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One for the Road: Public Transportation, Alcohol Consumption, and Intoxicated Driving

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One for the road: Public transportation, alcohol consumption, and intoxicated driving

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ABSTRACT

We exploit arguably exogenous train schedule changes in Washington DC to investigate the relationship between public transportation, the risky decision to consume alcohol, and the criminal decision to engage in alcohol-impaired driving. Using variation over time, across days of the week, and over the course of the day, we provide evidence that overall there was little effect of expanded public transit service on DUI arrests, alcohol related fatal traffic and alcohol related arrests. However, we find that these overall effects mask considerable heterogeneity across geographic areas. Specifically, we find that areas where bars are within walking distance to transit stations experience *increases* in alcohol related arrests and *decreases* in DUI arrests. We observe no sign of behavioral changes in neighborhoods without any bars within walking distance of transit stations.

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1. Introduction

There are 159 million self-reported episodes of alcohol-impaired driving among U.S. adults each year (Quinlan et al., 2005). During 2005, 17,602 people in the U.S. died in alcohol related motor vehicle crashes, representing 41% of all traffic-related deaths.¹ It is estimated that alcohol related crashes in the U.S. cost about \$51 billion each year (Blincoe et al., 2002).² The Center for Disease Control at the Department of Health and Human Services provides a variety of policy recommendations to reduce the incidence of alcohol-impaired driving.³ Virtually all these policies involve stricter laws, harsher penalties, and more aggressive enforcement intended to either increase the penalties associated with drinking while driving or to decrease general alcohol consumption among youth. These tough-on-crime policies affect a substantial fraction of adults; over 1 million drivers were arrested for driving under the influence of alcohol in 2007.⁴ In this paper we evaluate the impact of a different sort of public policy aimed at reducing the probability that a drinker gets behind the wheel of a car.

It is a commonly held belief that the provision of accessible public transportation could reduce the incidence of DUIs. For example, the

popular press regularly prints articles blaming high DUI incidence on the lack of public transportation.⁵ Both public and private organizations provide transportation to drinkers in order to reduce DUIs – for example both the MillerCoors and Anheuser-Busch Brewing Companies provide free transportation on popular holidays to and from “member” bars. The slogan of a current Illinois campaign to reduce DUI incidence is “designate a driver – stay overnight – use public transportation.”⁶ However, there is virtually no evidence on the relationship between the provision of public transportation and drunk driving, and there is no empirical quantitative evidence that providing public transportation would actually reduce the incidence of drunk driving. This lack of credible evidence is due, in large part, to the fact that alteration of public transportation, particularly fixed rail service, requires a huge investment in infrastructure and thus rarely changes.

Between November 5th 1999 and July 4th 2003, Washington DC's Metro system gradually extended its weekend operating hours – changing the end of service from midnight to 1 am, then 1 am to 2 am and then from 2 am to 3 am. We exploit the sequential expansion of Washington DC Metro's late night service to identify how risky behavior changes in response to public transit.⁷ Because the changes in schedule allow us to observe the same geographic area on the same day of the week during the same time of day, both with and without

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public transportation availability, one can use the changes in hours of operation of fixed rail transportation in DC to conduct a credible investigation into the relationship between public transportation provision and the incidence of alcohol-impaired driving.

We take advantage of four sources of variation created by this policy to estimate the impact of public transportation on drinking behavior. First, we use the change over time in drunk driving, comparing how late night weekend arrests for drunk driving change as Metro extends its hours of operation.

Second, in order to control for evolution in attitudes towards drinking, laws relating to drunk driving, or any general changes in DC nightlife, we take advantage of the fact that Metro only offered late night service on Friday and Saturday. Comparing changes in late night arrests on Friday and Saturday to changes in late night arrests on Thursday will allow us to difference out any impact of other policies that might impact drunk driving during the late evening.

Third, in order to control for general changes that might differentially affect weekend activity, we take advantage of the fact that Metro changes only affected service during the late evening and not the early evening. Comparing changes in late night arrests on Friday and Saturday to changes in evening arrests on Friday and Saturday will allow us to difference out any impact of other policies that might impact drunk driving during the weekend.

Finally, Metro stations are concentrated in certain parts of the city. We therefore expect to see larger temporal effects in neighborhoods with both Metro stations and bars than in neighborhoods with no Metro stops or no bars. Comparing the change in late night arrests in areas close to bars and Metro stations to the change in areas far away from Metro stations or with no bars will allow us to further identify the effect of Metro access on drunk driving.

Exploiting all sources of temporal variation we use a difference-in-difference (DID) strategy. This strategy compares the changes in arrests occurring between 10 pm and 5 am to arrests occurring between 6 pm and 10 pm during the weekend, to the same changes on Thursdays. When we focus solely on temporal variation in Metro service, we find that the aggregate impact of public transportation on drunk driving is small. This finding is robust to using each of the differences. However, when we look at the DID effects across neighborhoods we find substantial spatial heterogeneity. In neighborhoods where bars are located within walking distance of a Metro station there were sizable reductions in drunk driving arrests for each additional hour of Metro availability after midnight. In neighborhoods where bars are not located close to Metro stations, expanding Metro service does not appear to have changed the number of people arrested for intoxicated driving behavior.⁸

By making it easier to get home after a night of drinking, expanded public transportation may have a perverse effect on alcohol consumption outside the home, what we refer to as “risky” alcohol consumption. As such, while the estimated effects on DUI arrests may be the policy relevant estimates, because an increase in drinking will mechanically increase drunk driving, such estimates may not provide evidence on the behavioral effect of public transportation availability on drunk driving (i.e. the effect that public transportation has on the likelihood that a given drinker gets behind the wheel). To speak to the possible moral hazard associated with public transit and its effect on drunk driving conditional on drinking, we estimate not only how intoxicated driving changed, but also how the number of people drinking changed as Metro extended its hours.

Since DC law prohibits the release of site-identified alcohol sales, we draw on a large literature linking alcohol consumption and risky behavior and estimate the size of the drinking population using changes in the number of arrests for minor nuisance crimes, which we

refer to as “alcohol related” arrests. While not a perfect proxy for alcohol consumption, such nuisance crimes have been found to be strongly related to alcohol consumption. Using the same triple differences approach, we find evidence of moral hazard in the form of increased alcohol related arrests in the same neighborhoods where we observed a reduction in arrests for DUIs. When this increase in potential drunk drivers is taken into account, the implied localized reduction in the rate of intoxicated driving becomes quite large.⁹

The fact that alcohol related arrests and DUI arrests move in opposite directions it indicates that our effects are not driven by secular changes in overall crime and we conduct a variety of tests to support the validity of our identification strategy. Indeed, we show that our results are robust to a variety of alternate specifications, including neighborhood-specific time trends, relaxing our definitions of “late night” and “evening,” our definition of “bars” and “alcohol related” arrests, and our use of Thursday as a counterfactual for the weekend. We do find evidence consistent with a spillover effect on Thursday nights in areas where bars are located near Metro stations, implying that our main estimates of outcomes on Friday and Saturday evenings (that use Thursday as a comparison) may be interpreted as lower bounds of the overall effect.

While we are careful to control for numerous sources of confounding variation one shortcoming of all studies that use arrest data as a proxy for crime is that changes in arrests reflect both police behavior as well as criminal activity. Specifically, if police shifted resources towards nuisance crimes and away from DUIs, precisely in those areas with bars located near Metros, only between the hours of 10 pm and 5 am on Friday and Saturday nights, then our estimated effects would be too large. While we cannot empirically rule out this possibility, given that the specific kind of shifting that could generate our results would entail shifting resources away from crimes with a high social costs towards crimes with lower social costs, this scenario is unlikely. In fact, during our sample period the DC police engaged in a campaign to “crack down” on dangerous drivers,¹⁰ meaning that if anything our results may be conservative.

This paper presents the first credible evidence on the relationship between public transportation on intoxicated driving and alcohol consumption (both in areas directly served by public transportation and for the Metropolitan area as a whole). The remainder of the paper is as follows. Section 2 outlines the extant literature on alcohol consumption, crime and public transportation, and provides institutional detail of the Washington DC Metro expansion. Section 3 presents the analytical framework describing how public transportation may affect drunk driving and drinking behaviors, Section 4 presents the empirical strategy, Section 5 presents the results and Section 7 concludes.

2. Alcohol consumption, crime, and public transportation

2.1. Alcohol consumption and crime

The decision to drive while intoxicated is twofold: the *risky* decision to drink excessively outside of the home and the *criminal* decision to drive home once inebriated. As stated in Becker (1968) “a person commits a crime if the expected utility to him exceeds the utility he could get by using his time and other resources at other activities.”¹¹ Researchers have primarily focused on one side of this

⁹ If the average drinker who commits a crime is equally likely to drive drunk as the marginal drinker who commits a crime that is induced to drink more and commit a crime as a result of increased Metro access then scaling the number of DUIs by the number of alcohol related arrests will be appropriate for isolating the behavioral response. However, if the marginal drinker who commits a crime is less/more likely to drive drunk than the average drinker who commits a crime, then the scaling the number of DUIs by the number of alcohol related arrests will lead to an over/under estimate of the behavioral effect.

¹⁰ http://mpdc.dc.gov/mpdc/cwp/view,a,1240,Q,547928,mpdcNav_GID,1552,mpdcNav,%7C,asp.

¹¹ See Doob and Webster (2003) and Levitt (2002a,b) for reviews of the literature on risky behavior and deterrence.

⁸ The localized effects of public transportation on crime are consistent with research documenting that public transportation only affects worker commuting patterns of residents within 2 km of businesses within 6 miles of fixed rail transportation (Baum-Snow and Kahn, 2000; Holzer et al., 2003).

equation – reducing the prevalence of crime through policies intended to increase the expected private costs of illicit behavior. Economists have found that alcohol consumption can be reduced by increasing alcohol prices or taxes (Kenkel, 1996; Chaloupka et al., 1993; Cook and Moore, 1993a, 2002; Kenkel and Manning, 1996; Leung and Phelps, 1993) enforcing minimum drinking age laws (O'Malley and Wagenaar, 1991) and imposing harsher legal penalties on the frequency of alcohol consumption (Kenkel, 1993). However, since decisions to commit crime are also a function of the opportunity cost of illicit behavior, crime could theoretically be reduced by increasing the private benefit of not offending. We will refer to this mechanism as the “safer option.” To the best of our knowledge, the extant literature has not evaluated policies aimed at reducing the social harm associated with risky alcohol use.

Policies of this nature have been criticized on moral hazard grounds; by providing a safer way to engage in socially undesirable behaviors, one makes such behavior more attractive to individuals who do not internalize the full social costs of their actions (Pauly, 1974; Holmstrom, 1979; Boyum and Reuter, 1996). In fact, in severe cases such well-intentioned solutions could cause more harm than good (Hansen and Imrohoroglu, 1992).¹² While public transportation may lower the probability that a risky drinker gets behind the wheel,¹³ it may also increase the amount of alcohol consumed outside of the home.

