Ridesharing, Moral Hazards, and Alcohol Consumption

Jacob Burgdorf, Conor Lennon, and Keith Teltser*

Abstract

We ask if the introduction of ridesharing services, such as Uber, increases alcohol consumption. Identification comes from variation in the timing of Uber's introduction across US counties and Metropolitan Statistical Areas. We find that Uber's introduction is associated with positive but generally statistically insignificant increases in alcohol consumption. The exception is that we find Uber's entry is associated with a significant increase in the number of instances of binge drinking per month, particularly among younger females. We also find that Uber's introduction is associated with increases in employment and earnings for bar and restaurant employees, but only in certain specifications. Our findings have potentially important implications for the role of ridesharing in reducing harms associated with intoxicated driving.

Keywords: Uber, ridesharing, DUI, alcohol consumption, moral hazard

JEL: L62, L66, I12, K42, R41

1 Introduction

The introduction of ridesharing services, such as Uber and Lyft, has sparked research into their effects on local economic conditions, entrepreneurial activity, motor vehicle accidents and fatalities, arrests for intoxicated driving, and crime (Brazil and Kirk, 2016; Martin-Buck, 2017; Peck, 2017; Greenwood and Wattal, 2017; Dills and Mulholland, 2018; Burtch et al., 2018). The literature finds evidence that ridesharing services reduce motor vehicle accidents, vehicular fatalities, alcohol-related assault, and arrests for intoxicated driving.[1]

However, Dills and Mulholland (2018) note that the advent of ridesharing services may "increase alcohol consumption and other risky behavior."[2] If true, increased consumption could

*University of Louisville, Corresponding author: keith.teltser@louisville.edu

[1]See https://www.nytimes.com/2017/04/07/business/uber-drunk-driving-prevention.html for a brief and accessible overview of the effects of Uber on DUIs and traffic incidents.

[2]This echoes the work of Jackson and Owens (2011) who examine how expansion of late-night public transportation (specifically, the DC metro) affects alcohol consumption and related crime.

at least partially offset the potential reductions in harm from ride-sharing. Specifically, if social drinkers were constrained by the availability of a safe ride home prior to the advent of ridesharing, then ridesharing will cause an increase in the frequency and quantity of alcohol consumption. Moreover, because alcohol consumption is often a social activity, ridesharing may induce additional drinking by non-riders leading to an increase in alcohol-related harms.[3] Because of the competing safety and consumption effects, the overall effect of ridesharing on alcohol-related harms is ambiguous.

For this reason, we ask if the introduction of ridesharing services, such as Uber, affects the frequency and quantity of alcohol consumption. To do so, we examine self-reported alcohol consumption from the Behavioral Risk Factor Surveillance System (BRFSS) and the earnings of workers in establishments serving alcohol from the Quarterly Census of Employment and Wages (QCEW). We first use a difference-in-difference empirical strategy where identification comes from variation in the existence and timing of Uber's introduction across US counties and Metropolitan Statistical Areas (MSAs). We focus on Uber's taxi-like service UberX, as opposed to their limousine-like services such as Uber Black (for the purposes of the paper we treat UberX and Uber as synonymous). Using QCEW data, we find that Uber's introduction is associated with up to a 5.5% increase in employment and a 6.2% increase in total wages at drinking establishments. However, these estimates are sensitive to specification. We also use an event study approach to complement our difference-in-difference findings. The advantage of the event study is that it focuses on the period shortly before and after Uber's entry/introduction to an area. In these event study estimates, we find stronger evidence to support increased wages and employment at bars and restaurants after Uber's introduction. Using BRFSS data, we find that Uber's introduction is associated with an increase of 0.25 to 0.32 in the instances of binge drinking frequency per month among younger BRFSS respondents.[4]

Our findings suggest that existing studies might be underestimating the effect of Uber on road safety for a *given* level of alcohol consumption. If we are only concerned about overall measures of motor vehicle fatalities, DUIs, and other crimes, then there's no issue with the methods employed

[3]The expected utility from a "night out" can be viewed as an increasing function of the number of other people and their consumption of alcohol (see Jackson and Owens (2011) for more on this).

[4]The Center for Disease Control defines binge drinking as drinking five or more drinks in a single occasion for men or four or more drinks in a single occasion for women. See https://www.cdc.gov/alcohol/data-stats.htm.

by existing studies. On the other hand, existing approaches overlook an interesting and important question: how does ridesharing affect the occurrence of some negative outcome X per unit of alcohol consumption? If additional alcohol consumption is rational and sufficiently privately beneficial then Uber has positive welfare effects; agents can engage in a social activity that they enjoy and Uber reduces the associated (but unintentional) harms. However, the Center for Disease Control (CDC) estimates that alcohol consumption causes 88,000 deaths per year. The CDC also suggests that the cost of excessive alcohol use was $249 billion in 2010.[5] The majority of these costs are due to binge drinking and are borne by the individual (lost wages and well-being). However, 40% of the cost was borne by federal, state, and local governments (criminal justice, health care, and traffic incidents). If Uber significantly increases risky alcohol consumption among riders and non-riders, the overall welfare implications are unclear.

The paper proceeds as follows. Section 2 briefly examines the findings of the existing research on ridesharing. Section 3 explains our data and our approach to identification (Uber's expansion over space and time). Section 4 provides our main findings. Section 5 concludes.

2 Ridesharing, Alcohol Consumption, and Harm Reduction

In theory, ridesharing should be an attractive alternative to driving while inebriated. Despite this prediction, Brazil and Kirk (2016), using data from 2005 to 2014 for the 100 largest U.S. metropolitan areas, find that the arrival of Uber had "no association with the number of subsequent traffic fatalities, whether measured in aggregate or specific to drunk-driving fatalities or fatalities during weekends and holidays."

In contrast, Martin-Buck (2017), using a more comprehensive dataset, finds that "ridesharing reduces fatal alcohol-related auto accidents by 10% to 11.4%." Greenwood and Wattal (2017), using hand-collected data from the California Highway Patrol, finds that Uber's mainstream service, Uber, "'strongly and negatively affects the number of motor vehicle fatalities" but that "the time for such effects to manifest is nontrivial (upwards of 9 to 15 months)." Greenwood and Wattal claim that ridesharing reduces motor vehicle fatalities, by 3.6% to 5.6% per quarter, because it is cost-effective (as opposed to the effects being caused by increased "taxi" availability). They support

[5] See https://www.cdc.gov/features/costsofdrinking/index.html.

their argument by showing that ridesharing has no effect on traffic incidents and fatalities when "surge pricing" is in effect. However, the endogeneity of price and availability limits any strong conclusions.

