Southern Economic Journal 2018, 84(4), 965–991
DOI: 10.1002/soej.12255

Ride-Sharing, Fatal Crashes, and Crime

Angela K. Dills* and Sean E. Mulholland†

The advent of smart-phone based, ride-sharing applications has revolutionized the vehicle for hire market. Advocates point to the ease of use, lower prices, and shorter wait times compared to hailing a taxi or prearranging limousine service. Others argue that proper government oversight is necessary to protect ride-share passengers from driver error or vehicle parts failures and violence from unlicensed strangers. Using U.S. county-level data from 2007 through 2015, we investigate whether the introduction of the ride-sharing service Uber is associated with changes in fatal vehicle crashes and crime. We find that Uber's entry lowers the rate of DUIs and fatal accidents. For some specifications, we also find declines in arrests for assault and disorderly conduct. Conversely, we observe an increase in vehicle thefts.

JEL Classification: JEL Codes: R41, K42, D45

1. Introduction

The advent of smart-phone based, ride-sharing applications has revolutionized the vehicle for hire market. An alternative to traditional taxi and limousine services, ride-sharing applications, such as Uber and Lyft, enable potential passengers to "hail" nearby private drivers via geolocation. Potential passengers and drivers both broadcast their locations, quickly map the distance to one another, agree on a price, and estimate the likely wait time. Although matching drivers to potential passengers in real-time provides a greater ease of service, this innovation has encountered much scrutiny (Rogers 2015). Much of the scrutiny stems from the lack of state and municipal safety regulations that are required of ride-sharing's competitors: traditional taxis and limousines.

We investigate whether the introduction of the ride-sharing service, Uber, is associated with net changes in vehicular fatalities and arrest rates. Ride-sharing passengers, drivers, and others may respond to Uber in a variety of ways. With little to no regulation, ride-sharing passengers, as well as pedestrians and occupants in nearby vehicles, may be subject to a greater risk of injury from driver error or parts failures. The use of smartphone applications by drivers and increases in the number of passengers per vehicle potentially increase driver distraction. The increased interaction of nongovernment certified drivers and passengers may result in greater violence. Conversely, these applications reduce passenger wait times and may encourage some drowsy or intoxicated potential drivers to ride instead (Rayle et al. 2016). Yet, this ease of use might also increase alcohol consumption and other risky behavior. All of these behavioral responses affect the risk of

* Department of Economics, Management, and Product Management, College of Business, Western Carolina University, Forsyth 224A, 1 University Way, Cullowhee, NC, 28723, USA; E-mail: angeladills@gmail.com.

† Department of Economics, Management, and Product Management, College of Business, Western Carolina University, Forsyth 224D, 1 University Way, Cullowhee, NC, 28723, USA; E-mail: seanemulholland@gmail.com; corresponding author.

Received April 2017; accepted November 2017.

vehicular crashes and crime.[1] In this article, we empirically estimate the direction and magnitude of these effects.

To do so, we first use monthly data from the National Highway Traffic Safety Administration's Fatality Analysis Reporting System (FARS) to study whether Uber's entry is associated with changes in the overall rate of fatal automobile accidents. We also examine three related measures: alcohol-related fatal crashes, night-time fatal crashes, and the number of vehicular fatalities per 100,000. Using a differences-in-differences specification, we find that fatal accident rates generally decline after the introduction of Uber. Specifically, in the unweighted regressions, we estimate a 1.6% decline in the overall fatal crash rate for each additional quarter Uber is available. For the weighted regressions, we observe a 0.7% decline for each quarter Uber is available. These results are robust to a variety of specifications. For some specifications, we also observe a reduction in the rate of fatal night-time crashes, fatal crashes involving alcohol, and the number of vehicular fatalities for the months following the introduction of Uber.

Next, we use the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) program to explore whether the introduction of Uber is associated with changes in arrests for particular types of crime: aggravated assaults, other assaults, motor vehicle thefts, driving under the influence (DUI), drunkenness, and disorderly conduct. Again, using a differences-in-differences specification, with county-specific trends, we typically find a decline in the arrest rate for DUIs. Recognizing that it takes time for potential users to become aware of the service and for current users to become more familiar with the ride-hailing application, we estimate a 0.8% decline in DUIs for each additional month Uber is available in the unweighted regressions. For most specifications, we also observe declines in the arrest rates for other crimes, but these tend to be imprecisely estimated. However, the arrest rates for motor vehicle theft increase.

We expand the literature on transportation options, crime, and traffic rates by addressing a specific, new industry attracting significant public attention and talk of regulation. In the article most similar to ours, Greenwood and Wattal (2017) use a differences-in-differences approach to show that the entry of Uber into California markets between 2009 and 2014 was associated with a significant drop in the rate of motor vehicle homicides. We expand this analysis geographically to encompass all entry across the United States. Further, we buttress these results with an analysis of arrest rates, including arrests for DUIs, providing completely new evidence of reduced drunk-driving following the introduction of ride-sharing services.

In the following section, we discuss the possible relationships between ride-sharing, fatal traffic accidents, and a variety of crimes. In section 3, we present our data on entry, accidents, and crime. In section 4, we present our differences-in-differences empirical strategy. We reveal the estimation results in section 5 and then conclude in section 6.

2. The Interplay between Transportation, Traffic Accidents, and Crime

Much heat has been generated and ink spilled over the effects of ride-sharing. Although ride-sharing existed long before the advent of smart-phones, ride-sharing exploded when innovators such as Uber's Travis Kalanick and Garrett Camp and Lyft's Logan Green and John Zimmer

[1] We use the terms "crashes" and "accidents" interchangeably, though we note that the terms have unique connotations. For more, see Stromberg (2015).

began using the geolocation function of smart-phones to match private drivers with potential riders. These applications also enabled ride-sharing services to instantaneously alter prices in response to changes in supply and demand. Using geolocation, introducing more flexible pricing, and encouraging automated payments, ride-sharing services offer greater convenience, lower prices, and shorter wait times than other point-to-point transportation options.[2] Many hail these innovations. Others, including taxi and limousine owners and drivers, note the potential safety risks to such unregulated ride-sharing services.

To determine whether the lack of oversight has exposed citizens to greater harm, we investigate whether the introduction of Uber's ride-sharing service is associated with changes in vehicular fatality rates and arrest rates. The advent and expansion of ride-sharing services may affect traffic accidents and crime rates through a variety of mechanisms.

Jackson and Owens (2011) provide a theoretical framework to analyze how public transportation affects driving under the influence and alcohol consumption. Their model predicts that a lower price of public transportation lowers the cost of going out as well as the cost of drinking while out on the town. Ride-sharing services act similarly to public transportation in that individuals can substitute driving themselves or hailing a taxi with using a ride-sharing service.

Translating the predictions in Jackson and Owens (2011) to the case of ride-sharing, the availability of ride-sharing lowers the price of transportation which reduces the probability of driving one's self. If going out is a normal good, the availability of ride-sharing also lowers the cost of going out. This lower cost increases the demand for going out. The availability of ride-sharing also lowers the cost of drinking because it provides an additional transportation option that avoids driving after the consumption of alcohol. By providing a point-to-point transportation option, ride-sharing likely increases the demand for drinking. The net effect of these changes may increase or decrease fatal crashes as the model predicts increases in going out, alcohol consumption, and the use of alternate transportation.

Yet there are many characteristics and effects that ride-sharing does not share with most forms of public transportation. In fact, some of these features are precisely why some cities and counties have sought to regulate or prohibit Uber and other ride-sharing services from operating in their jurisdictions. These characteristics include increases in the number of vehicles on the road, changes in the likelihood of driving while distracted, drowsy, or drunk, and changes in the composition of drivers and vehicles on the road. Therefore, we must also consider how these unique characteristics may translate into changes in traffic accidents.