As public transit reduces the private cost of drinking in bars, *a priori*, we would expect public alcohol consumption to increase as Metro service expands, since alcohol consumption has been shown to be quite responsive to price changes (Chaloupka et al., 2002). An increase in drinking that is correlated with the Metro expansion could potentially have large negative social consequences. Approximately 40% of individuals under criminal justice supervision report being under the influence of alcohol at the time of offense (Greenfield, 1998), and alcohol is the only mood altering substance shown to increase violent behavior in a laboratory setting (Miczek et al., 1994). In addition, there is a large and growing literature demonstrating a positive correlation between alcohol consumption and crime (Markowitz and Grossman, 2000; Joksich and Jones, 1993; Carpenter, 2008; Dobkin and Carpenter, 2008; Cook and Moore, 1993b; Owens, 2010). In an extreme example in which Metro service does not reduce the propensity of any given drinker to drive home by more than it increases the number of people drinking in bars, this would generate a positive correlation between public transit and intoxicated driving. In order to estimate the moral hazard associated with public transit, we turn the established correlation between alcohol and crime on its head, and assume that variation in arrests for minor crimes reflects variation in the underlying population of risky drinkers.

It is important to note that it is theoretically unclear how expanded Metro service affects total alcohol consumption. To the extent that individuals respond to the increase in public transportation by shifting their drinking behavior from the home to a bar, total alcohol consumption could go down as the marginal cost of alcohol is higher at a bar (where you pay per drink) than at home (where you pay per bottle). While drinking in the home is costly to an individual (and their family), because (a) the individual may have internalized the risk to their future health and (b) because many of the negative behaviors to one family, such as domestic abuse and child abuse, occur irrespective of where the alcohol is consumed, the external costs of someone drinking in their own home are likely lower than the external costs of drinking outside the home.¹⁴ Widely cited estimates

from the health economic literature place the external cost of alcohol consumption at roughly \$0.48 per ounce of ethanol, and over half of this cost (\$0.26) coming from intoxicated driving (Manning et al., 1991). This motivates, in part, our focus on excessive drinking outside the home as an outcome of particular policy importance.

2.2. Public transportation in Washington, DC

The Washington Metropolitan Area Transit Authority (WMATA) officially received a charter from the Maryland, Virginia, Washington DC, and federal governments in 1966. The WMATA operates a bus service, MetroBus, and a fixed rail transit service, MetroRail, hereafter the “Metro.”¹⁵ The Metro was originally intended to service commuters from the Maryland and Virginia suburbs, not DC residents or individuals engaging in leisure activity; there are 106 miles of Metro track on five lines, with 86 Metro stations, but Metro does not provide equal service to all parts of the city.¹⁶ In Fig. 1 we show the location of each Metro station entry point, obtained from the DC government's GIS database,¹⁷ as well as each bar in Washington DC.¹⁸ Note that the highest concentration of Metro stations is in the central city, and then radiating outwards. Bars, on the other hand, are distributed more evenly across the city, with the exception of Southwest DC.

In 1999, Metro made two significant expansions in its service. First, on September 18th, the two “Green” lines, which extended from the outskirts of DC into northern or central Prince George's County and service both the University of Maryland and Howard University, were connected through downtown. The second Metro change is the focus of our analysis. Prior to November of 1999, the last Metro trains left the center of Washington, DC at midnight, seven days a week.¹⁹ With an eye on serving a “younger rider, who is out on the town, [and] probably could be drinking,”²⁰ beginning on November 5th 1999, the Metro system remained open for one additional hour on Friday and Saturday nights (technically Saturday and Sunday early mornings). This first expansion was considered a success, and Friday and Saturday evening service hours were extended to 2 am on July 1st 2000. A final schedule change occurred on July 4th 2003, in which late night service was extended until 3 am. This last schedule change also extended morning service on the weekends, moving opening hours from 8 am to 7 am on Saturdays and Sundays. We were able to obtain daily counts of total Metro ridership, broken into four times of day; opening to 9 am, 9 am to 3 pm, 3 pm to 7 pm, and 7 pm to close, time blocks which correspond to variation in weekday fares.²¹ It is clear from Fig. 2 that while there is a fair amount of noise in the month to month variation in ridership, the relationship between Metro ridership after 7 pm and before 7 pm was similar across days of the week during the first Metro schedule, with clear seasonal cyclicity and an upward trend that is evident on Thursday, Friday, and Saturday.²²

To show that the schedule changes lead to the expected “treatment”, (i.e. a *disproportionate* increase in evening ridership on the weekend) in Fig. 3 we present the natural log of ridership on

¹⁵ MetroBus has always operated for 24 h a day along routes designed to service DC resident. For more information on the difference between MetroBus and Metro see www.wmata.com/about_Metro/docs/Metrofacts.pdf.

¹⁶ For example, the Georgetown neighborhood has no Metro stations, as Georgetown University faculty has traditionally lived in that neighborhood.

¹⁷ http://dcgis.dcgis.dc.gov/catalog/results.asp?pretype=All&pretype_info=All&alpha=M.

¹⁸ During rush hour the expected wait time is 2 to 3 min, and after the evening rush hour that expected wait time is between 7 and 10 min. Roughly half of Metro stations (47) are underground, and all of the stations are controlled access, are well lit, and are monitored by both cameras and security guards during operating hours.

¹⁹ For additional detail on Metro and MetroBus service, see www.wmata.com/about_Metro/docs/Metrofacts.pdf.

²⁰ Jim Graham, The Washington Post, 9/17/1999.

²¹ These are the time blocks for which aggregate ridership data are provided.

²² This pattern is evident on all days of the week, but for purposes of clarity, we show only these three days.

¹² Researchers have linked abortion access to increased sexual activity (Klick and Stratmann, 2003) and improvements in the treatment of AIDS/HIV to risky sexual behavior (Sood and Goldman, 2006).

¹³ In addition, since drinking is a social activity (Boisjoly et al., 2003; Norton et al., 1998), increased alcohol consumption by Metro-riders could increase the amount of alcohol consumed by those who intend to drive home.

¹⁴ Indeed, actions that might impose essentially no cost of society at home may be considered socially harmful if done in public. For example, urinating in your own back yard does not impose much cost of society, while urinating in public is indecent exposure.

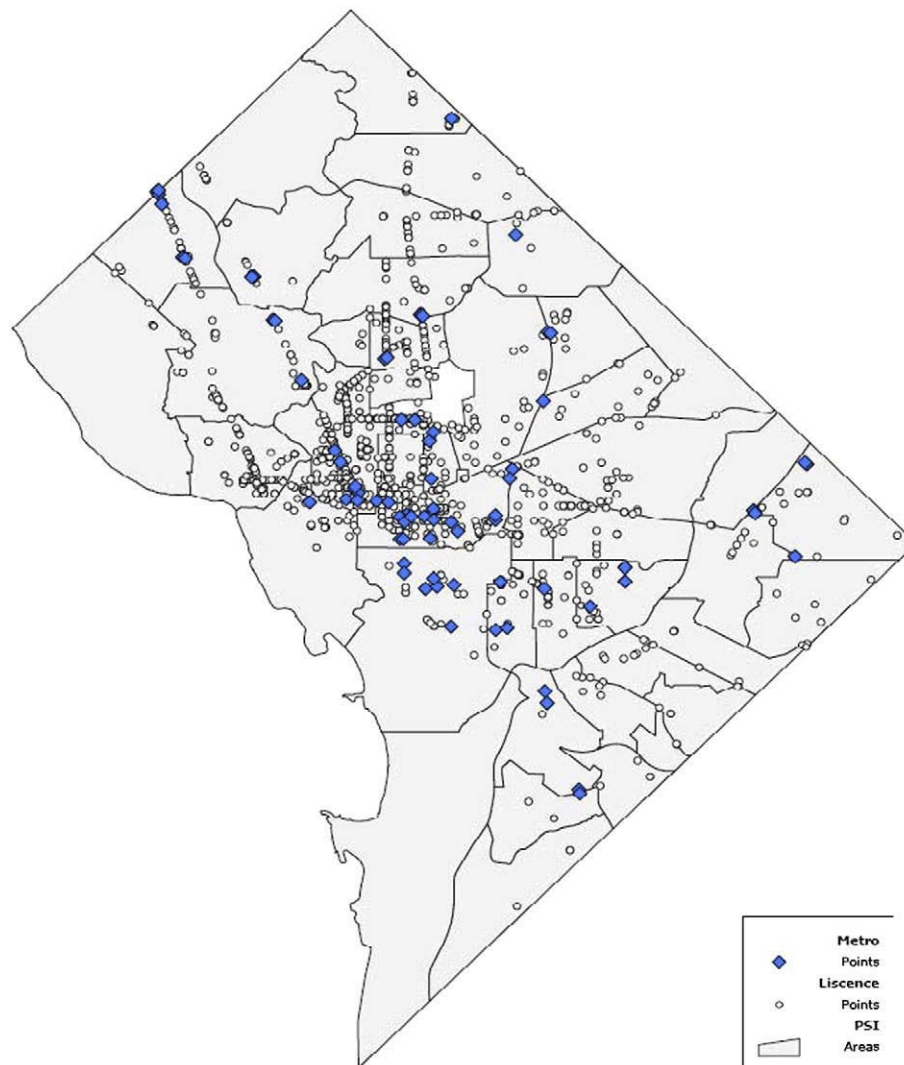


Fig. 1. Alcohol vendors and Metro stations in Washington, DC.

Friday late night (one of the days for which the schedule changed) minus the natural log of ridership on Thursday late night (during which there was no schedule change). For comparison we also show the natural log of ridership on Friday night minus the natural log of ridership on Thursday during night, (during which there are no schedule changes for either Thursday or Friday). Thursday is a uniquely appealing counterfactual to the weekend in Washington DC; roughly 12% of all working adults in the DC Metro area are federal government employees (Perrins and Nilsen, 2006),²³ and in 1999 the Office of Personnel Management estimated that half of government workers use an alternative work schedule in which they do not work every other Friday, substantially higher rate than that of the private sector.²⁴ Combined with the large population of college students enrolled in seven major universities,²⁵ Thursday night is arguably closer to a weekend night in Washington DC than in any other city in the United States.²⁶

²³ <http://www.bls.gov/opub/mlr/2006/12/art1full.pdf>.

²⁴ www.mith2.umd.edu/WomensStudies/GenderIssues/WomenInWorkforce/Work+FamilyNeeds/01introduction.

²⁵ Representatives from the University of Maryland, College Park, Howard University, George Washington University, and Georgetown University, contacted between April 30th, 2010 and March 5th 2010, reported that, while their institutions encourage students to only drink in moderation, if at all, they were aware of no University programs targeted specifically at drunk driving.

²⁶ We present further evidence of the suitability of Thursday night as a comparison for Friday and Saturday evenings in Section 4.

Using Thursday ridership as our baseline for comparison, the schedule changes affect ridership exactly as one would expect – (a) late night ridership increased on Fridays relative to Thursday late night ridership with each successive change and (b) there was no discernable change in the relationship between night ridership on Fridays relative to night on Thursdays.

We also present Wednesday ridership relative to Thursday ridership on the left panel. As one might expect, the schedule changes do not change the relationship between ridership on Wednesdays and Thursdays during any time of day – suggesting that the schedule changes affected late night ridership on the weekend, but not other days of the week.²⁷

It is clear that there is a large amount of cyclical variation in late night and night ridership that is common to Friday and Thursdays. Using a difference-in-difference-in-difference strategy that subtracts the increase in late night ridership on Thursdays (relative to the PM ridership) from the change on Fridays and Saturdays, we estimate that approximately 7% more one way trips was taken on weekend nights for each additional hour of Metro service.²⁸ There were an average of

²⁷ A similar graph using Saturday and Thursday is available on request.

