Residential Proximity to Late-Night Bus Routes in Austin: Impact on DWI Arrests

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Abstract

This paper examines the impact of late-night bus services in Austin, Texas on arrests for driving while intoxicated (DWI). I take advantage of a unique dataset containing the home addresses for people arrested for DWI to test whether these services reduce DWI arrests for those who live within a short walk of one of their stops. Using a difference-in-differences approach which leverages the differential availability of late-night bus services on different days of the week I find that Austin's late-night buses substantially reduce the number of DWI arrests for people who live close to their routes.

1 Introduction

Despite improvements over the past few decades, drunk driving remains a significant problem in the United States. Alcohol-related auto accidents claim over 11,000 lives and result in over 326,000 injuries annually. These accidents impose a substantial cost on society, with estimates of the harm caused ranging from $44 billion to over $200 billion each year.[1] In addition to the harm caused by accidents, drunk driving poses a significant criminal justice problem. In 2012, over 1.2 million US drivers were arrested for drunk driving[2], imposing significant cost in terms of enforcement, prosecution, and penalties faced by those convicted. Accordingly, substantial time and resources have been devoted to trying to reduce the incidence of drunk driving around the country.

Most drunk driving prevention policies focus on deterrence through increased police enforcement or stricter penalties. Such policies aim to make drunk driving less appealing by increasing the expected cost of doing so, either by increasing the likelihood of detection or increasing the punishments if caught. For this reason, most of the academic research on drunk driving prevention has focused on these deterrence methods as well. However, threat of punishment is not the only potential way to deter drunk driving. Increas-

[1] 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. Web. 6 March 2017.

[2] Federal Bureau of Investigation, “Crime in the United States: 2013.” Web. 6 March 2017.

ing the availability and attractiveness of alternative forms of transportation can potentially induce some people who would otherwise have driven drunk to instead take other transportation.

Late-night public transit is often promoted as a potential tool for reducing drunk driving. To date, limited research exists examining whether such transit services do reduce drunk driving rates. One issue with measuring the effectiveness of late-night transit is that not every person in a city has access to these services. Late-night routes often cover only a subset of city transit routes. Anyone who doesn't live in close proximity to one of them will not be able to use these services as an alternative to driving drunk.

In this paper, I take advantage of a unique dataset containing the home addresses for every person arrested for driving while intoxicated (DWI) by the Austin Police Department to asses how the availability of late-night bus services affects drunk driving outcomes. Using these home addresses along with the fact that Austin's late-night buses do not operate every day of the week I estimate the causal impact of Austin's late-night buses on DWI arrests for people who live within walking distance of one of these routes. This approach uses a difference-in-differences methodology which compares the change in number of DWI arrests for people living close to these routes from days of the week without late-night bus service to days with such services to the corresponding change for people who live farther away from these routes I estimate that Austin's late-night buses reduce DWI arrests by as much as 16.8% for those living within a short walk of a late-night bus stop.

The remainder of this paper proceeds as follows. Section 2 provides background on the problem of drunk driving in the U.S. as well as on Austin, Texas's late-night bus system. Section 3 describes the data sources used in the analyses. Section 4 details the empirical methodology for identifying the causal impact of Austin's late-night buses on DWI arrests. Section 5 presents the results of these estimates. Section 6 examines the robustness of these results. Finally, Section 7 concludes.

2 Background

2.a Drunk Driving Prevalence and Prevention

Drunk driving remains a persistent problem across the U.S. Nationally, over 11,000 people are killed each year in alcohol-related accidents. Over 1.2 million are arrested for driving under the influence annually. In Austin, Texas, which is the focus of this study, DWI arrests average around 6,000 each year. The costs imposed by both drunk driving and efforts to discourage it can be substantial. Nationally, the costs imposed by fatal alcohol-related accidents range from $44 billion to as much as $200 billion each year. Arrests for DWIs carry costs as well in terms of enforcement, prosecution, and lost productivity of convicted offenders. Bouchery et al (2011) estimate the cost of this lost productivity at $7.5 billion annually.

