Show Me The Way To Go Home: An Empirical Investigation of Ride Sharing and Alcohol Related Motor Vehicle Homicide

Abstract

In this work, we investigate how the entry of the driving service Uber influences the rate of alcohol related motor vehicle homicides. While significant debate has surrounded the entry of driving services like Uber and Lyft, limited rigorous empirical work has been devoted to uncovering the social benefits of such services (or the mechanism which drives these benefits). Using a difference in difference approach to exploit a natural experiment, the entry of Uber into markets in California between 2009 and 2013, findings suggest a significant drop in the rate of homicides during that time. Furthermore, results suggest that not all services offered by Uber have the same effect, insofar as the effect for the Uber Black car service is intermittent and manifests only in selective locations. These results underscore the coupling of increased availability with cost savings which are necessary to exploit the public welfare gains offered by the sharing economy. Practical and theoretical implications are discussed within.

Key Words*: Uber, drunk driving, vehicular homicide, difference in difference, natural experiment, platforms*

Introduction

The introduction of ridesharing platforms such as Uber and Lyft has sparked a host of policy debates over the last half decade. Detractors of such programs not only argue that the entry of these firms puts the public at significant risk through their limited liability corporate structure[1], but that patrons are equally at risk[2] and these firms upset the delicate balance of service providers[3]. Countervailing these perceptions, both scholars and policy makers have argued that such services resolve market failures by providing customers with a much needed service that circumnavigates the bureaucratic processes of licensed livery (Rempel 2014). However, limited empirical evidence exists to establish the social benefits (or lack thereof) of these platforms. To the extent that Uber has entered more than 53 countries and 200 cities worldwide, and many are debating legislation to allow or bar these platforms, and a robust estimate of any social benefits that these services provide could factor heavily in the legislative debates.

One social benefit consistently associated with these platforms, and presently being debated in the media, is the potential for reducing the instances of drunk driving (Badger 2014). As existing regulatory structures for traditional vehicle for hire services, viz. taxicabs, are designed to retard the number of licensed vehicles on the road in order to manufacture excess demand (Sternberg 1996), the absence of a sufficient number of taxis may result in citizens operating motor vehicles under the influence of alcohol (Grove 2013). Inasmuch as the result of these public welfare losses are often born by taxpayers, such as the cost of prosecuting and incarcerating individuals convicted of DUI, the effective management of the number of and type of vehicle for hire services poses a significant challenge for policy makers.

1 http://www.nytimes.com/2014/10/19/upshot/when-uber-lyft-and-airbnb-meet-the-real-world.html?abt=0002&abg=0

2 http://www.sfexaminer.com/sanfrancisco/uber-driver-suspected-of-attacking-passenger-in-sf-raises-safety-concerns/Content?oid=2907619

3 http://www.nytimes.com/2014/09/30/business/uniteds-deal-with-uber-raises-concerns.html

Preliminary analysis conducted by Uber and several industry analysts suggest that introduction of Uber and other ride sharing services has a negative influence on DUI arrests[4]. However, these studies have been questioned on several grounds: including involvement of Uber in the data analysis, methodological rigor (i.e. single city estimations), and the presence of confounding factors such as changes in city's population, bar scene, and tougher enforcement.

Moreover, a limited understanding of the mechanisms by which such services influence the rate of DUIs exists. On one hand, it is plausible that the decrease in DUI is simply the result of availability of vehicles for hire and that patrons are willing to pay a price premium for such services. Insofar as it is often difficult to hire a taxi, based on time, location, or even the race of the patron (Meeks 2010), it is plausible that the presence of the platform mitigates these market inefficiencies by soliciting the driver electronically, thereby significantly reducing search costs (Parker and Van Alstyne 2005) and creating excess utility for the consumer. On the other hand, it is equally plausible that the effect is a result of both availability and cost. Drawing from rational choice theory (Clarke and Cornish 1985, Cornish and Clarke 2014) it is conceivable that individuals who make the decision to drive under the influence do so based on the costs associated with conviction, the cost of searching for and hiring a taxi, and the probability of being stopped by the police and/or striking another driver. This broad question: what is the impact of Uber's introduction on alcohol related motor vehicle homicides in the local area and by what mechanisms, forms the core of the research investigated in this paper.

Empirically, we exploit a natural experiment, the introduction of the ride sharing service Uber into cities in the State of California between 2009 and 2014, to investigate the effect. Leveraging this econometric setup offers us several advantages. First, to the extent that the

[4] http://blog.uber.com/duiratesdecline

entrance of Uber is staggered temporally and geographically, we execute a difference in difference estimation to establish the effect. Second, Uber offers multiple services in each of the treated areas with varying price points (note that these services also enter at varying times and orders). On one hand, UberBlack, a town car service, offers transportation with a significant markup over taxicabs (~20% - ~30% price premium). On the other, the UberX service is a personalized driving service which offers significant *discounts* over taxis (~20% - ~30% price reductions). To the degree that each of these services identifies a different mechanism being at play (availability v. availability and price point), we are able to cleanly identify the dominant mechanisms at play. We test these using hand collected data from the California Highway Patrol (CHP) safety and crash dataset and a custom webscraper which indicates when each service entered a geographic area in California.

Results indicate that while the entry of UberX strongly and negatively affects the number of motor vehicle homicides which occur in townships, limited evidence exists to support previous claims that this occurs with the Uber Black car service as well (indicating that prior claims about the efficacy of Uber may have been overstated (Badger 2014)). Further, results indicate that the time for such effects to manifest vary is significant (upwards of 9 – 15 months). These results are robust to a variety of estimations (e.g. OLS, Poisson, and Quasi-Maximum Likelihood count models) and operationalizations. Finally, findings suggest an absence of a heterogeneous pre-treatment homicide trend in treated locations, indicating that the primary assumptions of the difference in difference model are not violated (Angrist and Pischke 2008, Bertrand et al. 2002). Further, results suggest no effect of Uber when surge pricing is likely in effect, thereby underscoring the importance of cost considerations. Economically, results indicate that the entrance of Uber X results in a 3.6% – 5.6% decrease in the rate of motor vehicle homicides per quarter in the state of California. With more than 1000 deaths[5] occurring in California due to alcohol related car crashes every year, this represents a substantial opportunity to improve public welfare and save lives.