²⁸ Specifically, we estimate the parameters of the following model: $\ln(\text{Ridership}_{dty}) = \beta \text{Hours}_{dty} + \mu_{dt} + T_{ym} + \epsilon_{dty}$ where Ridership_{dty} is the number of one way trips taken on day of the week d at time of day t during year y and month m , Hours_{dty} is the number of hours that Metro is open during that period, μ_{dt} is a vector of day of the week by time of day fixed effects, and a T is a set of year and month fixed effects.

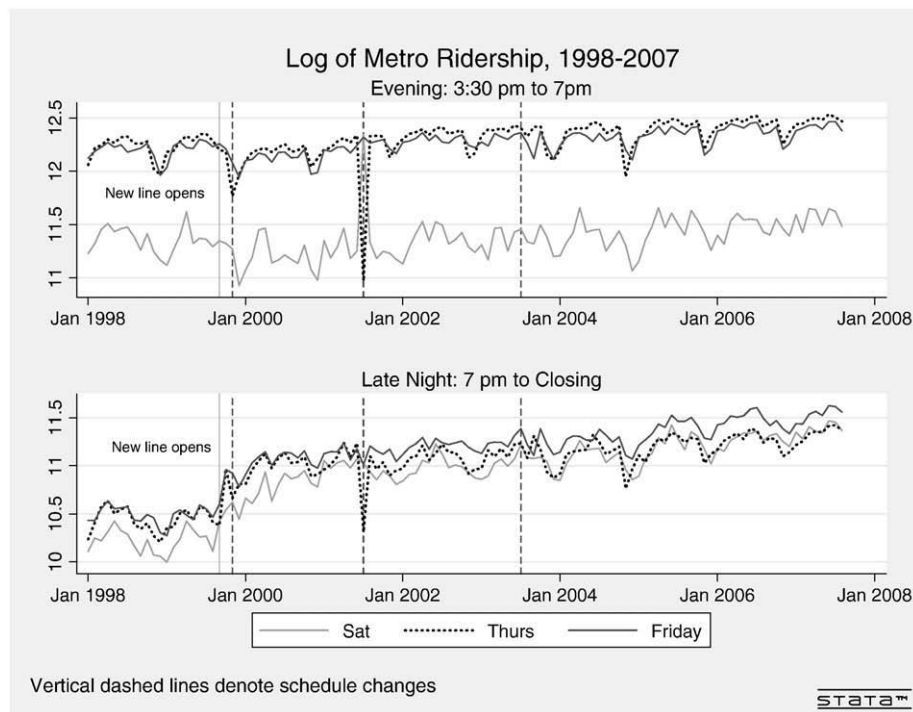


Fig. 2. Ridership on Thursdays, Fridays, and Saturdays.

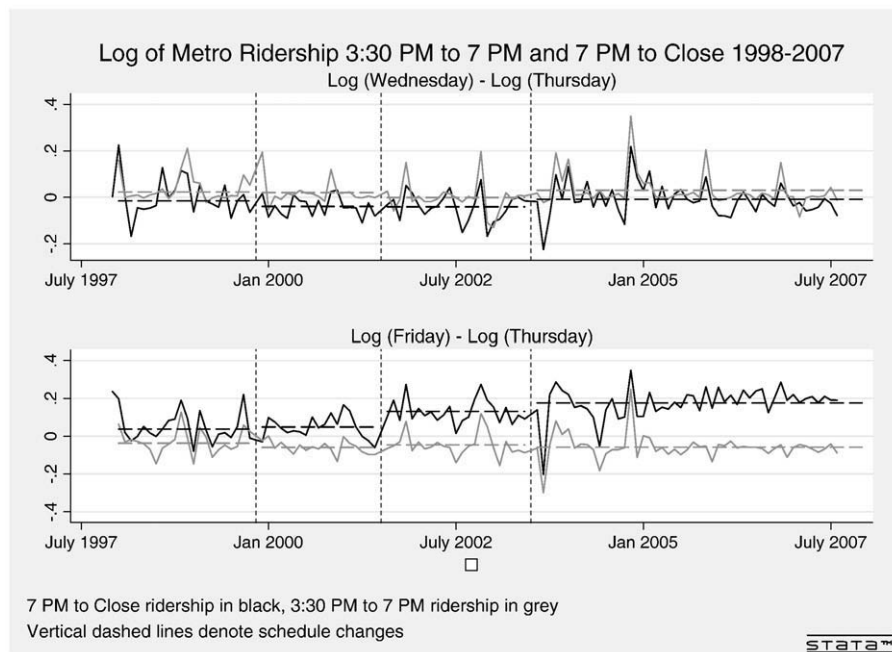


Fig. 3. Ridership on Wednesdays and Fridays relative to Thursday levels.

137,150 one way trips made each night on Fridays and Saturdays prior to the first schedule change so our estimates suggest that more than 1065 additional people may have been added to the DC nightlife as Metro service increased.²⁹

²⁹ In Web Appendix Table A1, we present full regression results, showing that this estimate is robust to a relaxation of parametric assumptions.

3. Analytic framework

In this section we present a simple model that links alcohol consumption and intoxicated driving to public transportation, provide some intuition for the possible moral hazard created by Metro's expanded late night service, and present a framework that would explain both temporal and geographic shifting of drinking activities toward areas and times when the private costs are lowest and the private benefits are highest.

A simple coordination game, combined with basic consumer demand and production theory can be used to analyze the potential effects of the expanded Metro hours of operation on DUI behaviors and on drinking behaviors.

3.1. The consumer problem

Individuals demand a night out N , with price C_N , and a numeraire good Y with price 1. Individual i 's utility from going out is an increasing function of aggregate going out for others in the population θ_i , so such that individual i 's maximizes utility

$$U_i = f_i(g(N, \theta_i), Y) \text{ s.t. the budget constraint } E_i = Y_i + N_i \cdot C_N. \quad [1]$$

Aggregate going out for others in the population is $\theta_i = \sum_{i' \neq i} N_{i'}$ and we abstract away from real issues of congestion and crowding that may occur at very high levels of θ_i and assume that $\partial g / \partial \theta_i > 0 \forall \theta_i$. The parameter θ_i , captures the fact that a night out drinking is a social activity.³⁰ The utility maximizing levels of the numeraire good Y and night out are given by $(\partial f_i / \partial Y) / (\partial f_i / \partial N_i) = C_N$ for individual i , so that individuals chose their desired level of nights out based on the shape of their individual utility functions.

3.2. The production of nights out

A night out is produced by combining two inputs, drinking D and transportation T . There are two modes of transportation, driving a car T_1 and taking the train T_2 . The price of driving a car is p_1 , the price of taking the train is p_2 and the price of drinking is p_d . The total price of a night out for individual i is

$$C_N = D \cdot P_{Di} + T_1 \cdot P_1 + T_2 \cdot P_{2i}. \quad [2]$$

Where P_{Di} is the individual i 's price of driving (determined by car ownership, the price of gas etc.) and P_{2i} is individual i 's price of public transportation (determined by Metro ticket prices, taxi rates, Metro availability, and Metro accessibility). When there is no public transportation available $P_{2i} = \infty \forall i$. The provision of transportation constitutes a *reduction* in the price of taking the train from infinity to P_{2i} such that $0 < P_{2i} < \infty$.

Prediction 1. As the price of taking the train falls, the demand for driving falls as long as modes of transportation are gross substitutes and they are both normal inputs.

Prediction 2. As the price of taking the train falls, the cost of a night out decreases so that demand for a night out goes up, as long as a night out is a normal good.

Prediction 3. As the price of taking the train falls, the cost of a night out decreases and the demand for drinking goes up as long as a night out is a normal input.

Prediction 4. Since going out for person i and going out for person i' are strategic complements, as the price of taking the train falls, individual demand for a night out goes up, so that aggregate demand for a night out goes up, which in turn, increases demand for a night

out. In equilibrium, there is an increase in aggregate going out and an increase in aggregate drinking for both drivers and non drivers.³¹

Prediction 5. In equilibrium, the effect on aggregate intoxicated driving is ambiguous. Because the number of individuals who go out drinking will increase, if the fraction of drinkers who drive home is not large enough, there may be a net increase in total intoxicated driving. Alternatively, as more bar patrons use the Metro, the amount of alcohol consumed by any given bar patron's peers, including drivers, will rise.

Prediction 6. If going out on the weekend and going out during the week are substitutes, on the margin, some individuals who would have gone out on Thursdays will go out during the weekend. Also, if a night out in one area is substitutable for going out in another, as the price of going out declines in areas close to Metro stations, individuals will substitute going out in areas far away from Metro stations to areas with Metro stations.

4. Data

The effect of extended Metro service on the cost of taking the train will be directly related to how close Metro stations are to bars. The spatial pattern of expected effects (i.e. larger effect in areas with bars serviced by Metro stations) will be critical to our identification strategy. To exploit geospatial variation in Metro access and access to alcohol, we divide DC into neighborhoods based on Police Service Areas (PSAs). PSAs are relatively large making the assumption that someone arrested for a DUI was drinking within the PSA somewhat tenable.³² We discuss the implications of a violation of this assumption for our findings in Section 5.2. The PSA boundaries are shown in Fig. 1. We identify the number of bars within each PSA using address information on establishments licensed to serve alcohol for on-premises consumption provided by the DC Alcoholic Beverage Regulation Administration.³³ While these data are the stock of all existing bars in 2008, most neighborhoods known for late night carousing, such as Adams Morgan (PSA 303) and Georgetown (PSA 206), have been under liquor license moratoriums since the late 1990s (District of Columbia Municipal Regulations Title 23 Chapter 3). Two neighborhoods, U Street (PSA 305) and H Street (PSA 102), have large numbers of bars in our database due to highly visible neighborhood revitalization efforts in the early 2000s. As information on alcohol vendors in these two neighborhoods is functionally missing, we exclude these two PSAs from our analysis.³⁴

We present some basic summary statistics describing the PSAs in Table 1. The PSAs in our sample have on average 19 alcohol vendors in their borders (Std dev = 39.4), and just under one half (47.8%) has a Metro station within their borders. For Metro service to affect drinking behaviors, it should be the case that transportation from bars within the PSAs to a Metro station is sufficiently small, what we call "Metro accessible." We measure the spatial pattern of bars and Metro stations by constructing circles with radii of 100 m, 400 m or 800 m around each Metro station. We then calculate, by PSA, the

³⁰ Consistent with this notion, the amount of alcohol one consumes is believed to be a positive function of the amount of alcohol others around you are drinking (Cook and Moore, 2000) and Metro's publicity campaign highlighted late night activities downtown using the phrase "Metro Opens Doors to Late Night Fun". Promotion of Metro's expanded hours enhanced public awareness of downtown alcohol vendors. The Washington Post characterized the service change as targeted at bar patrons, and Metro's publicity campaign highlighted late night activities downtown. The opening scene of the televised ad campaign showed a pair of Metro doors opening onto a crowded bar, and the words "Metro Opens Doors to Late Night Fun" The commercial can be viewed at http://www.lmo.com/case_studies-change_behavior.html.

³¹ This prediction is an artifact of the assumption that a person's utility of going out is strictly increasing in the fraction of the population who goes out. A more general model than that present here that allows for congestion externalities at very high levels of going out would not necessarily yield prediction 4 for all levels of going out. A more general would yield prediction 4 at low and modest level of going out.