First, ride-sharing services likely increase the total number of vehicles on the road. With new transportation options, more individuals go out, leading to more congestion and a higher probability of collisions. Those calling for increased regulation note that county or municipal restrictions typically limit the number of taxis and limousines. Expanding the number of vehicles providing point-to-point transportation likely increases vehicle miles traveled and the per capita incidence of vehicular accidents.

Second, ride-sharing may change the likelihood of driving while distracted, drowsy, or drunk. Jackson and Owens (2011) predict that a new transportation option increases the demand for alcohol consumption when going out; increased drinking occurs among drivers as well as those using the new transportation option. Some drinkers substitute away from driving toward ride-sharing. But some may not. Therefore, the net effect of drunk driving is ambiguous. In addition to

[2] Silverstein (2014) calculates the price for an Uber ride and a taxi ride in 21 cities. Without including a tip, Uber is less expensive in 19 of 21 cities; including a tip to the taxi driver, Uber is less expensive in all 21 cities.

any effect of drunk-driving, those driving for ride-sharing services may be distracted drivers. Passengers are often cited as the greatest source of distraction (NHTSA 2014). By increasing the number of private drivers with passengers, ride-sharing may increase the fraction of distracted drivers. Furthermore, using any phone-based application, whether hands-free or not, likely increases the level of distracted driving.[3] When a potential rider electronically hails a driver, the Uber application alerts a driver by sound, but the driver must then determine the time and distance to the potential rider. Interacting with potential riders via the smart-phone application is clearly driving while distracted.[4] This distraction increases the probability of a crash and lowers the safety of passengers as well as nearby drivers and pedestrians.

Third, ride-sharing may change the composition of point-to-point drivers through differing standards for drivers-for-hire. Ride-sharing drivers hold traditional private driver's licenses, whereas most taxi and limousine drivers must hold commercial driver's licenses. Commercially licensed taxi and limousine drivers undergo background checks, vehicle specific tests, a thorough driver history examination, and medical certification. This more intensive licensing process may reduce the likelihood of driver error and accidents. Medically certified commercial drivers may provide better medical care to passengers in the event of an accident.

Fourth, the quality of vehicles on the road may change. The number and type of inspections differ for commercial and private passenger vehicles. For instance, New York City taxis are inspected three times per year, while private vehicles are inspected at most once a year and, in some locations, not at all (NYC Taxi & Limousine Commission 2014). Fewer vehicle inspections increase the likelihood of accidents and injuries from parts failures, especially wear items such as tires and brakes. Those seeking more regulation also note that if a crash does occur, safety controls, such as airbags and seat belts, are more likely to operate properly in a well-inspected commercial vehicle. Conversely, ride-sharing drivers are more likely to own their vehicle. Because the owner-driver is the residual claimant of the vehicle's value, they are likely to be more concerned with the vehicle's appearance and safety equipment than a non-owner driver. Being an owner-driver reduces many of the principal-agent problems present in the vehicle-for-hire market, leading to safer drivers and vehicles. Overall, the net effect of ride-sharing on accidents is ambiguous.

In the article most similar to ours, Greenwood and Wattal (2017) use a differences-in-differences approach to show that the entry of Uber into California markets between 2009 and 2014 was associated with a significant drop in the rate of motor vehicle homicides. Since publicly posting our initial results in May 2016, new studies have surfaced that examine this question. Peck (2017) observes declines in drunk driving in New York post-Uber. Martin-Buck (2016) estimates similar effects to our observed declines in traffic fatalities and declines in arrests for DUI and assaults. In contrast, Brazil and Kirk (2016) observe no effect of Uber on traffic fatalities in the 100 most populous metropolitan areas. Given the differing conclusions when investigating fatal crashes in different areas and locations, we empirically investigate all U.S. locations served and not served by Uber for greater clarity.

Ride-sharing may also affect crime. Many articles have been written about assaults and homicides at the hands of ride-share drivers (Kiplinger 2016). Citing these incidents, some seek

[3] The "NHTSA (2014) reports that in 2012, 16% of all police-reported crashes involved any driver distraction, and that 7% of crashes that involved some form of distraction (and 1.1% of all crashes) involved distraction due to cell phone use" (Carney et al. 2015, p. 45). This is especially true for younger drivers (Doherty et al. 1998; Chen et al. 2000; Mayhew et al. 2003; Williams 2003; Williams et al. 2007). According to Carney et al. (2015), distraction was a factor in 58% of automobile accidents by 16–19-year-olds.

[4] For a discussion of ride-sharing and distracted driving see Richtel (2014).

government regulation of ride-sharing. Ride-sharing options may affect crime rates in a variety of ways: they may change the availability of victims, the cost of fleeing the scene, or increase alcohol consumption. The crimes we consider are ones likely to pick up these effects: robbery, assaults, motor vehicle thefts, DUI, drunkenness, and disorderly conduct.

Ride-sharing may affect these crimes in a number of ways. First, ride-sharing services may change the availability of victims by increasing how often people go out, by increasing interaction of riders and drivers, and by reducing potential riders' wait times. Jackson and Owens (2011) predict an increase in going out due to more transportation options; this would tend to increase crime by increasing social interactions. In addition, by providing a potentially safer alternative to drunk-driving for those who drove themselves to an event but find themselves too inebriated to drive, the availability of ride-sharing may affect the rate of motor vehicle theft by increasing the prevalence of vehicles parked overnight in less secure locations. Ride-sharing passengers may also be more likely to become crime victims if interacting with Uber drivers is more dangerous. Uber drivers are not subject to as thorough of a driver history and criminal background check as are taxicab and limousine drivers. This may increase the risk to ride-sharing passengers of theft, assault, and even death.[5] However, ride-sharing passengers may be less likely to become crime victims because passengers spend less time standing on the street due to the electronic hailing and price adjustments in ride-sharing applications. Uber drivers do not receive training on how to handle unruly passengers as do commercial drivers. Therefore, ride-sharing drivers may also be more likely to become a crime victim than a commercial driver.

Second, criminals also experience a greater ability to leave on short notice (WBAL TV 2015). Because this reduces the likelihood of apprehension, it may increase crime rates. We, however, analyze arrest rates. Greater ability to avoid arrest would appear as a decline in arrest rates holding crime rates constant.

Third, we expect increased alcohol consumption with increased transportation options. Alcohol consumption is associated with some of the crimes we study: robbery, aggravated and simple assaults, drunkenness, and DUI (Snyder et al. 2010 and Carpenter and Dobkin 2015).

As with fatal crashes, the net effect of ride-sharing on crime is also ambiguous. Increased alcohol consumption tends to increase the crimes we examine. Increased going out may increase the crimes we examine through increased social interactions. Some of these increases may be offset by reduced victim availability, as some substitute away from driving and toward ride-sharing.

Previous literature suggests that transportation options affect crime rates. For example, Philips and Sandler (2015) use closures of subway stations to estimate how the availability of public transportation affects crime rates. They find that closing a station reduces nearby crime, primarily in locations to which perpetrators are likely to travel to find victims. Jackson and Owens (2011) consider the effects of changing public transportation schedules on alcohol-related behavior. They find that the availability of late-night public transportation likely increases alcohol consumption, leading to more arrests for minor crimes near bars but fewer DUI arrests in those areas.

[5] The high-profile case of Uber driver Jason Dalton, who shot and killed six people while driving in Kalamazoo Michigan, has increased the level of scrutiny over passenger and pedestrian safety. For more on this case see: Kiplinger (2016). The website "Who's Driving You?" keeps a comprehensive list of incidents at http://www.whosdrivingyou.org/rideshare-incidents.

