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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 provision, the risky decision to consume alcohol, and the criminal decision to engage in alcohol–impaired driving. Using a triple differences strategy, we provide evidence that overall there was little effect on DUI arrests, alcohol related fatal traffic and alcohol related arrests. However, we find that these overall effects mask considerable heterogeneity across geographic areas and spatial shifting. Specifically, we find that areas close to bars that are within walking distance to Metro stations experience increases in alcohol related arrests and decreases in DUI arrests.

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## I Introduction

In 2007, over 1 million drivers were arrested for driving under the influence of alcohol[1] while 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[2] and it is estimated that alcohol-related crashes in the U.S. cost about $51 billion each year [Blincoe et al. (2002)].[3] 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.[4] 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. In this paper, we evaluate the impact 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,

[1] Sourcebook of Criminal Justice Statistics Online: http://www.albany.edu/sourcebook/pdf/t4272007.pdf
[2] National Highway Traffic Safety Administration: http://www-nrd.nhtsa.dot.gov/Pubs/810821.PDF
[3] http://www.cdc.gov/ncipc/factsheets/drving.htm
[4] The complete list is available on their website. See appendix for webpage.
[5] Marsha Dorgan (Oct 22, 2008) "CHP DUI checkpoint results" Napa Valley Register , Alan K. Category (Oct 2 2008) The Drunk Driving Situation in Los Angeles , Mutineer Magazine
[6] http://www.cyberdriveillinois.com/publications/pdf_publications/dsd_a1495.pdf

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

Public transportation may have had a perverse effect on alcohol consumption outside of the home, what we refer to as "risky" alcohol consumption. As such, we also investigate the relationship between public transportation provision and alcohol-related crimes. We also test for evidence of an overall spillover effects in Metro accessible areas on days when late night Metro service was not provided.

Using a difference in difference in difference identification strategy, where Thursday serves as our comparison day of the week, we find that the aggregate impact of public transportation on risky behavior on Friday and Saturday evenings is small. However, in neighborhoods where bars are located within walking distance of a Metro station there were sizable reductions in alcohol-impaired driving arrests for each additional hour of Metro

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[7] In addition to Washington, DC, Boston's Massachusetts Bay Transportation Authority and Austin's Capital Metro Authority introduced late night service with the last ten years.

availability after midnight. We also find evidence of moral hazard in the form of increased alcohol related arrests (our proxy for excessive alcohol consumption outside of the home) in these neighborhoods. When this increase in potential drunk drivers is taken into account, the localized reduction in DUIs per drinker becomes quite large. The fact that alcohol related arrests and DUI arrests move in the opposite direction is compelling evidence that our effects are not driven by secular changes in overall crime[8] and we conduct a variety of tests to support the validity of our identification strategy. We also 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 should be interpreted as lower bounds of the true behavioral change.

This paper presents the first credible evidence on the relationship between public transportation on drunk driving and alcohol consumption (both in areas directly served by public transportation and for the Metropolitan area as a whole). The behavioral effects estimated imply that even intoxicated individuals respond to incentives in a rational way, a point of contention in the research literature on criminal behavior. While we examine different populations, our spatial pattern of results is also consistent research in urban economics on the localized effects of public transit on worker mobility.[9]

The remainder of the paper is as follows. Section II outlines the extant literature on alcohol consumption, crime and public transportation, and provides institutional detail of the Washington DC Metro expansion. Section III presents the analytical framework describing how public transportation may affect drunk driving and drinking behaviors, section VI presents the

[8] We cannot exclude reallocation of police resources away from drunk driving to what are by and large nuisance crimes, although given the high social cost, and high profile, of drunk driving this seems an unlikely policy decision.
[9] 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]

empirical strategy, section V presents the results and section VII concludes.

## II Alcohol Consumption, Crime, and Public Transportation

### *i. 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. There is a large literature in economics on the first component of this decision. 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); and 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, the extant literature has not evaluated policies aimed at reducing the social harm associated with risky alcohol use. We aim to fill this gap in the literature by investigating how the provision of public transportation reduces the rate at which alcohol consumption translates into socially costly DUI incidents.

Conditional on alcohol consumption, individuals must then evaluate 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".[10] Researchers have primarily focused on one side of this equation – reducing the prevalence of crime through policies intended to increase the expected private costs of illicit behavior. 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".

Policies of this nature have been criticized on the grounds that providing less risky

[10] See Doob and Webster (2003) and Levitt (2002) for reviews of the literature on risky behavior and deterrence.

alternatives to certain externally costly actions (e.g. drunk driving) could hurt society overall by increasing the likelihood that persons engage in other undesirable behaviors (e.g. excessive drinking in bars) [Boyum and Reuter (1996)]. These policies may introduce a moral hazard – by providing a safer way to engage in socially undesirable behaviors, one makes socially undesirable behavior more attractive to individuals who do not internalize the full social costs of their actions [Pauly (1974); Holmstrom (1979)]. In fact, in severe cases such well-intentioned solutions could cause more harm than good [Hansen and Imrohoroglu (1992)].[11] While public transportation may lower the probability that a risky drinker drives home, it may also increase the amount of alcohol consumed outside of the home which has a potentially large social cost. In addition, since drinking is a social activity [Boisjoly et al. 2003, Norton et al.(1998)], the reduced costs of alcohol consumption for a few individuals could result in an increase in the total number of DUIs, even if the policy reduces the propensity of a given drinker to drive drunk.

With these moral hazards in mind, we look not only at how the availability of late transportation affects DUI arrests, but also its potentially deleterious effects on risky alcohol consumption. As this policy change reduces the private cost of drinking in bars, *a-priori,* we would expect public alcohol consumption to increase as Metro service expands, as alcohol consumption is quite responsive to price changes [Chaloupka et al. 2002]. However, it is unclear how *total* alcohol consumption changes as the cost of public alcohol consumption falls. 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 do down as the marginal cost of alcohol is higher at a bar (where you pay per drink) than an at home (where you pay per bottle). However, for policy purposes, alcohol consumed outside of the home is decidedly more

[11] 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)].

"risky" from a social perspective since the external costs of someone drinking in their own home are likely low (if that the individual has internalized the risk to their future health) while excessive drinking *outside the home* can impose substantial costs on others.[12]

An increase in risky drinking 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 [Greenfeld (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); Joksch and Jones (1993); Carpenter (2008); Dobkin and Carpenter (2008); Cook and Moore (1993b)].

*ii. Public transportation in Washington, D.C.*

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."[13] 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.[14] In Figure 1 we show the location of each Metro station entry point, obtained from the DC government's GIS database,[15] as well as each bar in Washington DC.[16]

[12] 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.
[13] MetroBus has always operated for 24 hours 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
[14] For example, the Georgetown neighborhood has no Metro stations, as Georgetown University faculty has traditionally lived in that neighborhood.
[15] http://dcatlas.dcgis.dc.gov/catalog/results.asp?pretype=All&pretype_info=All&alpha=M

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.[17] With an eye on serving a “younger rider, who is out on the town, [and] probably could be drinking,”[18] 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. It is clear from Figure 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 cyclicality and an upward trend that is evidence on Thursday, Friday, and Saturday.[19]

To show that the schedule changes lead to the expected "treatment", (i.e. a

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[16] During rush hour the expected wait time is 2 to 3 minutes, and after the evening rush hour that expected wait time is between 7 and 10 minutes. 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.
[17] For additional detail on Metro and MetroBus service, see www.wmata.com/about_Metro/docs/Metrofacts.pdf
[18] Jim Graham, The Washington Post, 9/17/1999
[19] This pattern is evident on all days of the week, but for purposes of clarity, we show only these three days.

*disproportionate* increase in evening ridership on the weekend) in Figure 3 we present the natural log of ridership on 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 early evening minus the natural log of ridership on Thursday during early evening, (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)],[20] and in1999 the Office of Personnel Management estimated that half of government workers use an alternative work schedule (AWS in which they do not work every other Friday, substantially higher than the private sector.[21] Combined with the large population of college students (who tend to go out drinking on Thursday evenings) enrolled in seven major universities, Thursday night is arguably closer to a weekend night in Washington DC than in any other city in the United States. We present further evidence of the suitability of Thursday night as a comparison for Friday and Saturday evenings in Section IV. Using Thursday ridership as our baseline for comparison, the schedule changes affect ridership exactly as one would expect ─ (a) late evening ridership increased on Fridays relative to Thursday late evening ridership with each successive change and (b) there was no discernable change in the relationship between early evening ridership on Fridays relative to early evening 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

[20] http://www.bls.gov/opub/mlr/2006/12/art1full.pdf
[21] www.mith2.umd.edu/WomensStudies/GenderIssues/WomenInWorkforce/Work+FamilyNeeds/01introduction

affected late night ridership on the weekend, but not other days of the week.[22]

It is clear that there is a large amount of cyclical variation in late evening and early evening 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 were taken on weekend nights for each additional hour of Metro service.[23] There were an average of 137,150 one way trips made each night on Fridays and Saturdays prior to the first schedule change so that our estimates suggest that more than 1,065 additional people may have been added to the DC nightlife as Metro service increased.[24]

## III **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.

*The consumer problem:* Individuals demand a night out N, with price $C_N$, and a numerair good $Y$ with price 1. Individual $i$'s utility from going out is an increasing function of aggregate

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[22] A similar graph using Saturday and Thursday is available on request.