Theoretically, these results add interesting nuance to extant understanding of the sharing economy. To the extent that researchers have proposed the sharing economy as a viable alternative to established market firms in many markets, e.g. AirBnB (Edelman and Luca 2014) and crowdsourcing for the funding of nascent ventures (Burtch et al. 2013), our results highlight the importance of cost considerations in resolving such market failures. While it is plausible that increased access to services, regardless of cost, would allow consumers to price point differentiate based on their own preferences, a preference of consumers towards established services as costs increase is suggested. Further, to the degree that results underscore the beneficial effects of ridesharing services, inasmuch as considerable public welfare loss in the form of motor vehicle homicide is avoided, this work informs the ongoing policy debate regarding ridesharing services. Finally, this work contributes to the small, but growing stream, of literature discussing the societal impacts of electronic platforms (Burtch et al. 2013, Chan and Ghose 2014, Greenwood and Agarwal 2013). To the degree that platforms have been found both enhance and diminish public welfare, our work contributes by drawing a richer picture of the public welfare implications of platform introduction.

Related Literature

To investigate which mechanism drives the observed change in the rate of alcohol related crashes we juxtapose two literatures: extant work regarding cost reduction through platforms and existing work from criminology regarding rational choice theory.

[5] http://apps.dmv.ca.gov/about/profile/rd/r_d_report/Section_5/S5-243.pdf

Extant work platforms has a rich tradition in information systems and economics spanning more than two decades (Bakos and Bailey 1997, Brynjolfsson et al. 2003, Brynjolfsson and Smith 2000, Malone et al. 1987, Parker and Van Alstyne 2005, Rochet and Tirole 2003). At root, two perspectives have been taken by this work. In the first, scholars have argued that the creation of platforms which facilitate commerce can reduce market inefficiencies by facilitating the buyer-seller match (Bakos and Bailey 1997). As a result, the implementation of the platform reduces the cost of transactions by increasing the likelihood that an individual who is leveraging the platform finds an acceptable trading partner. In the other, platforms have been argued to increase information transparency in markets by reducing information asymmetries (Brynjolfsson et al. 2003). In this work, researchers have argued that the platform facilitates frictionless commerce by protecting the buyer and seller from opportunism on the part of the other party through increased price transparency (Williamson 1981). While the perspectives taken by each of these literatures is rather different the end result is the same; by increasing the amount of publically available knowledge regarding prices and products, platforms are able to expedite the exchange of goods and services while creating a surplus of welfare for both the buyer and seller (Parker and Van Alstyne 2005).

While early manifestations of such work were either analytically driven to advance platform theory (Birkland and Lawrence 2009), or focused on more traditional examples of internet platforms such as eBay or Amazon.com (Brynjolfsson et al. 2003, Chevalier and Goolsbee 2003, Forman et al. 2008), a recent burgeoning literature on the societal impact of platforms has emerged. Interestingly, bevy of topics have been investigated, ranging from dating (Bapna et al. 2012), to the spread of HIV (Chan and Ghose 2014, Greenwood and Agarwal 2013), to crowdfunding (Burtch et al. 2013), to even the spread of hate crimes (Chan et al. 2014).

In each, much as was the case for commerce driven platforms, two mechanisms have been suggested to drive the effect: self-selection into using the platform and decreased search costs (Brynjolfsson and Smith 2000). It is within this budding literature on the societal impact of platforms where we position this work. To the degree that the regulating America's roadways has received significant attention from scholars (Feng et al. 2005, West 2004), due both to the economic scope of the industry and the externalities which it generates (Parry et al. 2007), it is an ideal context to further the scope of this literature.

Why might the introduction of Uber influence the rate of alcohol related motor vehicle homicides? As discussed above, extant platforms theory suggests many reasons why the introduction of electronic intermediaries may have an effect (Parker and Van Alstyne 2005). To the extent that it is often difficult to hire a cab (Meeks 2010), platform theory would suggest that the search costs associated with finding transportation would decrease significantly. Insofar as the Uber app mitigates significant information asymmetries between the patron and the driver by granting the user access to information like the type of vehicle and the time it will take the driver to get to the user's location, without relying on stochastic discovery of each other by the driver and patron (viz. standing on the side of the road). Furthermore, significant research suggests that consumers may be willing to pay a significant price premium for such a service by trading off the costs of searching for a cab with the certainty of knowing when an Uber will arrive. Because the process of discovering a traditional cab is not costless, as the search is characterized by considerable uncertainty, it is plausible that risk averse users will value the certainty of knowing when the Uber will arrive more than the time spent searching for a cab. As a result, users may be willing to pay a premium for the service. Following this logic through to completion, this would suggest that a decrease in the rate of drunk driving could conceivably be tied to a service like the

Uber Black car service, which charges users a price premium over taxis, but mitigates the vast majority of the uncertainty. We therefore propose the following:

H1: Implementation of the Uber Black car service will be associated with a negative and significant decrease in the rate of alcohol related motor vehicle homicides.

While the literature discussed thus far suggests that Uber users may be willing to pay a price premium for transportation, it is also plausible that the utility the user garners from hiring a cab, *ex ante*, is insufficient to justify hiring the cab in the first place, let alone pay a price premium for such a service. As received research suggests that the price of cabs is often a component in a person's decision to drive under the influence (Nagin and Paternoster 1993), it is therefore possible that premium services like Uber Black will not decrease the drunk driving rate, notably if the substitution of decreased search costs for uncertainty does not generate excess utility. More simply, if a user's willingness to pay for cabs to avoid a DUI is sufficiently low, and the decreased search cost associated with using the Uber app does not generate excess utility, then a premium service like Uber Black will likely not have an effect on the drunk driving rate despite the increased access, i.e. availability, to transportation the app provides.

While the notion that inebriated individuals make such rational calculations about willingness to pay during the decision to drive under the influence may seem counterintuitive, extant work from psychology and criminology suggests that this may be exactly the case (Clarke and Cornish 1985, Cornish and Clarke 2014). The main thrust of this body of literature, termed Rational Choice Theory, argues that individuals commit crimes out of a set of rational trade-offs which benefit them, as opposed to individual level psychoses or a natural predilection to engage in criminal enterprise (Clarke and Cornish 1985, Cornish and Clarke 2014). More simply, rational choice theory suggests that offenders respond selectively to particular situations based on the probability of being apprehended, the benefit they will reap from the crime, and the opportunity cost of selecting one option over another (Clarke and Cornish 1985).

Since the theory was originally proposed by Friedman in 1966, and applied in the field of criminology by Clarke and Cornish (1985), it has sparked a host of research relating to crime in economics Becker and Murphy (1988), sociology (Hechter and Kanazawa 1997), and even political science (Pétry 1995). While varying different modifiers and qualifiers have been discovered during that time: such as the individual's self-control (Nagin and Paternoster 1993), the ability to easily find co-conspirators (Cornish and Clarke 2014), and social conditions which change the availability of "marks" for criminals (Cohen and Felson 1979)[6], the core of the theory remains relatively unchanged. When presented with sufficient payouts, and a limited marginal cost, rational individuals are more likely to engage in criminal enterprise.