3. Data

When investigating the effects of ride-sharing on fatal vehicle crashes and crime, we focus on UberX. We chose UberX for four reasons. First, Uber is the oldest and largest of the ride-sharing applications.[6] In 2014, Uber performed over 10 million rides per month, while Lyft garnered second place in market share with an average of only 2.2 million per month (Miller 2015). According to MIT Technology Review, Lyft revealed in 2015 that the company provided only "7 percent of rides summoned over the Internet in [New York City], compared with Uber's 90 percent" (Bradley 2015). Uber has eight times the funding of Lyft and several times Lyft's roughly 100,000 active drivers (Bradley 2015). Second, Uber's website previously provided the day and month UberX began service in a city, county, or region (Uber 2015). Updating these data to include 2015 service areas involved identifying current areas of service and searching newspapers for dates of entry and potential exit and return. Third, UberX is the most widely available ride-hailing service offered by Uber. Fourth, much of the criticism for Uber comes from the concern that its UberX service does not abide by the same regulatory oversight as traditional taxi services. Critics and many government officials are concerned that without similar background checks, safety certification, and vehicle inspection as taxi drivers and vehicles, users of UberX are subject to greater risk of assault or injury.[7]

Although Uber's pilot program included a small number of trial runs in both New York and San Francisco in early 2010, Uber officially began service on May 31, 2010 in San Francisco (Uber 2015).

When Uber first began launching UberX and their other services, they would often hold launch parties and create location-specific posts on the Uber blog that included the dates and the locations served. This often included a new city-specific web page that included a map of the geographic reach of the service. With each new location, Uber would post the launch date on its blog and add a new city-specific web page to their website. For each of these launches, we code the county (or counties) centered in the service area as the county (or counties) receiving UberX. Uber would often slowly expand the geographic reach of a service area over time. From 2010 through 2014, most of these expansions would be announced on Uber's blog. Others would simply be announced in local newspapers or websites. As the number of service areas grew and the geographic reach of services areas expanded, Uber overhauled their website and combined many service areas into one. Therefore, Uber's overhauled website provides maps of current service areas that are typically more widespread than the initial service area. Uber also stopped formally announcing every time it expanded coverage of an existing service location. In addition, many of these expansions did not receive any local news coverage. Because we do not observe the exact timing of some of these expansions, the UberX indicator variable is zero for surrounding counties when we do not observe a reported launch date.

For example, on July 10, 2014, Uber announce the launch of UberX in Greenville, South Carolina, along with three other South Carolina cities (Uber 2014). Therefore, Greenville County switched from 0 to 1 for July 2014 and all months after July 2014. However, Uber's current map of

[6] Lyft and Sidecar were second and third in market share of ride-sharing services nationwide during the period we examine. In December 2015, Sidecar ceased operations.

[7] We do not include UberBlack in our analysis. Unlike UberX, UberBlack drivers must meet city and state limousine licensing requirements and carry commercial insurance. In many locations, UberBlack partners with traditional limousine services to fill their vehicles during downtimes. UberBlack is also much more expensive than traditional taxis and thus does not serve as a substitute for taxis, especially for price-sensitive customers. Moreover, UberBlack makes up only 6% of Uber rides (Bhuiyan 2017).

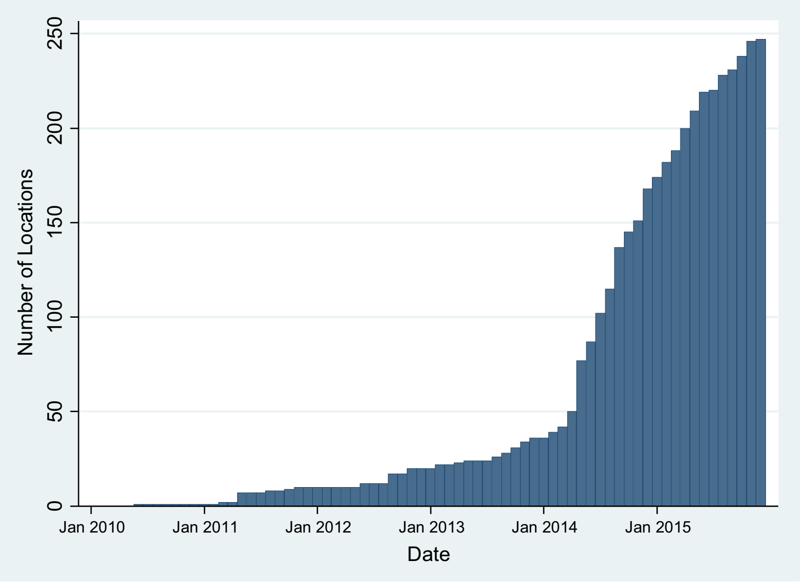

Figure 1. Number of Areas Served by Uber, By Month and Year.
Note: Because Uber has ceased operations in many locations, the number of ever-Uber locations is larger than the number of areas served in December of 2015. [Color figure can be viewed at wileyonlinelibrary.com]

the Greenville, SC Uber service area reveals that parts of Pickens and Oconee Counties are also included in the current coverage area (Uber 2017). Searching newspapers, we discovered that UberX launched in the Pickens county town of Clemson, SC on September 10, 2015 (Greenville Online 2015). Therefore, Pickens County's indicator variable switches from zero to one from September 2015 onward. Because no formal launch date was found for Oconee County, SC and because only part of the county is covered, its indicator variable remains zero throughout. This coding of the Uber variable implies we compare counties with Uber to counties that either do not have Uber or may have access to Uber's services. This control group makes it more difficult to find effects of Uber, likely understating any effect of Uber on the outcomes.[8]

In the full sample, we include all U.S. counties. Uber may enter areas that differ in their rates of crime or traffic crashes. To reduce concerns about endogenous entry, in some tables, we estimate the effect of Uber using only counties in which Uber enters at some point.

Figure 1 shows the number of areas in the United States served by Uber by month and year. By the end of 2011, Uber was serving 10 locations; by the end of 2012, the number was up to 20. By the end of 2015, Uber was serving 224 locations throughout the United States.[9]

To investigate whether Uber's entrance is associated with changes in the rate of fatal crashes, we use the National Highway Traffic Safety Administration's (NHTSA) Fatality Analysis Reporting System (FARS). The NHTSA's FARS data reports fatal automobile accident rates, whether a fatal crash is classified as alcohol-related, the time of the crash, and the total number of vehicular fatalities. We separately consider alcohol-related traffic fatalities because ride-sharing is expected to increase alcohol consumption and going out. We use nighttime accidents as a proxy for alcohol-related

[8] Ideally, we would have access to data on the number of users, drivers, or rides for each location. We have been unable to obtain these measures.

[9] Supporting Information Table A1 lists all areas served between 2010 and 2015.

Table 1. Summary Statistics: FARS Data

	Mean	Standard Deviation	Minimum	Maximum
Fatal Crashes per 100,000 ($N = 334{,}620$)				
Total	4.08	16.56	0	1675
Alcohol-involved	0.48	3.56	0	952
Night-time	0.99	7.63	0	1106
Motor Vehicle Fatalities per 100,000	5.02	29.46	0	4702

	Never Uber N = 256,428	Ever Uber ($N = 78{,}192$)		
		All	Uber = 0	Uber = 1
Fatal Crashes per 100,000				
Total	4.39	3.04	3.11	1.89
Alcohol-involved	0.53	0.33	0.34	0.17
Night-time	1.04	0.82	0.84	0.59
Motor Vehicle Fatalities per 100,000	5.43	3.66	3.74	2.18

accidents as a large fraction of nighttime accidents are alcohol-related (Dee 1999); time of the accident may be more accurately coded than alcohol involvement (Eisenberg 2003). Almost one-third of traffic fatalities are due to alcohol-involved crashes (Department of Transportation 2015).