³² See FAQs about PSA boundaries: <http://mpdc.dc.gov/mpdc/cwp/view,a,1239,q,543455.asp>.

³³ Note that this includes restaurants so that this might be an overestimate of the number of drinking establishments in a PSA, biasing our results toward zero. However, results using the number of taverns and nightclubs in a PSA, which underestimates of the number of late night drinking establishments in a PSA, are similar to those based on all on-premises licenses and are presented in Web Appendix Table A4.

³⁴ Our empirical results are qualitatively identical if we include information from these two PSAs.

Table 1
PSA characteristics ($n = 44$).

	Mean	Std dev
On site licenses	18.98	39.44
On site licenses within 100 m of Metro station	2.45	7.23
On site licenses within 400 m of Metro station	10.54	30.99
On site licenses within 800 m of Metro station	14.23	35.80
Metro station in PSA	0.478	0.505
Population under 18	2509	1444

number of bars that are within each of these areas.³⁵ Increasing the size of the circle we draw around Metro stations increases the number of Metro accessible bars, but we predict that one additional bar within 100 m of a Metro will induce a larger change in drinking behavior relative to one additional bar a half a mile away. Because residential neighborhoods may have different types of nightlife than commercial districts, we also obtained the DC Police department's estimate of the number of children (people under 18 years old) living in each PSA.

Our measures of intoxicated driving and alcohol consumption are based on intoxicated driving and alcohol related arrest data from Washington DC's Metropolitan Police Department (MPD), respectively. The data set contains information on all arrests made between 1998 and 2007, and includes information on the primary charge, date and time of the arrest, as well as the location of arrest. We code as DUI arrests (driving under the influence arrests) all arrests listed as DUIs, DWIs (driving while intoxicated), and refusing to submit to a breathalyzer.

While all crimes are more likely to occur if the victim or offender has been drinking, we argue that certain types of offenses are more likely to be associated with excessive drinking in bars than others. Guided by field research on drinking and disorderly conduct (Marsh and Kibby, 1992), we focus on crimes that have been found to be committed by individuals with an otherwise low criminal propensity, but have engaged in excessive drinking and we exclude serious offenses that involve premeditation or weapons. These crimes include urinating in public, obscene gestures, drinking in public, possession of open alcohol containers, or defacing a building, as well as minor crimes for which victims may have been at higher risk due to their own excessive drinking, but do not require any sort of premeditation on the offender's part.³⁶

People arrested for DUIs and alcohol related offenses are both older and whiter than people arrested for more serious offenses; of those arrested on Thursday, Friday and Saturdays between 6 pm and 5 am, 23% and 52% of those arrested for alcohol related and DUI offenses, respectively, are white, vs. only 15% of those arrested for more serious offenses, and the average recorded ages of those arrested for DUIs, alcohol related offenses, and serious crimes are 33, 32 and 31, respectively.³⁷

Prior to November 5th 1999 there are slightly fewer white people arrested for DUIs on the weekend (50% vs. 57% of those arrested are white) and slightly more white people arrested for alcohol related offenses on the weekends (26% vs. 18%), both of which are statistically significant differences, although these differences are constant over time. There is no statistically significant difference in the age of people

arrested for DUI offenses after on Thursdays and the weekend nights, although people who are arrested for alcohol related offenses are about 6 months younger on average on the weekends, again, a difference which is constant across Metro schedules, so it should not affect our DIDID analysis.

Because we have data on the exact time of arrests (unlike the Metro ridership data) we can differentiate between the evening and the late night – a central distinction for our identification strategy. In our analysis, we parse each day into three wide time “blocks” – 5 am to 6 pm (day time), 6 pm to 10 pm (evening) and 10 pm to 5 am the next morning (late night). There are two important reasons for doing so. First, forward looking individuals decide on their drinking, driving, and going out actions based on the anticipated availability of the Metro service at the end of the evening. For example, the fact that Metro has extending its service from 1 am to 2 am may induce some to have a third beer at 12:30. This type of response results in the whole late night period being “treated” by the schedule change, as opposed to the exact 1 am hour. Second, Metro closing hours correspond to when trains leave central stations in all directions (roughly 30 min from the end of each line) so the direction an individual is traveling, the last train going “home” from any given station could be up to 30 min before 30 min after official closing hours.³⁸ To assuage any concerns that our results might be driven by our choice of how to parse the day, in Web Appendix Tables A8 and A9 we show that the main results are robust to defining the late night as late as after midnight or as early as after 8 pm. Because the fourth Metro schedule change affected the day time hours as well as the late night hours, we limit our analysis to evening and late night hours only.

To construct our final dataset, we link each arrest to its PSA (with the associated Metro proximity and bar data) and aggregate our merged data into PSA×Month×Day of the Week×Time of Day cells. To avoid any classification error, we exclude observations that correspond with the exact dates of schedule changes (weekend late night observations during the months of September 1999, July 2000, and July of 2003). We also exclude December 31st in all years from our analysis prior to aggregation, as DC law allows bars to serve alcohol later on those nights.³⁹ The final dataset has 73,218 observations, for all 7 days of the week, 2 times of day (late night and evening) across 44 PSAs. These data are summarized in Table 2, where we report means for our entire sample, Fridays and Saturdays only, and Thursday through Saturday.

One econometric issue is immediately apparent. Even aggregating across an entire month, only 12% of PSA×Month×Day of the Week×Time of Day cells have any DUI arrests. While DUIs are relatively more common when we restrict our attention to weekends, DUI arrests occur less than 18% of the time. Arrests that we define as alcohol related are more common, with arrests occurring in roughly half of our observations, also occur more frequently on the weekend.⁴⁰ As shown in Table 3, most cells with any arrest have only one arrest. Our dependant variable is an integer which takes on only positive values, but in situations where most of the variation in the dependant variable is binary in nature count models will produce partial elasticities that are undefined over most of the distribution of

³⁸ Specifically, if 75% of individuals drinking around a Metro station, in the center of the city, were headed westbound, the last train would leave at 12:10. For the 25% of drinkers eastbound, the last train would leave at 12 am. On the perimeter of the city, the last train westbound would leave at 11:49 pm and at 12:21 am eastbound. Individuals wishing to transfer Metro lines are bound by the last train line at their transfer point (not all of which are close to the city center) Without knowing where the drinkers around any given station are headed, this essentially creates a window of unknown size around each station when the technically “last train” leaves an given station.

³⁹ Our results are robust to including these observations. The impact of all other holidays will be subsumed by our fixed effects.

⁴⁰ Notably, arrests for behavior that we designate as non-alcohol related, which includes more serious felonies and weapons violations, are actually slightly more common on Thursdays than Fridays and Saturdays, which is consistent with our assertion that they are less reliable proxies for drinking outside of the home.

³⁵ Note that the Metro station and bar do not have to be in the same PSA.

³⁶ Simple assault constitutes 22% of alcohol related arrests, open container violations 19%, “Other” misdemeanor arrests 18%, and disorderly conduct arrests 11%. Note that serious crime, such as aggravated assaults and forcible rape are excluded from “alcohol related” crimes. While these offenses may be positively correlated with alcohol consumption, variation in these crimes will likely also be driven by other individual factors, making them unsuitable proxies for alcohol consumption outside of the home. As there are roughly one half as many arrests for “drunk and disorderly” behavior, in our primary analysis we will use our broad measure of alcohol related arrests, as it is continuously defined. However, our results are robust to using this other measure of public alcohol consumption.

³⁷ Age, race, and gender breakdowns for each crime type, by day of the week, are presented in Web Appendix table A2.

Table 2
Arrests by neighborhood.

	Week, evening and late night (<i>n</i> = 73,218)		Thurs–Sat, evening and late night (<i>n</i> = 31,420)		Fri–Sat, evening and late night (<i>n</i> = 20,968)	
	Mean	Std dev	Mean	Std dev	Mean	Std dev
Any DUI arrests	0.123	0.328	0.161	0.367	0.176	0.381
Ln (DUI arrests + 1)	0.107	0.308	0.148	0.371	0.165	0.396
Any alcohol related arrests	0.469	0.499	0.512	0.500	0.524	0.499
Log (alcohol related arrests + 1)	0.503	0.618	0.575	0.661	0.593	0.669
Log (DUI arrests + 1) – Ln (alcohol related arrests + 1)	–0.397	0.634	–0.428	0.674	–0.428	0.679
Any drunk and disorderly arrests	0.269	0.444	0.322	0.467	0.336	0.472
Log (drunk and disorderly arrests + 1)	0.270	0.499	0.338	0.556	0.354	0.567
Any serious related arrests	0.604	0.489	0.631	0.482	0.625	0.484
Ln (serious arrests + 1)	0.753	0.754	0.806	0.772	0.785	0.757

the dependant variable. This issue will motivate and inform our econometric specification.

5. Empirical strategy

There are two sources of variation in public transportation that can be exploited: (1) the temporal difference in provision by comparing outcomes when public transportation is provided to times when it is not; and (2) the spatial variation in the impact of Metro on the cost of a night out. In our first pass, we estimate the effect of Metro service on intoxicated driving and risky alcohol consumption using only the temporal variation. This is a good starting point because it identifies the effect overall for all geographic areas. Exploiting both sources of variation, we then expand our model to see if the time effects we observe are stronger in areas with bars close to Metro stations.

5.1. Temporal variation

When there is a set public transportation schedule (e.g., trains always run at 10 pm and never run at 5 am), it is impossible to

Table 3
Frequency of monthly arrests per PSA, Friday and Saturday late nights, 1999–2007.

Number of arrests	Arrest type		
	DUI	Drunk and disorderly	Alcohol related
0	7553	6850	4708
1	1727	1825	2387
2	550	719	1298
3	247	437	725
4	155	224	429
5	100	144	274
6	51	94	195
7	37	56	151
8	18	43	91
9	15	17	73
10	9	20	32
11	4	16	38
12	4	12	17
13	5	6	14
14	1	3	9
15	2	6	14
16	0	4	9
17	1	0	4
18	0	2	4
19	2	0	2
20	0	1	2
21	0	0	0
22	1	0	0
23	0	0	0
24	0	1	3
25	0	0	0
26	1	1	2
27	1	0	0
>27	0	3	5

separate a time of day effect from a public transportation effect. To identify such effects requires observing outcomes during the same time of day (and day of the week) when Metro is available and when Metro is not available. A simple first difference strategy would only use data from Friday and Saturday late nights and compare outcomes before and after schedule changes. However, since the schedule changes may have coincided with other potentially confounding changes over time, like the Green line connection, this is unlikely to isolate the effect of Metro access on the outcomes.

To account for possible confounding time effects, one could use one of two difference-in-difference-(DID) strategies: (1) one that compares the difference between outcomes before and after the schedule changes on Friday and Saturday late nights to the difference between outcomes before and after the schedule changes on Friday and Saturday evenings, or (2) one that compares the difference between outcomes before and after the schedule changes on Friday and Saturday late nights to the difference between outcomes before and after the schedule changes on Thursday late nights. The first DID approach relies of the assumption that any changes over time, such as variation in BAC laws or state or local policies regarding alcohol and drunk driving, have the same effect on both late night and evening outcomes. Since we might expect certain changes to differentially affect risky alcohol consumption at night this assumption may not be desirable. The second DID approach relies of the assumption that any changes over time affect late night outcomes during the weekends and on Thursdays the same. While this assumption is also reasonable, there may be changes over time that affect outcomes on the weekends, but not on Thursdays that could confound the results.