[23] Specifically, we estimate the parameters of the following model: $Ln(Ridership_{dtym})=\beta Hours_{dtym} + \mu_{dt}+T_{ym} + \varepsilon_{dtym}$ where $Ridership_{dtym}$ is the number of one way trips taken on day of the week $d$ at time of day $t$ during year $y$ and month $m$, $Hours_{dtym}$ is the number of hours that Metro is open during that period, $\mu_{dt}$ 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,

[24] In appendix Table A1, we present full regression results, showing that this estimate is robust to a relaxation of parametric assumptions

going out for others in the population $\theta_{i'}$ , so such that individual *i*'s maximizes utility

$$U_i = f_i(g(N,\theta_{i'}),Y) \text{ s.t. the budget constraint } \quad E_i = Y_i + N_i \cdot C_N \qquad [1].$$

Aggregate going out for others in the population is $\theta_{i'} = \sum_{i' \neq i}^{I} N_{i'}$ and $\partial g / \partial \theta_{i'} > 0$. The parameter $\theta_{i'}$, captures the fact that a night out drinking is a social activity.[25] The utility maximizing levels of the numereair 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.

*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

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

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

[25]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 venders. 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

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.

*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 falls 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.

## IV **Data**

The effect of extended Metro service on the price of taking the train will be directly proportional 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.[26] The PSA boundaries are shown in Figure 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.[27] 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).[28]

We present some basic summary statistics describing the PSAs in Table 1. The PSAs in our sample have on average 19 alcohol venders in their borders (sd= 39.4), and just under one half (47.8%) have 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 meters, 400 meters or 800 meters around each Metro station. We then calculate, by PSA, the number of bars that are within each of these areas.[29] 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 meters of a Metro will induce a larger change in drinking behavior relative to one additional bar a half a mile

[26] See FAQs about PSA boundaries: http://mpdc.dc.gov/mpdc/cwp/view,a,1239,q,543455.asp
[27] Note that this includes restaurants.
[28] 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 venders in these two neighborhoods is functionally missing, we exclude these two PSAs from our analysis, although our empirical results are qualitatively identical if we include information from these two PSAs.
[29] Note that the Metro station and bar do not have to be in the same PSA.

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.[30] 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. As such, we code as alcohol related arrests, crimes that we consider most likely to be committed by individuals with an otherwise low criminal propensity, but have engaged in excessive drinking. These offenses include urinating in public, obscene gestures, drinking in public, possession of open alcohol containers, or defacing a building, as well as crimes for which victims may have been at higher risk due to their own excessive drinking (e.g. simple assault, unarmed robbery, attempted sexual assault without a weapon, indecent exposure, indecent sexual proposal).[31] While alcohol related arrests will not be a perfect proxy for *total* alcohol consumption, they are good proxies for alcohol consumption in commercial establishments such as bars or restaurants,

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[30] We exclude all arrests occurring on New Year's Eve, during which there is unusual drinking behavior and DC bars are allowed to operate until 4 am. Our results are robust to the inclusion of these observations.

[31] 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.

which is the primary concern in this paper.[32]

Because 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, changes in behavior caused by Metro changes between 2 am and 3 am may manifest themselves in changes in arrests hours before, and would typically not occur only between 2 am and 3 am. In addition, Metro "closing hours" correspond to when trains *leave stations* in the center of DC in all directions (roughly 30 minutes from the end of each line) so that depending on whether an individual is traveling inbound or outbound, the last train going "home" from any given station could be up to 30 minutes before 30 minutes after official closing hours.[33] We address both these issues by parsing each day into three 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). Since we have data on the exact time of the arrest (unlike the Metro ridership data) we can differentiate between the evening and the late night – a central distinction for our identification strategy. Since 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 out 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 (that is, weekend late night observations during the

[32] 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.

[33] 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 12:21am 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.

months of September 1999 and July of 2003).[34] The final dataset has 73,218 observations, for all 7 days of the week, 2 times of day (late evening and early 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, and also occur more frequently on the weekend.[35] Table 3 confirms that most cells with any arrests have only one arrest. Our dependant variable is an integer which takes on only positive values. However, in situations where most of the variation in the dependant variable is binary in nature, count models can yield misleading conclusions, as count models estimate partial elasticities that are undefined over most of the distribution of the dependant variable. This issue will motivate and inform our econometric specification.

## V 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; (2) the spatial variation by comparing outcomes in areas where there are many bars close to Metro stations to those of areas where Metro stations are not located near any bars. In our first pass, we estimate the effect of Metro service on intoxicated driving and risky

[34] We also exclude December 31st in all years from our analysis prior to aggregation.

[35] 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.

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.

*i. Temporal variation*

When there is a set public transportation schedule (e.g., trains always run at 10 pm and never run at 5am), it is impossible to separate a time of day effect from a public transportation effect. To identify Metro availability effects, one needs to compare outcomes during the same time of day (and day of the week) when Metro is available to when Metro is not available. *In principle*, 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 evenings to the difference between outcomes before and after the schedule changes on Friday and Saturday afternoons, or (2) one that compares the difference between outcomes before and after the schedule changes on Friday and Saturday late evenings to the difference between outcomes before and after the schedule changes on Thursday late evenings. The first DID approach relies of the assumption that any changes over time, such as variation in BAC laws, affect both late night and evening outcomes the same. While this is a reasonable assumption, 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 early evening before and after the schedule changes on Thursday (when there were no changes in Metro hours of operation over time) as the counterfactual change in outcomes for Friday and Saturday (when there were changes in the Metro's hours of operation over time). As we point out in the theoretical section, there may be shifting of drinking from Thursday night toward Friday and Saturday nights. Since, the DIDID strategy described above relies on the assumption that the schedule change did not lead to shifting of activity from Thursday to Friday and Saturday, we present empirical support for this assumption in section IViii. We also show that the results obtained using the DIDID models are similar to those from both the DID models — indicating that our findings are robust to different identifying assumptions.

To justify our use of Thursday as our comparison day, Appendix Figures A1 and A2 show the incidence of DUI arrests and alcohol related arrests by hour between 8pm and 5am. 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 peek at 8 pm and again around 2am, and (3) the time profile of DUI and alcohol related arrests on Friday and Saturdays are much better tracked by movements on Thursdays that any other day of the week. These patterns suggest that focusing on the late evening period is most appropriate for analyzing the effects of policy on DUI and alcohol related arrests and that Thursday is a good (and clearly the best) comparison day of the week for Fridays and Saturday evenings.

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

$$Y_{ismdt} = \beta \cdot Hours_{sdt} + \theta_i + \mu_{isd} + \mu_{ist} + \mu_{idt} + \mathrm{T}_m + \varepsilon_{isdt} \quad (1)$$

In equation (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 $\mu_{isd,}$ PSA by schedule by day of the week effects $\mu_{ist}$, and PSA by time of day by day of the week effects $\mu_{idt}$). The matrix T includes year fixed effects and month fixed effects. In (3), $\beta$ identifies the change in the difference between late night outcomes and early evening outcomes during the weekend and late night outcomes and early evening outcomes on Thursdays associated with a one hour increase in late night Metro access.

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 $t$. Following Cameron and Trivedi (1998) since our arrests data are count data 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. 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.[36]

*ii. Spatial variation*

The second potential source of variation is spatial in nature. One expects that 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. 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 test if there are larger effects in areas that have any Metro stations, areas than have a lot of drinking establishments and areas where those drinking establishments are located near Metro.[37] It is also possible that there was 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 equation (1) for each neighborhood, and directly examine the spatial pattern of Metro effects.

## VI **Results**

*i. Temporal variation*

Before turning to the regression results, we present visual evidence of our estimated

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[36] 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 10pm 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.

[37] 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- $\partial$ Arrests/$\partial$Hours$\partial$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 $(\beta_B+\text{Hours}\beta_{HB})\beta_H+\text{Bars}\beta_{HB}(\beta_B+(\text{Hours x Bars})\beta_{HB})+\beta_{HB}$, and note that we are unable to estimate $\beta_B$, the first order effect of the number of bars. For further discussion of this issue, see Owens (2009).

effects. Specifically, we plot the data used to construct the DID estimates that compare late evening outcomes on the weekends to the late evening outcomes on Thursdays. Figure 4 shows the monthly alcohol related arrests for each month on Thursday late evenings and Friday late evenings during each schedule. 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 very 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. Between schedules 1 and 2, alcohol-related arrests increase on both Thursdays and Fridays, but the increase is larger on Fridays then for Thursdays. Between schedules 2 and 3, both days experience a decline, however, the decline is larger for Thursdays than for Fridays - again suggesting that increased Metro access lead to an increase in alcohol-related crimes. The changes between schedule 3 and 4 however, does appear to show a larger increase in Thursday arrests that Friday arrests.

The right 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 in our predicted way, but is not particularly striking.