As reported in Table 1, there are 4.08 fatal vehicular crashes per 100,000 people. There are 0.48 fatal alcohol-related crashes per 100,000, 0.99 per 100,000 nighttime fatal crashes, and 5.02 vehicular fatalities per 100,000. About 60% of the county-months in the sample report no fatal crashes. The county with the highest number of fatal crashes was Los Angeles County, CA with 266 in October 2007. Given our investigation of whether Uber's entry is associated with crash rates, we also report rates for areas without Uber and areas where Uber is available for at least one month. Areas where Uber is never present have higher fatal accident rates overall and for each type. Therefore, it does not appear that Uber enters areas with higher accident rates. Among the counties that ever host Uber, traffic crash rates and fatalities per 100,000 are more common in the months without Uber than the months with Uber.

For our measures of crime rates, we use the FBI's Uniform Crime Reports Statistics from 2007 through 2015 (United States Department of Justice, various years). Victim surveys suggest alcohol use is common among perpetrators of robbery and aggravated and simple assaults (Snyder et al. 2010). Carpenter and Dobkin (2015) estimate significant effects of access to alcohol on arrests for robbery, aggravated assault, other assaults, drunkenness, and DUI although they find no effect on disorderly conduct. In addition to crimes investigated by Carpenter and Dobkin (2015), we add motor vehicle thefts because Uber relies on privately owned motor vehicles for its service. The remaining three crime categories: liquor law violations, forgery, and embezzlement are included as placebo tests. We do not expect Uber's entry to be associated with arrests for these three types of crime.

We report the arrest rate summary statistics in the top portion of Table 2.[10] There are 4.4 arrests per 100,000 for robbery; 25.8 per 100,000 for aggravated assaults; and 101.3 arrests for other types of assaults per 100,000. There are 4.8 arrests for vehicle thefts; 105.9 per 100,000 for DUI; 49.4 per 100,000 for drunkenness; and 57 per 100,000 for disorderly conduct.

In the bottom portion of Table 2, we investigate whether the arrest rates in areas that never have access to Uber are different from those where Uber is or becomes available. Arrest rates are

[10] We drop Carroll County, IN (FIPS = 18015) from the crime data analysis because the values reported do not appear to be reliable.

Table 2. Summary Statistics: UCR Arrest Data

	Mean	Standard Deviation	Minimum	Maximum
UCR data: Arrests per 100,000 ($N = 311{,}652$)				
Robbery	4.4	17.2	0	2667
Aggravated Assault	25.8	61.8	0	6452
Other Assaults	101.3	441.4	0	158465
Motor vehicle thefts	4.8	20.7	0	6452
DUI	105.9	1036.5	0	474715
Drunkenness	49.4	2068.0	0	837170
Disorderly	57.0	865.0	0	474763
Liquor law violations	48.5	2049.5	0	1107611
Forgery	5.9	28.6	0	6452
Embezzlement	1.4	10.1	0	3226

	Never Uber	Ever Uber ($N = 69{,}228$)		
	N = 242,424	All	Uber = 0	Uber = 1
Robbery	2.9	9.8	9.4	16.8
Aggravated Assault	19.7	47.1	45.2	80.0
Other Assaults	79.3	178.5	173.0	275.4
Motor vehicle thefts	4.1	7.4	7.2	10.7
DUI	84.1	182.1	179.7	223.3
Drunkenness	40.1	81.9	81.1	95.8
Disorderly	43.0	106.2	105.7	116.3
Liquor law violations	43.2	67.2	67.7	59.1
Forgery	5.1	8.6	8.6	9.1
Embezzlement	1.1	2.3	2.3	2.5

higher in the ever-Uber counties for all of the crime categories we consider. In most cases, arrest rates are two to three times higher in Uber-receiving counties. Among the ever-Uber counties, crime arrest rates are higher in the months when Uber is present than when it is not; the exception is liquor law violations.

If Uber chooses to enter counties with high or with rising arrest rates, this generates concern for endogenous entry. To help mitigate this concern, the empirical method described in the next section includes county fixed effects and county-specific linear trends. To further address endogeneity concerns, we supplement the estimates using the full sample with estimates using only the sample of counties that witness Uber's entry.

4. Empirical Methods

To determine whether the changes in fatal accidents and crime are associated with Uber's entry, we estimate for county *i* in month *m* and year *t* the following:

$$\text{number per } 100{,}000 \text{ residents}_{\text{imt}} = \beta \text{uber}_{\text{imt}} + X'\gamma + \theta_i + \tau_{\text{mt}} + \varphi_i \text{mt} + \epsilon_{\text{imt}} \qquad (1)$$

The equation is a standard differences-in-differences specification.[11] The monthly outcomes include fatal vehicle accidents per 100,000 residents as well as arrests per 100,000 residents for a

[11] The standard deviation is much larger than the mean for all of our dependent variables. Therefore, we decided against using a Poisson on an untransformed dependent variable given the abundance of observations above the mean.

variety of potentially related crimes. The variable of interest, Uber, indicates whether the ride-sharing service UberX was available to individuals located in the county in that month and year.

We examine four measures of traffic fatalities per 100,000: fatal traffic crashes, alcohol-involved fatal crashes, nighttime fatal crashes, and traffic fatalities. We examine arrests per 100,000 for seven different crimes: robbery, aggravated assaults, other assaults, motor vehicle thefts, DUI, drunkenness, and disorderly conduct. We focus on these crimes due to their association with physical safety, vehicles, alcohol consumption, or all three.

The vector X is a set of factors that influence driver safety, alcohol consumption, or both.[12] This includes graduated drivers' licensing laws, the real state beer tax rate, marijuana laws, the age and racial demographics of the county, real per capita income, the unemployment rate, and population density.[13] Dee et al. (2005) demonstrate that graduated driver licensing laws reduce fatalities among the teens whose driving is restricted. Saffer and Grossman (1987) suggest that beer taxes reduce traffic fatalities although Dee (1999) finds that this result is not robust. A vast literature examines the relationship between alcohol consumption and economic conditions (see Henkel 2011 for a review of some of this literature). We use two measures of economic conditions: state-level real per capita income and the unemployment rate. Anderson et al. (2013) find that medical marijuana laws reduce traffic fatalities, plausibly by reducing drunk-driving. We include three variables capturing the legal status of marijuana: indicators for whether marijuana has been decriminalized, for a medical marijuana law, and for a recreational marijuana law.[14] We control for population density to allow for areas with more people per square mile to differ in fatal traffic crash rates and crime rates. We do not control for vehicle miles traveled. Uber may itself increase or decrease vehicle miles traveled; omitting this control allows the effect of Uber to operate through changing vehicle miles traveled.

The specification also includes county-fixed effects, θ_i; indicators for each month-year in the sample, τ_{mt}; and county-specific linear, monthly time trends, $\varphi_i$mt. The county fixed effects account for any time-invariant differences between Uber and non-Uber counties. The county-specific linear time trends capture the possibility of ongoing differing trends by controlling for trends in the outcome variables specific to the geographic area. Standard errors are clustered by county to account for potential serial correlation within each county. We present both population-weighted and unweighted estimates. Population weights may generate estimates that are more efficient because the variance of per capita outcomes is smaller in areas that are more populous. Solon et al. (2015) suggest that researchers present both weighted and unweighted estimates as differences between these specifications can indicate specification errors.

A typical concern with differences-in-differences estimation is the possibility of endogenous entry. If, for example, Uber enters areas with differing trends in the propensities to go out, to drive drunk, or to commit crimes, the estimated effect of entry also captures these differing propensities.