In the context of Uber the implications of this research are particularly notable. While platform theory would suggest that intoxicated driving is the result of the individual being unable to hire a cab (i.e. availability), rational choice theory would suggest that individuals may be able to find drivers, but are electing to drive themselves based on the price point those taxi's offer (i.e. cost or a mix of availability and cost). More simply, because of the cost of hiring a taxi, and the perceived cost and probability of being apprehended by the police, individuals are making the rational trade-off to drive themselves while under the influence. Interestingly, the decision to engage in drunk driving, even when controlling for self-control and other individual level factors, has significant support in extant literature (Nagin and Paternoster 1993). As a result, this would suggest that services like Uber X, which offers a significant price reduction over traditional taxi cabs (~20% - 30% depending on location) would have a far greater negative

[6] Cohen and Felson's (1979) specific discussion surrounds the ability of pickpockets to find worthy targets, the ability of sex workers to solicit customers, etc.

effect on the drunk driving rate because it both increases the accessibility of transportation (much like Uber Black) and decreases the gap between the costs of being discovered driving under the influence, and the cost of hiring the driver. Therefore, we propose the following:

H2: Implementation of the Uber X car service will be associated with a negative and significant decrease in the rate of alcohol related motor vehicle homicides.

Before moving to our empirical analysis we note that these two hypotheses (H1 and H2) are not mutually exclusive. To the degree that some individuals may be motivated by costs, and others are willing to pay the premium cost associated with the black car service, it is plausible that both services have an effect. However, the goal of this investigation is to determine which effect dominates the other (i.e. has the largest effect on the rate of alcohol related motor vehicle homicides).

Methodology

Context

As discussed above, Uber is an app based ridesharing service currently operating in more than 50 countries and 200 cities across the globe. Founded in March of 2009 in San Francisco, California the service provides a platform for owner-operator drivers to find local fares electronically and provide them with transportation to their intended destination. As of December 2014 the firm was valued at over $40 billion with $10 billion in projected 2015 revenues[7]. Originally designed as a black car service, where users would pay a premium to be taken to their destination by a fleet of high end vehicles (e.g. Lincoln Town cars, Cadillacs), the service now offers a host of transportation options, including car seat services for families, SUV services, and even helicopter services for super luxury passengers which will take them from New York City to the Hamptons. Most pertinent to our research, however, in 2012 the firm introduced the lower price UberX where non licensed livery drivers could use their personal vehicles to transport patrons as well.

[7] http://www.businessinsider.com/uber-revenue-projection-in-2015-2014-11

Figure 1 contains a screen shot of the current Uber app. As can be seen, the app provides an estimated time it will take the patron to be picked up, as well as a sliding bar which allows the user to choose which service she wishes to use. Once the vehicle has been requested the fare is linked to the user's credit card (which is stored in the app) or PayPal account and after the transaction is complete the users account is electronically billed. The app also allows for ratings of both passengers and drivers through a traditional online reviews 1-5 star rating.

Importantly for our research question, the two dominant services used, Uber Black (the traditional black car service) and Uber X (the discount service), offer significantly different price points for providing their services. As discussed previously, Uber Black charges a significant premium over traditional taxi cab services (20%-30%) while Uber X offers a significant price reduction (20%-30% lower than taxis). Because both of these services offer the platform advantages of increased availability, but significantly different price points, this setup, as well as the staggered rollout, allow us to determine if either or both services will have an effect on the alcohol related vehicular homicide rate.

Data

To empirically estimate the effect of Uber entry on the motor vehicle homicide rate we create a unique dataset from several sources within the California Highway Patrol's Statewide Integrated Traffic Report System (SWITRS). This rich dataset gives us information not only on the number of crashes which occurred within each township in the state of California, but blood alcohol content of the driver (i.e. if alcohol was involved), the number of parties involved, weather, speed, and other environmental factors. Although California is a single state, the fact that it is the most populated state in the nation and has had Uber service the longest, makes it ideal for testing our research question. When combined, this dataset comprises 12420 observations spanning 23 quarters (January 2009 – September of 2014) over 540 townships in the state of California.

Summary statistics and correlations can be found in Table 1.

Variable Definitions

Dependent Variable: The dependent variable, *ln(NumDeaths)*, is the natural log (+1) of the number of people who were killed in a motor vehicle accident in town *j* during quarter *t* where at least one of the involved parties was under the influence of alcohol (i.e. a blood alcohol content >= 0.08%)[8]. We use the number of deaths, as opposed to the number of crashes or traffic stops, because there is a significant delay in the aggregation of data which does not involve significant injury. At the time of data collection (November 2014), non-injury collision data were available only through October 2013 (thereby dramatically limiting the variability in the entry of Uber services and the duration of treatment).

Independent Variables: Our primary independent variables of interest are two dichotomous treatment indicators, *UberX* and *UberBlack*, which indicate the entry of the Uber black car service and Uber X service, respectively, into the county where city *j* is located at time *t*[9]. A full listing of the counties which receive the Uber treatments is available in Table 2. As discussed previously, *Uber Black* is a premium car service which can be hired through the application (thereby eliminating the availability concerns which are present with hiring a taxi) at a price premium of roughly 20-30% depending on location. Further, *Uber X* is a discount service where drivers will bring the user to her requested location using their personal vehicles for a price reduction (again roughly 20-30% over taxis depending on location). Information about the data of Uber entry is retrieved by hand from the Uber website[10]. These variables are coded as 1 during the first *full* quarter the city has received treatment. Finally, to complete the difference in

[8] Note that results are consistent when estimated at the week and month level. We use quarters, as opposed to these time periods, to increase the interpretability of the later estimations, viz. the relative time model.
[9] Attempts to get the number of drivers working for Uber in each location were made but denied by the firm.
[10] blog.uber.com

difference estimation we include time (quarter) and city fixed effects.

Empirical Estimation

As the dependent variable of the investigation is a log we conduct our baseline estimation using an ordinary least squares regression. We estimate the effect of changes in treatment on the dependent variable (y_{jt}) using the following equation:

$$y_{jt} = M'\theta_1 + H'\eta_1 + R'\gamma_1 + \alpha + \varepsilon \qquad (1)$$

where y_{jt} represents the log of the number of drivers killed in alcohol related crashes, M is the vector of Uber treatments, H is the vector of time fixed effects, and R is the vector of town fixed effects. α and ε indicate the constant and error term. {θ, η, γ} represent the terms to be estimated. To reduce heteroscedasticity concerns we leverage robust standard errors clustered at the county level (i.e. the level of treatment). Results can be found in Table 3.