To address *both* these concerns with the two DID models, we propose another round of differencing, using the difference between outcomes in the late night to those in the night before and after the schedule changes on Thursday (when Metro service in constant) as the counterfactual change in outcomes for Friday and Saturday (when there were changes in the Metro's operating hours over time). As we point out in the theoretical section, there may be shifting of drinking from Thursday night toward Friday and Saturday nights. We will empirically test for evidence of shifting in [Section 4](#).

To justify our use of Thursday as our comparison day, Web Appendix Figures A1 and A2 show the incidence of DUI arrests and alcohol related arrests by hour between 8 pm and 5 am. For clarity and brevity, we show arrests for Tuesdays, Thursdays, and Saturdays.⁴¹ A few key patterns are apparent: (1) most DUI arrests take place between 10 pm and 3 am on Thursday through Saturday evenings, (2) alcohol related arrests peak at 8 pm and again around 2 am, and (3) the time profile of DUI and alcohol related arrests on Saturdays (and Fridays) are much better tracked by movements on Thursdays than Tuesdays. These patterns suggest that focusing on the

⁴¹ The temporal pattern of arrests on Tuesdays is identical to the temporal pattern on other week days, and Friday is the same as Saturday. When all days of the week are included, the sheer number of bars obscures the timing these peaks.

late night period is most appropriate for analyzing the effects of policy on DUI and alcohol related arrests and that the dinner and happy hour crowds on Thursday is a good (and clearly the best) comparison day of the week for Friday and Saturday evenings.

To implement this Difference-in-Difference-in-Difference (DIDID) model we estimate Eq. (1) below by OLS using late night and PM outcomes data from Thursdays, Fridays and Saturdays.

$$Y_{ismdt} = \beta \cdot \text{Hours}_{sdt} + \theta_i + \mu_{isd} + \mu_{ist} + \mu_{idt} + T_m + \varepsilon_{ismdt}. \quad (1)$$

In Eq. (1) Y_{ismdt} is the outcome in PSA i during schedule s on month m on day d for time of day t . Hours_{sdt} is the number of hours the Metro is in operation during time of day t during schedule s on day d . Since the number of hours of late night service varies at the schedule by day of the week by time of day level, we include all the two way interactions effects for each PSA (PSA by schedule by time of day effect μ_{isd} , PSA by schedule by day of the week effects μ_{ist} , and PSA by time of day by day of the week effects μ_{idt}).⁴² The matrix T includes year fixed effects and month fixed effects. In (3), β identifies the change in the difference between late night outcomes and night outcomes during the weekend and late night outcomes and night outcomes on Thursdays associated with a one hour increase in late night Metro access.⁴³

Our dependant variable is the number of arrests that occur in a given neighborhood i in a given month m on day of the week d at time of day t . We present both (a) a linear probability model where the outcome is equal to 1 if there were any arrests in a given month in a given PSA on a given day of the week during a given time of day and (b) a log linear model, functionally equivalent to a negative binomial count model, where the dependent variable is the natural log of the number of arrests in a given month in a given PSA on a given day of the week during a given time of day plus 1.⁴⁴ Where there are very few arrests, as is the case with DUI arrests, the linear probability model may be the most appropriate, while where the number of arrests is high, as is the case for alcohol related arrests, the log linear model will be most appropriate.⁴⁵

5.2. Spatial variation

Based on predictions 1–3, neighborhoods with Metro stations will be more greatly affected by the availability of Metro service than areas that are farther away from Metro stations. It is also reasonable to expect a larger effect on alcohol related outcomes in neighborhoods with several drinking establishments particularly if those drinking establishment are close to Metro stations; these are exactly the areas where Metro service will have the largest impact of the price of the train and a night out. We test these hypotheses by seeing if the marginal effects of Metro availability vary by geography, interacting

Hours_{sdt} with measures of the number and location of bars within that PSA. Specifically, we expect larger effects in areas that have any Metro stations and areas than have a lot of drinking establishments, but particularly in areas where those drinking establishments are located near Metro stations. To control for any underlying changes in geographic locations that may be associated with increased Metro use (such as gentrification or an increase in activity in the area) all models include PSA by schedule by day of the week fixed effects, PSA by schedule by time of day effects, and time of day by day of week by schedule fixed effects.

When using spatial variation, there is always a concern about shifting behaviors. It is possible that there could be shifting away from neighborhoods where bars were located far from Metro stations to neighborhoods where bars were close to Metro. We will explore this possibility by estimating Eq. (1) for each neighborhood, and directly examine the spatial pattern of Metro effects. We assume that most of the DUI arrests that occur in a PSA reflect drinking in that PSA. However, there will likely be some classification error in our treatment variable so that some DUIs that are caught inside a certain PSA are the result of drinking in another PSA. This will likely attenuate our DUI results toward zero.⁴⁶ We therefore interpret and observed effect of Metro access on DUI arrests as a lower bound.

6. Results

6.1. Temporal variation

Before turning to the regression results, we present visual evidence of our estimated effects. We plot the data used to construct DID estimates comparing late night outcomes on the weekends to the late night outcomes on Thursdays. Fig. 4 shows the three month moving average for late night alcohol related arrests for each month on Thursdays and Fridays during each schedule.⁴⁷ Vertical lines indicate the date of the schedule changes and the horizontal lines indicate the mean for each schedule. During the first schedule, the number of alcohol related arrests during Thursdays and those during the weekend move closely together – confirming our assumption that the movements in Thursday evenings are a good counterfactual for what the changes in the weekend evenings would have been in the absence of any schedule changes. For the first two schedule changes, alcohol related arrests (on the right) decrease on both Thursdays and Fridays, with larger decreases on Thursdays than on Fridays. Between schedules 3 and 4 there are increases in alcohol related arrests on both Fridays and Thursdays with a larger increase in Friday arrests – all suggesting that public transit lead to an increase in alcohol related crimes.

The left panel shows similar figures for DUI arrests. Much like alcohol related arrests, the number of DUI arrests during Thursdays and those during the weekend move closely together. The first two schedule changes show a decline in DUI arrests on Friday relative to Thursday, while the last change shows a slight increase in DUI arrests on Fridays relative to Thursdays. Taken in sum the visual evidence suggests that Metro access may have affected drinking behavior as the model predicted – increasing alcohol related crimes and decreasing drunk driving.

The regression results in Table 4 are consistent with this graphical analysis. While the *naïve* first difference results (column 1) indicate that alcohol related arrests increased by 5.7% and the likelihood of a DUI arrest increased by 7 percentage points with each additional hour of Metro service, all subsequent specifications tell a different story. Both DID approaches (comparing late nights and evenings on

⁴² This identification strategy is similar to that employed in Jackson (2009).

⁴³ As a robustness check we show that our findings are robust to including PSA specific linear trends. These results are presented in Web Appendix table A6.

⁴⁴ As in a count model, the estimated value of β is a partial elasticity. However, because of the expected spatial heterogeneity in the effect of Metro service, we are primarily interested in the cross partial elasticities – $\partial \text{Arrests} / \partial \text{Hours} \partial \text{Bars}$. In a log linear model, these effects are identical to the coefficients on the interactions terms. In a non linear model, however, this is not the case. In fact, given that we are not able to credibly estimate the first order effect of having a neighborhood bar on arrests (as the only variation is cross sectional) we are limited in our ability to interpret a true count model. Technically, in a negative binomial model, the estimate of interest would be $(\beta_B + \text{Hours} \beta_{HB}) / \beta_H + \text{Bars} \beta_{HB} (\beta_B + (\text{Hours} \times \text{Bars}) \beta_{HB}) + \beta_{HB}$, and note that we are unable to estimate β_B , the first order effect of the number of bars, in a model with neighborhood fixed effects.

⁴⁵ While survey data suggest that intoxicated driving may be a common event, arrests for intoxicated driving are rare. In fact, the average number of DUI and DWI arrests occurring in each PSA between 10 pm and 5 am on Friday and Saturday nights is 0.596. In fact, 87% of the time, there are no DUI arrests between 6 pm and 5 am in a PSA during an entire month, and in only 5.6% of our primary sample (Thursdays through Saturdays, 6 pm to 5 am) are there more than 2 DUI arrests.

⁴⁶ In order for this miss-classification to lead to a spurious reduction in DUIs close to Metro stations relative to those far away requires that increased alcohol consumption in a PSA leads to a larger increase in DUI arrests outside the PSA than in the PSA.

⁴⁷ The monthly data are similar but are much more noisy and difficult to see

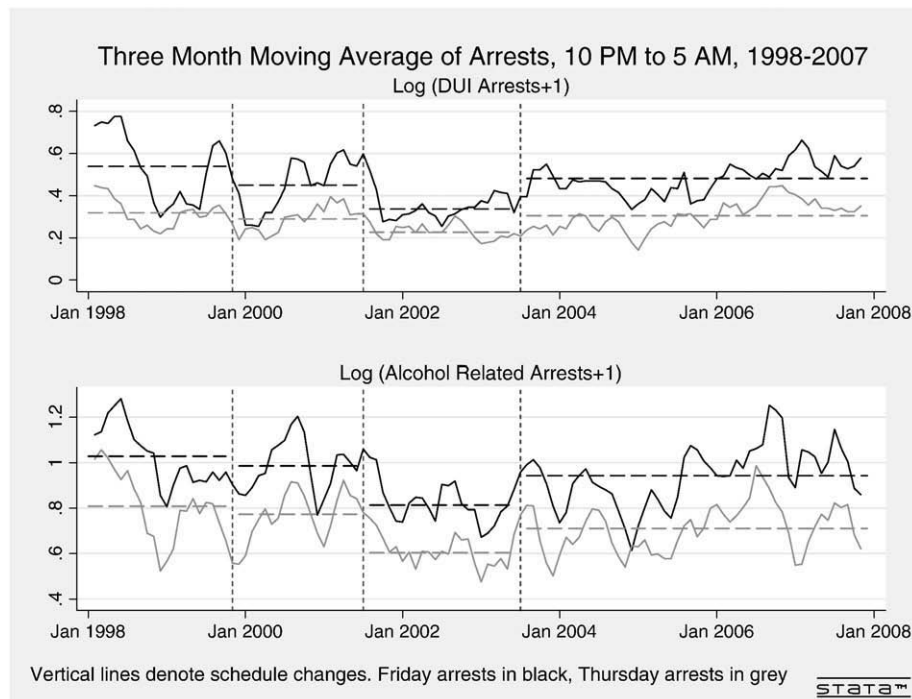


Fig. 4. Mean monthly arrests by day of the week and time of day, Washington DC 1998–2007.

weekends or comparing late nights from Thursday through Saturday) yield estimated increases in alcohol related arrests and decreases in DUI arrests, although these estimates are measured with inconsistent precision. In column 4, the DIDID results suggest that each additional hour of late night Metro service leads to a statistically insignificant 0.1% decrease in alcohol related arrests and a statistically insignificant 0.4 percentage point decrease in the likelihood of a DUI arrest. No obvious conclusions about Metro service and intoxicated driving can be drawn from our temporal results. The upper and lower bounds of the 95% confidence intervals of all of the estimates are 0.00987 and -0.0442 (obviously centered below zero). Furthermore, the standard errors of the estimated parameters also indicate that we do not have sufficient power to detect aggregate effects smaller than about a 2% change.