Peck (2017) focuses on New York City and finds that Uber's introduction is associated with a "25-35% decrease in the alcohol-related collision rate for the affected New York City boroughs, or about 40 collisions per month." Peck's estimates come from data on the universe of alcohol-related collisions in New York maintained by the state's Department of Motor Vehicles. This allows Peck to perform a synthetic control exercise to support her main difference-in-difference estimates.

Finally, Dills and Mulholland (2018), using county-level data from 2007 to 2015, find that ridesharing is associated with a 0.7-1.6% decline in fatal traffic incidents for each additional quarter Uber is available. That is, like Greenwood and Wattal they find the effect of ridesharing on traffic incidents increases over time. They also find that ridesharing is associated with a reduction in intoxicated driving and assault but an increase in vehicle theft (the mechanism here is possibly that some Uber passengers may be leaving their own car in less secure locations overnight).[6]

Dills and Mulholland appear to be the first to consider how ridesharing services may increase the moral hazard associated with alcohol consumption. They note that ride-sharing services may, by reducing the risk of penalties and injury associated with drink driving, cause an increase in how often people "go out" and how much alcohol they consume.[7] If true, the increase in alcohol consumption could negate some or all of the potential welfare gains associated with Uber's availability.

As a first step, in this version of the paper, we focus on establishing that and quantifying how ridesharing increases the consumption of alcohol, particularly in social settings outside of the home. To do so, we show that Uber's entry into a geographic area is associated with higher levels of self-reported alcohol consumption. Increases in consumption, if caused by Uber, should be away from a given agent's home.[8] This prediction is supported by administrative data that shows increased earnings for workers at establishments that serve alcohol. Because these are generally

[6] Dills and Mulholland also explain that ridesharing may affect the "availability of victims, the cost of fleeing the scene, or increase alcohol consumption."

[7] The size of the effect on alcohol consumption could be quite large; Manning et al. (1995) finds that moderate drinkers are most sensitive to price.

[8] Although, likely not all of the increased consumption will be away from home given the tendency to "pre-game."

tipped positions, we see this as strong evidence of increases in the quantity and frequency of alcohol consumption.[9] The next section describes our data and empirical framework.

3 Data and Empirical Framework

3.1 Data

Our employment and alcohol consumption data come from the QCEW and BRFSS. The QCEW is a quarterly census of employment and wages "covering more than 95 percent of U.S. jobs, available at the county, MSA, state and national levels by industry."[10] We present selected summary statistics from a sub-sample of the QCEW in Table 1. In the table, we stratify employment, average and total wages, and establishment count data by year for North American Industry Classification System (NAICS) code 7224: "Drinking places, alcoholic beverages." Our QCEW sub-sample includes only those counties with a population of 100,000 or more. In panel (a) we present data for the county-quarter pairs in our sample where Uber was not available at any time from 2010 to 2015. In panel (b), we present the same summary statistics for counties that have Uber in a given year. In panel (c), we present summary statistics for those counties that do not have Uber in the specified year but Uber is available at some point in the sample period. That is, there are 88 county-quarter observations in 2015 because Uber was not available in these counties until after the first quarter of 2015.[11]

[9] Future revisions will attempt to reconcile the welfare impact of these findings with the literature on DUIs and traffic fatalities.

[10] See https://www.bls.gov/cew/.

[11] The panel is slightly unbalanced due to QCEW data limitations. The imbalance is not as large as it seems because n refers to county-quarter pairs.

Table 1: QCEW Sample Characteristics for "Drinking Places" (NAICS 7224-10)

	2010		2011		2012		2013		2014		2015	
Panel (a): No UberX During Sample Period	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Avg. Emp	311.56	369.58	310.68	371.72	312.03	384.07	312.72	377.55	313.90	382.26	320.38	384.26
Avg. Weekly Wages	223.63	54.93	230.46	57.07	235.04	57.68	245.82	60.79	253.88	67.28	269.65	71.66
Qtrly. Wages (in $1,000's)	1007.05	1500.91	1021.35	1514.16	1055.94	1627.60	1080.25	1605.72	1135.09	1713.92	1215.78	1774.75
Establishment Count	43.63	41.23	43.08	40.52	42.20	39.76	41.86	39.25	41.12	38.57	40.56	37.82
Average Income $	48185.54	10019.74	48740.56	10173.45	49643.37	10579.97	50498.69	10682.43	52034.94	11878.70	53808.93	12314.85
Male %	49.26	1.07	49.26	0.99	49.31	1.05	49.32	1.04	49.33	1.02	49.35	1.05
Median Age	37.35	4.54	37.68	4.56	37.75	4.59	37.92	4.79	38.06	4.85	38.20	4.94
Avg. Population	288708.77	331776.54	288503.73	330094.68	283989.48	327169.20	284133.95	326668.59	287687.00	329684.75	285923.93	327502.48
White %	81.75	11.80	81.96	11.45	82.28	11.24	81.88	11.53	81.44	12.00	81.44	11.88
Over 21 %	70.93	3.45	71.24	3.42	71.42	3.45	71.66	3.47	71.93	3.51	72.17	3.53
n	734		734		752		754		751		749	
Panel (b): UberX Available												
Avg. Emp					1417.55	2083.90	1288.96	1923.71	848.87	1302.74	771.44	1199.53
Avg. Weekly Wages					366.10	103.82	322.05	74.63	298.68	84.39	303.36	73.36
Qtrly. Wages(in $1,000's)					9182.27	16581.05	6478.70	11641.48	3805.97	7322.24	3533.40	7139.28
Establishment Count					177.85	173.90	131.65	195.08	88.49	129.22	78.12	109.52
Average Income$					66976.50	17386.31	66004.72	14762.44	62520.11	15384.35	61275.03	14762.32
Male %					48.42	1.16	48.90	0.95	49.00	0.82	49.00	0.85
Median Age					37.84	3.21	36.81	3.22	37.37	3.73	37.60	4.07
Avg. Population					1130275.13	772305.01	1117096.85	1685084.57	677870.18	974199.62	569369.41	826058.87
White %					57.19	17.23	67.98	17.58	74.65	15.51	75.42	15.23
Over 21 %					74.49	4.95	72.01	3.52	71.95	2.87	72.35	2.83
n					20		167		779		1,170	
Panel (c): UberX Not Yet Available												
Avg. Emp	696.76	1022.18	700.79	1055.84	698.20	1062.74	638.15	907.97	579.03	869.38	710.50	1270.46
Avg. Weekly Wages	256.94	60.92	260.89	63.08	267.41	62.44	272.77	62.22	268.40	71.63	275.56	76.70
Qtrly. Wages(in $1,000's)	2617.32	4874.63	2731.96	5400.52	2771.94	5390.10	2519.27	4716.72	2390.38	5552.14	3326.34	8532.59
Establishment Count	81.25	109.91	80.18	108.48	76.92	105.62	70.34	84.53	61.72	62.57	67.48	74.19
Average Income$	54513.67	12976.39	54744.65	13215.75	55965.19	13497.97	56109.76	13046.12	53287.12	10374.83	54628.18	9103.08
Male %	48.95	0.86	48.96	0.85	48.97	0.84	48.99	0.83	48.94	0.87	49.02	0.95
Median Age	36.67	3.75	36.77	3.83	37.03	3.93	37.33	4.03	37.52	4.30	37.40	3.27
Avg. Population	562335.65	809853.46	560640.18	808652.78	543732.73	798801.67	468292.01	508646.02	360337.06	311641.45	379234.73	406477.15
White %	76.18	15.23	76.13	15.12	76.50	14.91	77.25	14.35	78.08	13.77	77.17	14.58
Over 21 %	71.09	2.81	71.24	2.81	71.48	2.75	71.79	2.67	72.29	2.64	72.36	2.16
n	1,239		1,244		1,252		1,097		478		88	

