THE EFFECT OF RIDESHARING SERVICES ON DRUNK DRIVING

An Undergraduate Research Scholars Thesis

by

ZACHARY KALMBACH

Submitted to Honors and Undergraduate Research
Texas A&M University
in partial fulfillment of the requirements for the designation as an

UNDERGRADUATE RESEARCH SCHOLAR

Approved by
Research Advisor: Dr. Amy Glass

May 2015

Major: Economics

TABLE OF CONTENTS

ABSTRACT

The Effect of Ridesharing Services on Drunk Driving. (May 2015)

Zachary Kalmbach
Department of Economics
Texas A&M University

Research Advisor: Dr. Amy Glass
Department of Economics

Drunk driving is a significant problem in today's society, and the recent development of ridesharing services, like Uber, offer a new way to avoid driving under the influence. In this paper, I examine whether the presence of Uber has caused a reduction in the number of DUI violations per month in nine large American cities. I found significant evidence that uberX, the most popular and affordable form of Uber, causes a 26% reduction in DUIs in the month the service is launched. The results suggest that this effect fades quickly, although the estimates after the first month are imprecise and statistically insignificant. I suggest that a future study using the same model as this paper with a larger pool of available data would reach clearer conclusions about the overall long-term effect of ridesharing services on the number of DUI violations.

SECTION I

INTRODUCTION

Driving under the influence of alcohol is a major problem in America. To give a brief depiction of the extent of this problem, Mothers Against Drunk Driving reports that someone in America is injured in a drunk driving accident every two minutes, 28 people die every day in America as a result of drunk driving accidents, and drunk driving costs the U.S. nearly $200 billion every year (MADD—Mothers Against Drunk Driving). Organizations like Mothers Against Drunk Driving as well as law enforcement agencies are constantly looking for ways to curb this problem with approaches like education programs, DUI checkpoints, or increased penalties for Driving Under the Influence (DUI).

The recent development and popularization of smart phone app-based ridesharing services like Uber provide an additional option when potential drunk drivers are facing the decision of whether to get behind the wheel, and many people believe that these services will generate a significant reduction in drunk driving in today's society. For example, a recent article released by MADD states, "Not only is Uber a convenient transportation option…it can also be a powerful tool in the fight to reduce the number of drunk-driving crashes" (Unlike traditional taxi services, these ridesharing services market themselves as a form of social networking, with a safe ride home essentially in the palm of your hand. Because anti-drunk driving organizations and law enforcement agencies are making it a priority to reduce the occurrence of drunk driving, these app-based services are something agencies and organizations could potentially emphasize in their quest to prevent drunk driving. Further, ridesharing could be viewed as a more positive way to prevent drunk driving, in contrast to policies like frequent DUI checkpoints that could be seen as limiting personal freedoms. Taxi companies and governments in many cities have banned ridesharing services, claiming that ridesharing is the same as taking a taxi, and should therefore be regulated as if they were a taxi company. Results proving that ridesharing is in fact reducing drunk driving across the nation would force a conversation about the cost and benefits of banning an easy and affordable way of preventing drunk driving.

Valued at $40 billion, Uber is by far the most prominent ridesharing service available. In fact, they are valued at sixteen times more than their closest competitor, Lyft. Their most popular service is called uberX, which is the least expensive version of Uber. The reason for this is because uberX drivers use their own cars and are not required to be licensed chauffeurs. My goal in this paper is to find out if Uber, or specifically uberX's presence in major American cities has had a significant effect on the number of DUI violations.

The rest of this paper is broken down into four sections. First I discuss the previous literature on this subject. So far, Uber itself has released the majority of studies relating ridesharing and drunk driving. Only one of their studies directly relates the presence of the service and the number of DUI violations, and the study only consisted of two west-coast cities. My study aims to reach a more far-reaching conclusion on the impact of Uber on DUI rates across America. Second I discuss the data I gathered, which consists of the number of DUI violations per month in Austin, Atlanta, Chicago, Dallas, Houston, Philadelphia, Pittsburgh, San Francisco, and Seattle as well as the date that Uber and uberX first entered each city. I controlled for the legalization of marijuana by including the date that marijuana was legalized in Washington. I then present my results and reach a conclusion. While the results suggest that uberX significantly decreases DUIs in the month it is launched, this effect seems to fade after the first month, although the estimates after the first month are imprecise. The results tell nothing significant about the presence of any form of Uber other than uberX. While there wasn't enough time for me to gather DUI data for more cities, and because Uber is still a very new service, a future study using the same model as this paper could be able to reach more statistically significant conclusions and make claims about Uber's effect with more confidence than I can in this paper.