Before discussing the results we first remediate several well-known concerns with the difference in difference estimation (Angrist and Pischke 2008, Bertrand et al. 2002). Chief among them is the assumption that there is no difference in the pre-treatment trend across observations which is not resolved by the location fixed effects. To the extent that randomly distributed factors across the state of California may result in pre-treatment heterogeneity, such as non-random selection (i.e. endogenous entry) into different counties, we replicate our investigation using the relative time model discussed in Greenwood and Agarwal (2013). This is done by creating a second series of time dummies, in addition to the chronological time dummies, which indicate the relative chronological distance between time *t* and the time Uber is implemented in city *j*. Intuitively, what this model allows us to do is measure the effect of treatment over time (both before and after the treatment is applied). Econometrically, the primary benefit of this model is that it can determine if a pre-treatment trend exists (i.e. a significant difference between treated and untreated counties) in order to determine if the untreated counties are an acceptable control group. If such a trend exists, it would violate one of the primary assumptions of the difference in difference model (Bertrand et al. 2002). We therefore model the number of motor vehicle homicides in j at time t using the following specification:

$$y_{jt} = \rho'[s_2 * \varphi] + H'\eta_2 + R'\gamma_2 + \alpha + \varepsilon \qquad (2)$$

As before y_{jt} represents the log of the number of people killed in alcohol related crashes, H is the vector of time fixed effects, and R is the vector of town fixed effects. α and ε indicate the constant and error term, respectively. s_2 is a dichotomous variable which indicates whether or not Uber will ever affect city j during the study and the vector $\{\rho\}$ contains the relative time parameters to be estimated (i.e. the chronological distance between time t and the time the Uber service will be implemented at city j). Standard errors are robust and clustered at the county level. Results can be found in Table 4. Note that the full model, i.e. with the relative time controls for both *UberX* and *Uber Black*, cannot be run concurrently because the model will be over-specified. For this reason, we estimate the relative time models independently.

Results

With respect to our independent variables of interest, *Uber X* and *Uber Black,* the results are intriguing. While results suggest that introducing *Uber X* (Columns 1 and 3) into a city has a significant dampening effect on the number of alcohol related driving deaths, the introduction of *Uber Black* (Columns 2 and 3) does not. All else equal this suggests several key pieces of information. First, it suggests that previous within city investigations of the effect of Uber entry may have been overstated (e.g. Badger 2014). Second, it suggests that a coupling of cost and availability is the key driving force behind the decrease in DUI related deaths, indicating that patrons are unwilling to pay a price premium for the *Uber Black* service, even in the short term. Economically, these results suggest an average decrease in DUIs related homicides of 3.6% in locations treated by *Uber X* in the state of California.

The results from the relative time model (Table 4) further underscore these findings. We first note that none of the pre-treatment time dummies (i.e. Rel Time$_{(t-x)}$) are significant, thereby allowing us to validate the assumptions of the difference in difference model (Angrist and Pischke 2008, Bertrand et al. 2002)[11]. The absence of significance suggests that there is no significant heterogeneity, pre-treatment, across cities which receive the Uber treatment, and those which do not, which has not been accounted for. Second, we see that while an effect manifests almost immediately for *Uber X*, it does not become stable until roughly nine months after treatment. This further underscores the absence of an effect for *Uber Black*, even in the long term. Finally, the fact that the stable effect takes a significant period of time to manifest casts further doubt on prior investigations which claim an effect appears in weeks or even days (not months as our results indicate).

Taken in sum, results indicate a significant effect for *Uber X*, and the absence of an effect for *Uber Black*. To the extent that *Uber X* provides significant cost savings over traditional taxi cabs, our results suggest that the dominant mechanism which is driving the observed decrease in motor vehicle homicide is cost.

Robustness Checks

Selection Model

While our preliminary results indicate the absence of a significant pre-treatment trend, the assumption that Uber entry into varying locations is purely exogenous remains questionable. To further test this assumption we include a robust set of controls which may influence the decision by Uber executives to enter local markets. More specifically, to account for population level factors (e.g. age, education, population, wealth) which might influence the entry of Uber into a local area we combine the existing dataset with information from the US Department of Health

[11] Note that the other relative time dummies (those greater than 4 quarters pre-treatment and 5 quarters post treatment) are included in the model and omitted in the interest of space. Full results are available upon request.

and Human Services' Area Resource File and the Federal Bureau of Investigation's Law Enforcement Officers Killed and Assaulted dataset.

The resulting dataset contains three additional sets of controls. First, because the population in locales may influence entry we include the log of the local population (to control for the size of the market), median income (to control for the wealth of the market), and number of college graduates (to control for the market of likely users). Second, to control for the portion of the extant population unlikely to leverage the Uber service, we include the log of the population living in poverty, who have limited disposable income and are less likely to use cutting edge IT (DiMaggio et al. 2004), and those over the age of 65 (i.e. the elderly), who are also likely to suffer from digital inequalities (Warschauer 2004). Third, as the expansion of Uber has been contentious legally we include the log of the number of individuals within the county working in law enforcement. We then replicate the estimation of equations 1 and 2 with these controls included. Results are available in Tables 5 and 6.

Before considering the effect of *Uber Black* and *Uber X* in these estimations we first consider the effects from our control variables. Interestingly, we see that a change in any of the other controls significantly influences the number of motor vehicle homicides involving alcohol during the period of investigation. This further underscores the fact that the fixed effects for the local municipalities are effectively controlling for across city heterogeneity in the estimations. Recall that, as there are time fixed effects in the estimations as well, these variables should be interpreted as changes in the independent variable. Moreover, results from the primary variables of interest remain consistent insofar as we see a negative and significant effect of *Uber X* and no significant effect of *Uber Black.*

Count Model

Although our initial regressions have shown remarkable consistency across several specifications, other potentially confounding problems remain. The first is that the distribution of the dependent variable is not strictly Gaussian, despite being logged. To the extent that this violates one of the basic assumptions of the Gauss-Markov theorem, because the distribution of the error term will not be Gaussian, it may lead to inconsistent estimations of the results. To remedy this concern we re-estimate our results using a non-transformed dependent variable to increase our confidence in the baseline estimations.

Empirically, we perform these regressions using two different estimators. The first is a traditional OLS. The second is a Poisson quasi-maximum likelihood estimator (Simcoe 2007) (QMLE) which has been used extensively in recent work (Azoulay et al. 2010, Greenwood and Gopal 2012). We use the QMLE in lieu of other options, such as the Poisson or Negative Binomial estimators for several reasons. First, it allows for the creation of robust standard errors when the distribution of the dependent variable is not Negative Binomial or Poisson (Azoulay et al. 2010). Second, because the QMLE is not constrained by the same assumptions as the Negative Binomial or Poisson estimators (i.e. that the conditional variance of y given x is equal to the conditional mean), the assumptions of the model are not violated if the distribution of the dependent variable is not Negative Binomial or Poisson. A full description of the estimator, as well as its derivation, can be found in Wooldridge (1997). As before, we replicate the estimation of both equation 1 and 2 using the non-transformed DV. Results are in Tables 7 and 8.