QCEW data is aggregated at the county level. Therefore "*n*" refers to the number of county-quarter pairs within a given year. For instance, $n = 1,170$ in 2015 for "Uber Available" means that Uber was available in roughly 1,170/4 counties with an adjustment for the fact that some counties have only partial year county-quarter pairs. There are 3,007 counties in the U.S. and Uber operated in 309 counties by the end of 2015 (see Figure 1). Earnings and employment data are provided for NAICS 7224 "Drinking places, alcoholic beverages." Population and demographic information comes from the American Community Survey and refers to the total population for all counties entered in a given year.

The data show that the counties Uber entered earliest generally had higher wages and employment levels (at least for NAICS Code 7224). There are also more "drinking places" in counties Uber entered earliest. We augment the QCEW data with population and county-level demographic information from the American Community Survey. The counties appear to be broadly comparable. Perhaps one exception is the "White %" being significantly lower relative to other counties in the sample for the counties that Uber entered in 2012 and 2013. This likely represents the unique demographics of the large cities Uber entered first.[12]

Table 2 presents the same QCEW employment and wage statistics but for "Full Service Restaurants" (NAICS 7225-11). Again, it appears that Uber entered counties with higher employment levels and wages. These counties also had many more full service restaurants. Population and demographic information is omitted as it is the same as in Table 1.

Table 3 provides some summary statistics on alcohol consumption from BRFSS. BRFSS completes more than 400,000 adult interviews each year. According to the Centers for Disease Control and Prevention, the "Behavioral Risk Factor Surveillance System (BRFSS) is the nation's premier system of health surveys that collect state data about U.S. residents regarding their health-related risk behaviors and events, chronic health conditions, and use of preventive services. Currently, BRFSS collects data in all 50 states, the District of Columbia, and three U.S. territories."[13] We use BRFSS responses only from metro areas with a population greater than 200,000. As in Tables 1 and 2, summary statistics are stratified by year. They are also split into three panels: no UberX in the sample period, UberX available, and UberX not yet available. Because UberX began in 2012, there are no associated summary statistics for 2010 and 2011 for UberX counties. Moreover, because the BRFSS data are annual and our sample ends in 2015, there are no statistics for 2015 for counties where Uber is "not yet available." To produce these statistics, we use the BRFSS Selected Metropolitan/Micropolitan Area Risk Trends (SMART) survey data.[14] The table illustrates that self-reported alcohol consumption was broadly comparable across counties with and without Uber in the period.

[12] For example, our data suggests UberX entered only the New York Metro area (Westchester, Bronx, Kings, Queens, and so on) and the San Francisco bay area (San Francisco, Marin, Richmond, San Mateo, and so on) in 2012.

[13] See https://www.cdc.gov/brfss/factsheets/pdf/DBS_BRFSS-SMART-BRFSS_12.pdf.

[14] SMART BRFSS uses BRFSS data to provide prevalence rates for selected conditions and behaviors for cities and their surrounding counties.

Table 2: QCEW Sample Characteristics for "Full Service Restaurants" (NAICS 7225-11)

	2010		2011		2012		2013		2014		2015	
Panel (a): No UberX During Sample Period	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Avg. Emp	3200.01	4529.70	3118.78	4643.98	3285.09	4874.23	3272.61	5035.14	3361.48	5193.08	3421.19	5329.61
Avg. Weekly Wages	302.57	151.92	319.65	263.56	323.45	182.51	322.08	169.42	334.14	193.77	338.17	176.93
Qtrly. Wages(in $1,000's)	13108.35	21443.02	13054.55	22348.10	14226.33	24276.34	14399.01	25672.31	15256.10	27410.90	16269.62	29691.60
Establishment Count	157.09	226.70	151.89	225.24	157.72	233.93	154.37	236.06	155.90	238.31	155.89	240.56
n	1088		1144		1123		1166		1166		1181	
Panel (b): UberX Available												
Avg. Emp					20581.52	29342.61	17784.13	29173.09	11163.31	17683.98	9814.52	15608.76
Avg. Weekly Wages					435.50	75.05	362.47	72.37	343.94	55.35	351.83	56.61
Qtrly. Wages(in $1,000's)					140322.69	232966.60	97710.04	174472.27	56479.26	105307.51	50760.05	96835.45
Establishment Count					1223.05	1193.24	833.15	1311.53	476.07	757.67	410.46	646.95
n					20		193		881		1325	
Panel (c): UberX Not Yet Available												
Avg. Emp	8154.83	12255.77	8382.90	12783.43	8516.94	12994.54	7620.32	9007.04	6265.83	6321.88	7293.84	9196.56
Avg. Weekly Wages	303.71	50.22	309.97	49.92	318.28	46.59	320.28	44.38	320.77	43.93	327.74	44.22
Qtrly. Wages(in $1,000's)	36099.74	65787.19	37992.76	70434.08	39169.03	69904.52	34406.95	46826.74	28175.28	34900.02	34714.50	52447.68
Establishment Count	367.57	574.70	374.02	581.01	370.06	576.75	319.49	362.04	264.49	245.79	277.00	305.13
n	1413		1415		1399		1225		536		89	