Common drunk driving prevention strategies can carry substantial costs as well. Sobriety checkpoints are a common enforcement-based drunk driving prevention method. Miller et al (1998) estimate that operating a single checkpoint costs as much as \$4,000 per hour. Enhanced police patrols will likewise incur additional public costs in terms of personnel and equipment. These strategies can be effective at reducing drunk driving, with Shults et al (2001) showing that sobriety checkpoints can reduce fatal alcohol-related accidents by 18-20%. One question for policymakers is whether these methods are a cost-effective way to achieve reductions in drunk driving.

Enforcement strategies aim to deter drunk driving by increasing the expected cost of doing so, either through increasing the likelihood of detection or increasing the severity of punishment. This is only one possible method for deterring drunk driving, however. When deciding to consume alcohol outside the home individuals face the choice between driving themselves (and potentially driving under the influence on their return trip) or taking some alternative form of transportation. Holding the available transportation options fixed, increasing the expected cost of drunk driving makes the former less appealing relative to the latter. This decision can also be influenced by making alternative transportation more appealing relative to self-driving. This can be accomplished by increasing the availability of alternative transportation methods, increasing their convenience, or decreasing their cost. Greenwood and Wattal (2015) and Dills and Mulholland (2016) have shown that increasing the availability of alternative transportation can reduce rates of drunk driving. Jackson and Owens (2011) look specifically at the effect of late-night public transit in Washington D.C. and find significant, but highly localized effects on drunk driving. They show that extended subway operating hours reduce drunk driving arrests but only in neighborhoods with both subway stations and large numbers of bars.

2.b Late-Night Buses in Austin

There are previous studies which provide evidence that improving the attractiveness of alternative transport relative to self-driving can reduce drunk driving. It is possible that the availability of late-night public transit services could reduce drunk driving as well. Austin, Texas operates two types of late-night bus services. Their "Night Owl" service consists of five routes which cover a wide range of neighborhoods. The other late-night service is the "Entertainment Bus" (E-Bus). This service consists of two routes and primarily connects areas with large amounts of student housing to the downtown entertainment districts. Both operate far later than the typical Austin transit operating hours, running until 3:30 am. Standard buses in Austin typically have final departures between 10:30 pm and 11:30 pm, depending on the route. The Night Owl service operates Mondays through Saturdays while the E-Bus only operates Thursday through Saturday.

3 Data

The analyses in this study take advantage of a unique dataset provided by the Austin Police Department. Most drunk driving studies rely on data which at their most detailed only provide location information for the locations where drunk driving accidents or arrests occur. These data are useful but not ideal for measuring the impact of expanding public transit systems, as the key to these systems' usefulness in terms of drunk driving prevention stems from their accessibility to potential drunk drivers' homes. The data I use in this study contain the home addresses for every person arrested for DWI by the Austin police department from January 1, 2014 through November 30, 2015. These data allow me to calculate the number of DWI arrests for people who live near a late-night bus route separately from the number of arrests for people who do not. To determine which addresses are close to late-night bus routes, I utilize the Google Maps Directions API to calculate the walking time from each address to the closest late-night bus stop.[3] This method finds the closest late-night bus route (if applicable) to each address, so if an address is close to both a Night Owl route and an E-Bus route I only count the closer of the two bus services.

To supplement this direct treatment and outcome data I gathered Zipcode-level data from the U.S. Census Bureau's American Community Survey (ACS).[4] I gathered data on Zipcode demographics for each of the 52 Zipcodes in Austin for 2015. Table 1 presents summary statistics for the Zipcode-level demographic data.

[3]Many addresses are too far from a late-night route for Google Maps to calculate a walking time, I classify these addresses as not close to a late-night bus route.

[4]ACS data gathered using the U.S. Census Bureau's American FactFinder at https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml.

[Table 1 about here.]

These data allow me to explore demographic differences in numbers of DWI arrests in Austin. While these are not causal estimates, correlations between neighborhood demographics and DWI arrest rates can be informative and the data I use in this study is uniquely suited to explore this. For this estimation I use the same group definitions described above, but separate each group by Zipcode. This means that for each Zipcode in each day there is an observation containing the total number of arrests for people in that Zipcode who fall into each of the three groups determined by their home's proximity to a late-night bus route.[5] Table 2 presents the results of regression analysis on the influence of Zipcode demographics on the number of DWI arrests. All specifications include time fixed effects and cluster standard errors at the Zipcode level.

[Table 2 about here.]