Table 4
Effect of Metro access on DUI arrests and alcohol related arrests.

	Independent variable is number of hours of Metro access			
	1	2	3	4
Any alcohol related arrests	0.021 [0.021]	−0.003 [0.008]	0.001 [0.007]	−0.004 [0.008]
log(alcohol related arrests + 1)	0.057* [0.027]	0.004 [0.015]	0.002 [0.010]	−0.010 [0.011]
Any DUI arrests	0.070** [0.017]	−0.0121*** [0.006]	−0.009 [0.006]	−0.004 [0.006]
log(DUI arrests + 1)	0.080** [0.017]	−0.010 [0.008]	−0.007 [0.007]	−0.004 [0.007]
Days included	Fri and Sat	Fri and Sat	Thurs–Sat	Thurs–Sat
Times of day included	Late	Late and ev.	Late	Late and ev.
PSA*Sched*TOD			X	X
PSA*Sched*DOW		X		X
PSA*TOD*DOW	X	X	X	X
N	10,484	20,968	15,718	31,420

Heteroskedasticity robust standard errors clustered at the PSA level in brackets. All models include PSA fixed effects, year fixed effects and month of the year fixed effects.

* Significant at 5%.
** Significant at 1%.
*** Significant at 10%.

6.2. Spatial variation

Before turning to the regression estimates, we present some visual evidence of heterogeneity by geography. In the left panel of Fig. 5, we plot the natural log of the three month moving average of alcohol related arrests on Fridays minus the log of alcohol related arrests on Thursdays over time for PSAs that have more than 20 bars and those with fewer than 20 bars (this is equivalent to splitting the sample at the 75th percentile of the distribution of bars). It appears that as the Metro expanded its hours of operation, there was an increase in alcohol related arrests in areas with more than 20 bars relative to areas that do not have more than 20 bars – however this relationship does not appear to hold for the last schedule change.⁴⁸ The left panel of Fig. 5 presents the same analysis for DUI arrests. Unlike the strong patterns for alcohol related arrests, there is little visually apparent effect on DUI arrests. However, if public alcohol consumption has increased in these areas, as the arrests suggest, one would expect, *ceteris paribus*, to observe an increase in intoxicated driving in these neighborhoods.

The regression estimates, in Table 5, are consistent with the visual analysis. We test for whether additional hours of Metro access have a differential effect in areas based on the number of bars in the PSA, whether the PSA actually has a Metro station within its borders, and the number of bars in the PSA that are close to a Metro station (even if the Metro station does not lie within the borders of the PSA). We do this by interacting PSA specific characteristics with the Metro Hours variable in the preferred DIDID model. In column 1, we present the linear probability model for the DUI arrests. The interaction between the number of hours of Metro access and the total number of on-site licenses within the PSA is negative and the coefficients on the interactions with the number of licenses within 100 m, and 400 m of a

⁴⁸ We believe that the results for the last schedule change reflect the fact that most people who go out do stay out past midnight but do not stay out until after 3 am. As such, while most bar patrons will be affected by the first two schedule changes, we believe that the last schedule change will not be as large. Even though DC law allows license establishments to serve alcohol until 3 am on Friday and Saturday nights, only 66% of licensed taverns report serving alcohol until 3 am on the weekend.

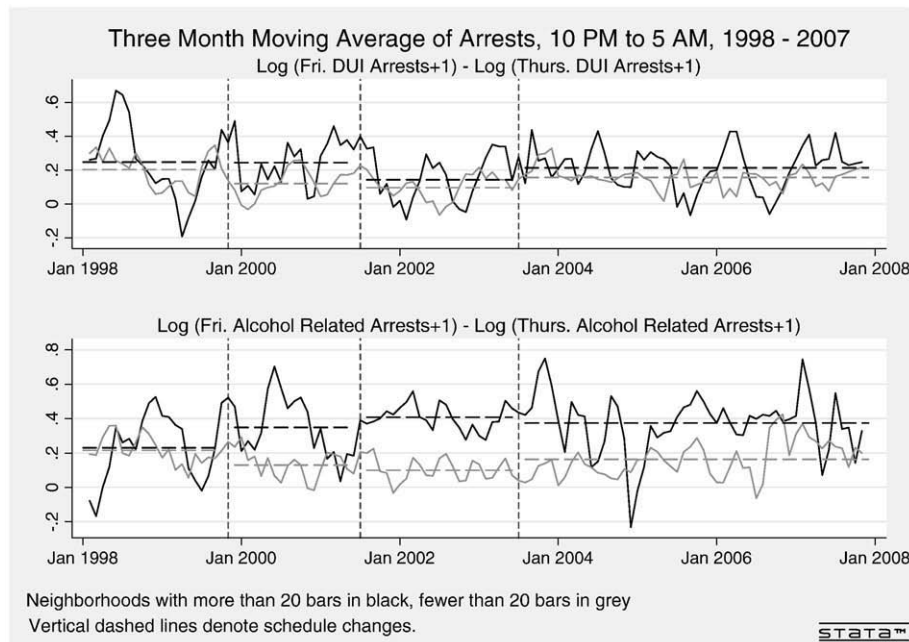


Fig. 5. The difference between outcomes on Fridays relative to Thursdays in areas with more than and fewer than 20 bars.

Metro station are also negative, and the marginal effects are diminishing as we relax our definition of “near” a Metro station.

While only one of these estimates is statistically significant at the 10% level, the number of bars within 100 m of the Metro, they all move in the hypothesized direction; areas with more bars and where those bars are close to Metro stations experienced a decrease in DUI arrests relative to areas that were farther away from Metro stations or where, due to the location of bars, the “cost” of a night out did not fall as much as Metro expanded. In addition, it is worth noting that the magnitude of the relationship between bars within 100 m of a Metro and DUIs is large. Alcohol vendors tend to be located together; while there are on average 2.45 “Metro accessible” bars in a neighborhood, if there is at least one on-premises vendor, there is an average of 8 others. A 2 percentage point reduction in the probability of there being a DUI arrest corresponds with almost a 5% reduction per hour of Metro service relative to the average DUI probability in those areas. Recall that our definition of “bar” includes vendors that have restaurant licenses, meaning that they are required to sell food. Restricting our definition of “bar” to only vendors with a tavern or nightclub license yields qualitatively identical results, which are available in Web Appendix table A4.

In column 4, we present the log linear model for the alcohol related arrests. Consistent with the visual evidence in Fig. 5, there is a clear indication that areas with more on-site alcohol licenses station experienced a greater increase in alcohol related crimes as the Metro expanded the hours of late night service. The coefficient on the interaction between the number of licenses and Metro hours is statistically significant at the 1% level. Each additional bar increases the effect of Metro service on alcohol related arrests by 0.16 percentage points. Neighborhoods in the 75th percentile of number of bars have more risky drinking when Metro is open later. There is also a substantively important 0.4 percentage point increase in the “Metro effect” for each bar located with 100 m of a Metro station, although this result is statistically imprecise ($p = 0.16$). The coefficients on the other interactions do not tell any consistent story and are not statistically significant.

One striking pattern in Table 5 is that those areas that are associated with statistically significant increases in alcohol related crimes are the same areas that experience the largest reductions in DUI arrests, and vice versa. In order to approximate the change in the probability that an intoxicated person drives home due to Metro

service, we subtract the natural log of alcohol related arrests from the natural log of DUIs. As opposed to simply looking at DUI arrests, this difference provides some scale for this effect by taking into account the potentially endogenous changes in the underlying drinking population. If changes in alcohol related arrests were a perfect measure of changes in the heavy drinking population, this difference is the number of “DUIs per drinker” in DC.

We present estimates of the relationship between this measure and the spatial distribution of bars and Metro stations in column 5. As one can see, both the number of bars in a PSA and the number of bars in a PSA that are located within 100 m of a Metro station are associated with reductions in the number of DUI arrests relative to alcohol related arrests, and both are statistically significant at the 5% level. As Metro expanded its late night service, the fraction of heavy drinkers that drove home fell by 0.23 percentage points for each bar in a neighborhood. If that additional bar is located within 100 m of a Metro station, the probability that a heavy drinker drove home fell by 0.82 percentage points, a reduction of roughly 2% per additional hour of late night public transportation. The results presented in columns 6 through 8 use all weekdays as a comparison instead of only Thursday – results are very similar.

As Figs. 6 and 7 show, there is a very suggestive pattern in the magnitude and direction of the “Metro effect” across neighborhoods. In Fig. 6, we report the number of bars within each neighborhood, as well as the location of Metro entrances. The reduction in DUIs per drinker appears to be concentrated in central DC. This is where most bars are located, but there are seven PSAs with more than 10 bars in which there is an observed increase in DUIs per drinker as Metro expands. While it is possible (and common) to take taxis from Metro stations to bars, expanded Metro service should have the largest effect on the behavior of heavy drinkers in neighborhood where bars are located within walking distance to Metro stations. In Fig. 7, we limit our attention to only the number of bars within 100 m of a Metro. When we focus on these areas, it is clear that in those neighborhoods with many bars but an apparent increase in DUIs per drinker, those bars are located far from Metro stations. It is therefore unlikely that expanded Metro service would substantially reduce the private cost of the safer option for drinkers. Two of neighborhoods with no “Metro accessible” bars that are positively affected by Metro have over 70 on-premises alcohol vendors – Georgetown (81 bars) and Adams Morgan (74 bars). As noted previously, these neighborhoods are historic destinations for DC

Table 5
Geographic variation in the effect of Metro access on Metro ridership, DUI arrests, and alcohol related arrests.

Dependent variable	Any DUI arrests	log (DUI arrests + 1)	Any alcohol related arrests	log (Alcohol related arrests + 1)	log (DUI arrests + 1) – log (alcohol related arrests + 1)	Any DUI arrests	log (alcohol related arrests + 1)	log (DUI arrests + 1) – log (alcohol related arrests + 1)	Any serious arrests	log (serious arrests + 1)
Hours	0.00456 [0.0180]	–0.00697 [0.0155]	–0.0125 [0.0186]	–0.0337*** [0.0198]	0.0267 [0.0227]	0.0014 [0.00990]	–0.0463** [0.0164]	0.0375*** [0.0206]	–0.0341*** [0.0196]	–0.0443 [0.0350]
Hours*On site licenses	–0.000511 [0.000636]	–0.00067 [0.000509]	0.000587*** [0.000340]	0.00162* [0.000362]	–0.00229** [0.000620]	0.000178 [0.000268]	0.00264** [0.000868]	–0.0026** [0.0004]	0.00112 [0.000807]	0.00212 [0.00162]
Hours*# within 100 m	–0.00316*** [0.00174]	–0.00238 [0.00272]	0.00232 [0.00426]	0.00351 [0.00285]	–0.00589* [0.00264]	–0.00322 [0.000875]	0.000563 [0.00238]	0.00318*** [0.00161]	0.0027 [0.00634]	0.00248 [0.00695]
Hours*# within 400 m	–0.000705 [0.00137]	–0.00222 [0.00232]	–0.000313 [0.00199]	–0.00264 [0.00168]	0.000423 [0.00240]	0.000964 [0.000828]	–0.00164 [0.00179]	0.00298 [0.00189]	0.00391 [0.00319]	0.00722 [0.00470]
Hours*# within 800 m	0.00155 [0.00140]	0.00302 [0.00211]	–0.000504 [0.00144]	0.00113 [0.00146]	0.00189 [0.00222]	–0.000545 [0.000787]	–0.000947 [0.00188]	0.000258 [0.00196]	–0.00516*** [0.00260]	–0.00882*** [0.00439]
Hours*Metro within borders	–0.000607 [0.0131]	0.00419 [0.0132]	–0.00672 [0.0178]	–0.0234 [0.0179]	0.0276 [0.0200]	0.00476 [0.00756]	–0.0044 [0.0171]	–0.0044 [0.0135]	–0.0341*** [0.0196]	–0.0443 [0.0350]
Days included	Thurs-Sat	Thurs-Sat	Thurs-Sat	Thurs-Sat	Thurs-Sat	All	All	All	Thurs-Sat	Thurs-Sat
Times of day included	Late and ev.	Thurs-Sat	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.
R ²	0.301	0.432	0.289	0.411	0.281	0.268	0.375	0.274	0.336	0.518
N	31,420	31,420	31,420	31,420	31,420	73,218	73,218	73,218	31,420	31,420

Heteroskedasticity robust standard errors clustered at the PSA level in brackets.