QCEW data is aggregated at the county level. Therefore, "*n*" refers to the number of county-quarter pairs within a given year. Earnings and employment data are provided for NAICS 7225 "Full Service Restaurants." Population and demographic information is not provided as it is the same as in Table 1.

Uber operates in hundreds of U.S. metro areas and counties.[15] We present Uber's expansion from 2009 through the end of 2015 in Figure 1. Note that UberX is just one version of the product whereas the figure depicts date of entry of any Uber product. There are 3,007 counties in the United States.[16] Our data suggests that Uber operated in some capacity in 701 of these counties by the end of 2015. For 2009 to 2015, we use the date of entry into an area provided directly by Uber; the company provided such information on its website for many years but stopped providing this information in 2015. Uber still lists the areas in which it operates but does not provide the dates it entered the area. Therefore, for more recent entry into an area we rely on news reports of Uber's availability.

[15] See https://www.uber.com/cities/.

[16] There are a further 134 county-like entities, including 64 parishes in Louisiana, 16 boroughs in Alaska, and 42 independent cities. See https://www.usgs.gov/faqs/how-many-counties-are-there-united-states.

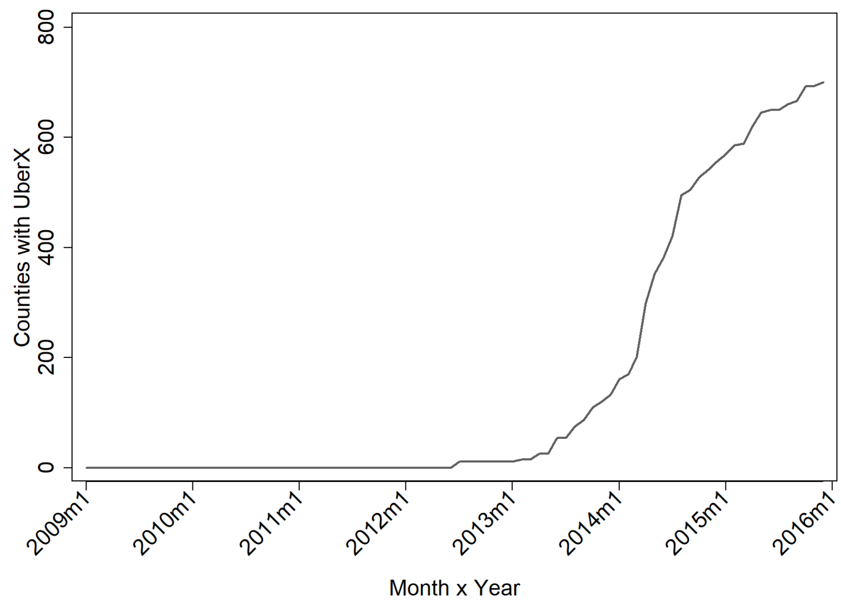

Figure 1: Expansion of Uber by county - 2009 to 2015

3.2 Estimation

We use a difference-in-difference approach that compares how some outcome of interest, Y, is affected by the introduction of Uber over time and across place. Our estimating equation is as follows;

$$Y_{it} = \alpha Uber_{it} + X_{it}\beta + \delta_i + \gamma_t + \epsilon_{it}. \tag{1}$$

In the equation, Y_{it} refers to some outcome of interest in geographic unit i (county for QCEW, metro area for BRFSS) in time period t. Our outcomes of interest vary across specifications; they include QCEW measures of employment and wages at establishments serving alcohol, and BRFSS measures of alcohol consumption. When using the QCEW data, the $Uber_{it}$ term is an indicator that equals one when Uber's service is available in county i in quarter t and zero otherwise. For the yearly BRFSS data, $Uber_{it}$ indicates the fraction of the year t Uber is available in metro area i. Depending on specification, we include controls such as aggregate-level demographics and location-specific linear time trends, X_{it}. All specifications include geographic unit fixed effects, δ_i, time period fixed effects, γ_t, and an idiosyncratic error term, ϵ_{it}.[17] If the identifying assumption

[17] We adjust our standard errors for clustering at the county level for the QCEW regressions, and at the metro area level for the BRFSS regressions.

holds - that nothing else differentially affects the outcomes of interest in locations with and without Uber over the time period studied - then α represents the causal effect of Uber's introduction on the outcome of interest, Y_{it}.

4 Main Findings

4.1 Uber's Effect on Wages and Earnings at Bars and Restaurants

Table 4 examines how Uber's introduction affected QCEW measures of employment, total wages, and average wages at "drinking establishments" (NAICS code 7224-10). The count of observations refers to the number of county-quarter pairs. The first columns of the table presents the estimates from a parsimonious specification with only county and quarter fixed effects. The coefficient estimates associated with the indicator term for Uber approximate percentage changes because the dependent variable in each case is in logs.[18] In the first column, we see Uber's introduction was associated a 5.53% increase in employment (significant at the 1% level). With a large measured increase in employment, it is unsurprising that Uber is also associated with 6.2% higher total wages (again, significant at the 1% level). The effect should be viewed as the relative increase in employment/wages compared to before Uber's introduction vesus the same change in counties without Uber service.[19] However, the estimate for average weekly wages is small and statistically insignificant. It appears that the increase in total wages is coming wholly from the increase in employment.

In the second column, we add demographic controls for income, population, median age, % over 21, % White, and % Male in a county. These county-level demographics come from the American Community Survey. The effect sizes on employment and total wages remain large and statistically significant (the estimate for average weekly wages remains small and statistically insignificant).