Areas with higher populations tend to have higher numbers of DWI arrests. Further, I find that the larger the proportion of the population that is made up of young males (a particularly high-risk group for drunk driving), the more observed DWI arrests. Economic factors do not appear to play a large role in DWI arrests in the data. Unemployment rate, median income, and the poverty rate having small and mostly insignificant effects. The only

[5] Some Zipcodes are not served by one or both of the types of late-night bus services.

other factors that appear to be associated with different levels of DWI arrests are education and the proportion of households who rent rather than own their home. The proportion of rental households is associated with a significantly higher number of DWI arrests. The proportion of residents who did not finish high school is associated with a small but highly significant increase in arrests. While none of these results imply any causal impact of these factors on DWI arrests, it may be useful to policymakers to understand the neighborhood characteristics that tend to be associated with higher rates of drunk driving.

To estimate the causal effects of Austin's late-night buses on DWI arrests, comparing the number of DWI arrests for people who live close to late-night bus routes to those who don't is insufficient. Any differences between the two groups could be purely compositional, with different types of people living in areas close to such routes than those who do not. To properly estimate the effect of late-night buses I rely on the fact that these services do not operate every day of the week. Austin's "Night Owl" bus routes only operate Monday through Saturday. The "Entertainment Buses" (E-Bus) only operate Thursdays through Saturdays. This variation allows me to compare the change between days when these services do not operate to days when they do for each group of addresses. I separate the DWI arrests into three groups, those that live close to one of the "Night Owl" routes, those that live close to one of the "Entertainment Bus" (E-Bus) routes, and those that live close to neither. Table 3 presents summary statistics for each group and day of the week. Figure 1 shows graphically how the average number of arrests for each group vary by day of the week. All three groups follow a similar pattern, with DWI arrests increasing later in the week and on the weekend.

[Table 3 about here.]

[Figure 1 about here.]

4 Methodology

4.a Econometric Model

4.a.1 City-wide Effects

To estimate the potential causal impact of Austin's late-night bus services I use a fixed effects difference-in-differences approach. For each group I create an indicator for whether on that day they have access to each of the two types of late-night bus services. For addresses not near either of the late-night bus types these indicators are always equal to zero. For addresses located near one of the routes these indicators equal one on days the services are operating and zero otherwise.

$$y_{i,t} = \alpha_0 + \beta_1 NightOwl_{i,t} + \beta_2 EBus_{i,t} + \delta_i + \phi_t + \epsilon_{i,t} \tag{1}$$

In this estimation equation $NightOwl_{i,t}$ is an indicator for whether the

Night Owl late-night bus service is available for group i on date t. As described previously, there are three "groups": one for people who live within walking distance of a "Night Owl" route; one for people who live within walking distance of an "E-Bus" route; and one for people who live near neither. $EBus_{i,t}$ is an indicator for whether the Entertainment Bus late-night service is available for group i on date t. For each of these, the indicator will always equal zero if group i does not live near the respective late-night bus route. Each acts as an interaction term between an indicator for whether the service is operating and an indicator for whether group i is the group within walking distance of that late-night service. β_1 and β_2 are the coefficients of interest, representing the effect of late-night bus services on DWI arrests. δ_i and ϕ_t represent group and date fixed effects, respectively. These fixed effects control for any time-specific factors that are common across all Austin residents as well as for any time-invariant differences in the average number of DWI arrests across the three groups.

4.a.2 Zipcode-level Effects

It is possible that there is significant variation in the average level of DWI arrests in different areas of the cities, even amongst those with access to the same types of late-night buses. To test for this I expand the group definition described in Section 3 to include Zipcode information. Now there will be a separate group for each of the three original groups (lives close to Night Owl bus, lives close to Entertainment Bus, and lives close to neither) for each

Zipcode. Not every Zipcode will have each of the three groups, as some are not served by one (or by either) of the late-night bus routes.[6] The estimation equation for this version is as follows.

$$y_{i,z,t} = \alpha_0 + \beta_1 NightOwl_{i,z,t} + \beta_2 EBus_{i,z,t} + \delta_{i,z} + \phi_t + \epsilon_{i,z,t} \qquad (2)$$

The only difference between this and the previous estimation equation is that the level of observation is now at the Zipcode-group-date level. This permits a larger set of group fixed effects by Zipcode rather than simply group fixed effects. This additional granularity controls for any differences in the average level of DWI arrests for people across all possible Zipcode and group combinations.

