whether alcohol was a factor in the accident. I collected these data from the earliest available year, 1975, through 2014 which is the latest year for which data have been published. For the early years of data, before GPS systems became widely available, locations were recorded as state, county, and city identifiers. In the latest 15-20 years of data, geographic locations are recorded via precise coordinates. Whenever available, I use the coordinate data to determine which observations are in each sample city.[8] When these data are unavailable I use the city codes to match accidents to the sample cities. All of the data are incident-level, so each observation represents a separate fatal accident. After matching each observation to the sample cities

[8] Any accident within 10 miles of the city centroid is considered within that city.

I aggregate them into total monthly fatal alcohol-related auto accidents for each city.

4.b DUI/DWI Arrests

The Federal Bureau of Investigation (FBI) through their Uniform Crime Reporting (UCR) system collects data on monthly arrests for various crimes from police departments across the U.S.. I collected monthly UCR reports for DUI/DWI arrests for each municipal police agency in my city sample. I gathered these data for 1980 through 2014. Reporting of DUI/DWI arrests in the UCR program is voluntary, accordingly not every police agency reports these arrest statistics every month. For the cities in my sample, half of them report data for over 93% of the months between 1980 and 2014. All but four report data for at least 78% of months, and all but two report data for over 39% of months. Two cities, Chicago and Washington DC, report for only a small proportion of months. Excluding them from the following analyses does not affect the results.

4.c Rapid Transit System Data

Determining whether rapid transit had any effect on fatal accidents requires data on how the availability of rapid transit has changed over the sample period. For each of the cities in my sample I gathered data for each line and station in their rapid transit system.[9] For each transit line I have the date when it first began operation. For each station I have the opening date of the station, information on which lines stop at the station, the date each line began operating at that station, and an indicator for whether the station is a connection between two or more lines. In many transit systems, two or more lines will run parallel for a section of their route, stopping at all of the same stations over that section. In these cases, I count the stations at which the lines converge or diverge as connection stations while the intermediate shared stations are not counted as such. The purpose of including data on line connections is to test whether more inter-connected systems are more appealing under the theory that they provide more comprehensive coverage of the city. These data provide several measures for the quality of a city's rapid transit system. For this analysis I calculate the total number of stations, the total number of transit lines, and the total number of line connections in each sample city's rapid transit system in each month between 1975 and 2014.

[9] All rapid transit system data were gathered from the corresponding municipal transit authority.

5 Methodology

5.a Econometric Model

To quantify any potential effects rapid transit services had on fatal alcohol-related auto accidents in the sample cities I use a fixed effects difference-in-differences methodology. Between 1975 and 2014, 10 of the sample cities developed their rapid transit systems while the systems in the remaining six cities remained largely static, having been built out during the early 20th century. The cities whose systems were already established by 1975 effectively act as a control group for the treatment cities which built their systems over the late 20th and early 21st centuries. I estimate Equation 3 using Negative Binomial estimation techniques because the outcomes of interest (fatal accidents and DUI arrests) are discrete count variables.

$$y_{i,t} = \alpha_0 + \beta Z_{i,t} + \gamma X_{i,t} + \delta_i + \phi_t + \epsilon_{i,t} \tag{3}$$

In this equation, $y_{i,t}$ represents the measure of drunk driving prevalence which for this analysis are the numbers of fatal alcohol-related auto accidents and DUI/DWI arrests each month. $Z_{i,t}$ is a vector of potential measures of rapid transit system quality such as number of stations, number of lines, and/or number of line connections for city i at time t. β is the coefficient of interest for this analysis, it captures the effect of these rapid transit measures on drunk driving outcomes. $X_{i,t}$ is a vector of other potentially important covariates such as city population and state unemployment rates. δ_i and ϕ_t are a full set of city and time fixed effects.