A threat to identification is that Uber's decision to enter a market appears to be correlated with the level of wages and/or employment in drinking establishments (see Table 1). Moreover, it could

[18]Given the estimates are small, the estimates are very close to percentage changes.

[19]Suppose county X has wages $w_{x,t}$ at time t and wages $w_{x,t+1}$ at time $t+1$. Symmetrically, suppose county Y has wages $w_{y,t}$ at time t and $w_{y,t+1}$ at time $t+1$. Our estimates imply that if Uber enters county X at time $t+1$, and not county Y, then total wages in county X will be 6.2%+y% higher at time $t+1$ where y is the percentage change in wages in county Y between time t and time $t+1$. The effect is causal if nothing else differentially affects the outcomes of interest in counties with and without Uber from 2010 to 2015.

be the case that Uber happened to enter counties that were “booming” (for lack of a better word). For that reason, we add county-specific linear time trends in the specification in the third column. Our estimates of the effect of UberX’s introduction are considerably smaller and are generally statistically insignificant. The final column includes fixed effects, controls, and the county time trends but also weights the estimates by county population. The effect of Uber availability is statistically zero for all outcomes of interest in such a specification.

For completeness, panel (d) of Table 4 presents estimates where establishment count is the dependent variable. We repeat the same four specifications as described in the preceding paragraphs. We see these estimates as examining the “extensive” margin effect of Uber’s introduction on the number of bars. We would only expect to see an effect on this margin if drinking establishments were generally operating at capacity prior to Uber’s introduction.

Table 3: BRFSS Sample Characteristics

	2010		2011		2012		2013		2014		2015	
Panel (a): No UberX During Sample Period	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Avg. Drinks per Day	2.01	1.97	2.16	2.29	2.10	2.05	2.15	2.11	2.14	2.23	2.15	2.32
Days with ≥1 Drink	2.04	2.25	2.20	2.24	2.13	2.29	2.10	2.26	2.12	2.26	2.08	2.24
Maximum Drinks in One Occasion	4.42	11.23	4.69	11.00	4.95	11.98	4.72	11.25	4.92	12.17	4.80	11.59
Instances of Binge Drinking	0.80	3.03	1.00	3.28	0.97	3.18	1.02	3.45	0.99	3.39	1.02	3.48
N	12,052		13,238		14,375		10,955		9,346		9,789	
Panel (b): UberX Available												
Avg. Drinks per Day					1.88	1.71	2.04	1.97	2.06	2.13	2.06	2.04
Days with ≥1 Drink					2.58	2.29	2.16	2.27	2.12	2.28	2.12	2.27
Maximum Drinks in One Occasion					4.19	9.67	4.66	11.36	4.63	11.35	4.64	11.34
Instances of Binge Drinking					0.75	2.31	0.92	3.13	0.92	3.22	0.94	3.27
N					370		26,422		78,781		83,318	
Panel (c): UberX Not Yet Available												
Avg. Drinks per Day	2.00	1.89	2.12	2.18	2.12	2.10	2.15	2.17	2.10	2.38		
Days with ≥1 Drink	2.07	2.24	2.20	2.25	2.09	2.25	2.06	2.25	2.18	2.32		
Maximum Drinks in One Occasion	4.40	11.02	4.74	11.34	4.82	11.66	4.82	11.51	4.89	12.14		
Instances of Binge Drinking	0.82	3.02	0.96	3.20	0.99	3.28	1.03	3.41	0.97	3.35		
N	95,959		118,076		102,683		67,278		9,729			

We use the BRFSS SMART survey data. The number of observations is the number of BRFSS respondents who meet the selection criteria in a given year.

Table 4: Earnings and Employment at QCEW Drinking Establishments

Panel (a): Employment				
Uber	0.0553***	0.0422***	0.0178*	0.0088
	(0.015)	(0.015)	(0.010)	(0.008)
Log Income		0.2809**	-0.0618	0.0457
		(0.132)	(0.105)	(0.092)
Log Population		1.3221***	1.3648**	1.7948***
		(0.361)	(0.583)	(0.560)
Panel (b): Total Wages				
Uber	0.0620***	0.0447***	0.0194	0.0070
	(0.017)	(0.017)	(0.012)	(0.009)
Log Income		0.4450***	-0.0465	0.0663
		(0.161)	(0.120)	(0.099)
Log Population		1.7905***	1.6414**	2.7812***
		(0.408)	(0.647)	(0.634)
Panel (c): Average Wages				
Uber	0.0067	0.0026	0.0017	-0.0016
	(0.007)	(0.007)	(0.006)	(0.004)
Log Income		0.1640***	0.0155	0.0211
		(0.063)	(0.053)	(0.048)
Log Population		0.4669***	0.2799	0.9900***
		(0.146)	(0.334)	(0.341)
Panel (d): Establishment Count				
Uber	0.0067	0.0026	0.0017	-0.0016
	(0.007)	(0.007)	(0.006)	(0.004)
Log Income		0.1640***	0.0155	0.0211
		(0.063)	(0.053)	(0.048)
Log Population		0.4669***	0.2799	0.9900***
		(0.146)	(0.334)	(0.341)
County & Qtr Fixed Effects	Yes	Yes	Yes	Yes
Controls (Median Age, % Over 21, White, and Male)	No	Yes	Yes	Yes
County-Specific Linear Time Trend	No	No	Yes	Yes
Weighted by Population	No	No	No	Yes
n	11,951	11,951	11,951	11,951

Notes: Dependent variables are in logs, observations are at the county-quarter level. Again, n refers to county-quarter pairs. County and quarter fixed effects and covariates are included (as indicated) in all regressions. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Figure 2 we present a plot of the estimates from an event study specification. We examine the wage and employment outcomes presented in Table 4, five quarters before and after Uber's entry into a county. The estimating equation is similar to the equation (1) in Section 3;

$$Y_{ct} = \sum_{j=-5}^{5} \alpha_j U_c 1(t - T_c = j) + \delta_c + \gamma_t + \epsilon_{ct}. \tag{2}$$

The difference is that we replace the indicator variable for Uber's entry into an area with a set of interactions $(U_c 1(t - T_c = -5), ..., U_c 1(t - T_c = 5))$, where U_c equals 1 only if county c ever experiences an Uber introduction and $1(t - T_c = j)$ equals 1 only if quarter t falls j quarters before or after the county's quarter of treatment T_c. The α_j terms associated with these indicators therefore capture the difference in the outcome of interest, Y_{ct}, in areas with Uber (relative to areas without Uber) in the five quarters before and after Uber's entry. In practice, we collapse periods more than 5 quarters after introduction into period $j = 5$ and periods more than 5 quarters before introduction into period $j = -5$. To avoid presenting a table with more than a dozen estimates per specification, Figure 2 plots the difference in Y_{ct} based upon the α_j coefficient estimates.