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 percent and the likelihood of a DUI arrest increased by 7 percentage points with each additional hour of late Metro service all subsequent specification tell a different story. Both DID approaches (comparing late nights and evenings on 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 evening Metro service leads to a statistically insignificant 0.1 percent 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 bound of the 95 percent confidence intervals of all of the estimates is 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 effects smaller that about a 2 percent change.

*ii. Spatial variation*

A pure temporal analysis ignores the spatial distribution of Metro stations and bars. If our proposed mechanisms are correct, one would expect that the marginal effects of greater Metro availability would be greatest in areas with a large number of drinking establishments, and in particular areas where those establishments are closer to Metro stations. We test for this type of response heterogeneity by including interactions of the main three-way effect with measures of geographic distance to a Metro station and the prevalence of alcohol venders. Before turning to the regression estimates, we present some visual evidence of heterogeneity by geography. In the left panel of Figure 5, we plot the natural log of alcohol related and 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 75$^{th}$ 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. The right panel of Figure 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, we would expect, *ceteris paribus*, to observe an *increase* in intoxicated driving in these neighborhoods.

The regression estimates are consistent with the visual analysis. We test for whether additional hours of Metro access has 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 these PSA specific characteristics with the Metro Hours variable in the preferred DIDID model. The results are presented in Table 5. 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 100m, and 400m of a 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 percent level, the number of bars within 100 meters 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 the location of bars, the "price" 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 meters of a Metro and DUIs is large. Alcohol venders 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 vender, 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 the average DUI probability in those areas.

In column 4, we present the log linear model for the alcohol related arrests. Consistent with the visual evidence in Figure 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 percent level. Each additional bar increases the effect of Metro service on alcohol related arrests by 0.16 percentage points. Neighborhoods in the $75^{th}$ 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 meters 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. This suggests a strong behavioral response on the part of drinkers. Under the assumption that the marginal drinker consumes the same amount of alcohol as the average drinker, the elasticity of drunk driving with respect to risky drinking should be close to one. In order to isolate 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 to estimate the number of "DUIs per drinker" in DC. We present estimates of the relationship between DUIs per drinker 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 meters of a Metro station are associated with reductions in "DUIs per drinker" and both are statistically significant at the 5 percent 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 meters 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 working days of the week as a comparison instead of only Thursday ─ results are very similar.

As Figures 6 and 7 show, there is a very suggestive pattern in the magnitude and direction of the "Metro effect" across neighborhoods. In Figure 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 Figure 7, we limit our attention to only the number of bars within 100 meters 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 venders- Georgetown (81 bars) and Adams Morgan (74 bars). As noted previously, these neighborhoods are historic destinations for DC 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 meters 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 meters 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.[38]

*iii. 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 does not reflect real DUI behaviors because people may not be caught driving drunk where they drink. We address these remaining concerns below in turn.

*iii. a) 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

[38] Using a logit or probit model yields substantively the same result.

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.[39]

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.[40] The geographic patterns are similar in the Wednesday to Thursdays (i.e. reductions in DUIs in areas with more bars within 100 meters of a Metro and increases in alcohol-related arrests is areas with more bars within 400 meters 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.[41] 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; 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

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[39] 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.

[40] This approach allows us to include PSA x Time of Day x 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.

[41] 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.

Thursdays (or any other day of the week) by imposing the weekend Metro schedule on all days of the week (in essence, aggregating across all days of the week). If our results were driven by shifting of activity from Thursdays (or other days of the week) to Fridays and Saturdays any increase on Fridays and Saturdays will be undone by a reduction on Thursdays so that there would be an net zero effect overall. These results in columns 1b – 4b of Table 6 are in the same direction as the main DIDID results using Thursday as the comparison day, so that it is clear that the main findings are not driven by any shifting of behaviors across days of the week

*iii. b) The geographic patterns we estimate reflect 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 our less alcohol related, or "Other" arrests. If changes in the size or behavior of police officers were driving our results in columns 1 though 7, we would expect to see no difference in the relationship between our alcohol related arrests and other arrests. While we pick up two statistically precise estimates, there is no clear spatial pattern in the magnitude or sign of the coefficients.[42]

*iii. c) Using DUI arrests in D.C. only might not be picking up all the DUIs because a drinker may drive outside of DC.*

In Figure 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,

[42] We also present results for Drunk and Disorderly arrests only in Appendix Table A2.

using data for the entire DC Metro area.[43] 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.[44] If the schedule 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 percent increase in alcohol related accidents (column 1) and a 0.7 percent 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 serviced or not serviced by Metro. 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

[43] 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.
[44] In other words, we divide MD and VA into DC area and non-DC area observations.

presented in the lower panel of Table 7. All of the point estimates are imprecise, and the sign follow no systematic patterns - 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).

## VII **Conclusion**

Using a triple differences strategy, we find that as the DC Metro expanded its late night hours of operation there was very little effect on DUI arrests, fatal alcohol related automobile accidents or total non-alcohol related arrests in the aggregate. This null aggregate effect masks striking spatial variation. Looking at particular neighborhoods within DC, we find that in neighborhoods with at least one bar within 100 meters of a Metro station, expanding Metro service by 3 hours 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. 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 "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 actually 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 even excessive drinkers respond to changes in costs in a rational way.

**References:**


Baum-Snow, N. and Kahn, M. (2000) “The effects of new public projects to expand urban rail transit” Journal of Public Economics 77: 241-263.

Becker, G. (1968). “Crime and punishment: an economic approach.” The Journal of Political Economy, 76(2):169-217.

Blincoe L. J., Seay A. G., Zaloshnja E., Miller T. R., Romano E. O., Luchter S. and Spicer, R.S. (2002) “The Economic Impact of Motor Vehicle Crashes, 2000.” Washington (DC): Department of Transportation, National Highway Traffic Safety Administration.

Boisjoly, J., Duncan, G. J., Kremer, M., Levy, D. M., and Eccles, J. (2003) “Peer effects in binge drinking among college students.” mimeo.

Boyum, D. and Reuter, P. (1996) An Analytic Assessment of US Drug Policy Washington, DC: American Enterprise Institute Press.

Carpenter, C. (2008) “Heavy Alcohol Use and Crime: Evidence from Underage Drunk Drving Laws.” Journal of Law and Economics 50(3): 539-557.

Chaloupka, F. J., Saffer H., and Grossman M. (1993) “Alcohol-Control Policies and Motor-Vehicle Fatalities," Journal of Legal Studies. 22:161-186.

Chaloupka, F. J., Grossman, M., and Saffer, H. (2002) “The Effects of Price on Alcohol Consumption and Alcohol-related Problems.” Alcohol Research & Health 26:22-34.

Cook, P. and Moore, M. (1993a). "Taxation of Alcoholic-Beverages." In: Hilton, M.E., and Bloss, G., [eds.] Economics and the Prevention of Alcohol-Related Problems. NIAAA Research Monograph No. 25. Rockville MD: National Institute on Alcohol Abuse and Alcoholism. 33-58.

Cook, P., and Moore, M. (1993b) "Violence Reduction through Restrictions on Alcohol Availability." Alcohol Health & Research World 17(2): 151-156.

Cook, P. and Moore, M. (2000) “Alcohol” in AJ Culyer and JP Newhouse [eds.] Handbook of Health Economics New York: North-Holland 1629-1673.

Cook, P. and Moore, M. J. (2002). "The Economics of Alcohol Abuse and Alcohol-Control Policies." Health Affairs 21(2): 120 - 133.

Corman H., and Mocan, N. (2000) “A time series analysis of crime, deterrence, and drug abuse in New York City.” American Economic Review 90: 584–604.

Di Tella, R., and Schargrodsky, E. (2004) “Do Police Reduce Crime? Estimates Using the Allocation of Police Forces after a Terrorist Attack.” American Economic Review 94: 115–33.

Dobkin, C. and Carpenter, C. (2008) “The Drinking Age, Alcohol Consumption, and Crime.” mimeo.

Doob, A. N. and Webster, C. M. (2003) “Sentence Severity and Crime: Accepting the Null Hypothesis” in Michael Tonry (Ed) Crime and Justice: A Review of Research, 30:143-195. Chicago: University of Chicago Press

Evans, W. and E.G. Owens (2007) “COPS and Crime” Journal of Public Economics 91:181-201.

Greenfeld, L. A. (1998) Alcohol and Crime: An Analysis of National Data on the Prevalence of Alcohol Involvement in Crime. National Institute of Justice Research Report # NCJ168632

Hansen, G. D. and Imrohoroglu, A. (1992) “The Role of Unemployment Insurance in and Economy with Liquidity Constraints and Moral Hazard” The Journal of Political Economy 100(1): 118-142.