4.b Identification

Identification in these empirical models comes from the difference-in-differences approach I use. It is possible to compare the change from days without late-night bus service to days with these services, and then contrast this change for people who live near late-night bus lines with the same change for those who do not. This approach allows the estimation of the causal impact Austin's late-night bus services have on DWI arrests. The underlying assumption in this identification strategy is that absent the late-night bus services the change between days when the services don't operate to the days in which

[6]The 52 Zipcodes in Austin along with the 1-3 "groups" per Zipcode results in 76 Zipcode-specific groups.

they do would follow a similar pattern for each of the groups. While this assumption is not directly testable using the DWI arrest data in this study, there is a very consistent pattern across different cities and states as well as over time in the rate of both drunk driving arrests as well as drunk driving accidents in which they increase significantly during the weekend compared to weekdays. It is not unreasonable to assume that a similar pattern exists among residents in different areas of the same city, though further research into these patterns would be informative.

Since identification in this study relies upon variation in transit availability by day of the week rather than using the initial launch of these late-night services there are some factors which could bias my estimates of the effect these services have on drunk driving. It is possible that people who live near a late-night bus route might shift their drinking to nights of the week on which the services operate. If this happens that would potentially result in fewer DWI arrests on days when late-night services aren't operating for people who live near late-night bus stops. This would bias my estimates towards finding a smaller effect of late-night buses on drunk driving.

Potential drunk drivers aren't the only ones who might have a behavioral response to these bus services. Police looking for drunk drivers might adjust their target areas based on where the late-night buses operate, targeting areas without these services for greater scrutiny on days when the buses operate. This could potentially bias my estimates towards finding a greater effect of late-night buses on drunk driving because it could increase the observed arrests for the control group relative to the treatment group independent of the number of people in each group who actually drive drunk. This may not be a significant concern as it would require drunk drivers who live near late-night bus routes to mostly drive near these routes and conversely for drunk drivers who do not live near them to primarily drive away from the routes. Since the late-night routes serve central entertainment districts and run along major corridors it is unlikely that police officers would significantly shift their drunk driving enforcement away from these areas on days the late-night services run, which are also high-risk days for drunk driving.

Finally, it is important to consider the external validity of these estimates. It is very likely that the days of the week chosen for late-night bus operation were done to maximize their utilization. For the “E-Bus” especially, the Thursday through Saturday operation covers the highest-risk days for drunk driving. This means that my estimated effects of these services may be greater than the effect would be if these services began operating on other, lower-risk days of the week. This study also uses data on DWI arrests and late-night bus service for only a single city, Austin, Texas. The effect of similar services on other cities might differ from the effects in Austin. Preferences for public transit, population density, location of drinking establishments, and many other factors could impact the effect late-night buses have on drunk driving.

5 Results

5.a City-wide Results

To estimate the effects of Austin's late night buses on DWI arrests I begin by grouping the home addresses for people arrested for DWI into three groups: those who live within walking distance of a Night Owl bus route; those who live within walking distance of an Entertainment Bus (E-Bus) route; and those who don't live close to either. As I described in Section 3, I use the Google Maps Directions API to calculate the walking time to the closest late night bus stop. To classify each address into one of these three groups I use four different definitions of "walking distance": within 5 minutes, 10 minutes, 15 minutes, and 20 minutes. I estimate the effect of the late night bus services under each of these four definitions.

I use the actual count of DWI arrests for each group for each day in my estimation. Accordingly, I utilize Poisson estimation techniques to account for the distribution of observed daily DWI arrests. I begin by estimating the effects using fixed effects for the "group" as previously described as well as fixed effects for day of the week, calendar month, and year. I cluster all standard errors at the group level. Table 4 presents the results of this estimation for each definition of "walking distance" from a late-night bus route. The first and second row give the estimated effect of each of the two late-night bus services on DWI arrests.

[Table 4 about here.]