5.b Identification

Identification of the causal effect of rapid transit systems comes from their gradual and staggered development. Rapid transit, particularly rail systems are large, expensive projects and typically take years or decades to complete. Systems for the cities in my sample began operation at quite different points in time. Washington DC opened its first heavy rail line in 1976 while Miami's didn't open until 1984 and Los Angeles' until 1990. This gradual roll out of systems across cities allows me to estimate the causal effect of rapid transit service independent of other time-specific factors. Figures 1 and 2 graphically presents the number of lines and stations, respectively, in operation in each sample city from 1975 through 2014.[10] This in conjunction with the difference-in-differences approach which uses the control cities to remove any trends in drunk driving outcomes as well as any seasonal variation that is common across cities allows me to make causal inference about the effects of rapid transit.

[Figure 2 about here.]

[10] New York City is excluded due to its unusually large number of lines and stations. Over the entire period it had a constant 27 lines and 494 stations. For stations, Philadelphia and San Francisco are excluded as well since their street-car lines have a very large number of stations. Each has a constant number of stations over the full sample period.

6 Results

Table 1 presents the results of estimating Equation 3 using the number of rapid transit lines as the measure of system size. Specifications (1) through (3) presents Negative Binomial estimates of the effect of adding additional rapid transit lines on monthly fatal alcohol-related auto accidents. Each model progressively adds more control variables. Specification (1) controls linearly for city population. Specification (2) adds quadratic population controls. Finally, specification (3) adds controls for city economic and demographic factors.[11] The results indicate that adding an additional transit line reduces fatal alcohol-related accidents by 11.5% to 13.8%.[12] Specifications (4) through (6) in Table 1 present the same estimations using DUI/DWI arrests as the dependent variable rather than fatal alcohol-related accidents. The effects of adding additional rapid transit lines on DUI/DWI arrests are very similar to the effects on fatal accidents, with reductions of 12.7% to 14.4% from adding additional lines.

[Table 1 about here.]

The number of lines is not the only potential measure of a rapid transit system's size. A transit line is potentially less useful if it only serves a

[11]The additional controls include state-level unemployment rates, poverty rates, the proportions of the population which are children, elderly, male, and males aged 21-44 (each included separately). Unemployment rates and population are annual, other covariates are from decennial census data.

[12]The coefficients reported in the table represent the change in the mean of the natural log of the number of fatal accidents. To convert these into percentage changes I calculate $exp(coefficient) - 1$.

limited number of stations. Accordingly, I also estimate the effect of adding additional rapid transit stations on drunk driving outcomes. Table 2 presents the results of this estimation. As in Table 1, specifications (1)-(3) present the effects on fatal alcohol-related auto accidents and specifications (4)-(6) give the effects on DUI/DWI arrests. The results indicate that each additional rapid transit station reduces fatal alcohol-related accidents by 1% to 1.2%. The estimated impact on DUI/DWI arrests is comparable, with each station reducing arrests by 1.4% to 1.8%.

[Table 2 about here.]

These results, both for additional transit lines and additional stations indicate that increasing the size of a city's rapid transit system has a significant impact on drunk driving outcomes.[13] Next I try to delve into the effect of the comprehensiveness of a city's rapid transit system. Here I jointly estimate the effects of the number of rapid transit lines, the number of stations per line, and the number of connections between lines. Table 3 presents the results of this estimation.

[Table 3 about here.]

As in the previous two tables, the first three specifications examine the impact on fatal alcohol-related accidents and the last three look at the effect

[13]The coefficients on city population indicate higher population corresponds with fewer fatal alcohol-related accidents and more DUI/DWI arrests. The negative coefficient for fatal accidents may be due to increased density and traffic congestion in larger cities, leading to slower traffic speeds and fewer fatal crashes.

on DUI/DWI arrests. Estimating each of these three measures jointly shows that the impact of rapid transit systems on drunk driving outcomes seems to be driven by the number of lines each system operates. Of the three measures of system quality only the number of lines has a significant effect. The effects of additional rapid transit lines on drunk driving outcomes are similar to those presented in Table 1. I estimate in Table 3 that each additional line reduces fatal alcohol-related accidents by 13.1% to 18.6%. For DUI/DWI arrests each line corresponds to a 10.5% to 12.0% reduction. All of these results indicate that increasing the size of a city's rapid transit system significantly reduces drunk driving outcomes.