SECTION II

LITERATURE REVIEW

Uber itself has released the majority of studies relating ridesharing and drunk driving. As far as looking for a direct connection between Uber and the number of violations for Driving Under the Influence (DUI), the company released a study titled "DUI Rates Decline in Uber Cities". The company used a difference-in-differences framework with Seattle and San Francisco and concluded that Uber is responsible for a 10% reduction in DUI violations in Seattle (Chris). This study is the most similar to my paper, but there are two key differences. First, Uber used the number of DUIs per day, while this paper uses the number of DUIs per month. I chose to study the number of DUI violations per month in order to look at Uber's effect not only in the month of launch, but also months after the service enters a city. Second, my paper not only compares San Francisco and Seattle, but also seven other cities across the America in addition to the two West Coast cities. In this way, I aim to get a big-picture look at whether or not Uber has significantly decreased the instance of drunk driving across America. Uber has released three subsequent studies on the topic of drunk driving. Two of them, titled "Making Pennsylvania Safer: As Uber Use Goes Up, DUI Rates Go Down" (Catherine) and "Providing Rides When They Are Most Needed" (Ryan), focused their attention on the times of day that Uber is requested the most in Philadelphia and Austin, respectively. Both of these studies found that Uber receives the most requests for rides during the times where the rate of drunk driving is the highest. Uber partnered with Mothers Against Drunk Driving in their most recent report, "Making Our Roads Safer—For Everyone" (Michael). They concluded that alcohol related accidents fell by 60 crashes per month among drivers under 30 years old in markets where Uber operates following the launch of the uberX. These studies are all exciting for the prospect of Uber causing a reduction in drunk driving, but I believe that law enforcement agencies would want to see that the service significant effects DUI rates across the country in the long-term rather than just a couple West Coast cities and Philadelphia before they would fully embrace the fact that ridesharing services work and subsequently start investing in ways to promote them. These agencies might also look more seriously upon a study that is done outside of Uber by an impartial third party, since any positive results released by Uber could be seen as the company promoting themselves through potentially biased methods.

SECTION III

DATA

This paper uses a difference-in-differences framework where the number of DUI arrests per month is the response variable and the presence of uberX, any other form of Uber, and the legalization of marijuana are the explanatory variables. The data on DUI violations was found in online databases for Seattle (Seattle Police Department), San Francisco (San Francisco Police Department), Philadelphia (Pennsylvania State Police), and Pittsburgh (Pennsylvania State Police). Austin ("Chief's Monthly Reports") and Atlanta ("APD Uniform Crime Reports") published monthly crime reports on their police department websites. I submitted a public information request to the Texas Department of Public Safety and was provided with monthly DUI data through 2013 for Dallas and Houston. To obtain the data for Chicago, I contacted the Illinois Criminal Justice Information Authority and was provided with the monthly statistics. The summary of the DUI statistics per month is given in Table 1.

The launch dates of Uber and uberX were obtained from Uber's website, specifically from their "Launch" blog, which posts a new article every time the service is launched in a new city ("Launch"). Since I am grouping the DUI arrest numbers by month, I used the month that Uber and uberX entered into the cities rather than the exact date as the independent variable. The months and years that Uber and uberX entered the selected cities is given in Table 2.

Table 1. Number of DUI Violations

City	Mean	Standard Dev.
Austin	470.94	79.16
Atlanta	113.28	24.28
Chicago	342.95	45.39
Dallas	198.92	63.75
Houston	561.50	68.84
Philadelphia	901.86	407.90
Pittsburgh	72.10	17.41
San Francisco	31.22	6.93
Seattle	197.96	57.54

Table 2. Month of Uber Launch

City	Uber	uberX
Austin	June 2014	June 2014
Atlanta	October 2012	July 2013
Chicago	October 2011	May 2013
Dallas	September 2012	November 2013
Houston	February 2014	February 2014
Philadelphia	June 2012	October 2013
Pittsburgh	March 2014	March 2014
San Francisco	June 2010	July 2012
Seattle	August 2011	April 2013

In a difference-in-differences model I will describe in the results section, I used the presence of Uber and uberX as binary variables, where the variable “uberx” equals 1 if the service is present in the city, and 0 if it is not. Further, I controlled for the potential effect of any prior presence of another form of Uber by adding another binary variable, denoted “uber”. This variable most often refers to Uber’s service called “Uber Black”, which is a more expensive and less requested version of uberX. The launch dates for this was found from Uber’s aforementioned “Launch” blog.