---

[12] We also report basic the difference-in-difference estimation without any control variables in Tables A6 and A7 of the Online Appendix.

[13] Land area is from the 2010 Census. Population and demographic data are from the Surveillance, Epidemiology, and End Results (SEER) Program. Melanie Guldi generously provided her data on graduated drivers' licensing laws. Beer tax rates are from the Tax Foundation. State per capita income are from the Federal Reserve Economic Data series. Unemployment rates are from the Bureau of Labor Statistics. Marijuana laws are from Dills et al. (2017). These data are measured at the annual level.

[14] Previous research documents effects of zero tolerance laws, minimum legal drinking ages, seat belt laws, and laws lowering the legally intoxicated blood alcohol level to 0.08 on traffic fatalities (Dee 2001; Eisenberg 2003; Dee 1999 but see Miron and Tetelbaum 2009; Cohen and Einav 2003). However, these laws exist in all states for the full sample period and are subsumed by the county fixed effects.

We address the possibility of endogenous entry in one additional way: we limit the sample to counties who will ever witness Uber entry. In these regressions, we compare counties where Uber currently operates (the "treatment") with counties where Uber will eventually, or used to, operate (the "control"). The "control" group likely shares more characteristics with the "treatment" group when we use this limited sample, reducing possible bias due to endogenous entry.[15]

One concern with including county-specific trends is that the time trend in the outcome may be confounded with the effect of the policy change of interest. For example, if the effect of Uber increases over time as more residents, visitors, and drivers become aware of the possibility of using or driving for the service then this effect will be picked up in the county-specific trend. Wolfers (2006) points out that fitted county-specific linear trends capture both the pre-existing trend and the policy response. To account for this possibility, we estimate specifications that allow the effect of Uber to grow or shrink the longer Uber exists in a county. We estimate specifications that allow entry to affect both the mean and the post-entry trend for county i in month m and year t:

$$\text{number per } 100{,}000 \text{ residents}_{\text{imt}} = \alpha_1 \text{uber}_{\text{imt}} + \alpha_2 \text{uber}_{\text{imt}} * t + X'\gamma + \theta_i + \tau_{\text{mt}} + \varphi_i \text{mt} + \epsilon_{\text{imt}} \qquad (2)$$

We explore a variety of fatal crash rates, the number of vehicular fatalities per 100,000, and arrest rates for a variety of crimes. The vector X as defined above, county fixed effects, month-by-year indicators, and county-specific linear monthly time trends complete the specification.

We estimate one other specification using the lags and leads of Uber's entry into a county. We estimate the following equation for county i in month m and year t:

$$\begin{aligned} \text{number per } 100{,}000 \text{ residents}_{\text{imt}} &= \beta_0 \text{uber}_{\text{imt}+3} + \beta_1 \text{uber}_{\text{imt}+2} + \beta_2 \text{uber}_{\text{imt}+1} + \beta_3 \text{uber}_{\text{imt}} \\ &+ \beta_4 \text{uber}_{\text{imt}-1} + \beta_5 \text{uber}_{\text{imt}-2} + \beta_6 \text{uber}_{\text{imt}-3} + \beta_7 (\text{Uber 4 or more years previous})_{\text{imt}} \\ &+ X'\gamma + \theta_i + \tau_{\text{mt}} + \varphi_i \text{mt} + \epsilon_{\text{imt}} \end{aligned} \qquad (3)$$

The omitted timing of Uber is Uber entering in four or more years.[16] This specification allows for two possibilities. First, the coefficients on the leads of Uber's entry estimates any pre-existing differences in counties prior to entry. If β_0 or β_1 are statistically significant, this provides evidence of endogenous entry. The estimate of β_2 provides mixed evidence: although a statistically significant estimate suggests endogenous entry, some locations experienced "soft" entries by Uber. These "soft" entrances were unpublicized and are not reflected in the coding of Uber's entry. Effects of Uber beginning prior to Uber's official launch date may reflect effects due to unpublicized earlier entry. Second, the inclusion of a variety of lags of Uber's entry allows the effect of Uber to differ over time in a flexible way.[17]

---

[15] Because we are concerned that both fatal crash rates and crime rates are naturally truncated at zero, we estimate Equations 1 and 2 using a tobit estimation. Supporting Information Tables 2 and 3 present these results. We generally find larger negative effects than those reported in our main specification. We also estimate Equations 1 and 2 for both fatal crashes and crime using a trimmed sample of counties. We estimate the predicted probability of Uber's entry into a county given county characteristics in 2007. We trim the sample to include the ever Uber counties and any counties with at least a 50% or higher probability of Uber entering. The results tend to be more negative and more precisely estimated. These are reported in Supporting Information Tables A4 and A5.

[16] The lag and leads specifications without any controls appear in Supporting Information Tables A6 and A7.

[17] We also estimate nonlinear effects of Uber using the logged outcomes. Results are in Supporting Information Tables A8 and A9 and are generally similar to estimates using lags and leads. We observe no significant effects of Uber on logged arrest rates. We observe large, negative, and significant effects of Uber on fatal traffic crash rates and vehicular fatality rates.

5. Results

Traffic Fatalities

Table 3 presents results examining whether the entry of Uber into a county is associated with any change in fatal crash rates. We consider four measures of fatal traffic accidents per 100,000: total, alcohol-related, nighttime, and the number of fatalities. Panel A presents results using the differences-in-differences specification with county-specific linear trends. These estimates are small, split between positive and negative, and statistically insignificant. To provide a sense of the magnitude, the estimate in column 8 implies that Uber's entry corresponds to a 0.0169 reduction in vehicular fatalities per 100,000, a 0.3% decline at the mean. Recognizing that it takes time for potential users to become aware of the service and for current users to become more familiar with the process, Panel B of Table 3 allows the effect of entry to differ as time passes. Our unweighted estimates are consistent with Uber leading to larger declines in fatal accidents the longer the service is available. For example, the estimates in column 1 imply that Uber's entry initially increases, insignificantly, fatal traffic crashes. After about six months of operation, the effect of Uber is a decline in fatal traffic crashes. Fatal crashes decline by 0.02 per 100,000 for each additional month, a (0.0224/4.08=) 0.5% decline. Per quarter of operation, this corresponds to a 0.07 per 100,000 decrease or (0.07/4.08=) 1.6% decrease per quarter at the mean. The exception in the unweighted estimates is alcohol-related crashes. These decline initially and then show a slight increase over time, turning to a positive effect after (0.0114/0.000602=) 17 months. None of the estimated effects on alcohol-related crash rates are statistically significant.

In the weighted regressions, the estimated effect over time tends to be smaller and statistically significant. We observe a 0.009 per 100,000 declines in fatal accidents and a 0.0099 per 100,000 declines in traffic fatalities for each additional month Uber is available. These correspond to percent decreases of (0.009/4.08=) 0.2% in fatal crash rates and (0.0098/5.02=) 0.2% in traffic fatalities per month of operation. Our estimates are a fifth of the size as those in Greenwood and Wattal (2017) who find a "3.6–5.6% decrease in the rate of motor vehicle homicides per quarter [or 0.9–1.4% per month] in the state of California." Overall, our estimates suggest that Uber reduced fatal traffic crashes, at least after several months of operation.

Our results in Table 3 may be biased if Uber enters areas that differ from the rest of the country. To alleviate this concern about endogenous entry, we restrict the sample to only those areas that ever witness the entry of Uber. The treatment and control groups, in this restricted sample, likely share many more characteristics.