In the figure, we present three post-estimation coefficient plot estimates (comparable to column one of Table 4; clustered standard errors at the county level plus county and quarter fixed effects). The first sub-figure examines percent changes in average employment ("lnavgemp"). The second examines total wages ("lntotwage"). The third sub-figure examines average wages ("lnavgwage"). Focusing on the period immediately before and after UberX introduction within each county highlights that Uber's entry is clearly associated with increases in the wage and employment outcomes of interest at drinking establishments. However, these graphs also suggest the existence of confounding pre-trends, which justify the inclusion of location-specific linear time trends in our main regression specifications.

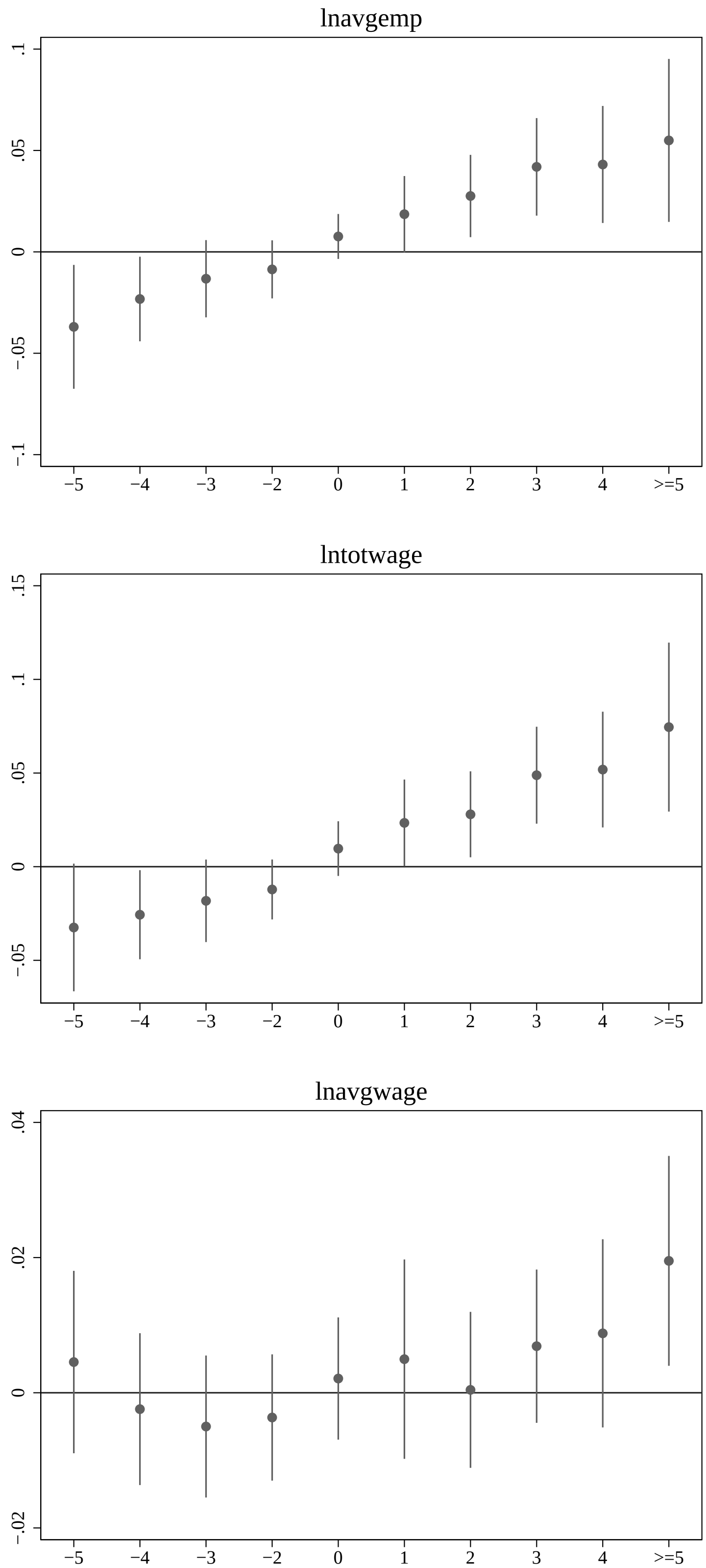

Figure 2: Event Study Figures for Drinking Establishments

The figure is based on estimates from an event study specification where we examine the various outcomes of interest five quarters before and after of Uber's entry to an area.

Table 5: Earnings and Employment at QCEW Full Service Restaurants

Panel (a): Employment				
Uber	-0.0060	0.0120***	0.0006	0.0012
	(0.010)	(0.004)	(0.003)	(0.002)
Log Income		0.0991***	0.0561**	0.0538**
		(0.034)	(0.026)	(0.023)
Log Population		1.0859***	0.7935***	0.8505***
		(0.109)	(0.199)	(0.200)
Panel (b): Total Wages				
Uber	0.0088	0.0119***	-0.0032	-0.0058**
	(0.009)	(0.005)	(0.003)	(0.003)
Log Income		0.2136***	0.0798***	0.0572**
		(0.037)	(0.027)	(0.027)
Log Population		1.1387***	1.7632***	2.2426***
		(0.126)	(0.286)	(0.348)
Panel (c): Average Wages				
Uber	0.0148***	-0.0001	-0.0038**	-0.0070***
	(0.004)	(0.002)	(0.002)	(0.002)
Log Income		0.1144***	0.0238*	0.0039
		(0.018)	(0.014)	(0.018)
Log Population		0.0540	0.9650***	1.3886***
		(0.057)	(0.156)	(0.220)
Panel (d): Establishment Count				
Uber	0.0050	0.0128***	-0.0021	-0.0006
	(0.007)	(0.003)	(0.002)	(0.002)
Log Income		0.0549*	0.0559**	0.0714***
		(0.029)	(0.024)	(0.023)
Log Population		0.8669***	-0.1163	-0.1637
		(0.095)	(0.142)	(0.146)
County & Qtr Fixed Effects	Yes	Yes	Yes	Yes
Controls (Median Age, % Over 21, White, and Male)	No	Yes	Yes	Yes
County-Specific Linear Time Trend	No	No	Yes	Yes
Weighted by Population	No	No	No	Yes
n	15,323	13,669	13,669	13,669