6.a Robustness

One potential concern about the interpretation of these estimates is that the identifying variation might be driven by expansion of rapid bus services rather than more traditional heavy and light rail transit services. While rapid bus systems are much less common than rail services for the cities in my sample all of them were developed during the sample period, potentially increasing their influence on the estimates of rapid transit's effects on drunk driving. The concern is that this might limit the applicability of my estimated effects to rail transit systems. To test this I repeat the estimation in Table 1 excluding rapid buses from the number of transit lines.[14] Table 4 presents

[14] I also repeated the analysis in Tables 2 and 3 excluding rapid bus services and found no change in those results.

these estimates. As each shows, removing rapid buses has no effect on the estimated reduction in fatal alcohol-related accidents or DUI/DWI arrests. This demonstrates that the estimated effects are not driven primarily by rapid bus services but rather apply to rail transit services as well.

[Table 4 about here.]

Another concern regards statistical inference using clustered standard errors. In all of my analyses I cluster standard errors at the city level. Cameron and Miller (2015) show that clustering can lead to overly small standard errors when the number of clusters is relatively small. Since the number of clusters in my primary analyses is only 16 I re-estimate each specification clustering instead at the month level. Doing so increases the number of clusters from 16 to 480, which is sufficiently large for reliable statistical inference. Table 5 presents the results of estimating the effect of the number of rapid transit lines on each of the drunk driving outcomes using date clustering. Contrary to the concern drawn from Cameron and Miller (2015), the standard errors using this larger number of clusters are substantially smaller than when I cluster at the city level.[15] This result provides some support that the standard errors I estimate in my primary results are not significantly underestimated.

[Table 5 about here.]

[15]I likewise find significantly smaller standard errors when re-estimating the specifications in Tables 2 and 3 clustering at the date level.

7 Conclusion

Drunk driving exacts a large cost, both in terms of lives lost and in economic damage. Providing convenient, affordable transportation alternatives represents a potential avenue to reducing this cost. Rapid transit systems have the potential to move people around cities more quickly and efficiently than traditional bus systems. Furthermore, they are typically far cheaper than private transportation options such as taxis. Despite this potential, there is very little research on the effects rapid transit have on drunk driving rates. In this study I use the build out of rapid transit systems across the U.S. over the past 40 years to estimate the causal effect of these systems on fatal alcohol-related auto accidents. Using a fixed effects difference-in-differences methodology I estimate that expanding rapid transit systems significantly reduces both fatal alcohol-related auto accidents and DUI/DWI arrests. I find that adding an additional rapid transit line reduces fatal accidents by 11.5% to 13.8% and DUI/DWI arrests by 12.7% to 14.4%. Alternatively, using number of stations as the measure of system size I find a 1% to 1.2% reduction in fatal accidents and a 1.4% to 1.8% reduction in drunk driving arrests per additional station.

These results provide essential evidence for policymakers when weighing the costs and benefits of building or expanding rapid transit systems in their cities. The estimates above imply that each additional rapid transit line a city builds results in on average four fewer fatal drunk driving accidents each year. At a minimum this corresponds to a reduction of almost $40 million in damage per line each year.[16] These systems operate for many decades after they are developed, meaning these benefits from drunk driving reduction will continue to accumulate year after year.