Results in Table 7 add interesting nuance to the previous estimations. While the effect of *Uber Black* remains insignificant using both estimators, the effect of *Uber X* is significant only using the OLS estimator. However, when considering the results from Table 8 the reason behind the insignificant result becomes clear. While the log relative time model (Tables 4 and 6) and the

OLS count model (Table 8 Column 2) both suggest the effect becomes significant and consistent after roughly nine months, the QMLE suggests that the effect takes significantly longer to manifest (5 quarters). All else equal, this suggests that the delay in the time for the effect to manifest, i.e. the initially insignificant effect, is masking the later significant effect. Furthermore, both models show an intermittent effect for *Uber Black* (Columns 2 and 4), although the rarity with which the effect appears makes any conclusion being drawn from the estimations dubious.

Coarsened Exact Match

Our next concern is that while the controls and fixed effects account for much of the unobserved heterogeneity between treated and untreated groups, insofar as changes in the controls in Tables 5 and 6 yield no significant effect on the dependent variable, it is plausible that the untreated cities are not a representative counterfactual for treated cities[12]. To resolve this we execute a coarsened exact matching (CEM) procedure to limit the *ex-ante* differences between the treatment and control samples (Blackwell et al. 2009, Iacus et al. 2012). Principally, the CEM allows us to match explicitly on observable characteristics and simultaneously limit the differences between the two groups from both a multivariate and univariate perspective. To the extent that this increase the homogeneity between the two samples, it increases the strength of the causal claims from change in the treatment (Overby and Forman 2014), i.e. Uber entry. To execute this procedure we match on three different criteria: the population of the city as determined by the SWITRS dataset, per capita income of the city, and current period[13]. We then replicate the analysis from Table 3. Results, once again, indicate a strong and significant effect of *Uber X* entry, and an insignificant effect of *Uber Black* entry. Moreover, we note that the size of

[12] Recall that the level of the observation is the city but the treatment is applied at the county.
[13] The inclusion of additional matching variables reduced the size of the sample, and therefore power of the estimations, to a point where robust conclusions could not be drawn from the data.

the *Uber X* coefficient is significantly larger in this far more constrained model (more than 1.5x the size).

Random Treatment Model

The final robustness test we run is a random implementation model to determine with what probability the observed effect could have occurred purely by chance. To the extent that significant changes in the motor vehicle homicide rate may be occurring in untreated locations, or the effect of the Uber treatment is substantially driven by a single location, this model provides an important robustness check against outliers.

To execute this model we take two approaches. In the first we randomly apply the *Uber X* treatment to 862 city-quarters (1249 for *Uber Black*). We then regress the log of the alcohol related motor vehicle homicide rate upon this “pseudo” treatment and store the coefficient. This analysis is then replicated 1000 times and the draw of the actual treatment is compared against the mean and standard deviation of the pseudo-treatments. In the second approach we apply the pseudo treatment only to cities which eventually receive the *Uber* treatment. Results are in Table 10. As can be seen from the results, the probability of a similar coefficient occurring purely by chance is exceptionally likely for *Uber Black* (which is unsurprising given the insignificant coefficient in the majority of the estimated models). However, in both random treatments (both purely random and random within treated cities) the probability of a similarly sized coefficient appearing purely by chance for *Uber X* is exceptionally low ($P<0.001$).

Empirical Extensions

While our empirical estimations thus far suggest that cost considerations are of the utmost importance when patrons avoid operating under the influence it is worth considering the boundary conditions of this effect, i.e. when the strength of the effect is intensified or attenuated. To explore these conditions we consider two potential moderators to demand: days of the year when demand is likely to spike, thereby causing Uber's surge pricing to be put into effect, and the size of the local population, which should correlate with the steady state demand in the local market.

Surge Pricing

The first empirical extension we investigate is whether or not the effect of Uber still manifests during spikes in demand. To the extent that spikes in demand will cause Uber's surge pricing[14] to be put into effect, thereby raising the price of hiring either an Uber X or Uber Black car, this is an important extension to conduct because of the dependence of our results on low cost options. If, for example, the effect of Uber intensified or stayed constant during periods of higher demand, this would suggest that the lack of supply of taxis is the dominant mechanism by which the drop in alcohol related motor vehicle homicides occurs. Alternatively, if the effect attenuates during spikes in demand, when cost concomitantly rises due to the surge pricing, this would suggest that cost is indeed the driving mechanism because Ubers of either price are no longer being hired to avoid driving under the influence.

To estimate the effect of Uber entry during these times we recalculate the dependent variable as the total number of alcohol related motor vehicle deaths during Friday and Saturday nights (i.e. weekend nights where drinking is more prevalent) and US major holidays which involve drinking[15], thereby resulting in an increased load on the vehicles for hire in the local area. We then re-estimate equation 1. Results are in Table 11 and indicate no significant effect of Uber entry on the number of persons killed during these times. Taken in sum, this underscores

[14] A full explanation of surge pricing from Uber can be found here: https://support.uber.com/hc/en-us/articles/201836656-What-is-surge-pricing-and-how-does-it-work-

[15] The full list of holidays includes: Fourth of July, Memorial Day, Labor Day, Cinco de Mayo, Thanksgiving, the day before Thanksgiving, Christmas, Christmas Eve, Halloween, Easter, New Years Eve, and Superbowl Sunday. The source of these data is: http://content.time.com/time/specials/packages/article/0,28804,1986906_1986905_1986891,00.html

findings thus far which indicate that costs are the most significant factor in understanding the negative effect of Uber entry on the decrease in the alcohol related motor vehicle homicide rate.

Population

Our final set of empirical estimations relate to the size of the population in the local area. To the extent that the size of local population will affect the size of the steady state demand, and by extension the supply of Ubers in the local area because Uber drivers will respond to extant market forces, it is reasonable to assume that local markets will exist in a steady state equilibrium of Uber distribution. While this would suggest that there would be no difference of the per capita effect of Uber, by city population size, the opposite may also be true. On one hand, it is plausible that the relative size of the effect in larger cities may be smaller because larger cities often have more established alternative transportation options, viz. public transportation. Alternatively, it is also possible that the effect would be larger in large cities because smaller townships have too small a population to garner significant attention from Uber drivers. To the extent that an *a priori* expectation of the effect is tenuous, and an understanding of how different locations are affected differently paints a richer picture of how the sharing economy influences public welfare, we allow our empirical analysis to guide us.