Notes: Dependent variables are in logs, observations are at the county-quarter level. Again, *n* refers to county-quarter pairs. County and quarter fixed effects and covariates are included (as indicated) in all regressions. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 repeats the estimates in Table 4 for full service restaurants rather than drinking establishments. Again, the estimates should be viewed as relative to the change in the same dependent variable in non-Uber counties.[20]

Taken together, the effects on wages and employment we see in Table 4 and Table 5 suggest Uber likely caused little to no reliably measured increase in visits to establishments that serve alcohol. However, Figure 3 presents three post-estimation coefficient plot estimates (the specification is similar to column one of Table 5; clustered standard errors at the county level plus county and quarter fixed effects). The first sub-figure examines percent changes in average employment ("lnavgemp") at full service restaurants before and after Uber's entry. The second examines total wages ("lntotwage"). The third sub-figure examines average wages ("lnavgwage"). Compared to the difference-in-difference estimates of wage and employment effects, we see that focusing on the period immediately before and after UberX introduction within each county highlights that Uber's entry is clearly associated with increases in the wage and employment outcomes of interest. The difference-in-difference estimates did not reveal this. However, there still appear to be confounding pre-trends in the outcomes of interest.

[20]As a reminder, our sample includes all counties with a population over 100,000.

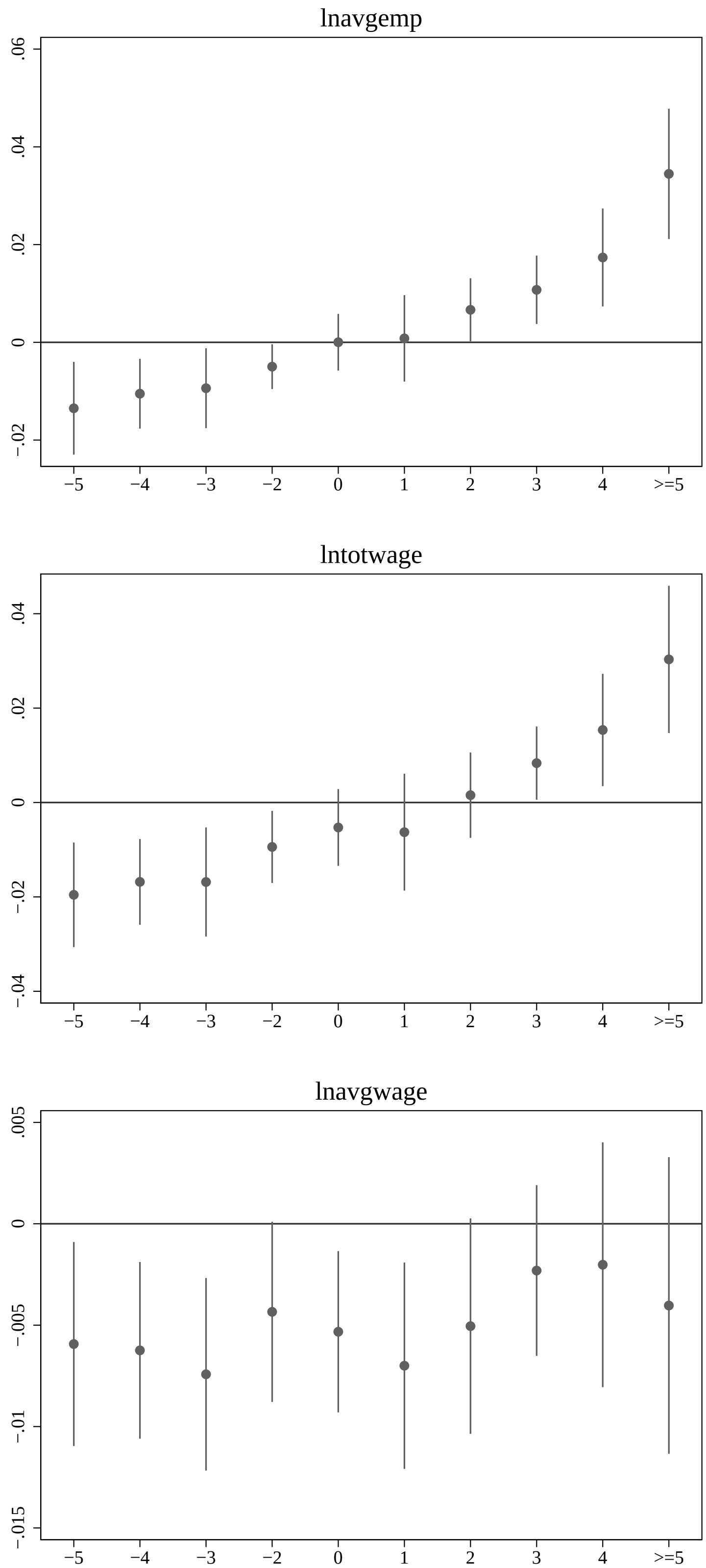

Figure 3: Event Study Figures for Full Service Restaurants

The figure is based on estimates from an event study specification where we examine the various outcomes of interest five quarters before and after of Uber's entry to an area.

4.2 Uber's Effect on Individual Alcohol Consumption

Table 6 uses self-reported alcohol consumption data from BRFSS to illustrate that Uber entry is associated with increases in alcohol consumption and in particular, binge drinking. Moreover, this consumption is potentially harmful. In particular, Table 6 uses the same estimating equation presented in Section 3 to examine four outcomes of interest. Each specification uses BRFSS responses only from metro areas with a population greater than 200,000. First, we present estimates for the full sample ("All"). We find no significant effect on the average number of drinks consumed per day. The same is true for the number of days per week with one or more drink, although the estimates are positive. We find a negative impact on the maximum number of drinks in a single occasion in the last 30 days, though this is not significant when time trends are included. We suspect that Uber does not affect the relevant constraint here for many alcohol consumers. On the other hand, we find Uber is associated with statistically significant increases in the frequency of binge drinking in the past 30 days. Specifically, we find that instances of binge drinking increase by 0.101-0.171 occasions per month (significant at the 5% level).