I also felt it was necessary to control for the legalization of marijuana in Seattle because the database where I found DUI violation statistics did not distinguish between Driving Under the Influence of Alcohol and Driving Under the Influence of Drugs. Like the variables “uberx” and “uber”, the legalization in marijuana is a binary variable labeled “pot”, where “pot” equals 1 if marijuana is legalized and 0 if it is not.

SECTION IV

RESULTS

To test for Uber and uberX's possible effect on the number of DUIs per month, I used a difference-in-differences framework. This method determines the effect of an independent variable on a response variable by comparing the mean change in the response variable over time in a control group to the mean change in the response variable over time in a treatment group. This is a useful method because it controls for any other variables that may be confounding the treatment, assuming that the outcome in the control and treatment group would have the same trend if there were no treatment. This is commonly referred to as the "parallel trends assumption". In this study, where I use panel data and where there are multiple cities, time periods, and treatments, I am able to use an ordinary least squares regression model with fixed effects to obtain difference-in-differences estimates.

In each model I use, each observation is a place at a given time, like Austin in May 2014. The main variables of interest are $uberx_{it}$, which represents uberX and $uber_{it}$, which represents any other form of Uber. The variables $uberx_{it}$ and $uber_{it}$ are equal to 1 if the service is present in the city and 0 otherwise. Further, pot_{it} equals 1 if marijuana is legal in the city and 0 otherwise, and $uber_{it}$ equals 1 if a different form of Uber is present in the city, and 0 otherwise. The fixed effects in the model are u_i and T_t, where u_i is a fixed effect to control for how one city is different from all of the other cities, such as access to public transportation in the cities, and T_t is a fixed effect to control for how one month is different from another month. The error term is denoted as ε_{it}. The coefficients on the explanatory variables represent the mean percentage change in the number of DUIs when the binary variables equal 1 instead of 0, that is, when uberX or Uber is present and marijuana is legalized.

As I previously mentioned, the difference-in-differences model depends on what is known as the "parallel trends assumption". This assumes that the outcome in the treatment and control groups would follow the same trend if there were no treatment. It essentially assumes that nothing in the groups that would affect the response variable changes at the exact same time as the treatment goes into effect. For example, suppose that in the same month that uberX enters a city, the city decides to suspend the use of DUI checkpoints. The suspension of DUI checkpoints by itself would most likely decrease the number of reported DUI violations, and this effect would be falsely attributed to uberX. In this situation where DUI checkpoints are suspended, the parallel trends assumption would no longer hold, and any conclusion reached would not be valid. A good way to test this assumption is to test for pre-treatment trends, which can be done by including leading variables in difference-in-differences models like Model 1. These "leads" are the explanatory variables for uberX and Uber for the months before they go into effect. If the coefficients on the leads are close to 0, then there is no evidence for pre-treatment effects, and the parallel trends assumption most likely holds. I do this in Model 1:

$$\log{(dui)_{it}} = \alpha + \beta_1 uberx_{it-3} + \beta_2 uberx_{it-2} + \beta_3 uberx_{it-1} + \beta_4 uberx_{it} + \beta_5 uber_{it-3} + \beta_6 uber_{it-2} + \beta_7 uber_{it-1} + \beta_8 uber_{it} + \beta_9 pot_{it} + u_i + T_t + \varepsilon_{it} \qquad (1)$$

The results of this model, given in Table 3 in the column labeled "Model 1", suggest that the parallel assumption holds. The coefficient for uberX's effect three months prior to its launch is a bit high, but the estimate is very noisy, and shouldn't be a cause for concern. Nevertheless, while the parallel trends assumption most likely holds, I will not completely reject the assumption.