To investigate in which cities Uber has a stronger and weaker effect we trichotomize the population data from the SWITRS dataset into three groups: small cities (which serves as the base case), medium sized cities (those with populations greater than 50,000 people and less than 250,000 people), and large cities (those with populations greater than 250,000 people). We then interact these new variables with the Uber treatment and replicate our estimations[16]. Results are in Table 12. Strikingly, these findings suggest several interesting differences. First, we see that as

[16] Note that the base effect, i.e. the non-interacted term, of the newly created variables will not be estimated because the city fixed effect perfectly predicts the base effect.

the population of local cities increases, there is a concomitant rise in the effect of Uber entry. Moreover, we see that a significant effect also manifests for *Uber Black* car services (although the size of the effect declines precipitously in the presence of *Uber X* (Column 3)). Taken in sum, these results suggest a significantly stronger negative effect on the alcohol related motor vehicle homicide rate in larger cities when compared with smaller cities.

Discussion and Conclusion

In this work we investigated the effect of the entry of various different services offered by the ridesharing service Uber on the incidence rate of alcohol related motor vehicle homicide. While intuition would suggest the rate of alcohol related crashes should decrease after Uber enters a local market, we argued that the willingness to pay for such a service and the necessary conditions for an effect to manifest is still unknown. On one hand, it is plausible that an effect would manifest as a result of the increased availability of driving services, due to the decrease in search costs and the difficulty in hiring a cab based on the location, time, or even race of the individual. On the other hand, it is equally plausible that both cost and availability are the main mitigating factors preventing individuals from hiring cabs. To the extent that rational choice theory (Clarke and Cornish 1985, Cornish and Clarke 2014) suggests that most decisions to engage in illegal activity are a function of the reward, potential penalty, and the probability of being apprehended by law enforcement, it is possible that these homicides are a result of rational choice on the part of consumers. Results indicate that there is a significant effect of the entry of lower priced Uber options, viz. Uber X, indicating that price is the main barrier to reducing the DUI rate in many jurisdictions. Furthermore, results suggest a significantly stronger effect in larger cities. Finally, findings suggest that there is no effect when surge pricing is likely in effect (i.e. during weekends and drinking holidays), thereby underscoring the importance of cost in affecting the number of deaths which occur in alcohol related crashes.

Economically, results indicate that the entrance of Uber X results in a 3.6% – 5.6% decrease in the rate of motor vehicle homicides per quarter in the state of California. With more than 13k deaths occurring nationally each year due to alcohol related car crashes at a cost of 37 billion dollars[17], results indicate that a complete implementation of Uber X would create a public welfare net of over 1.3 billion to American taxpayers and save roughly 500 lives annually. Moreover, with costs to the individual (e.g. court costs, insurance rate increases, loss of income) usually totaling between 5k and 12k dollars for the first DUI offence[18], significant welfare accrues to the individual as well by leveraging these services.

Theoretically, these results have many implications for the sharing economy. To the degree that vendors such as AirBnB, Uber, and Lyft have been proposed as solutions to many market failures our work provides cautionary evidence that consumers will continue to use established vendors when prices increase. As a result, while lower priced hotels and car services may be usurped by these emerging business models, minimal evidence exists to suggest that premium vendors will be displaced (as evidenced by the absence of a stable and consistent effect for Uber Black Car services).

Furthermore, findings have important implications for the ongoing debate regarding the legality of services like Uber. Although the results of this investigation cannot speak to public welfare losses which may result from improper vehicle handling or safety on the part of consumers, they provide important insights into the potential benefits of the sharing economy. To the extent that much of the debate surrounded Uber is speculative, with the absence of hard data and robust empirical investigations to quantify the losses or gains of such services, this work provides a key insights into the benefits such services can provide to policy makers.

[17] http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/by_the_numbers/drunk_driving/index.html
[18] http://dui.drivinglaws.org/resources/how-much-does-a-first-offense-dui-cost.htm

Finally, this work contributes to the small, but growing, literature in information systems about the effect of information sharing platforms on public welfare (Bapna et al. 2012, Burtch et al. 2013, Chan and Ghose 2014, Greenwood and Agarwal 2013). To the degree that platforms have been found both enhance (Burtch et al. 2013) and diminish (Chan and Ghose 2014, Greenwood and Agarwal 2013) public welfare, our work contributes by drawing a richer picture of the public welfare implications of platform introduction. Moreover, it serves as an open call to extend this research into other aspects of the sharing economy; such as education market places, government to citizen platforms, and innovation market places.

It is important to note that this work is subject to several limitations. First, we conduct our analysis only in the State of California due to data availability. While California is a large and economically diverse state, which offers the ability to study Uber over a protracted period of time, this is simply a limitation and further research will be necessary to ensure the robustness of the results. Second, although results indicate an absence of unaccounted for heterogeneity before the implementation of Uber, it is important to note that the entry of the service is not purely exogenous. As a result, further work is necessary to ensure that there are not confounding factors which also influence the results. Finally, to the degree that limited information is available about the drivers of vehicles which are involved in the crashes, we are unable to uncover which populations and sub-populations are influenced to the greatest degree based on race, gender, age, or socio-economic status. Given the paucity of data available about such factors, we leave them as topics for future research.

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Figure 1: Screen Shot of Uber App

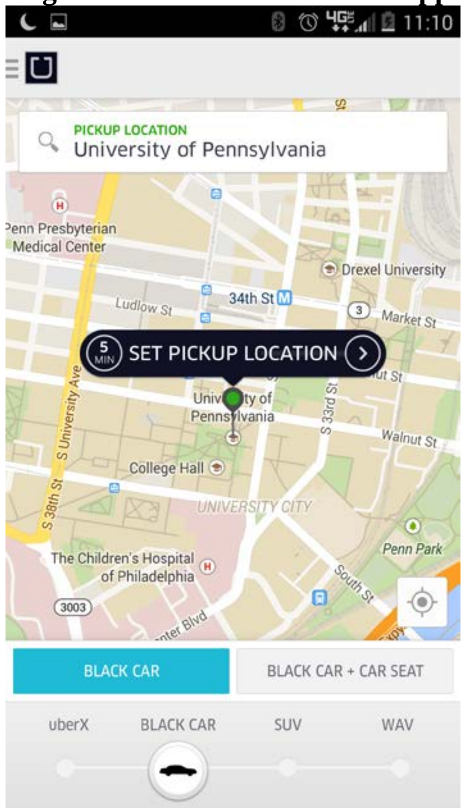

Table 1: Summary Statistics and Correlations
N – 12420

	Mean	Std. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)ln(Num Deaths)	0.202	0.444								
(2)UberX	0.069	0.254	-0.041							
(3)UberBlack	0.101	0.301	-0.007	0.506						
(4)ln(Population)	13.636	1.725	0.080	0.241	0.393					
(5)ln(Median)	10.927	0.230	-0.025	0.008	-0.008	0.322				
(6)ln(Poverty)	2.808	0.297	0.054	0.098	0.148	0.017	-0.869			
(7)ln(Elderly)	11.541	1.618	0.072	0.248	0.408	0.994	0.346	-0.026		
(8)ln(Police)	7.033	1.675	0.080	0.259	0.429	0.978	0.214	0.092	0.976	
(9)ln(College)	12.304	1.888	0.065	0.230	0.387	0.982	0.458	-0.131	0.987	0.949