We then present estimates for males and females aged 21-45 separately. We do so because the CDC reports that those aged 21-34 are twice as likely to be involved in a fatal traffic incident than any other age group.[21] Moreover, those aged 21-45 are potentially more aware and familiar with Uber than older groups (or were in the time period studied here). We therefore expect the effect of Uber's entry on alcohol consumption to be larger for these demographic groups.

Focusing on instances of binge drinking, we find that Uber is associated with an increase in binge drinking in males 21-45, but the magnitude is negligible when time trends are not included. Even then, the estimate is significant only at the 10% level. Females aged 21-45 however, see a larger and statistically significant increase in binge drinking frequency. We estimate Uber is associated with an increase in binge drinking for this group by 0.178-0.258 occasions in a month. Overall, our estimates suggest that Uber's entry relaxed some constraints on binge drinking (four or more drinks for females, five for males) for younger drinkers.[22]

[21] See https://www.cdc.gov/motorvehiclesafety/impaired_driving/states-data-tables.html.

[22] We cannot repeat the event study we used with the QCEW data because our BRFSS data is annual and the sample period is only six years in total.

Table 6: BRFSS Alcohol Consumption Estimates

All	Avg. Drinks Per Occasion		Days Per Week w/ ≥ 1 drink		Max Drinks on One Occasion		Binge Drinking Frequency	
Uber	0.0264	0.0031	0.0121	0.0235	-0.6525***	-0.3706	0.1009**	0.1710**
	(0.041)	(0.053)	(0.022)	(0.027)	(0.186)	(0.352)	(0.043)	(0.069)
N	661,577	661,577	1,152,111	1,152,111	670,780	670,780	662,309	662,309
Males, 21-45								
Uber	0.0515	-0.0100	-0.0121	0.0299	-1.0080**	-0.1364	0.0091	0.3213*
	(0.097)	(0.155)	(0.053)	(0.066)	(0.459)	(0.816)	(0.127)	(0.194)
N	102,595	102,595	144,165	144,165	104,146	104,146	102,812	102,812
Females, 21-45								
Uber	-0.0103	0.0896	0.0227	0.0015	-1.0149***	-0.6261	0.1779**	0.2577***
	(0.068)	(0.064)	(0.035)	(0.033)	(0.368)	(0.633)	(0.073)	(0.086)
N	113,906	113,906	185,300	185,300	115,107	115,107	113,981	113,981
CBSA-specific Time Trends	No	Yes	No	Yes	No	Yes	No	Yes
Controls (Median Age, % Over 21, White, and Male)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are in levels, observations are at the individual level, weighted by the MMSA-level (metropolitan statistical areas, micropolitan statistical areas, and metropolitan divisions) weight as provided by BRFSS. Each specification uses BRFSS responses only from metro areas with a population greater than 200,000. Core-based Statistical Area (CBSA) fixed effects, year fixed effects, and demographic controls are included in all regressions. Standard errors are clustered at the CBSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

We use QCEW and BRFSS data to examine the effect of Uber's introduction on alcohol consumption. On the one hand, ridesharing services provide an attractive alternative to intoxicated driving and should reduce some of the harms associated with alcohol consumption. On the other, if drinkers were constrained by the availability of transportation prior to the advent of Uber, Uber could increase alcohol consumption. Moreover, because alcohol consumption is a social activity, the advent of ridesharing could increase the quantity and frequency of drinking outside the home both for Uber users *and* non-users. The complementary nature of alcohol-related social activity ensures that the effect of ridesharing on road safety and many other harms associated with alcohol consumption (assault, theft, nuisance, and health) is theoretically ambiguous.

We use a difference-in-difference empirical strategy to establish that Uber leads to an increase in alcohol consumption. First, our estimates suggest that Uber is associated with increases in employment and wages at establishments that serve alcohol, though these estimates are sensitive to specification. Because these are generally tipped positions, we see this as evidence of increases in the quantity and frequency of alcohol consumption. Second, we use self-reported BRFSS data to show that Uber is associated with additional instances of binge-drinking. The effects are concentrated among younger female drinkers.[23] The introduction of Uber causes these effects if our identifying assumption holds - that nothing else differentially affects the outcomes of interest in locations with and without Uber over the time period studied.

Our findings complement the existing literature on Uber's effects on society. That literature suggests that in some places, and at some times, Uber is associated with large reductions in alcohol-related harm. In others places and times, the reductions are negligible. We see our findings as helping to explain this apparent paradox.

[23] In contrast, younger males are more likely to be involved in alcohol-related traffic incidents, according to the CDC. That is, many males were already drinking excessively regardless of transportation options. See discussion in Section 4 for more on this.

References

Brazil, N. and Kirk, D. S. (2016). Uber and metropolitan traffic fatalities in the United States. *American journal of epidemiology*, 184(3):192–198.

Burtch, G., Carnahan, S., and Greenwood, B. N. (2018). Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science*.

Dills, A. K. and Mulholland, S. E. (2018). Ride-sharing, fatal crashes, and crime. *Southern Economic Journal*, 84(4):965–991.

Greenwood, B. N. and Wattal, S. (2017). Show me the way to go home: An empirical investigation of ride-sharing and alcohol related motor vehicle fatalities. *MIS quarterly*, 41(1):163–187.

Jackson, C. K. and Owens, E. G. (2011). One for the road: public transportation, alcohol consumption, and intoxicated driving. *Journal of Public Economics*, 95(1-2):106–121.

Manning, W. G., Blumberg, L., and Moulton, L. H. (1995). The demand for alcohol: the differential response to price. *Journal of Health Economics*, 14(2):123–148.

Martin-Buck, F. (2017). Driving safety: An empirical analysis of ridesharing's impact on drunk driving and alcohol-related crime. *University of Texas at Austin Working Paper*.

Peck, J. L. (2017). New york city drunk driving after Uber. *CUNY Graduate Center Working Paper Series*, (13).