I use Model 2 to test for the overall average effect of Uber and uberX since the services launched in the selected cities:

$$\log{(dui)_{it}} = \alpha + \beta_1 uberx_{it} + \beta_2 pot_{it} + \beta_3 uber_{it} + u_i + T_t + \varepsilon_{it} \qquad (2)$$

The results of Model 2 are shown in the column labeled "Model 2" in Table 3. In this model, the coefficient β_1 equals -0.16, meaning the impact of uberX is an average decrease in DUI violations by about 16% per month. However, the p-value for this estimate is 0.24, so a significant conclusion cannot be drawn about this estimate. Further, β_2 equals .49, with a p-value of .001, so we can conclude with 99% confidence that the average impact of the legalization of marijuana is an increase in DUI violations by about 49%. Finally, β_3 equals 0.10, but a p-value of .33 makes this very insignificant.

In Model 3, I estimate the effects of Uber and uberX in the month of and in the months after Uber or uberX was launched. I do this by running a regression similar to Model 2, but with lagging variables rather than leading variables, that is, Model 3 estimates the effect of the service in the month of and each of the three months after launch as opposed to the average effect since launch:

$$\log{(dui)_{it}} = \alpha + \beta_1 uberx_{it} + \beta_2 uberx_{it+1} + \beta_3 uberx_{it+2} + \beta_4 uberx_{it+3} + \beta_5 uber_{it} + \beta_6 uber_{it+1} + \beta_7 uber_{it+2} + \beta_8 uber_{it+3} + \beta_9 pot_{it} + u_i + T_t + \varepsilon_{it} \qquad (3)$$

The results of Model 3 are shown in the column labeled "Model 3" in Table 3. While, like the other models, this model tells us nothing significant about the effect of any other form of Uber, it gives a very interesting picture of the effect of uberX on DUI rates. Here, the coefficient on $uberx_{it}$ is -0.30. When you calculate $e^{-0.30} - 1$, you find that the percentage impact is a reduction in DUIs of about 26% in the month that uberX is launched. This estimate is statistically significant at a 95% confidence level. However, as you can see from the results, this effect quickly fades; after the first month, about half of this effect is lost, and after the third month the overall effect goes down to about -12.17%. It is important to note that after the first month, a lot of precision is lost, as only the estimate for the month of launch is statistically significant. The fact that Uber and uberX are so new means that there wasn't a lot of data for months after the service was launched, and this is a big contributing factor to the loss of precision in the months after the services are launched.

Another possible reason that the effect seems to dissipate after the first month could be because Uber advertises heavily when they first enter a city, and in most cases a user's first ride is free or highly discounted. Further, when a user signs up they are given a promotion code that they can give to their friends, and they receive free or discounted rides when their friends use the code. This could potentially create a scenario in which Uber is a "fad" that fades after people exhaust their free rides. This would explain Uber's effect fading after the month of launch. However, to test this claim I would need to obtain ridership data from Uber, something that I have not been able to accomplish.

Table 3. Regression Output

Variable	Model 1	Model 2	Model 3
$uberx_{it}$	-0.04 (0.10)	-0.16 (0.13)	-0.30 (0.11)*
pot_{it}	0.51 (0.11)**	0.49 (0.10)**	0.47 (0.09)**
$uber_{it}$	0.03 (0.03)	0.10 (0.10)	0.13 (0.08)
$uberx_{it-1}$	-0.03 (0.08)		
$uberx_{it-2}$	-0.00 (0.09)		
$uberx_{it-3}$	-0.13 (0.11)		
$uber_{it-1}$	-0.05 (0.04)		
$uber_{it-2}$	0.10 (0.07)		
$uber_{it-3}$	0.05 (0.10)		
$uberx_{it+1}$			0.13 (0.11)
$uberx_{it+2}$			-0.01 (0.11)
$uberx_{it+3}$			0.05 (0.10)
$uber_{it+1}$			-0.11 (0.08)
$uber_{it+2}$			-0.06 (0.08)
$uber_{it+3}$			0.16 (0.09)
R^2	0.16	0.16	0.20
Observations	552	579	552

Notes: Table 3 shows the coefficients in the variables given in Column 1. Each column describes a logistic regression model where the response variable is the number of DUI violations per month. Column 1 shows a standard logistic regression model. Column 2 shows a model with leads included, and Column 3 shows a model with lags. R^2 pertains to "within" variation. All results are robust.
* Variable is statistically significant at the 95% confidence level.
** Significant at the 99% confidence level