Estimates in panel A of Table 4 are mostly positive and statistically insignificant. One exception is with alcohol-involved fatal crashes. In the ever-Uber sample, Uber's entry is associated with a decline of 0.0346 crashes per 100,000; at the mean, this is a (0.0346/0.33=) 10% decrease. Allowing for the change in slope in panel B suggests that most of the decline in alcohol-related incidents occurs quickly. The estimates in Panel B suggest that fatal traffic crashes, nighttime fatal crashes, and vehicular fatalities decline post-Uber (column 1), but that these declines may take ten months to occur.[18] The coefficients in the weighted sample in Panel B are smaller and less statistically significant. We observe statistically significant declines in the rate of fatal crashes that occur within (0.0430/0.00678=) seven months postentry. The magnitude of this result is, at the ever-

---

[18] For example, in column 1, the coefficient on Uber divided by the coefficient on the Uber and trend interaction is 0.228/0.0244=9.5. In column 4, the 0.237/0.0235 = 10.3.

Table 3. Uber Entry and Fatal Traffic Crashes per 100,000

	Unweighted				Population Weighted			
	(1) Fatal Crashes	(2) Alcohol-involved fatal crashes	(3) Night-time fatal crashes	(4) Vehicular Fatalities	(5) Fatal Crashes	(6) Alcohol-involved fatal crashes	(7) Night-time fatal crashes	(8) Vehicular Fatalities
Panel A: Differences-in-differences with linear county trends								
Uber	−0.0398	−0.00697	−0.00585	0.0715	−0.0327	0.000630	0.00145	−0.0169
	(0.181)	(0.0227)	(0.0716)	(0.230)	(0.0348)	(0.00606)	(0.0156)	(0.0615)
R-squared	0.076	0.031	0.036	0.054	0.125	0.071	0.058	0.069
Panel B: Differences-in-differences with linear county trends, post-entry trend								
Uber	0.124	−0.0114	0.0402	0.190	0.0154	0.00386	0.00818	0.0338
	(0.222)	(0.0210)	(0.0711)	(0.253)	(0.0328)	(0.00553)	(0.0153)	(0.0510)
Uber*trend	−0.0224**	0.000602	−0.00628	−0.0161	−0.0094***	−0.000630	−0.00132	−0.00989*
	(0.00929)	(0.00131)	(0.00394)	(0.0133)	(0.00236)	(0.000410)	(0.00101)	(0.00523)
R-squared	0.076	0.031	0.036	0.054	0.125	0.071	0.058	0.069

There are 334,620 observations. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

Table 4. Uber Entry and Fatal Traffic Crashes per 100,000, Sample of Counties Ever Hosting Uber

	Unweighted				Population Weighted			
	(1) Fatal Crashes	(2) Alcohol-involved fatal crashes	(3) Night-time fatal crashes	(4) Vehicular Fatalities	(5) Fatal Crashes	(6) Alcohol-involved fatal crashes	(7) Night-time fatal crashes	(8) Vehicular Fatalities
Panel A: Differences-in-differences with linear county trends								
Uber	0.0774	−0.0346*	0.00897	0.0925	0.0201	0.00286	0.00161	0.0425
	(0.195)	(0.0196)	(0.0674)	(0.231)	(0.0339)	(0.00613)	(0.0155)	(0.0582)
R-squared	0.127	0.061	0.072	0.088	0.207	0.127	0.105	0.107
Panel B: Differences-in-differences with linear county trends, postentry trend								
Uber	0.228	−0.0313	0.0411	0.237	0.0430	0.00483	0.00717	0.0701
	(0.232)	(0.0197)	(0.0716)	(0.259)	(0.0327)	(0.00576)	(0.0153)	(0.0514)
Uber*trend	−0.0244**	−0.000539	−0.00520*	−0.0235*	−0.0068**	−0.000582	−0.00165	−0.00818
	(0.00948)	(0.00115)	(0.00315)	(0.0126)	(0.00270)	(0.000452)	(0.00112)	(0.00569)
R-squared	0.127	0.061	0.072	0.088	0.207	0.127	0.105	0.107

There are 78,192 observations. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25 to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

Uber mean, 0.0068 fewer fatal crashes per 100,000 per month, a decline of (0.00678/3.04=) 0.2% per month for fatal crashes. This is roughly similar to the monthly decline in the full sample.

In Tables 5 and 6, we investigate the effects of Uber using the lags and leads of Uber's entry. Table 5 presents estimates of Equation 3 using the full sample; Table 6 uses the ever-Uber sample. In Table 5, most coefficients on the leads of Uber are statistically insignificant, supporting our assumption of exogenous entry. There are some exceptions, however. The coefficient on Uber in three years for vehicular fatalities in the unweighted sample (column 4) is a statistically significant, and large, −0.298. In addition, all of the leading variables for fatal crashes in the unweighted sample (column 1) and alcohol-involved fatal crashes in the weighted sample (column 6) are statistically significant. This suggests caution in interpreting the effects of Uber on alcohol-involved fatal crashes for the full sample. The lagged effects of Uber support the earlier findings. We observe declines in fatal crashes that increase the longer Uber is in an area (columns 1 and 5). Once Uber has operated in a county for four or more years, we observe fatal crashes per 100,000 that are 0.7 to 1.6 per 100,000 lower (columns 5 and 1); these reflect declines of (0.7/4.08=) 17 to (1.6/4.08=) 40%. This amounts to an average annual decline of 3.4 to 8%.[19] In the weighted estimates, alcohol-involved fatal crashes are lower in Uber-receiving counties before Uber's entry and decrease even more the longer Uber remains in a county.

The estimates in Table 6 use the ever-Uber sample. Limiting the focus to counties that will eventually receive Uber reduces any observed endogenous entry. In this sample, the leads of Uber are almost never statistically significant. We continue to observe declines in fatal traffic crashes and fatalities that grow the longer Uber remains in a county. These declines occur for all outcomes although, in most cases, these declines are not statistically significant. We observe statistically significant declines in fatal crashes per 100,000 (columns 1 and 5) and alcohol-involved fatal crashes per 100,000 (column 6) with magnitudes similar to those observed in Table 5.

At first glance, these magnitudes may seem large. Eisenberg (2003) considers a range of drunk-driving related policies and estimates effects from 4% to 9.4% on drunk-driving fatalities. Dills (2010) finds a 9% decline in drunk-driving fatalities due to social host laws. Thus, our estimates are not far off from the effects of changes in drunk-driving policies and social host laws. Yet, Uber is, in many ways, different from these legal restrictions. Unlike most policy changes, the adoption and use of Uber is voluntary. That is, potential drivers voluntarily choose to ride-share because they view it as the best alternative and not because there is a threat of punishment. Moreover, those most likely to adopt and use Uber are exactly the groups mostly likely to be involved in collisions: traffic fatality rates are higher among younger drivers and fall by age until 65 (Chang 2008). Smartphone owners are more likely to be aged 18 to 35 (Smith 2012). And most importantly, 40% of Uber's users are aged 25 to 34 and another 28% are 35 to 44. Providing what customers believe to be a superior point-to-point transportation alternative for those most likely to be in a collision is likely to have larger effects than those found in broad, punishment-based policies.

Overall, our findings suggest that Uber does not increase overall fatal crash rates and, for some specifications, is associated with a decline in fatal crash rates.

[19] This assumes five years of operation.