Table 2: Listing of Uber Black and Uber X Treated Counties (Month/Year)

County	UberBlack	UberX
Riverside		5/2014
San Bernardino		5/2014
Bakersfield		7/2014
Fresno		2/2014
Los Angeles	3/2012	9/2013
Modesto		4/2014
Orange	4/2014	9/2013
Palm Springs		9/2013
Sacramento	1/2013	11/2013
San Diego	2/2012	5/2013
San Francisco	6/2010	7/2012
San Luis Obispo		7/2014
Santa Barbara	10/2013	4/2014
Ventura		7/2014

Table 3: Time Series OLS Estimations of Uber Entry on Alcohol Related Driving Fatalities

	(1)	(2)	(3)
Dependent Variable	ln(Num Deaths)	ln(Num Deaths)	ln(Num Deaths)
UberX	-0.0369**		-0.0362**
	(0.0180)		(0.0179)
UberBlack		-0.0142	-0.00156
		(0.0153)	(0.0151)
Constant	0.250***	0.250***	0.250***
	(0.0123)	(0.0123)	(0.0123)
Time Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
N	12,420	12,420	12,420
R-squared	0.035	0.035	0.035
Number of Groups	540	540	540

Robust standard errors in parentheses (Clustered on County)
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Relative Time Model of Uber Entry on Alcohol Related Motor Vehicle Deaths

	(1)	(2)
Dependent Variable	ln(Num Deaths)	ln(Num Deaths)
Model	Uber X	Uber Black
Rel Time $_{(t-4)}$	0.0435	-0.0269
	(0.0280)	(0.0346)
Rel Time $_{(t-3)}$	-0.00199	0.0141
	(0.0270)	(0.0360)
Rel Time $_{(t-2)}$	-0.0314	-0.0112
	(0.0274)	(0.0361)
Rel Time $_{(t-1)}$	-0.0159	0.00498
	(0.0272)	(0.0361)
Rel Time $_{(t0)}$	Omitted Base Case	
Rel Time$_{(t+1)}$	-0.0494*	-0.0155
	(0.0292)	(0.0346)
Rel Time$_{(t+2)}$	-0.0301	0.0315
	(0.0312)	(0.0414)
Rel Time$_{(t+3)}$	-0.0539*	-0.0205
	(0.0314)	(0.0372)
Rel Time$_{(t+4)}$	-0.214***	-0.0353
	(0.0705)	(0.0402)
Rel Time$_{(t+5)}$	-1.124***	-0.0277
	(0.300)	(0.0390)
Constant	0.216***	0.251***
	(0.0185)	(0.0158)
Time Fixed Effects	Yes	Yes
City Fixed Effects	Yes	Yes
N	12,420	12,420
R-squared	0.041	0.041

Robust standard errors in parentheses (Clustered on county)
*** p<0.01, ** p<0.05, * p<0.1

Table 5: OLS Estimations of Uber Entry on Alcohol Related Driving Fatalities including Controls

	(1)	(2)	(3)
Dependent Variable	ln(Num Deaths)	ln(Num Deaths)	ln(Num Deaths)
UberX	-0.0321**		-0.0324**
	(0.0141)		(0.0153)
UberBlack		-0.0105	0.000716
		(0.0125)	(0.0136)
ln(Population)	-75.04	-27.13	-76.68
	(664.4)	(664.8)	(665.1)
ln(Median)	0.0163	0.0351	0.0160
	(0.145)	(0.145)	(0.146)
ln(Poverty)	-0.108	-0.111	-0.108
	(0.0707)	(0.0709)	(0.0709)
ln(Elderly)	0.162	0.166	0.163
	(0.171)	(0.174)	(0.174)
ln(Police)	0.000451	0.000353	0.000559
	(0.0350)	(0.0351)	(0.0351)
ln(College)	74.68	26.71	76.31
	(664.5)	(664.9)	(665.2)
Constant	103.0	39.66	105.1
	(883.8)	(884.4)	(884.8)
Time Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
N	12,420	12,420	12,420
R-squared	0.036	0.035	0.036

Robust standard errors in parentheses (Clustered on county)
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Relative Time Model of Uber Entry on Alcohol Related Motor Vehicle Deaths

	(1)	(2)
Dependent Variable	ln(Num Deaths)	ln(Num Deaths)
Model	Uber X	Uber Black
Rel Time $_{(t-4)}$	0.0428	-0.0296
	(0.0280)	(0.0348)
Rel Time $_{(t-3)}$	-0.00251	0.0116
	(0.0270)	(0.0361)
Rel Time $_{(t-2)}$	-0.0316	-0.0138
	(0.0274)	(0.0362)
Rel Time $_{(t-1)}$	-0.0160	0.00491
	(0.0272)	(0.0361)
Rel Time $_{(t0)}$	Omitted Base Case	
Rel Time$_{(t+1)}$	-0.0487*	-0.0154
	(0.0292)	(0.0346)
Rel Time$_{(t+2)}$	-0.0291	0.0318
	(0.0312)	(0.0414)
Rel Time$_{(t+3)}$	-0.0530*	-0.0200
	(0.0314)	(0.0373)
Rel Time$_{(t+4)}$	-0.212***	-0.0346
	(0.0705)	(0.0402)
Rel Time$_{(t+5)}$	-1.114***	-0.0270
	(0.301)	(0.0390)
ln(Population)	-242.4	-34.69
	(665.4)	(321.4)
ln(Median)	0.00978	0.0495
	(0.148)	(0.145)
ln(Poverty)	-0.104	-0.0939
	(0.0713)	(0.0658)
ln(Elderly)	0.122	0.128
	(0.173)	(0.190)
ln(Police)	-0.00972	-0.00628
	(0.0351)	(0.0306)
ln(College)	242.2	34.27
	(665.5)	(321.6)
Constant	324.4	49.95
	(885.1)	(425.9)
Time Fixed Effects	Yes	Yes
City Fixed Effects	Yes	Yes
N	12,420	12,420
R-squared	0.042	0.041
Number of Groups	540	540