For people who live very close (within a 5-minute walk) of one of the Night Owl bus routes I estimate that the availability of these services reduces the incidence of DWI arrests by 16.8%. For the E-Bus service, I find no effect of their presence on DWI arrests for people living within a 5-minute walk of an E-Bus stop. As I expand the distance from the late-night bus stops the effect of the Night Owl buses decreases but remains a 6.5% to 7.7% reduction in the number of DWI arrests for people who live within a 10-20 minute walking distance of the stops. For the E-Bus service the effect on DWI arrests increases as I expand the walking distance radius. While effects remain imprecisely estimated, the point estimates of the reduction in DWI arrests increase to a 4.8% to 6.6% reduction for a walking radius of 10-20 minutes from the E-Bus stops. The difference in DWI reduction between the two types of late-night bus services may be driven by the different populations each serves. The E-Bus service focuses on areas with large amounts of student housing, while the Night Owl service covers a much broader range of neighborhoods. The coefficient estimates for the group living in close proximity to an E-Bus route shows that this population is substantially less likely to be arrested for DWI on average than those living in other areas.

I next estimate the same models but instead of using fixed effects for day of the week, calendar month, and year, I use a full set of date fixed effects. This potentially controls better for variation over time, though at a cost of estimation power due to the large number of fixed effects. Table 5 presents the results of this estimation. The estimates of the effect of each type of late-night bus service do not change with the inclusion of the full date fixed effects. These results can be used to infer that the day of the week, calendar month, and year fixed effects are properly capturing variation over time that is common to all three groups.

[Table 5 about here.]

5.b Zipcode-level Results

It is possible that there is heterogeneity among residents in different parts of the city, even if they fall into the same group in terms of access to late-night bus transit. To account for residential location differences, I separate the DWI arrest addresses by both late-night bus group and by Zipcode. Table 6 presents the results using day of the week, calendar month, and year fixed effects as well as a full set of Zipcode by group fixed effects. All standard errors are clustered at the Zipcode by group level. Inclusion of the Zipcode-level fixed effects has no impact on the point estimates of the impact of the late-night bus services, though it does substantially increase the standard errors.

[Table 6 about here.]

As with the city-wide estimates, I also estimate the Zipcode-level effects using a full set of date fixed effects to more precisely control for variation over time that is common across groups and Zipcodes. The results are presented in Table 7. As in the city-wide results, adding the full date fixed effects has no impact on the estimated effect of either late-night bus service.

[Table 7 about here.]

5.c Robustness

A concern when using clustered standard errors is their reliability when the number of clusters is small. Cameron and Miller (2015) demonstrate that small numbers of clusters can lead to artificially small standard errors. My primary analysis clusters at the "group" level, meaning there are only three clusters in the city-wide estimates. To ensure that the standard errors I calculate are not significantly underestimated I repeat the estimation in Table 5 clustering at the date level instead of the group level. This results in 699 clusters instead of the three used in the original analysis. This level of clustering accounts for correlation in the errors across "groups" within a particular day. This is reasonable, as day-specific factors such as weather or special events could affect not only the level of DWI arrests, which are captured by the date fixed effects, but also the variability. The results of this estimation are presented in Table 8. As Cameron and Miller (2015) demonstrate, it appears that the small number of clusters used in Table 5 resulted in significantly underestimated standard errors. Correcting for this by clustering at the date level results in the same 16.8% reduction in DWI arrests for people who live within a five-minute walk of a Night Owl bus stop but no statistically significant effect for those who live farther away or for those living near an E-Bus stop.

[Table 8 about here.]

6 Conclusion

Drunk driving is a persistently common problem in the U.S., causing over 11,000 deaths and 326,000 injuries annually. Around 1.2 million Americans are arrested each year for driving under the influence. Accordingly, discouraging individuals from driving drunk is an important issue for policymakers around the country. Traditional prevention methods tend to focus on discouragement through increased enforcement and enhanced penalties for those caught driving drunk. Most academic research has focused on measuring the effectiveness of these types of strategies.

Increasing the expected cost of drunk driving isn't the only potential method for reducing the incidence of drunk driving. Increasing the availability and attractiveness of alternative forms of transportation can potentially induce some people who would otherwise drive drunk to instead take alternative transportation. In Austin, Texas, late-night bus services provide an alternative way for people who live near their routes to get to and from drinking establishments.