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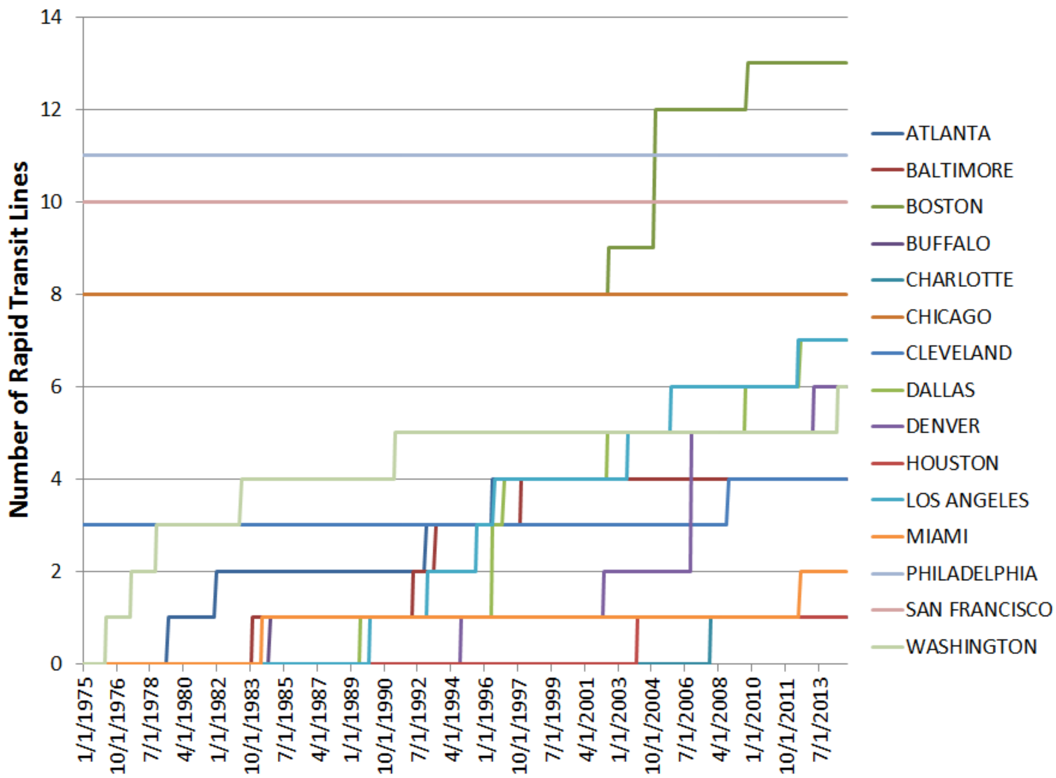
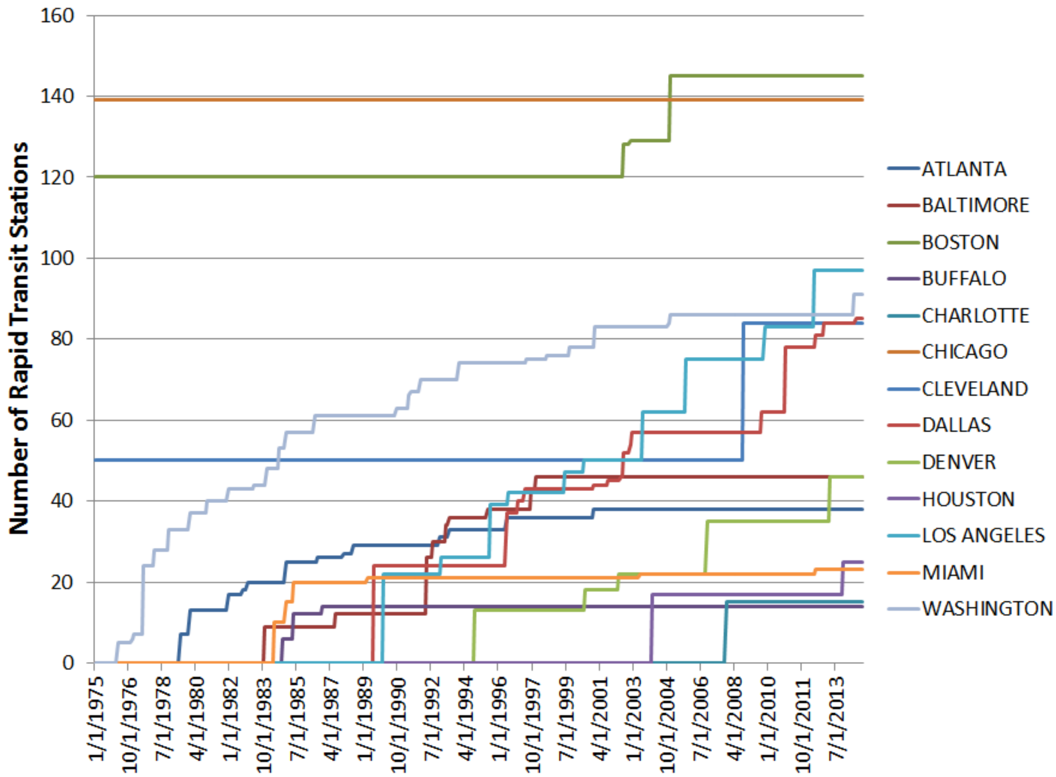
Figure 1: Number of Rapid Transit Lines



*New York City excluded for clarity, it has a constant 27 lines over the sample period.