Holmstrom, B. (1979) “Moral Hazard and Observability” The Bell Journal of Economics 10(1): 74-91.
Holzer, H., Quigley, J. and Raphael, S. (2003) “Public transit and the spatial distribution of minority employment: Evidence from a natural experiment” Journal of Policy Analysis and Management 22(3): 415-441.
Joksch, H. C., and Jones, R. K. (1993). “Changes in the Drinking Age and Crime.” Journal of Criminal Justice 21: 209-221.
Kenkel, D. (1996). "New Estimates of the Optimal Tax on Alcohol," Economic Inquiry 34: 296-319.
Kenkel, D. (1993) “Drinking, driving and deterrence: The effectiveness and social costs of alternative policies.” Journal of Law and Economics 36(2):877–914.
Kenkel, D. and Manning, W. (1996). “Perspectives on Alcohol Taxation.” Alcohol Health & Research World 20(4): 230-238.
Klick, J. and Stratmann, T. (2003) “The Effect of Abortion Legalization on Sexual Behavior: Evidence from Sexually Transmitted Diseases.” The Journal of Legal Studies, 32(2): 407-434.
Klick, J. and Tabarrok, A. (2005) "Using Terror Alert Levels to Estimate the Effect of Police on Crime," Journal of Law & Economics 48(1): 267-279
Lee, D., and McCrary, J., (2007) “Crime, Punishment, and Myopia” NBER working paper 11491.
Levitt, S. (2002) "Deterrence” In James Q. Wilson and Joan Petersillia [Eds.] Crime: Public Policies for Crime Control Oakland: ICS Press.
Levitt, S. (2002) "Using Electoral Cycles in Police Hiring to Estimate the Effects of Police on Crime: Reply." American Economic Review, 92(4): 1244-1250.
Leung, S. F., and Phelps, C.E. (1993) “My kingdom for a drink . . .? A review of estimates of the price sensitivity of demand for alcoholic beverages.” In: Hilton, M.E., and Bloss, G., [eds.] Economics and the Prevention of Alcohol-Related Problems. NIAAA Research Monograph No. 25. Rockville MD: National Institute on Alcohol Abuse and Alcoholism. pp. 1–32.
Manning, W., Keeler, E., Newhouse, J., Sloss, E., and Wasserman J. (1991) The Costs of Poor Health Habits Cambridge: Harvard University Press.
Markowitz, S., and Grossman, M. (2000) “The effects of beer taxes on physical child abuse.” Journal of Health Economics. 19(2) 271-282.
Miczek, K. A., DeBold, J. F., Haney, M., Tidey, J., Vivian, J. and Weerts, E. (1994) “Alcohol, Drugs of Abuse, Aggression, and Violence” in A. Reiss, Jr. and J. Roth [Eds.] Understanding and Preventing Violence Volume 3: Social Issues. Washington, DC: National Academy Press. 377-570.
Norton, E., Lindroth, R., and Ennett, S. (1998). “Controlling for the endogeneity of peer substance use on adolescent alcohol and tobacco use.” Health Economics. 7:439–453.
O’Malley, P. M., and Wagenaar, A. C. (1991) “Effects of minimum drinking are laws on alcohol use, related behaviors and traffic crash involvement among American youth: 1976-1987.” Journal of Studies on Alcohol. 52(5):478-491
Owens, E. G. (2009) “More Time, Less Crime? Estimating the Incapacitative Effect of Sentence Enhancements” Journal of Law and Economics 52(3)
Pauly, M. V. (1974) “Overinsurance and Public Provision of Insurance: The Roles of Moral Hazard and Adverse Selection” The Quarterly Journal of Economics 88(1):44-62.

Perrins, G. and Nilsen, D. (2006) “Industry dynamics in the Washington, DC, area: has a second job core emerged?” Monthly Labor Review Online 129(12): 3-20.
Quinlan K.P., Brewer R.D., Siegel P., Sleet D.A., Mokdad A.H., Shults R.A., and Flowers N. (2005) “Alcohol-impaired driving among U.S. adults, 1993-2002.” American Journal of Preventive Medicine. 28(4):345-350.
Raphael, S. and Ludwig, J. (2003) "Prison Sentence Enhancements: The Case of Project Exile." In Jens Ludwig and Philip J. Cook [Eds.] Evaluating Gun Policy, Washington, DC: Brookings Institution Press. pp. 251-286.
Saffer, H., and Grossman, M. (1987) "Drinking Age Laws and Highway Mortality Rates: Cause and Effect." Economic Inquiry 25(3): 403-417.
Sood, N., and Goldman, D. (2006) "HIV Breakthroughs and Risky Sexual Behavior," The Quarterly Journal of Economics, 121(3):1063-1102.