In this study I take advantage of the fact that Austin's late-night bus services only operate on some days of the week to use a difference-in-differences approach to identify the impact of these services on DWI arrests. Using a unique dataset containing the home addresses for everyone arrested for DWI by the Austin Police Department I find that Austin's Night Owl late night bus service substantially reduces DWI arrests for people who live near one of the Night Owl bus stops. I estimate that this bus service reduces DWI arrests for people living within a five-minute walk of a Night Owl bus stop by 16.8%. For people who live farther from these lines, within 10-20 minute walk of a bus stop, the reduction in DWI arrests is 6.5-7.7% and is imprecisely estimated. Austin's Entertainment Bus, which serves areas of the city with substantial amounts of student housing has a more limited effect on DWI arrests, with imprecisely-estimated reductions of 1.3-6.6%.

These results add to the small but growing literature on the effects of alternative transportation on drunk driving. Quantifying the impacts of services like late-night buses can help provide policymakers with evidence to better weigh the costs of such services against the potential benefits. Additionally, it allows them to compare the costs and benefits, in terms of drunk driving prevention, of increasing the availability of alternative transportation versus traditional enforcement-based prevention strategies.

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Figure 1: Average DWI Arrests by Day of the Week

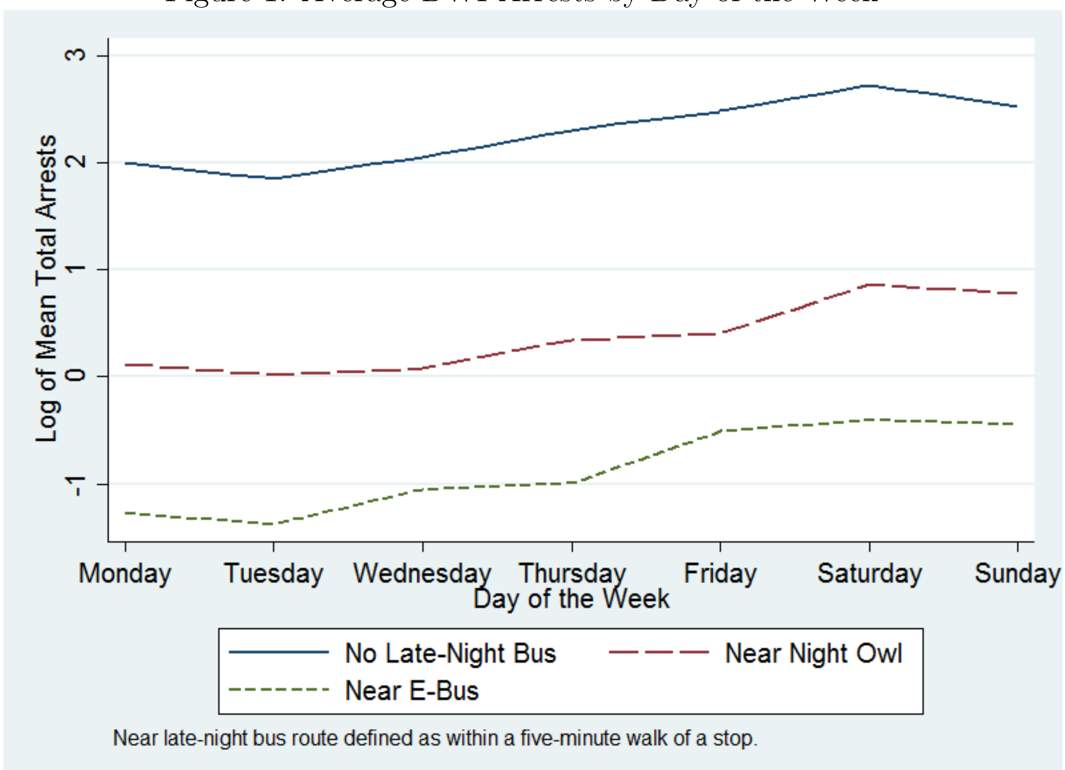

Table 1: Zipcode-Level Demographic Summary Statistics

	Mean	Min	Max
Population	35,234	748	79,067
Age 21-44 Male %	23.1%	10.6%	37.3%
Rental HH %	54.6%	4.7%	88.8%
Unemployment Rate	6.2%	2.4%	15.6%
Median HH Income	$58,606	$12,385	$132,980
Poverty %	19.6%	1.5%	66.4%
Less than HS %	15.4%	0.4%	40.0%
HS Grad %	42.3%	14.2%	58.9%
Post HS Educ. %	42.3%	9.8%	84.2%