Table 5. Uber Entry and Fatal Traffic Crashes per 100,000 with Lags and Leads of Uber Entry

	Unweighted				Weighted			
	(1) Fatal Crashes	(2) Alcohol-involved	(3) Night-time	(4) Vehicular Fatalities	(5) Fatal Crashes	(6) Alcohol-involved	(7) Night-time	(8) Vehicular Fatalities
Uber in three years	−0.242**	−0.0146	0.00216	−0.298*	−0.00768	−0.0135**	−0.00786	−0.0140
	(0.117)	(0.0284)	(0.0539)	(0.179)	(0.0340)	(0.00634)	(0.0172)	(0.0482)
Uber in two years	−0.286*	−0.0120	−0.0512	−0.338	−0.0162	−0.0198**	0.00241	−0.0485
	(0.150)	(0.0392)	(0.0807)	(0.237)	(0.0469)	(0.00884)	(0.0225)	(0.0670)
Uber next year	−0.376*	−0.0321	−0.0558	−0.273	−0.0679	−0.035***	—0.0248	−0.0205
	(0.209)	(0.0476)	(0.112)	(0.338)	(0.0621)	(0.0109)	(0.0282)	(0.0986)
Uber this year	−0.354	−0.0336	−0.0294	−0.210	−0.0907	−0.0334**	−0.0125	−0.0383
	(0.301)	(0.0549)	(0.144)	(0.430)	(0.0873)	(0.0140)	(0.0366)	(0.134)
Uber last year	−0.775**	−0.0410	−0.172	−0.654	−0.220**	−0.055***	−0.0558	−0.196
	(0.302)	(0.0679)	(0.164)	(0.499)	(0.108)	(0.0200)	(0.0452)	(0.180)
Uber two years ago	−0.981**	−0.0554	−0.209	−0.603	−0.317**	−0.0615***	−0.0359	−0.238
	(0.400)	(0.0906)	(0.225)	(0.709)	(0.137)	(0.0234)	(0.0591)	(0.262)
Uber three years ago	−1.133**	−0.101	−0.242	−0.746	−0.434**	−0.0889***	−0.0972	−0.375
	(0.499)	(0.111)	(0.284)	(0.859)	(0.178)	(0.0284)	(0.0673)	(0.309)
Uber four or more years ago	−1.620***	−0.138	−0.298	−0.899	−0.700***	−0.121***	−0.118	−0.398
	(0.614)	(0.133)	(0.340)	(1.100)	(0.247)	(0.0336)	(0.0827)	(0.591)
R-squared	0.076	0.031	0.036	0.054	0.125	0.071	0.058	0.069

There are 334,620 observations. The omitted category is Uber in four years. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

Table 6. Uber Entry and Fatal Traffic Crashes per 100,000 with Lags and Leads of Uber Entry Sample of Counties Ever Hosting Uber

	Unweighted				Weighted			
	(1) Fatal Crashes	(2) Alcohol-involved	(3) Night-time	(4) Vehicular Fatalities	(5) Fatal Crashes	(6) Alcohol-involved	(7) Night-time	(8) Vehicular Fatalities
Uber in three years	−0.0738	0.0221	0.0280	−0.0107	0.0147	−0.00903	0.00170	0.0241
	(0.107)	(0.0243)	(0.0471)	(0.154)	(0.0328)	(0.00622)	(0.0168)	(0.0467)
Uber in two years	−0.247	0.0112	−0.0423	−0.355	0.00352	−0.0169*	0.00830	−0.00802
	(0.164)	(0.0303)	(0.0735)	(0.246)	(0.0453)	(0.00876)	(0.0220)	(0.0636)
Uber next year	−0.283	−0.00812	−0.0474	−0.272	−0.0374	−0.032***	−0.0243	0.0402
	(0.234)	(0.0367)	(0.111)	(0.350)	(0.0645)	(0.0106)	(0.0284)	(0.0981)
Uber this year	−0.156	−0.0307	−0.00809	−0.155	−0.0217	−0.0306**	−0.0138	0.0746
	(0.350)	(0.0407)	(0.140)	(0.447)	(0.0922)	(0.0140)	(0.0380)	(0.133)
Uber last year	−0.606*	−0.0479	−0.158	−0.624	−0.103	−0.051***	−0.0596	−0.0239
	(0.358)	(0.0543)	(0.166)	(0.502)	(0.118)	(0.0196)	(0.0482)	(0.180)
Uber two years ago	−0.746	−0.0589	−0.149	−0.702	−0.181	−0.0587**	−0.0464	−0.0391
	(0.455)	(0.0693)	(0.203)	(0.647)	(0.153)	(0.0233)	(0.0626)	(0.258)
Uber three years ago	−0.914*	−0.107	−0.165	−0.983	−0.261	−0.086***	−0.113	−0.139
	(0.554)	(0.0849)	(0.251)	(0.794)	(0.199)	(0.0289)	(0.0734)	(0.309)
Uber four or more years ago	−1.433**	−0.142	−0.211	−1.268	−0.470*	−0.117***	−0.136	−0.0984
	(0.657)	(0.104)	(0.301)	(1.004)	(0.280)	(0.0345)	(0.0909)	(0.609)
R-squared	0.127	0.061	0.072	0.088	0.207	0.128	0.105	0.107

There are 78,192 observations. The omitted category is Uber in four years. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25 to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

Table 7. Uber Entry and Arrests per 100,000: Differences-in-Differences Estimates

	(1) Robbery	(2) Aggravated Assault	(3) Other Assaults	(4) Motor vehicle thefts	(5) DUI	(6) Drunk	(7) Disorderly conduct
Panel A: with linear county trends (unweighted)							
Uber	−0.191	−1.594	−3.935	1.420*	0.377	18.56	−0.836
	(0.425)	(2.847)	(6.312)	(0.792)	(10.99)	(20.91)	(10.35)
R-squared	0.396	0.679	0.133	0.149	0.050	0.035	0.043
Panel B: with linear county trends (weighted)							
Uber	−1.299	−0.116	−8.756	−3.549	−7.550	2.567	2.782
	(1.515)	(4.564)	(8.206)	(5.375)	(10.23)	(11.24)	(5.496)
R-squared	0.907	0.968	0.551	0.789	0.309	0.077	0.290
Panel C: with linear county trends, postentry trend (unweighted)							
Uber	0.288	1.228	3.159	0.0202	6.550	13.72	7.186
	(0.493)	(2.321)	(5.931)	(0.520)	(8.574)	(16.03)	(8.055)
Uber*trend	−0.0636	−0.375	−0.942*	0.186**	−0.820	0.643	−1.065*
	(0.0496)	(0.330)	(0.554)	(0.0755)	(0.583)	(0.774)	(0.602)
R-squared	0.396	0.679	0.133	0.149	0.050	0.035	0.043
Panel D: with linear county trends, postentry trend (weighted)							
Uber	0.0519	1.513	−6.019	−1.729	−4.272	−3.886	6.587
	(0.821)	(4.139)	(8.001)	(2.615)	(7.418)	(9.346)	(5.143)
Uber*trend	−0.232	−0.279	−0.469	−0.312	−0.562	1.106	−0.652
	(0.151)	(0.364)	(0.651)	(0.496)	(1.021)	(0.917)	(0.537)
R-squared	0.907	0.968	0.551	0.789	0.309	0.077	0.290

There are 311,652 observations. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

Arrests

To investigate whether ride-sharing is associated with changes in crime, we consider the effect of Uber's entrance on arrests per 100,000 for a variety of crimes. We focus on crimes that a new transportation option likely affects through increased alcohol consumption: DUI, drunkenness, and disorderly conduct. The increased interaction of strangers may affect another group of crimes: aggravated assault and other assaults. Because drowsiness and intoxication are more likely when returning home than when departing, the availability of Uber may increase the number of vehicles parked overnight in unsecured locations. Because ride-sharing likely increases the availability of unsecured cars, we include motor vehicle thefts.

Table 7 presents estimates for all counties. Panels A and B contain the differences-in-differences estimates without and with population weights, respectively. In the unweighted sample, the coefficient estimates are almost all statistically insignificant with a mix of positive and negative estimates. The exception is a statistically significant increase in the arrest rate for motor vehicle thefts. In the weighted sample, the estimated effects are all negative, of economically important magnitudes, but statistically insignificant.