**Figures:**

*Figure 1: Alcohol Venders and Metro Stations in Washington, DC*

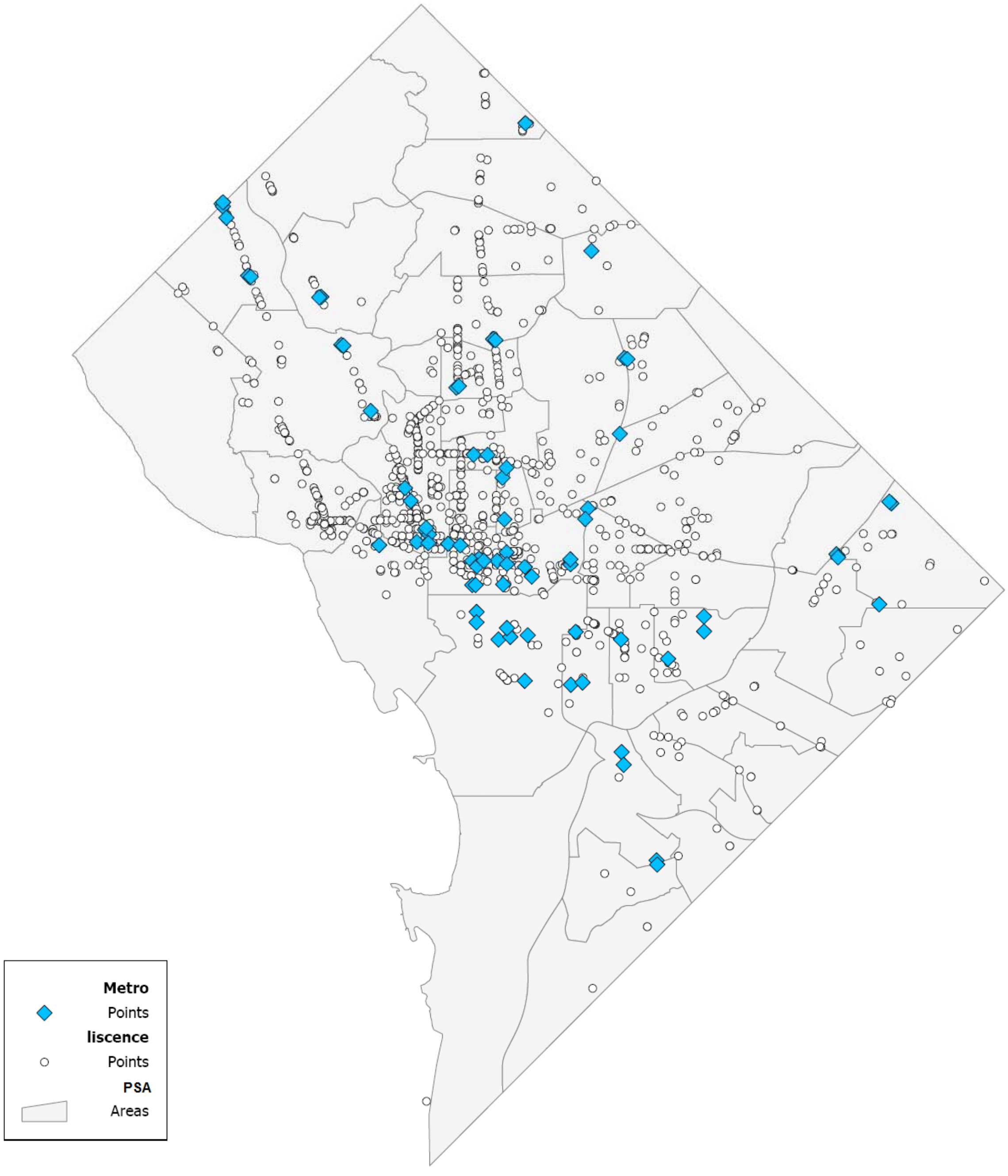


*Figure 2: Ridership on Thursdays, Fridays, and Saturdays.*

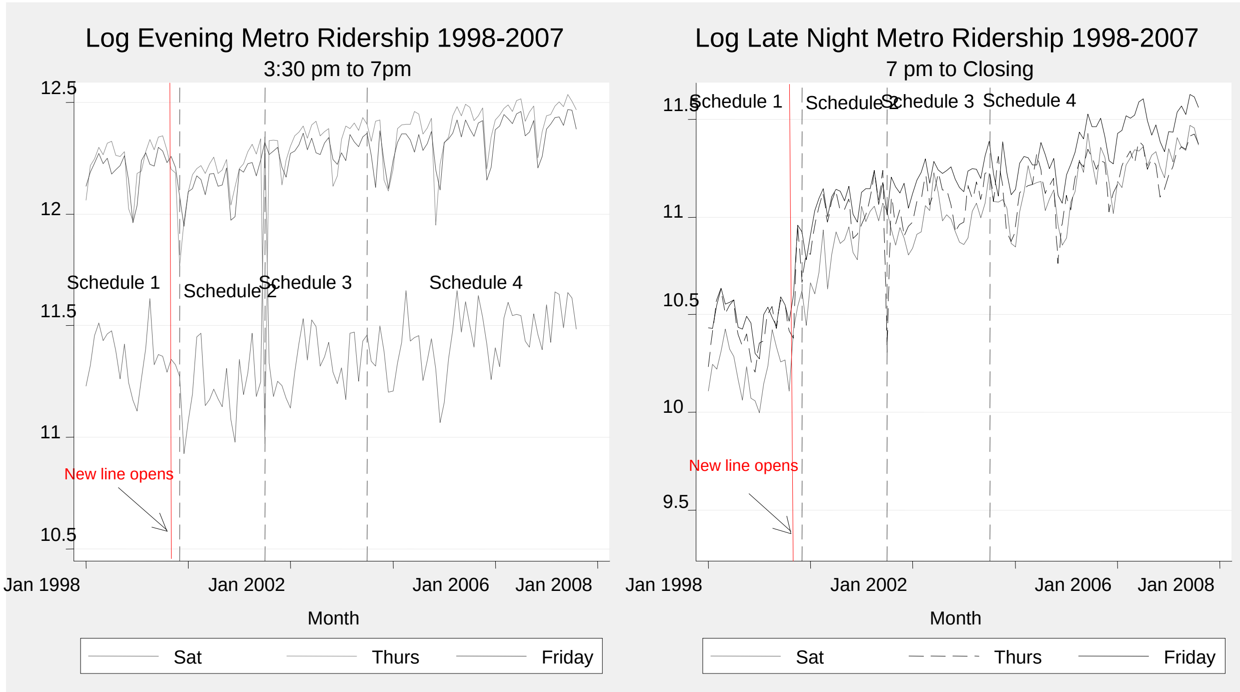



*Figure 3: Ridership on Wednesdays and Fridays Relative to Thursday Levels.*

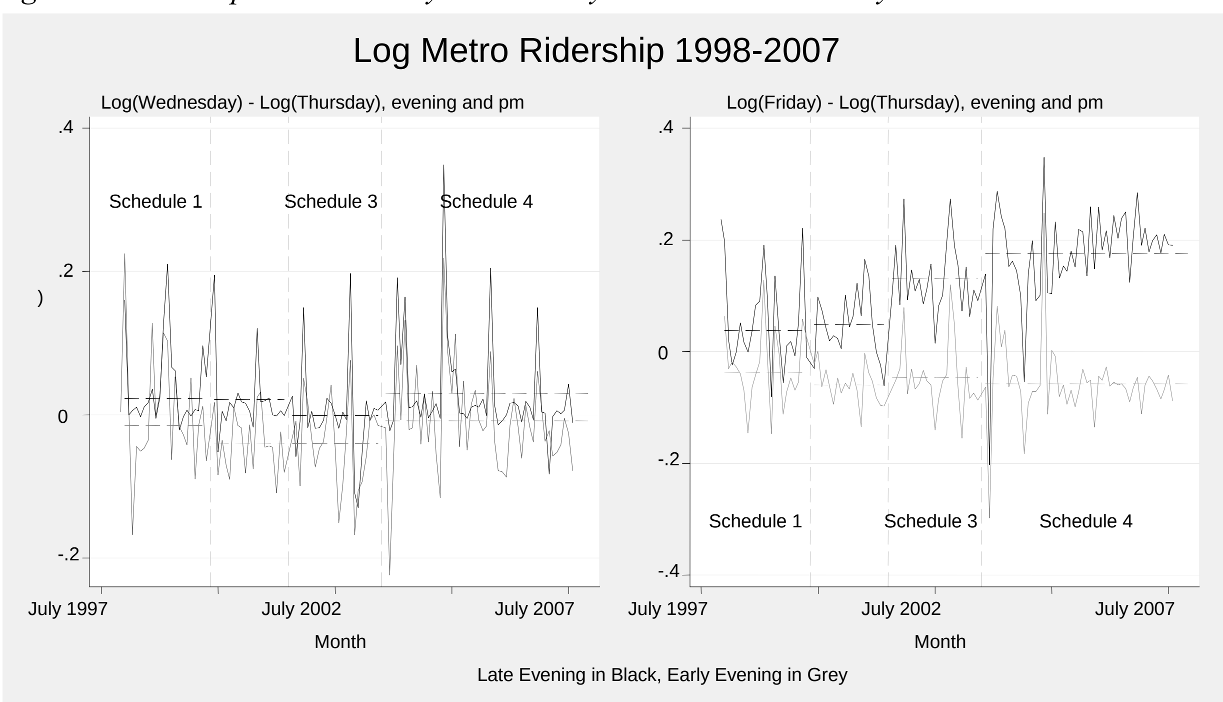


*Figure 4: Mean Monthly Arrests by Day of the Week and Time of Day, Washington DC 1998-2007*

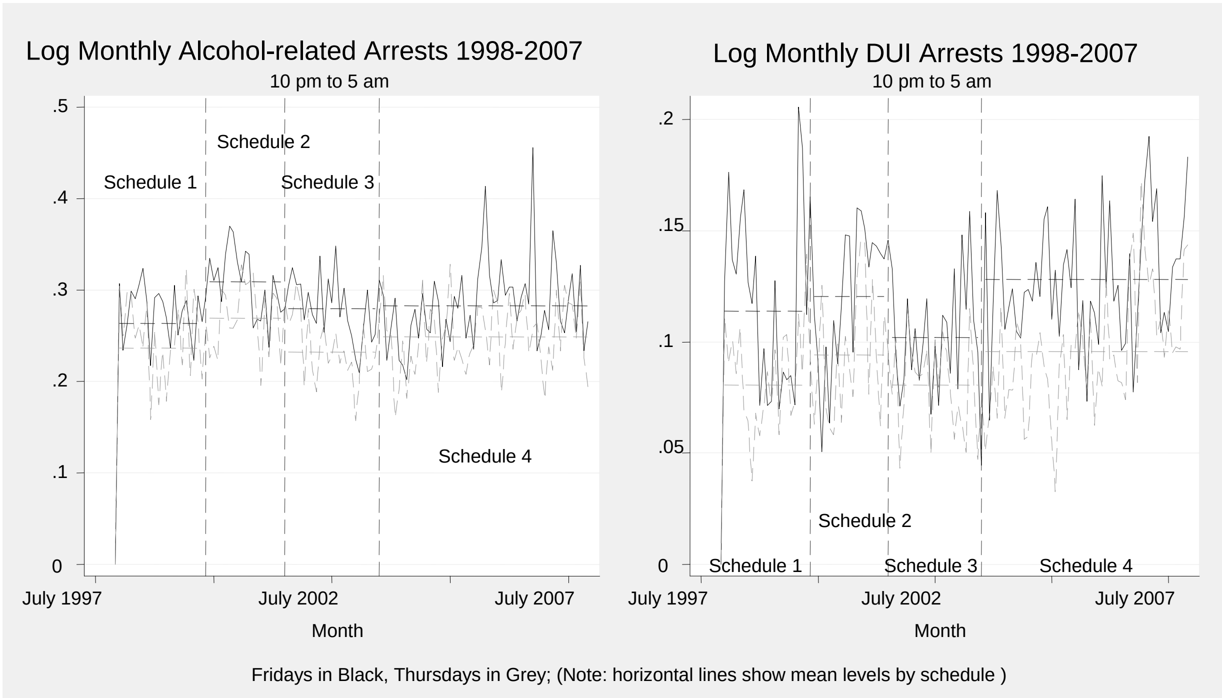



*Figure 5: The difference between outcomes on Fridays relative to Thursdays in areas with more than and fewer than 20 bars.*