All models include PSA*Schedule fixed effects, PSA*TOD effects, PSA*Sched*TOD, PSA*Sched*DOW, PSA*TOD*DOW, PSA fixed effects, and year fixed effects and month of the year fixed effects, as well as interactions between Metro operating hours and the number of PSA residents under 18, and a dummy variable indicating that there is a Metro station in the PSA.

* Significant at 5%.

** Significant at 1%.

*** Significant at 10%.

nightlife, and it seems reasonable that drinkers might use taxi service from Metro stations to these neighborhoods.

The pattern of marginal effects is striking. With the exception of one neighborhood on the northwest DC border, every PSA with more than 2 bars located within 100 m of a Metro state has a reduction in DUIs per drink of at least 10% per hour of Metro service. Incorporating the number of bars within 100 m of a Metro station using a linear probability model where the outcome is a reduction in DUIs per drinker, we estimate that there is only a 2% chance we would observe this pattern of results at random.⁴⁹

6.3. Specification tests

There are three specific endogeneity concerns that may generate downward bias in our estimate of Metro service of DUIs and upward bias of the effect of Metro on risky drinking. Specifically, one might worry that (1) our temporal results are confounded by any independent effect the schedule change may have on Thursday outcomes, (2) the geographic patterns we estimate reflect factors that affect all crimes, and (3) our measures of intoxicated driving do not reflect real DUI behaviors because people may not be caught driving drunk where they drink. We address these remaining concerns below in turn.

6.3.1. Is there an effect of the schedule change on Thursday's outcomes?

It is important to point out that our estimates of the effect of increased Metro access on arrests, using Thursday as a comparison day, will be biased if the Metro expansions had an independent effect on outcomes on Thursdays. There are two primary reasons why one might worry that our DIDID estimates may not reflect the true overall policy effect: (1) the schedule changes led to an increase in the attractiveness of taking the Metro or going out on all nights in our sample, in which case our results *understate* the total effect of Metro service or (2) the schedule changes may have caused people to shift their risky public drinking from Thursday late night to Friday late night, in which case our results *overstate* the total effect of Metro service.⁵⁰

In Table 6, we explore possible spillover effects in detail. In columns 1a–4a we impose the weekend schedule on Thursdays, and comparing changes in Thursdays arrests relative to Wednesday arrests.⁵¹ The geographic patterns are similar in the Wednesday to Thursdays (i.e. reductions in DUIs in areas with more bars within 100 m of a Metro and increases in alcohol related arrests in areas with more bars within 400 m of a Metro station). Instead of people shifting behavior from Thursday to the weekend, if anything, alcohol related behaviors on Thursday are trending in the same direction as drinking behaviors on Friday and Saturday. This could be a real spillover effect of Metro service, for example, if the DC bar and restaurant market changed in response to Metro operation.⁵² Alternately, this effect on Thursday could reflect unrelated changes in drinking or police behavior over time. Regardless, this apparent change on Thursday highlights the importance of our DIDID approach that looks at changes

⁴⁹ Using a logit or probit model yields substantively the same result.

⁵⁰ Specifically, if Metro caused people to go out on Fridays or Saturdays *en lieu* of Thursdays, it would lead to a reduction in Thursday ridership, alcohol arrests, and DUI arrests and an increase in Friday ridership, alcohol arrests, and DUI arrests. Under such a scenario, any increase in alcohol related arrests will be overstated, and any decrease in DUI arrests will be understated.

⁵¹ This approach allows us to include PSA×Time of Day×Schedule fixed effects, meaning that the identification of the Metro effect is the same as our main specification. A DID model with Friday and Saturday does not allow for any temporal variation in the relationship between late night and evening arrests, making it unclear how to map observed spatial heterogeneity in the effect of Metro service to the DIDID results.

⁵² We have no way of testing for a dynamic response of bar owners, but Title 23-402.7 of the DC code suggests this is unlikely; since 1986 bars have been prohibited from being open after 3 am on weekends. The existence of this law limiting closing times implies that at least some bars found it profitable to open past 3 am, even without Metro service.

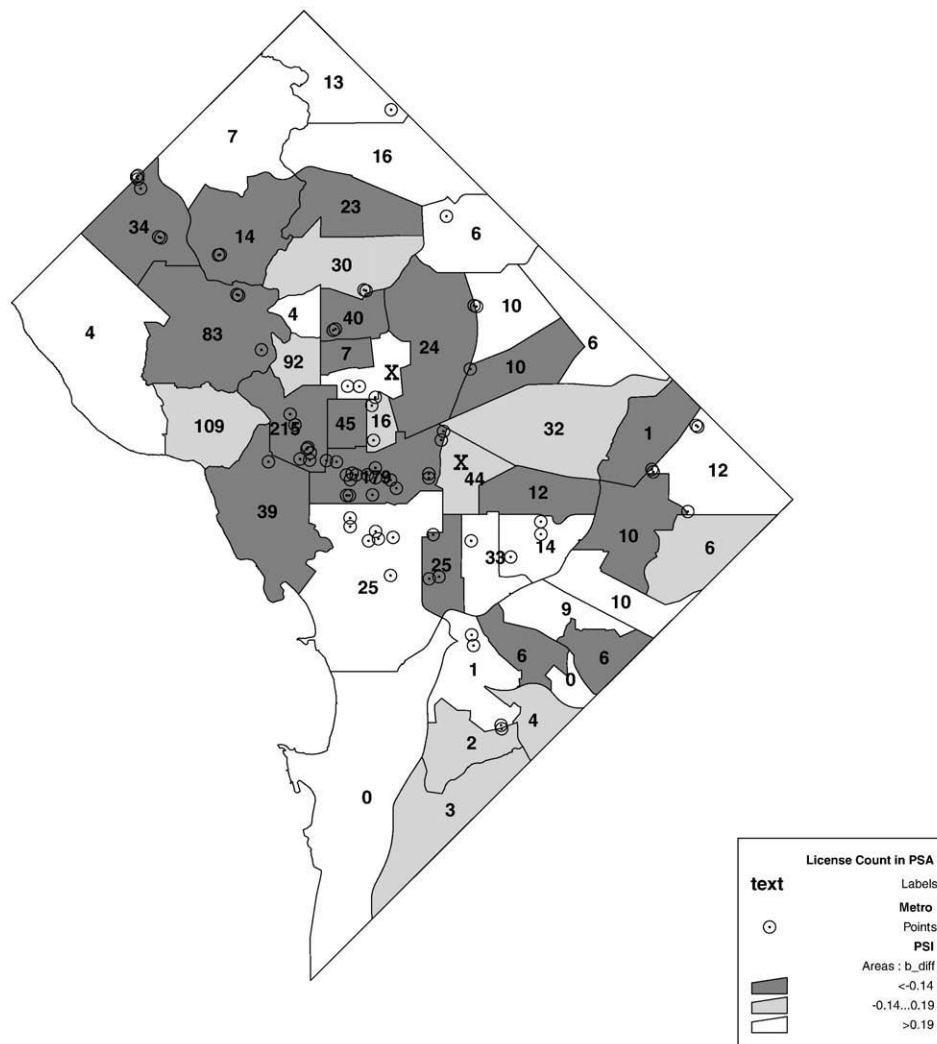


Fig. 6. Distribution of marginal effects across PSAs, by number of alcohol vendors within the PSA. U street and H street neighborhoods marked with an "X".

in outcomes during the weekend relative to Thursday (i.e. conditioning on any omitted factors that could affect outcomes on both Thursdays and Fridays, such as changes in blood alcohol content laws, or any spillover effects) if this model is incorrectly specified, we are being *conservative* in our estimates of the policy effect while if this is the correct specification, not including Thursday as a comparison day of the week would lead us to overstate the spatial distribution of the Metro effect on Fridays and Saturdays arrests.

We further test for whether our estimates are affected by any shift in behaviors from Thursdays (or any other day of the week) to the weekend by imposing the weekend Metro schedule on all days of the week. If our results were driven by individuals simply altering when they went out, any increase on Fridays and Saturdays will be undone by a reduction on Thursdays, meaning that there would be a net zero effect overall. These results, in columns 1b–4b of Table 6, are qualitatively identical to our preferred specification, implying that our effects are not being driven by people who used to go out on Thursdays, but were induced by the Metro change to only go out on the weekend.

6.3.2. The geographic patterns we estimate reflect other factors that affect all crimes

While the geographic patterns in the marginal effect of Metro service follow *a priori* expectations, one may worry that the patterns we estimate reflects changing unobserved factors that affect all crimes. To test this possibility, in the last two columns of Table 5, we allow for spatial heterogeneity in the Metro effect with respect to

arrests for more serious crimes. If changes in the size or behavior of police officers were driving our results in columns 1 through 7, we would expect to see a similar pattern for serious arrests. While we pick up three marginally statistically precise estimates, there is no clear spatial pattern in the magnitude or sign of the coefficients.⁵³

6.3.3. Using DUI arrests in DC only might not be picking up all the DUIs because a drinker may drive outside of DC

In Fig. 7 there appears to be an increase in DUIs relative to drinking on the northwestern and northeastern DC borders. This is driven primarily by a reduction in alcohol related arrests in those areas, but may also indicate some negative spatial spillovers. Since drunk drivers are mobile it is possible that DUI arrests outside of DC increased, which DUI arrests in DC remained constant. To address this concern, we examine fatal alcohol related car crashes, using data for the entire DC Metro area.⁵⁴ First, we identify the effect of the Metro extension on fatal traffic accidents by estimating the full Thursday through Saturday DIDID model using crash data for DC, Maryland, and Virginia. *En lieu* of aggregating the data at the PSA-month level, data are aggregated at the state-MSA-month level.⁵⁵ If the schedule

⁵³ We also present results for "Drunk and Disorderly," arrests only, essentially excluding people arrested for yelling angrily at each other (which is in practice what an arrest for simple assault means) in Web Appendix Table A2.

⁵⁴ As there are at least six police jurisdictions in the DC suburbs, obtaining arrest data for the DC metropolitan area would be involve prohibitively high costs.