Table 2: Zipcode-Level Demographic Regressions

	(1) DWI Arrests	(2) DWI Arrests
Population	0.801***	0.793***
	(0.107)	(0.098)
Age 21-44 Male %	0.672*	0.620*
	(0.285)	(0.267)
Rental HH %	0.403*	0.451**
	(0.160)	(0.162)
Unemployment Rate	0.001	-0.001
	(0.005)	(0.005)
Median Income	0.002+	0.002+
	(0.001)	(0.001)
Poverty %	-0.001	-0.001
	(0.002)	(0.002)
Less than HS %	0.006***	0.006***
	(0.002)	(0.002)
HS Grad %	-0.001	0.0003
	(0.002)	(0.002)
Day of Week x Month FE	√	
Full Date FE		√
N	3043	3043

Standard errors in parentheses, clustered at the Zipcode level.

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

All specifications use Poisson estimation.

Population is in units of 100,000 people.

Median income is per household in units of $1,000.

Table 3: DWI Arrests Summary Statistics by Late-Night Bus Proximity and Day of the Week

	Control	Night Owl	E-Bus
Sunday			
Mean	12.44	2.18	0.64
Std. Dev.	(3.73)	(1.49)	(0.88)
Monday			
Mean	7.38	1.13	0.28
Std. Dev.	(2.83)	(1.13)	(0.53)
Tuesday			
Mean	6.36	1.02	0.25
Std. Dev.	(2.38)	(0.98)	(0.48)
Wednesday			
Mean	7.80	1.08	0.35
Std. Dev.	(3.56)	(1.04)	(0.58)
Thursday			
Mean	10.04	1.41	0.37
Std. Dev.	(3.36)	(1.11)	(0.61)
Friday			
Mean	11.95	1.50	0.60
Std. Dev.	(3.91)	(1.30)	(0.87)
Saturday			
Mean	15.31	2.37	0.67
Std. Dev.	(4.03)	(1.69)	(0.83)

*Night Owl and E-Bus groups are within a 5-minute walk.

Table 4: City-wide Effects of Late-Night Buses on DWI Arrests

	(1) Within 5 Minute Walk	(2) Within 10 Minute Walk	(3) Within 15 Minute Walk	(4) Within 20 Minute Walk
Treat Night Owl	-0.184***	-0.067*	-0.074*	-0.080*
	(0.013)	(0.034)	(0.036)	(0.037)
Treat E-Bus	-0.013	-0.053	-0.068^{+}	-0.049
	(0.009)	(0.033)	(0.037)	(0.052)
Day of Week				
Monday	-0.526***	-0.536***	-0.528***	-0.521***
	(0.018)	(0.035)	(0.041)	(0.055)
Tuesday	-0.666***	-0.676***	-0.668***	-0.661***
	(0.020)	(0.042)	(0.044)	(0.045)
Wednesday	-0.478***	-0.487***	-0.479***	-0.472***
	(0.014)	(0.033)	(0.037)	(0.034)
Thursday	-0.230***	-0.238***	-0.229**	-0.222**
	(0.022)	(0.073)	(0.084)	(0.078)
Friday	-0.058*	-0.065^{+}	-0.056^{+}	-0.050
	(0.026)	(0.035)	(0.030)	(0.060)
Saturday	0.209***	0.201***	0.210***	0.217***
	(0.012)	(0.026)	(0.029)	(0.029)
Near Night Owl	-1.748***	-1.170***	-0.695***	-0.375***
	(0.011)	(0.028)	(0.030)	(0.030)
Near E-Bus	-3.108***	-2.700***	-2.510***	-2.367***
	(0.005)	(0.017)	(0.019)	(0.027)
N	2097	2097	2097	2097

Standard errors in parentheses, clustered at the late-night bus proximity group level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All specifications include calendar month and year fixed effects and use Poisson estimation.
Addresses are "near" a bus route if they are within the specified walking distance.