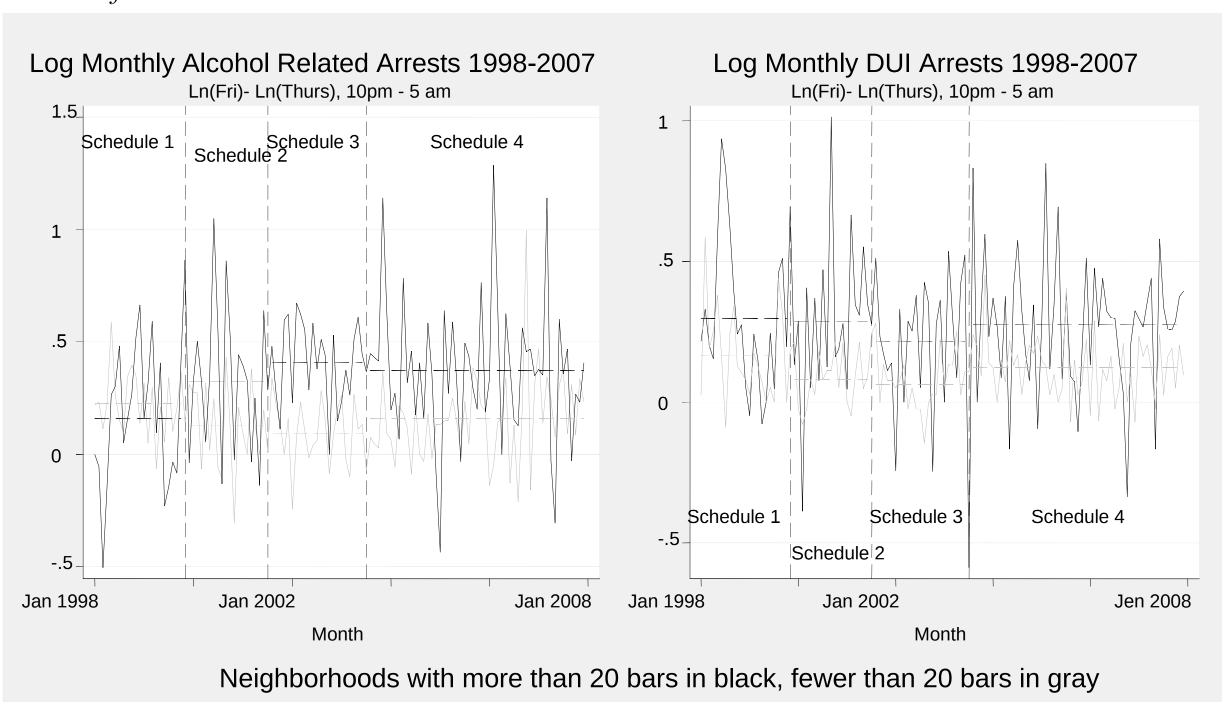
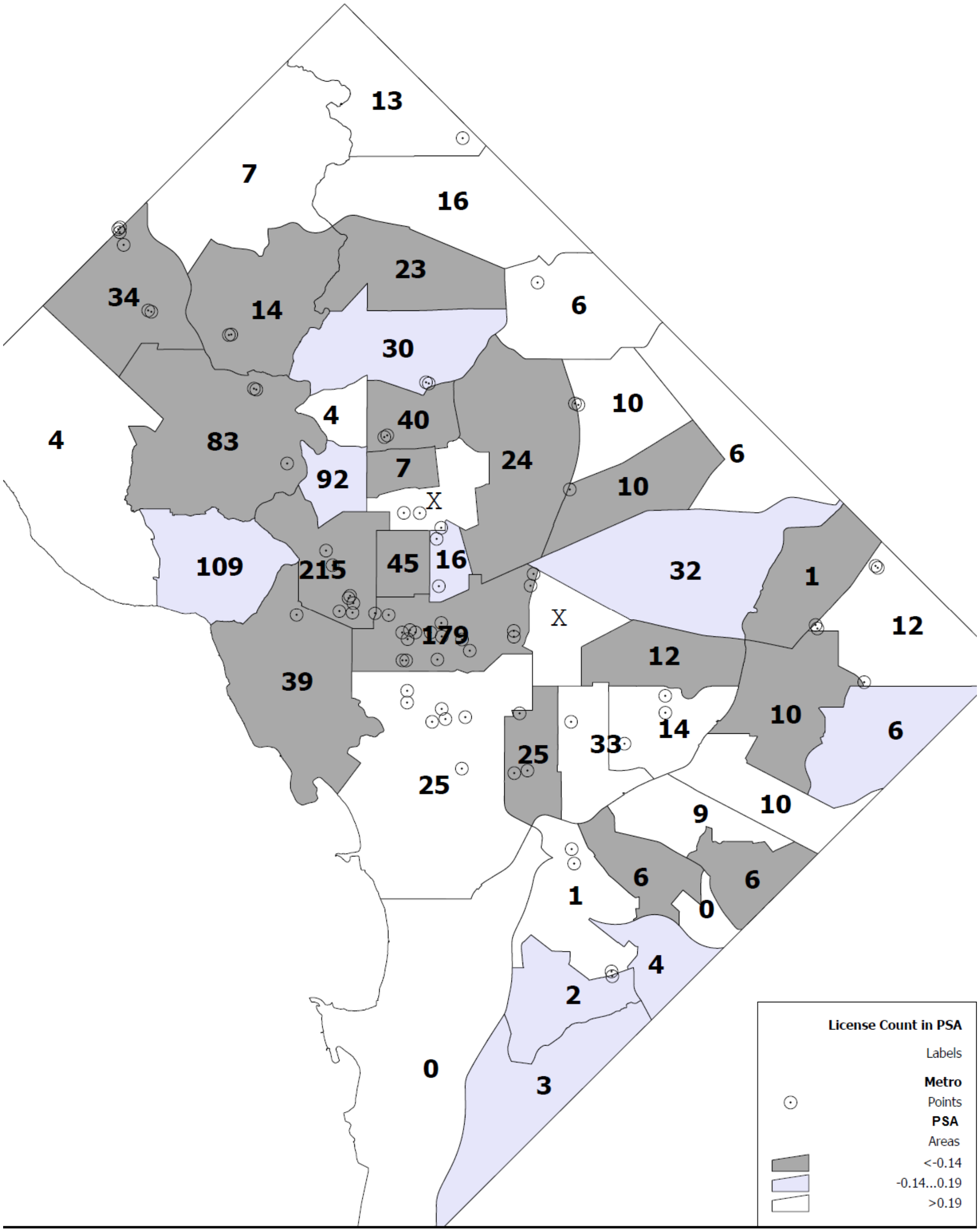
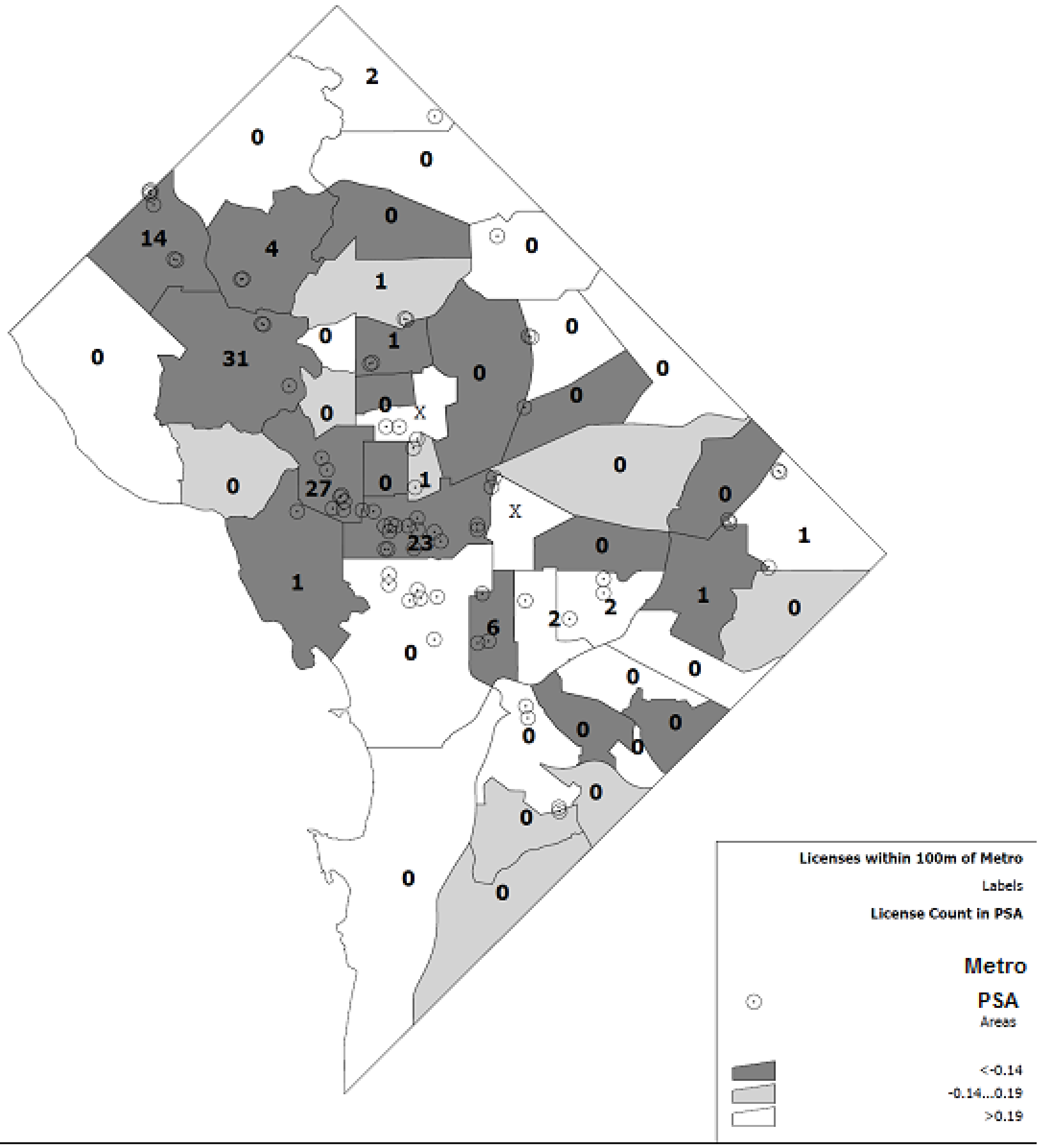


Figure 6: *Distribution of Marginal Effects Across PSAs, by Number of Alcohol Venders within the PSA.*




Note: U street and H street corridors, excluded from analysis, are marked with an "X"