SECTION V

CONCLUSION

Drunk driving continues to be a significant problem in America, and ridesharing services like Uber offer a safe, easy, and affordable ride home. In this paper, I explored the effect of Uber on drunk driving across America. My overall conclusion from this paper is that while the overall picture is imprecise, that is, the overall effect of uberX is statistically insignificant, uberX definitely seems to have an impact in its first month. This effect, however, seems to fade away quickly. Because my timeline did not allow me to wait any longer on other American cities to provide me with DUI statistics and Uber and ridesharing in general is such a new service, lack of data may have contributed to the imprecise overall conclusion. However, the fact that Uber gives out so many free rides from promotions in month of launch could be a potential driving factor for the decrease in the effect after the first month. With more months after the launch of Uber and uberX in the data, the results for the months following launch would most likely be more precise. I believe that with the passage of time providing more months to observe after the service's launch as well as data for more cities, a future study using the same models as this paper could provide a clearer picture of Uber's effect on drunk driving.

There are also other ridesharing services, like Lyft and Sidecar, that are starting to build momentum, and including them in a future study could give an even better portrayal of the ridesharing industry's effect on drunk driving that law enforcement agencies and anti-drunk driving organizations couldn't ignore. Those sorts of results could add a new factor into the government's decision on whether to ban ridesharing services that are helping to prevent drunk driving.

REFERENCES

"APD Uniform Crime Reports." *Atlanta Police Department.* Atlanta Police Department, n.d. Web. 07 Feb. 2015. <http://www.atlantapd.org/uniformcrimereports.aspx>.

Catherine. "Making Pennsylvania Safer: As Uber Use Goes Up, DUI Rates Go Down." *Uber Uber Blog.* Uber, 21 July 2014. Web. 07 Feb. 2015. <http://blog.uber.com/Pittsburgh-DUI-Rates-Decline>.

"Chief's Monthly Reports." *The Official Website of the City of Austin.* Austin Police Department, n.d. Web. 07 Feb. 2015. <http://www.austintexas.gov/page/chiefs-monthly-reports>.

Chris. "DUI Rates Decline in Uber Cities." *Uber Blog.* Uber, 05 May 2014. Web. 07 Feb. 2015. <http://blog.uber.com/duiratesdecline>.

"Launch." *Uber Blog.* Uber, n.d. Web. 07 Feb. 2015. <http://blog.uber.com/tag/launch/>.

"MADD—Mothers Against Drunk Driving." *MADD.* MADD, n.d. Web. 03 Feb. 2015. <http://www.madd.org/statistics/>.

"MADD – New Report from MADD, Uber Reveals Ridesharing Services Important Innovation to Reduce Drunk Driving." *MADD.* MADD, 27 Jan. 2015. Web. 07 Feb. 2015. <http://www.madd.org/media-center/press-releases/2015/new-report-from-madd-uber.html>.

Michael. "Making Our Roads Safer—For Everyone." *Uber Blog.* Uber, 27 Jan. 2015. Web. 07 Feb. 2015. <http://blog.uber/uber-madd>.

Pennsylvania State Police. Uniform Crime Reporting Unit. *Pennsylvania Uniform Crime Reporting System.* Harrisburg: Uniform Crime Reporting Unit, n.d. *Monthly Summary Arrest Reports.* Web. 06 Feb. 2015. <http://www.paucrs.pa.gov/UCR/Reporting/Monthly/Summary/MonthlySumArrestUI.asp>.

Ryan. "Providing Rides When They Are Most Needed." *Uber Blog.* Uber, 13 Sept. 2014. Web. 07 Feb. 2015. <http://blog.uber.com/atxsaferides>.

San Francisco Police Department. *DataSF.org Data File Depository.* N.p: n.p, n.d. Web. 06 Feb. 2015. <http://apps.sfgov.org/datafiles/index.php?dir=Police>.

Seattle Police Department. *Seattle Police Department 911 Incident Response.* Seattle: n.p., n.d. *Data.seattle.gov.* Web. 06 Feb. 2015. <https://data.seattle.gov/Public-Safety/TrafficViolations-Accidents-DUIs/csrv-gf2j>.