⁵⁵ In other words, we divide MD and VA into DC area and non-DC area observations.

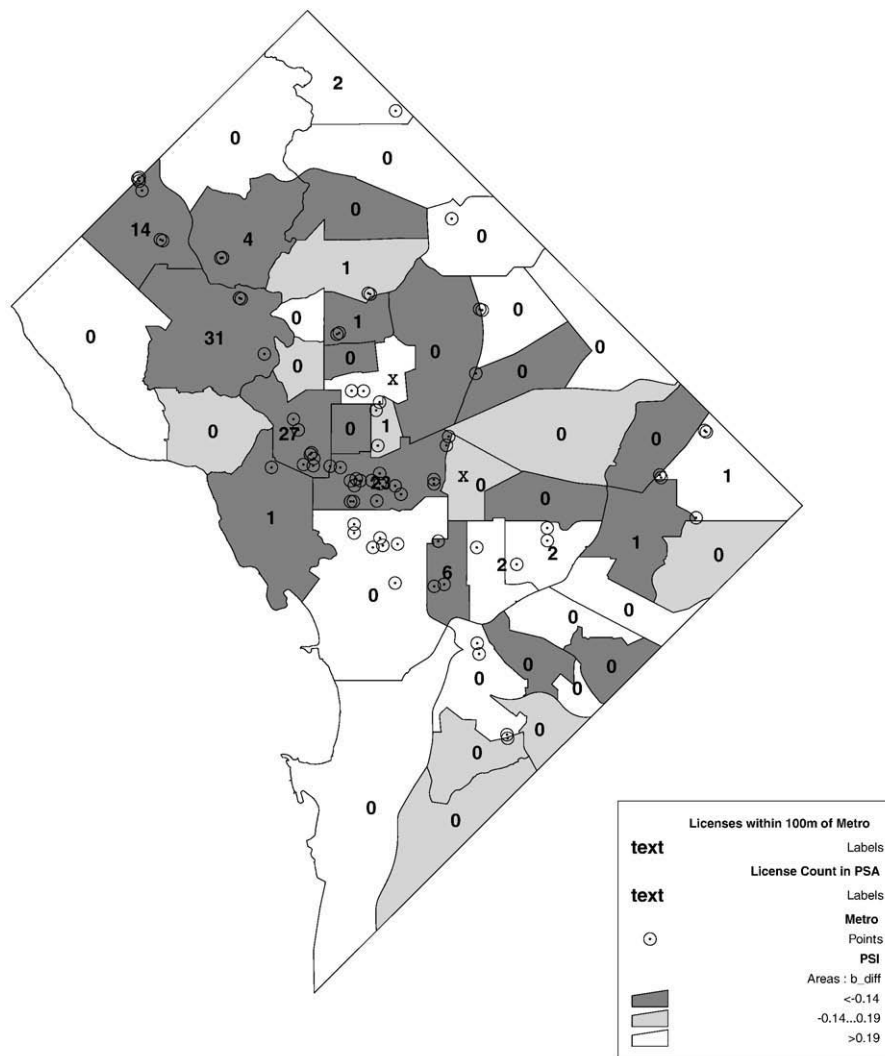


Fig. 7. Distribution of marginal effects across PSAs, by number of alcohol vendors within 100 m of Metro station. U street and H street neighborhoods marked with an "X".

changes led to an increase in intoxicated driving one might expect a larger increase in alcohol related fatal crashes than those not involving alcohol. We show the effects separately for crashes where alcohol was deemed to be involved and accidents where alcohol is not reported to be a factor.

These results, using accidents in the DC Metro area, are resented in the top panel of Table 7. The DIDID estimate indicates that each additional hour of Metro service is associated with a statistically insignificant 2.3% increase in alcohol related accidents (column 1) and a 0.7% increase in non-alcohol related accidents (column 7). The interaction between the Metro hour and indicator variables for Virginia and Maryland are small and statistically significant for both alcohol related accidents (column 2) and non-alcohol related accidents (column 6). The evidence suggests that the schedule changes had no effect on fatal car crashes in DC, Maryland and Virginia (so that the lack of any effect on DUI arrests did not reflect geographic shifting).

As another test for an effect on fatal crashes, we look at crashes in Maryland and Virginia separately by whether the area is in a municipality which contains a Metro station.⁵⁶ Specifically, we interact Metro hours with an indicator variable that is equal to 1 if the area is serviced by Metro and 0 if it is not. Since one would expect

the schedule changes to have an effect on covered areas, and no effect on non-covered areas, the DIDID effect in non-covered areas provides a credible control for underlying changes in fatal accidents over time for the covered areas. These results are presented in the lower panel of Table 7. All of the point estimates are imprecise, and the signs follow no systematic pattern – suggesting that there is no effect of the Metro schedule changes on fatal crashes overall, either in the DC area or in the outer lying parts of Maryland and Virginia.

7. Conclusion

Using a triple differences strategy, we find that as the DC Metro expanded its late night hours of operation there was very little aggregate effect on DUI arrests, fatal alcohol related automobile accidents or total non-alcohol related arrests. This null effect masks striking spatial variation. Looking at particular neighborhoods within DC, we find that in neighborhoods with at least one bar within 100 m of a Metro station, expanding Metro service by 3 h reduced the probability of a DUI arrest occurring by approximately 14%. At the same time, the number of arrests for alcohol related crimes increased by at least 5.4% in the same neighborhoods – suggesting a moral hazard effect. Using arrests for these crimes as a proxy for changes in the size of risky drinkers, a typically non-measurable population, we estimate that expanding Metro's hours of operation from midnight to 3 am reduced the number of drinkers who drove home by 2.46% per

⁵⁶ In Maryland, this includes Montgomery and Prince George's County, and in Virginia, Fairfax (county and city) Alexandria, Arlington, and Falls Church.

Table 6

Geographic variation in the effect of Metro access on Metro ridership, DUI arrests, and alcohol related arrests.

Dependent variable	Any DUI arrests	log (DUI arrests + 1)	Any alcohol related arrests	log (alcohol related arrests + 1)	Any DUI arrests	log (DUI arrests + 1)	Any alcohol related arrests	log (alcohol related arrests + 1)
	1a	2a	3a	4a	1b	2b	3b	4b
Hours	−0.00552 [0.0141]	−0.0078 [0.0135]	−0.00066 [0.0179]	−0.0038 [0.0220]	−0.0009031 [0.01113]	−0.00699 [0.0133]	−0.0256927 [0.0139938]	−0.0383* [0.0159]
Hours*On site Licenses	0.000667 [0.000684]	0.000637 [0.000912]	0.000723** [0.000232]	0.00049 [0.000776]	0.000519 [0.000625]	0.000447 [0.00105]	0.00186** [0.000302]	0.00236* [0.000992]
Hours*# within 100 m	−0.00301*** [0.00167]	−0.00238 [0.00192]	−0.00529 [0.00383]	−0.004 [0.00389]	−0.00219*** [0.00116]	−0.00188 [0.00136]	−0.00312** [0.00103]	−0.00134 [0.00195]
Hours*# within 400 m	0.000238 [0.00113]	0.00153 [0.00160]	0.00324*** [0.00185]	0.00379 [0.00240]	0.00162*** [0.000945]	0.00297* [0.00121]	0.00220*** [0.00111]	−0.000486 [0.00156]
Hours*# within 800 m	−0.00032 [0.00125]	−0.00145 [0.00178]	−0.00283* [0.00120]	−0.00396*** [0.00208]	−0.00159 [0.00110]	−0.00262 [0.00161]	−0.00321** [0.00105]	−0.00187 [0.00178]
Hours*Metro within borders	0.0118 [0.0143]	0.00771 [0.0126]	0.0188 [0.0188]	0.0285 [0.0217]	0.00627 [0.00914]	0.00686 [0.00988]	0.0154 [0.0142]	0.00268 [0.0183]
Days included	Wed–Thurs	Wed–Thurs	Wed–Thurs	Wed–Thurs	All	All	All	All
Times of day included	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.	Late and ev.
R ²	0.27	0.36	0.27	0.38	0.27	0.38	0.27	0.38
PSA*Sched*TOD	X	X	X	X				
PSA*Sched*DOW	X	X	X	X	X	X	X	X
PSA*TOD*DOW	X	X	X	X	X	X	X	X
N	20,885	20,885	20,885	20,885	73,218	73,218	73,218	73,218

Heteroskedasticity robust standard errors clustered at the PSA level in brackets. All models include interactions between Metro operating hours and the number of PSA residents under 18, and a dummy variable indicating that there is a Metro station in the PSA.

a. The weekend schedule is imposed on Thursday as a “placebo” treatment.

b. The weekend schedule is imposed on all days of the week during the same schedule. This indicates that the data are aggregated across all days of the week. (This does not compare weekend days to other days of the week).

* Significant at 5%.

** Significant at 1%.

*** Significant at 10%.

Table 7

Fatal crashes in Maryland, Virginia, and Washington, DC.

	Alcohol related accidents				Non-alcohol related accidents			
	log (Accidents + 1)		Any accidents		log (Accidents + 1)		Any accidents	
	1	2	3	4	5	6	7	8
Hours	0.0231 [0.0192]	0.0181 [0.0236]	0.0222 [0.0188]	0.0262 [0.0209]	0.00788 [0.0306]	−0.0135 [0.0238]	−0.00693 [0.0221]	−0.0177 [0.0217]
Hours*MD		0.00615 [0.0453]		−0.00593 [0.0432]		−0.0144 [0.0742]		−0.0181 [0.0524]
Hours*VA		0.00883 [0.0428]		−0.00609 [0.0420]		0.0785 [0.0591]		0.0504 [0.0460]
R ²	0.136	0.136	0.144	0.144	0.127	0.127	0.13	0.13
N	2970	2970	2970	2970	2970	2970	2970	2970
	Alcohol related accidents				Non-alcohol related accidents			
	log (Accidents + 1)		Any accidents		log (Accidents + 1)		Any accidents	
	VA	MD	VA	MD	VA	MD	VA	MD
Hours	0.0669 [0.0577]	−0.00592 [0.0503]	0.0606 [0.0447]	0.00881 [0.0427]	0.0906 [0.0811]	−0.119 [0.0806]	0.0936* [0.0455]	−0.0456 [0.0462]
Hours*DCMSA	−0.0349 [0.0674]	0.0368 [0.0623]	−0.0329 [0.0568]	0.0166 [0.0555]	−0.0345 [0.0959]	0.0998 [0.104]	−0.0688 [0.0591]	0.0115 [0.0643]
R ²	0.356	0.264	0.317	0.255	0.278	0.176	0.287	0.166
N	2136	2136	2136	2136	2136	2136	2136	2136

All models are based on the DIDID that use Thursday as the counterfactual day.

“Metro accessible” bar in these neighborhoods on average, or 19.7%. The magnitude of the effect warrants attention. At the same time, the benefit of reduced DUIs per drinker dissipates rapidly as alcohol venders become more remote to Metro stations. Given that the literature in urban economics finds similar spatial effects when examining commuting patterns, this dissipation of effects lends confidence in our results. While the social benefit of providing a “safer option” for drinkers appear to be localized to areas directly served by the Metro, it does appear that those who would commit alcohol related crimes respond to changes in costs in a rational way.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at [doi:10.1016/j.jpubeco.2010.09.010](https://doi.org/10.1016/j.jpubeco.2010.09.010).

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