Robust standard errors in parentheses (Clustered on county)
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Count Model Estimates of Uber Entry on Alcohol Related Motor Vehicle Deaths

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Num Deaths	Num Deaths	Num Deaths	Num Deaths	Num Deaths	Num Deaths
Estimator	OLS	OLS	OLS	QMLE	QMLE	QMLE
UberX	-0.142*		-0.126**	-0.0345		-0.00921
	(0.0726)		(0.0534)	(0.0902)		(0.0950)
UberBlack		-0.0931	-0.0493		-0.0576	-0.0556
		(0.0839)	(0.0766)		(0.0623)	(0.0656)
Constant	18.36	0.546***	0.546***			
	(11.46)	(0.0350)	(0.0350)			
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	12,420	12,420	12,420	9,200	9,200	9,200
R-squared	0.030	0.029	0.030			
χ-squared				325.89	326.56	326.55

Robust standard errors in parentheses (Clustered on County)
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Count Based Relative Time Model of Uber Entry on Alcohol Related Motor Vehicle Deaths

	(1)	(2)	(3)	(4)
Dependent Variable	Num Deaths	Num Deaths	Num Deaths	Num Deaths
Model	Uber X	Uber Black	Uber X	Uber Black
Estimator	OLS	OLS	QMLE	QMLE
Rel Time $_{(t-4)}$	0.158**	-0.0874	0.0438	-0.203
	(0.0715)	(0.0742)	(0.142)	(0.147)
Rel Time $_{(t-3)}$	0.0108	0.0387	-0.160	0.0134
	(0.0690)	(0.0693)	(0.158)	(0.124)
Rel Time $_{(t-2)}$	-0.0435	-0.00880	-0.228	-0.0683
	(0.0698)	(0.0706)	(0.145)	(0.135)
Rel Time $_{(t-1)}$	-0.0481	-0.00129	-0.211*	-0.0437
	(0.0696)	(0.0814)	(0.126)	(0.154)
Rel Time $_{(t0)}$		Omitted Category		
Rel Time$_{(t+1)}$	-0.118	-0.0401	-0.393**	-0.147
	(0.0745)	(0.0933)	(0.175)	(0.186)
Rel Time$_{(t+2)}$	-0.124	0.108	-0.266	0.124
	(0.0796)	(0.0910)	(0.220)	(0.148)
Rel Time$_{(t+3)}$	-0.155*	-0.122	-0.450	-0.168
	(0.0800)	(0.141)	(0.351)	(0.226)
Rel Time$_{(t+4)}$	-0.660***	-0.225*	-0.580	-0.354*
	(0.180)	(0.137)	(0.572)	(0.194)
Rel Time$_{(t+5)}$	-2.723***	-0.125	-14.84***	-0.115
	(0.767)	(0.119)	(1.023)	(0.185)
Rel Time$_{(t+6)}$	-1.650**	-0.287**	-0.761***	-0.467***
	(0.768)	(0.114)	(0.146)	(0.168)
Rel Time$_{(t+7)}$	-2.580***	-0.0928	-14.26***	-0.00810
	(0.768)	(0.149)	(1.027)	(0.225)
Rel Time$_{(t+8)}$	-2.433***	-0.242	-11.96***	-0.477
	(0.768)	(0.195)	(1.118)	(0.337)
Constant	0.414***	0.541***		
	(0.0473)	(0.0372)		
Time Fixed Effects	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Observations	12,420	12,420	9,200	9,200
R-squared	0.037	0.036		
χ-squared			353.04	350.28
Number of Groups	540	540	400	400

Robust standard errors in parentheses (Clustered on County)
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Coarsened Exact Match OLS of Uber Entry on Alcohol Related Motor Vehicle Deaths

	(1)	(2)	(3)
Dependent Variable	ln(Num Deaths)	ln(Num Deaths)	ln(Num Deaths)
Uber X	-0.0559**		-0.0566**
	(0.0236)		(0.0234)
Uber Black		-0.0542	-0.0567
		(0.0550)	(0.0547)
Constant	0.186***	0.216***	0.217***
	(0.0194)	(0.0355)	(0.0354)
Time Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
Observations	2,037	2,037	2,037
R-squared	0.056	0.054	0.057

Robust standard errors in parentheses (Clustered on County)
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Output of Random Implementation Model

	Random Implementation		Random Implementation In Treated	
Sample	Uber X	Uber Black	Uber X	Uber Black
μ of Random β	0.00215	-0.00027	-0.00041	-0.00039
σ Random β	0.01060	0.00897	0.01028	0.00856
Estimated β	-0.0362	-0.00156	-0.0362	-0.00156
Replications	1000	1000	1000	1000
Z-Score	-3.619029	-0.144076	-3.481857	-0.137099
P-Value	p<0.001	0.44272	p<0.001	0.44548

Table 11: Estimations of Uber Entry on Alcohol Related Deaths on High Demand Days
High Demand Days Defined as Weekends and Drinking Holidays

	(1)	(2)	(3)
Dependent Variable	ln(Num Deaths)	ln(Num Deaths)	ln(Num Deaths)
UberX	-0.00240		-0.00628
	(0.0110)		(0.0120)
UberBlack		0.00640	0.00859
		(0.00893)	(0.00973)
Constant	0.0922***	0.0922***	0.0922***
	(0.00892)	(0.00892)	(0.00892)
Time Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
N	12,420	12,420	12,420
R-squared	0.011	0.011	0.011
Number of Groups	540	540	540

Robust standard errors in parentheses (Clustered on county)
*** p<0.01, ** p<0.05, * p<0.1

Table 12: OLS Estimations of Uber Entry Interacted with Population
Medium City indicates Population 50,000 – 250,000
Large City indicates Population >= 250,000

	(1)	(2)	(3)
Dependent Variable	ln(Num Deaths)	ln(Num Deaths)	ln(Num Deaths)
UberX	0.00745		0.00404
	(0.0166)		(0.0174)
UberX * Medium City	-0.164***		-0.166***
	(0.0534)		(0.0552)
UberX * Large City	-0.523***		-0.426***
	(0.111)		(0.115)
UberBlack		0.0128	0.00709
		(0.0145)	(0.0151)
UberBlack * Medium City		-0.0745*	0.00401
		(0.0427)	(0.0412)
UberBlack * Large City		-0.411***	-0.196*
		(0.0953)	(0.104)
Constant	0.250***	0.250***	0.250***
	(0.0123)	(0.0123)	(0.0123)
Time Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
N	12,420	12,420	12,420
R-squared	0.044	0.039	0.045
Number of Groups	540	540	540

Robust standard errors in parentheses (Clustered on county)
*** p<0.01, ** p<0.05, * p<0.1