Figure 2: Number of Rapid Transit Stations



*New York City, Philadelphia, and San Francisco are excluded for clarity. They have a constant 494, 415, and 242 stations, respectively, over the full sample period.

Table 1: Effects of Number of Rapid Transit Lines

	(1) Fatal Crashes	(2) Fatal Crashes	(3) Fatal Crashes	(4) DUI Arrests	(5) DUI Arrests	(6) DUI Arrests
Lines	-0.122*	-0.149**	-0.133**	-0.136**	-0.144**	-0.155**
	(0.060)	(0.058)	(0.051)	(0.053)	(0.050)	(0.055)
Population	-0.074*	-0.006	-0.077	0.082	0.149	0.134
	(0.031)	(0.060)	(0.059)	(0.051)	(0.103)	(0.124)
Population^2		-0.001^{+}	-0.0000		-0.001	-0.001
		(0.0004)	(0.0004)		(0.001)	(0.001)
Unemployment Rate			0.018			-0.063^{+}
			(0.035)			(0.036)
Poverty Rate			0.015			-0.057
			(0.040)			(0.039)
Male %			0.372*			0.005
			(0.152)			(0.211)
Male (21-44) %			-0.164			0.144
			(0.133)			(0.147)
Children (0-17) %			-0.107			0.085
			(0.068)			(0.062)
Elderly (65+) %			0.106			0.101
			(0.136)			(0.103)
N	7680	7680	7488	5139	5139	5139

Standard errors in parentheses, clustered at the city level.
Fixed effects for city and month by year are included in the regressions but are not reported.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are estimated using Negative Binomial specification.
Population measures are in units of 100,000.
Rates and percentages are in percentage points.

Table 2: Effects of Number of Rapid Transit Stations

	(1) Fatal Crashes	(2) Fatal Crashes	(3) Fatal Crashes	(4) DUI Arrests	(5) DUI Arrests	(6) DUI Arrests
Stations	-0.010^{+}	-0.012*	-0.011**	-0.014***	-0.015***	-0.018***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Population	-0.073*	-0.007	-0.080	0.100*	0.173^{+}	0.132
	(0.030)	(0.060)	(0.055)	(0.051)	(0.101)	(0.116)
Population^2		-0.001	0.0000		-0.001	-0.005
		(0.0004)	(0.0004)		(0.001)	(0.009)
Unemployment Rate			0.017			-0.046
			(0.035)			(0.038)
Poverty Rate			0.019			0.005
			(0.038)			(0.029)
Male %			0.378*			0.044
			(0.158)			(0.191)
Male (21-44) %			-0.171			0.156
			(0.137)			(0.147)
Children (0-17) %			-0.112^{+}			0.121*
			(0.068)			(0.059)
Elderly (65+) %			0.124			0.169
			(0.137)			(0.108)
N	7680	7680	7488	5139	5139	5139

Standard errors in parentheses, clustered at the city level.
Fixed effects for city and month by year are included in the regressions but are not reported.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are estimated using Negative Binomial specification.
Population measures are in units of 100,000.
Rates and percentages are in percentage points.