*Figure 7: Distribution of Marginal Effects Across PSAs, by Number of Alcohol Venders within 100m of Metro Station*




Note: U street and H street corridors, excluded from analysis, are marked with an "X"

**Tables:**

*Table 1 PSA Characteristics (n=44)*

| | Mean | *Std Dev* |
|---|---|---|
| On site Licenses | 18.98 | *39.44* |
| On site Licenses within 100m of Metro station | 2.45 | *7.23* |
| On site Licenses within 400m of Metro station | 10.54 | *30.99* |
| On site Licenses within 800m of Metro station | 14.23 | *35.80* |
| Metro Station in PSA | 0.478 | *0.505* |
| Population under 18 | 2,509 | *1,444* |

*Table 2: Arrests by Neighborhood*

| | Week, Evening & Late Night (n=73,218) | | Thurs-Sat, Evening & Late Night (n=31,420) | | Fri-Sat, Evening & Late Night (n=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* |
| Ln (Alcohol related arrests +1) | 0.503 | *0.618* | 0.575 | *0.661* | 0.593 | *0.669* |
| Ln(DUI arrests + 1) - Ln(Alcohol related arrests +1) | -0.397 | *0.634* | -0.428 | *0.674* | -0.428 | *0.679* |
| Any Drunk & Disorderly arrests | 0.269 | *0.444* | 0.322 | *0.467* | 0.336 | *0.472* |
| Ln (Drunk & Disorderly arrests +1) | 0.270 | *0.499* | 0.338 | *0.556* | 0.354 | *0.567* |
| Any Non-Alcohol Related arrests | 0.604 | *0.489* | 0.631 | *0. 482* | 0.625 | *0.484* |
| Ln(Non-Alcohol Related arrests+1) | 0.753 | *0.754* | 0.806 | *0.772* | 0.785 | *0.757* |

*Table 3: Frequency of Monthly Arrests per PSA, Friday and Saturday Late Nights, 1999-2007*

| | **Arrest Type** | | |
|---|---|---|---|
| **Number of Arrests** | DUI | Drunk and Disorderly | Alcohol Related |
| **0** | 7,553 | 6,850 | 4,708 |
| **1** | 1,727 | 1,825 | 2,387 |
| **2** | 550 | 719 | 1,298 |
| **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 |

*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 | -0.003 | 0.001 | -0.004 |
| | [0.021] | [0.008] | [0.007] | [0.008] |
| log (Alcohol related arrests +1) | 0.057* | 0.004 | 0.002 | -0.010 |
| | [0.027] | [0.015] | [0.010] | [0.011] |
| Any DUI arrests | 0.070** | -0.0121+ | -0.009 | -0.004 |
| | [0.017] | [0.006] | [0.006] | [0.006] |
| log (DUI arrests + 1) | 0.080** | -0.010 | -0.007 | -0.004 |
| | [0.017] | [0.008] | [0.007] | [0.007] |
| Days included | Fri & Sat | Fri & Sat | Thurs -Sat | Thurs -Sat |
| Times of Day included | Late | Late & PM | Late | Late & PM |
| 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 |

+ significant at 10%; * significant at 5%; ** significant at 1%

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.

*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 Other arrests | log (Other related arrests +1) |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Hours | 0.00456 | -0.00697 | -0.0125 | -0.0337+ | 0.0267 | 0.0014 | -0.0463** | 0.0375+ | **-0.0380+** | -0.0444 |
| | [0.0180] | [0.0155] | [0.0186] | [0.0198] | [0.0227] | [0.00990] | [0.0164] | [0.0206] | **[0.0201]** | [0.0345] |
| Hours*On site Licenses | -0.000511 | -0.00067 | **0.000587+** | **0.00162**** | **-0.00229**** | 0.000178 | **0.00264**** | **-0.0026**** | 0.000808 | 0.0014 |
| | [0.000636] | [0.000509] | **[0.000340]** | **[0.000362]** | **[0.000620]** | [0.000268] | **[0.000868]** | **[0.0004]** | [0.000912] | [0.00154] |
| Hours*# within 100 meters | **-0.00316+** | -0.00238 | 0.00232 | 0.00351 | **-0.00589*** | **-0.00322**** | 0.000563 | **-0.00318+** | 0.00282 | 0.00157 |
| | **[0.00174]** | [0.00272] | [0.00426] | [0.00285] | **[0.00264]** | **[0.000875]** | [0.00238] | **[0.00161]** | [0.00549] | [0.00647] |
| Hours*# within 400 meters | -0.000705 | -0.00222 | -0.000313 | -0.00264 | 0.000423 | 0.000964 | -0.00164 | 0.00298 | 0.00307 | 0.00648 |
| | [0.00137] | [0.00232] | [0.00199] | [0.00168] | [0.00240] | [0.000828] | [0.00179] | [0.00189] | [0.00299] | [0.00522] |
| Hours*# within 800 meters | 0.00155 | 0.00302 | -0.000504 | 0.00113 | 0.00189 | -0.000545 | -0.000947 | 0.000258 | **-0.00431+** | -0.00736 |
| | [0.00140] | [0.00211] | [0.00144] | [0.00146] | [0.00222] | [0.000787] | [0.00188] | [0.00196] | **[0.00256]** | [0.00488] |
| Hours*Metro within borders | -0.000607 | 0.00419 | -0.00672 | -0.0234 | 0.0276 | 0.00476 | -0.0088 | -0.0044 | 0.0172 | 0.0282 |
| | [0.0131] | [0.0132] | [0.0178] | [0.0179] | [0.0200] | [0.00756] | [0.0171] | [0.0135] | [0.0183] | [0.0322] |
| Days included | Thurs - Sat | Thurs - Sat | Thurs - Sat | Thurs - Sat | Thurs - Sat | All | All | All | Thurs - Sat | Thurs - Sat |
| Times of day included | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM |
| $R^2$ | 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 |

+ significant at 10%; * significant at 5%; ** significant at 1%

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

All models include PSA*Schedule fixed Effects, PSA*TOD Effects, PSA*DOW Effects, PSA*Sched*TOD, PSA*Sched*DOW, PSA*TOD*DOW , PSA fixed effects, year fixed effects and month of the year fixed effects.

*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 | -0.0078 | -0.00066 | -0.0038 | -0.0009031 | -0.00699 | -0.0256927 | **-0.0383*** |
| | [0.0141] | [0.0135] | [0.0179] | [0.0220] | 0.011113 | [0.0133] | 0.0139938 | [0.0159] |
| Hours*On site Licenses | 0.000667 | 0.000637 | **0.000723**** | 0.00049 | 0.000519 | 0.000447 | **0.00186**** | **0.00236*** |
| | [0.000684] | [0.000912] | [0.000232] | [0.000776] | [0.000625] | [0.00105] | [0.000302] | [0.000992] |
| Hours*# within 100 | **-0.00301+** | -0.00238 | -0.00529 | -0.004 | **-0.00219+** | -0.00188 | **-0.00312**** | -0.00134 |
| | [0.00167] | [0.00192] | [0.00383] | [0.00389] | [0.00116] | [0.00136] | [0.00103] | [0.00195] |
| Hours*# within 400 | 0.000238 | 0.00153 | **0.00324+** | 0.00379 | **0.00162+** | **0.00297*** | **0.00220+** | -0.000486 |
| | [0.00113] | [0.00160] | [0.00185] | [0.00240] | [0.000945] | [0.00121] | [0.00111] | [0.00156] |
| Hours*# within 800 | -0.00032 | -0.00145 | **-0.00283*** | **-0.00396+** | -0.00159 | -0.00262 | **-0.00321**** | -0.00187 |
| | [0.00125] | [0.00178] | [0.00120] | [0.00208] | [0.00110] | [0.00161] | [0.00105] | [0.00178] |
| Hours*Metro within | 0.0118 | 0.00771 | 0.0188 | 0.0285 | 0.00627 | 0.00686 | 0.0154 | 0.00268 |
| | [0.0143] | [0.0126] | [0.0188] | [0.0217] | [0.00914] | [0.00988] | [0.0142] | [0.0183] |
| Days included | Wed-Thurs | Wed-Thurs | Wed-Thurs | Wed-Thurs | All | All | All | All |
| Times of day included | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM | Late & PM |
| $R^2$ | 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 |

+ significant at 10%; * significant at 5%; ** significant at 1%
Heteroskedasticity robust standard errors clustered at the PSA level in brackets.