Table 5: City-wide Effects of Late-Night Buses on DWI Arrests - Full FE

	(1) Within 5 Minute Walk	(2) Within 10 Minute Walk	(3) Within 15 Minute Walk	(4) Within 20 Minute Walk
Treat Night Owl	-0.184***	-0.067*	-0.074*	-0.080*
	(0.013)	(0.034)	(0.036)	(0.037)
Treat E-Bus	-0.013	-0.053	-0.068^{+}	-0.049
	(0.009)	(0.033)	(0.037)	(0.052)
Near Night Owl	-1.748***	-1.169***	-0.695***	-0.375***
	(0.011)	(0.028)	(0.030)	(0.030)
Near E-Bus	-3.108***	-2.700***	-2.510***	-2.367***
	(0.005)	(0.017)	(0.019)	(0.027)
N	2097	2097	2097	2097

Standard errors in parentheses, clustered at the late-night bus proximity group level.

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

All specifications include date fixed effects and use Poisson estimation.

Addresses are "near" a bus route if they are within the specified walking distance.

Table 6: Zipcode-Level Effects of Late-Night Buses on DWI Arrests

	(1) Within 5 Minute Walk	(2) Within 10 Minute Walk	(3) Within 15 Minute Walk	(4) Within 20 Minute Walk
Treat Night Owl	-0.184^{+}	-0.067	-0.074	-0.080
	(0.100)	(0.075)	(0.070)	(0.067)
Treat E-Bus	-0.013	-0.053	-0.068	-0.049
	(0.061)	(0.055)	(0.061)	(0.054)
Day of Week				
Monday	-0.526***	-0.536***	-0.528***	-0.521***
	(0.051)	(0.056)	(0.053)	(0.057)
Tuesday	-0.666***	-0.676***	-0.668***	-0.661***
	(0.061)	(0.063)	(0.068)	(0.067)
Wednesday	-0.478***	-0.487***	-0.479***	-0.472***
	(0.063)	(0.059)	(0.065)	(0.067)
Thursday	-0.230***	-0.238***	-0.229***	-0.222***
	(0.056)	(0.058)	(0.061)	(0.065)
Friday	-0.058	-0.065	-0.056	-0.050
	(0.039)	(0.043)	(0.047)	(0.050)
Saturday	0.209***	0.201***	0.210***	0.217***
	(0.037)	(0.038)	(0.042)	(0.048)
N	53124	53124	53124	53124

Standard errors in parentheses, clustered at the late-night bus proximity group level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All specifications include calendar month and year fixed effects and use Poisson estimation.
Addresses are "near" a bus route if they are within the specified walking distance.

Table 7: Zipcode-Level Effects on DWI Arrests - Full FE

	(1) Within 5 Minute Walk	(2) Within 10 Minute Walk	(3) Within 15 Minute Walk	(4) Within 20 Minute Walk
Treat Night Owl	-0.184^{+}	-0.067	-0.074	-0.080
	(0.100)	(0.075)	(0.070)	(0.067)
Treat E-Bus	-0.013	-0.053	-0.068	-0.049
	(0.061)	(0.055)	(0.061)	(0.054)
N	53124	53124	53124	53124

Standard errors in parentheses, clustered at the late-night bus proximity group by Zipcode level.

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

All specifications include date fixed effects and use Poisson estimation.

Addresses are "near" a bus route if they are within the specified walking distance.

Table 8: City-wide Effects of Late-Night Buses on DWI Arrests - Date Clustering

	(1) Within 5 Minute Walk	(2) Within 10 Minute Walk	(3) Within 15 Minute Walk	(4) Within 20 Minute Walk
Treat Night Owl	-0.184*	-0.067	-0.074	-0.080
	(0.080)	(0.071)	(0.065)	(0.065)
Treat E-Bus	-0.013	-0.053	-0.068	-0.049
	(0.119)	(0.107)	(0.104)	(0.102)
Near Night Owl	-1.748***	-1.170***	-0.695***	-0.375***
	(0.071)	(0.065)	(0.059)	(0.060)
Near E-Bus	-3.108***	-2.700***	-2.510***	-2.367***
	(0.085)	(0.077)	(0.075)	(0.074)
N	2097	2097	2097	2097

Standard errors in parentheses, clustered at the date level.

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

All specifications include date fixed effects and use Poisson estimation.

Addresses are ”near” a bus route if they are within the specified walking distance.