Table 3: Joint Impact of Rapid Transit Measures

	(1) Fatal Crashes	(2) Fatal Crashes	(3) Fatal Crashes	(4) DUI Arrests	(5) DUI Arrests	(6) DUI Arrests
Lines	-0.177**	-0.206***	-0.140**	-0.111*	-0.119*	-0.128+
	(0.056)	(0.053)	(0.041)	(0.050)	(0.048)	(0.067)
Stations per Line	0.009	0.003	0.009	0.009	0.005	0.001
	(0.007)	(0.010)	(0.009)	(0.008)	(0.010)	(0.008)
Line Connections	0.034	0.042	0.004	-0.025	-0.023	-0.023
	(0.028)	(0.029)	(0.031)	(0.028)	(0.029)	(0.034)
Population	-0.074**	-0.007	-0.091	0.069	0.137	0.123
	(0.029)	(0.068)	(0.064)	(0.051)	(0.115)	(0.128)
Population^2		-0.001	0.0001		-0.001	-0.001
		(0.0005)	(0.0004)		(0.001)	(0.001)
Unemployment Rate			0.013			-0.062+
			(0.033)			(0.036)
Poverty Rate			0.012			-0.057
			(0.040)			(0.039)
Demographics			√			√
N	7680	7680	7488	5139	5139	5139

Standard errors in parentheses, clustered at the city level.

Fixed effects for city and month by year are included in the regressions but are not reported.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

All models are estimated using Negative Binomial specification.

Population measures are in units of 100,000.

Rates and percentages are in percentage points.

Table 4: Effects of Number of Rapid Transit Lines - Excluding Buses

	(1) Fatal Crashes	(2) Fatal Crashes	(3) Fatal Crashes	(4) DUI Arrests	(5) DUI Arrests	(6) DUI Arrests
Lines	-0.118^{+}	-0.144*	-0.133*	-0.132**	-0.144**	-0.178**
	(0.063)	(0.063)	(0.057)	(0.057)	(0.053)	(0.057)
Population	-0.075*	-0.011	-0.085	0.083	0.156	0.119
	(0.032)	(0.065)	(0.060)	(0.054)	(0.106)	(0.122)
Population^2		-0.001	0.0001		-0.001	-0.001
		(0.0004)	(0.0004)		(0.001)	(0.001)
Unemployment Rate			0.012			-0.068^{+}
			(0.033)			(0.038)
Poverty Rate			0.013			-0.061
			(0.041)			(0.039)
Male %			0.394*			0.109
			(0.157)			(0.200)
Male (21-44) %			-0.154			0.145
			(0.132)			(0.147)
Children (0-17) %			-0.097			0.121*
			(0.073)			(0.061)
Elderly (65+) %			0.132			0.158
			(0.135)			(0.108)
N	7680	7680	7488	5139	5139	5139

Standard errors in parentheses, clustered at the city level.
Fixed effects for city and month by year are included in the regressions but are not reported.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are estimated using Negative Binomial specification.
Population measures are in units of 100,000.
Rates and percentages are in percentage points.

Table 5: Effects of Number of Rapid Transit Lines - Date Clustering

	(1) Fatal Crashes	(2) Fatal Crashes	(3) Fatal Crashes	(4) DUI Arrests	(5) DUI Arrests	(6) DUI Arrests
Lines	-0.122***	-0.149***	-0.133***	-0.136***	-0.144***	-0.155***
	(0.008)	(0.009)	(0.009)	(0.005)	(0.005)	(0.006)
Population	-0.074***	-0.006	-0.077***	0.082***	0.149***	0.134***
	(0.006)	(0.010)	(0.015)	(0.006)	(0.013)	(0.018)
Population^2		-0.001***	-0.0000		-0.001***	-0.001***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Unemployment Rate			0.014			-0.057***
			(0.009)			(0.006)
Poverty Rate			0.015$^+$			0.002
			(0.008)			(0.007)
Male %			0.372***			0.005
			(0.039)			(0.031)
Male (21-44) %			-0.164***			0.144***
			(0.029)			(0.023)
Children (0-17) %			-0.107***			0.085***
			(0.017)			(0.016)
Elderly (65+) %			0.106***			0.101***
			(0.025)			(0.018)
N	7680	7680	7488	5139	5139	5139

Standard errors in parentheses, clustered at the date level.
Fixed effects for city and month by year are included in the regressions but are not reported.
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are estimated using Negative Binomial specification.
Population measures are in units of 100,000.
Rates and percentages are in percentage points.