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)

*Table 7: Fatal Crashes in Maryland, Virginia, and Washington, DC.*

| | Alcohol related Accidents | | | | Non-alcohol related accidents | | | |
|---|---|---|---|---|---|---|---|---|
| | Ln(Accidents+1) | | Any accidents | | Ln(Accidents+1) | | Any accidents | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Hours | 0.0231 | 0.0181 | 0.0222 | 0.0262 | 0.00788 | -0.0135 | -0.00693 | -0.0177 |
| | [0.0192] | [0.0236] | [0.0188] | [0.0209] | [0.0306] | [0.0238] | [0.0221] | [0.0217] |
| Hours * MD | | 0.00615 | | -0.00593 | | -0.0144 | | -0.0181 |
| | | [0.0453] | | [0.0432] | | [0.0742] | | [0.0524] |
| Hours * VA | | 0.00883 | | -0.00609 | | 0.0785 | | 0.0504 |
| | | [0.0428] | | [0.0420] | | [0.0591] | | [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 | | | |
|---|---|---|---|---|---|---|---|---|
| | Ln(Accidents+1) | | Any accidents | | Ln(Accidents+1) | | Any accidents | |
| | VA | MD | VA | MD | VA | MD | VA | MD |
| | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
| Hours | 0.0669 | -0.00592 | 0.0606 | 0.00881 | 0.0906 | -0.119 | 0.0936* | -0.0456 |
| | [0.0577] | [0.0503] | [0.0447] | [0.0427] | [0.0811] | [0.0806] | [0.0455] | [0.0462] |
| Hours * DCMSA | -0.0349 | 0.0368 | -0.0329 | 0.0166 | -0.0345 | 0.0998 | -0.0688 | 0.0115 |
| | [0.0674] | [0.0623] | [0.0568] | [0.0555] | [0.0959] | [0.104] | [0.0591] | [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.

## Appendix:

*Appendix Table A1: Effect of Metro Access on Metro Ridership: DV=Log(One Way Trips)*

| | Ln(Metro Hours) | | | | | | Ln(Metro Hours) | |
|---|---|---|---|---|---|---|---|---|
| Hours | 0.081 | 0.112 | 0.460 | 0.503 | 0.074 | -0.046 | 0.46 | . |
| | [0.017] | [0.023] | [0.083] | [0.097] | [0.018] | [0.092] | [0.111] | . |
| Hours * Sched 2 | | -0.017 | | -0.016 | | 0.088 | | 0.042 |
| | | [0.045] | | [0.044] | | [0.018] | | [0.081] |
| Hours * Sched 3 | | -0.033 | | -0.022 | | 0.102 | | 0.056 |
| | | [0.023] | | [0.021] | | [0.089] | | [0.02] |
| Hours * Sched 4 | | -0.032 | | 0.0017 | | 0.12 | | 0.076 |
| | | [0.022] | | [0.018] | | [0.090] | | [0.019] |
| $R^2$ | 0.83 | 0.83 | 0.83 | 0.83 | 0.82 | 0.82 | 0.82 | 0.82 |
| N | 7,620 | 7,620 | 7,620 | 7,620 | 5,715 | 5,715 | 5,715 | 5,715 |
| TOD | All | All | All | All | No Morning | No Morning | No Morning | No Morning |

Robust standard errors in brackets.
All models include Sched*DOW, Sched*TOD, TOD*DOW, year, and month fixed effects.

*Appendix Table A2: The Effect of Metro Access Drunk and Disorderly Conduct Arrests.*

| Dependent Variable | Any Drunk and Disorderly arrests | ln(Disorder arrests + 1) | Any Drunk and Disorderly arrests | ln (Disorder arrests + 1) |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Hours | -0.0101 | -0.0276* | -0.0286 | -0.0457* |
| | [0.00927] | [0.0128] | [0.0170] | [0.0196] |
| Hours*On site Licenses | | | 0.00111** | 0.000912+ |
| | | | [0.000388] | [0.000463] |
| Hours*# within 100 meters | | | 0.00371 | 0.00460+ |
| | | | [0.00353] | [0.00256] |
| Hours*# within 400 meters | | | -0.00271+ | -0.00489** |
| | | | [0.00161] | [0.00150] |
| Hours*# within 800 meters | | | 0.00117 | 0.00364* |
| | | | [0.00114] | [0.00135] |
| Hours*Metro within borders | | | 0.00667 | -0.0023 |
| | | | [0.0177] | [0.0220] |
| $R^2$ | 0.262 | 0.344 | 0.263 | 0.344 |
| N | 31,420 | 31,420 | 31,420 | 31,420 |

+ significant at 10%; * significant at 5%; ** significant at 1%

Heteroskedasticity robust standard errors clustered at the PSA level in brackets.
All models include PSA*Schedule fixed Effects, PSA*TOD Effects, PSA*DOW Effects, PSA*Sched*TOD, PSA*Sched*DOW, PSA*TOD*DOW , PSA fixed effects, year fixed effects and month of the year fixed effects.

**Appendix Table A3: Fatal Traffic Accidents**

| | Whole Week, Evening & PM (n=2,884) | | | | | |
|---|---|---|---|---|---|---|
| | Washington, DC | | Maryland | | Virginia | |
| | Mean | *Std Dev* | Mean | *Std Dev* | Mean | *Std Dev* |
| Any Fatal Accident | 0.130 | *0.337* | .302 | *.459* | .237 | *.426* |
| log (Fatal Accident + 1) | 0.209 | *0.598* | .495 | *.861* | .351 | *.705* |
| Any Alcohol Related Accident | 0.026 | *0.160* | .113 | *.317* | .119 | *0.324* |
| log (Alcohol Related Accident + 1) | 0.028 | *177* | .108 | *.322* | .109 | *.316* |
| Any Non-Alcohol Related Accident | 035 | *0.184* | .246 | *.431* | .152 | *.359* |
| log (Non-Alcohol Related Accident + 1) | 0.041 | *0.242* | *0.334* | *.671* | .194 | *.507* |
| | Thurs-Sat, Evening & PM (n=1,236) | | | | | |
| | Washington, DC | | Maryland | | Virginia | |
| | Mean | *Std Dev* | Mean | *Std Dev* | Mean | *Std Dev* |
| Any Fatal Accident | 0.171 | *0.376* | 0.487 | *0.500* | 0.502 | *0.500* |
| log (Fatal Accident + 1) | 0.292 | *0.712* | 0.896 | *10.06* | 0.967 | *10.12* |
| Any Alcohol Related Accident | 0.037 | *0.189* | 0.266 | *0.442* | 0.339 | *0.473* |
| log (Alcohol Related Accident + 1) | 0.041 | *0.218* | 0.280 | *0.507* | 0.386 | *0.602* |
| Any Non-Alcohol Related Accident | 0.042 | *0.203* | 393 | *0.489* | 0.363 | *0.481* |
| log (Non-Alcohol Related Accident + 1) | 0.050 | *0.266* | 0.567 | *0.806* | 0.533 | *0.802* |
| | Fri-Sat, Evening & PM (n=824) | | | | | |
| | Washington, DC | | Maryland | | Virginia | |
| | Mean | *Std Dev* | Mean | *Std Dev* | Mean | *Std Dev* |
| Any Fatal Accident | 0.198 | *0.398* | 0.525 | *0.500* | 0.534 | *0.499* |
| log (Fatal Accident + 1) | 0.345 | *0.770* | 1.00 | *1.10* | 1.06 | *1.16* |
| Any Alcohol Related Accident | 0.0390 | *0.193* | 0.305 | *0.461* | 0.382 | *0.486* |
| log (Alcohol Related Accident + 1) | 0.044 | *0.231* | 0.329 | *0.543* | 0.447 | *0.641* |
| Any Non-Alcohol Related Accident | 0.048 | *0.215* | 0.427 | *0.495* | 0.394 | *0.489* |
| log (Non-Alcohol Related Accident + 1) | 0.059 | *0.297* | 0.629 | *0.838* | 0.581 | *0.825* |

*Figure A1: DUI Arrests By hour and Day of the Week*

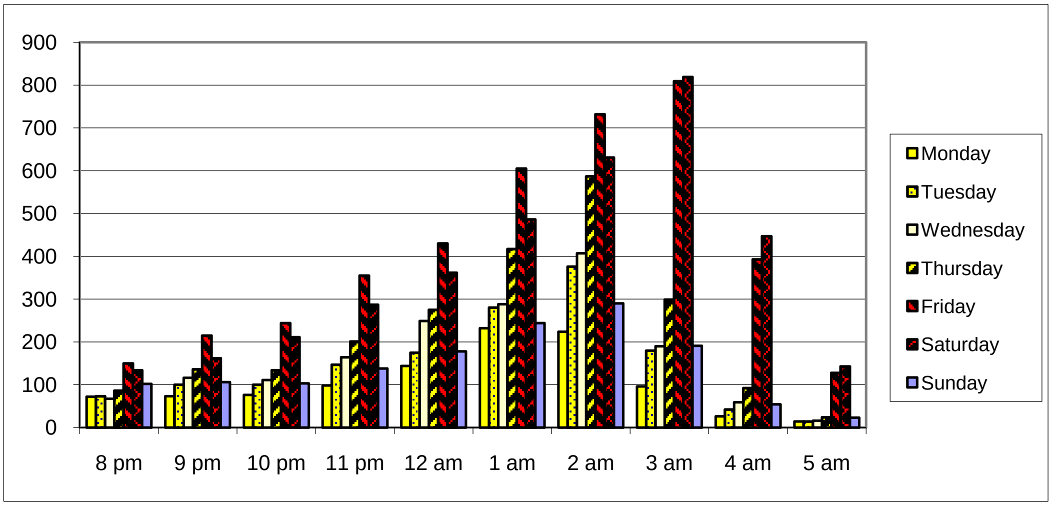



*Figure A2: Alcohol Related Arrests By hour and Day of the Week*