The specifications in Panels C and D allow Uber's entry to affect the post-entry trend. In the unweighted estimates, the estimated effects are again of mixed signs. Three estimates are

Table 8. Uber Entry and Arrests per 100,000, Sample of Counties Ever Hosting Uber: Differences-in-Differences Estimates

	(1) Robbery	(2) Aggravated Assault	(3) Other Assaults	(4) Motor vehicle thefts	(5) DUI	(6) Drunk	(7) Disorderly conduct
Panel A: with linear county trends (unweighted)							
Uber	−0.136	−0.254	−4.601	0.858	−7.637	−1.141	−3.360
	(0.438)	(2.689)	(4.853)	(0.851)	(4.667)	(3.545)	(8.449)
R-squared	0.643	0.803	0.765	0.181	0.786	0.704	0.820
Panel B: with linear county trends (weighted)							
Uber	−2.011	−1.527	−6.706	−6.923	−3.984	3.250	4.666
	(2.226)	(6.306)	(8.974)	(7.099)	(11.13)	(11.87)	(5.778)
R-squared	0.933	0.973	0.828	0.808	0.927	0.895	0.890
Panel C: with linear county trends, postentry trend (unweighted)							
Uber	0.280	2.150	1.235	0.0875	−0.597	−1.071	4.929
	(0.491)	(2.284)	(5.240)	(0.519)	(3.984)	(3.598)	(6.405)
Uber*trend	−0.0651	−0.376	−0.914	0.121	−1.102**	−0.0109	−1.298**
	(0.0517)	(0.351)	(0.570)	(0.0931)	(0.516)	(0.423)	(0.647)
R-squared	0.643	0.803	0.765	0.181	0.786	0.704	0.820
Panel D: with linear county trends, postentry trend (weighted)							
Uber	−0.541	0.360	−5.048	−3.765	−3.562	−2.288	7.299
	(1.173)	(5.116)	(8.311)	(3.734)	(7.864)	(9.335)	(5.347)
Uber*trend	−0.366	−0.469	−0.413	−0.786	−0.105	1.378	−0.655
	(0.249)	(0.503)	(0.774)	(0.774)	(1.399)	(1.191)	(0.594)
R-squared	0.934	0.973	0.828	0.809	0.927	0.895	0.891

There are 69,228 observations. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. We also control for whether marijuana is decriminalized, medicalized, or legalized; the percent of the population who are black, aged 20 to 24, aged 25to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

statistically significant: we observe increases over time in motor vehicle thefts and decreases over time for other assaults and disorderly conduct. The weighted estimates in Panel D are mostly negative and all statistically insignificant.

Because we are concerned that Uber may enter areas with characteristics correlated with crime rates, we restrict the sample to only those areas where Uber ever offers its services. We then repeat the analysis from Table 7. The estimated difference-in-differences effects in Panels A and B of Table 8 are somewhat more negative than those in Table 7. These estimates are never statistically significant. When we allow for Uber's effect to change over time, we observe some declines in arrests for DUIs and disorderly conduct over time (columns 5 and 7, Panel C). Weighting the sample results in smaller and less precisely estimated effects on these outcomes. However, the estimates in Panel D are almost all negative and statistically insignificant.

Tables 9 and 10 present the estimates using the leads and lags of Uber's entry. In Table 9, in the unweighted estimates, we estimate significant differences in robbery, other assaults, motor vehicle thefts, and disorderly conduct prior to Uber's entry. For other assaults, rates of arrests are lower in Uber counties before entry and this gap increases over time. For motor vehicle thefts and robbery, rates are higher in Uber counties before entry and this gap increases over time. We also see declines in arrests for DUIs that are larger the longer Uber remains. These effects are

Table 9. Uber Entry and Arrests per 100,000 with Lags and Leads of Uber Entry, Full Sample of Counties

	(1) Robbery	(2) Aggravated Assault	(3) Other Assaults	(4) Motor vehicle thefts	(5) DUI	(6) Drunk	(7) Disorderly conduct
Panel A: no weights, county-specific trends							
Uber in three years	1.033	3.587	−8.930**	2.717	−4.556	−4.060	9.184*
	(0.791)	(3.005)	(4.232)	(2.565)	(4.013)	(3.653)	(5.110)
Uber in two years	0.745*	3.410	−18.11***	1.326**	−14.33	−18.42	3.767
	(0.435)	(3.053)	(6.607)	(0.626)	(9.347)	(16.67)	(7.636)
Uber next year	1.122**	0.137	−19.95**	2.555**	−19.45*	−23.51	12.22
	(0.508)	(1.942)	(8.136)	(1.064)	(10.77)	(19.48)	(10.63)
Uber this year	1.235**	1.833	−22.45**	3.837***	−15.24**	−1.443	11.28
	(0.561)	(2.704)	(9.513)	(1.293)	(7.395)	(6.892)	(8.798)
Uber last year	0.378	−2.787	−33.32***	5.352***	−26.79**	−8.152	6.241
	(0.776)	(5.555)	(12.39)	(1.402)	(10.98)	(9.074)	(14.20)
Uber two years ago	0.310	−2.079	−52.21***	11.10***	−43.73***	−0.0665	−4.773
	(1.229)	(7.503)	(17.91)	(2.533)	(14.81)	(18.20)	(16.62)
Uber three years ago	1.466	−2.522	−50.90**	12.19***	−48.41**	25.64	−0.530
	(1.492)	(9.761)	(22.02)	(2.776)	(19.07)	(25.21)	(20.40)
Uber four+ years ago	4.548**	6.112	−22.12	15.34***	−42.74	48.69	15.98
	(2.063)	(14.20)	(27.51)	(4.251)	(26.31)	(39.75)	(22.73)
R-squared	0.396	0.679	0.133	0.149	0.050	0.035	0.043
Panel B: weights, county-specific trends							
Uber in three years	1.212	5.072	−5.773	−0.201	6.083	−2.948	14.87*
	(0.937)	(3.713)	(6.681)	(1.462)	(5.966)	(6.832)	(7.821)
Uber in two years	1.071	10.29*	−6.553	−2.425	13.92	−6.016	23.59*
	(1.022)	(5.409)	(10.22)	(4.239)	(11.11)	(11.36)	(13.43)
Uber next year	1.992	10.36*	−7.336	−5.267	8.728	−16.69	35.86**
	(1.360)	(5.693)	(14.69)	(8.118)	(16.98)	(22.07)	(17.81)
Uber this year	1.201	12.47*	−13.22	−8.455	9.476	−8.420	41.53**
	(2.103)	(7.010)	(20.02)	(12.68)	(22.70)	(24.95)	(20.58)
Uber last year	−1.374	12.30	−22.91	−11.69	−3.886	−8.745	42.59*
	(3.408)	(8.557)	(24.45)	(18.62)	(32.78)	(31.36)	(25.20)
Uber two years ago	−2.866	15.68	−21.26	−15.02	−0.189	2.338	49.97
	(5.165)	(11.45)	(33.48)	(26.31)	(44.46)	(46.71)	(30.99)
Uber three years ago	−3.084	13.66	−11.19	−22.83	9.160	29.84	61.85
	(6.622)	(12.88)	(40.39)	(33.98)	(56.38)	(53.91)	(38.03)
Uber four+ years ago	−0.842	25.43	43.46	−28.96	35.48	56.09	90.79*
	(10.39)	(17.51)	(67.11)	(46.76)	(75.86)	(69.54)	(48.29)
R-squared	0.907	0.968	0.551	0.789	0.309	0.077	0.290

There are 311,652 observations. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. The omitted category is Uber in four years. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

statistically significant for the first three years of Uber's presence. In the weighted estimates in Panel B, we observe fewer pre-existing differences in outcome variables. The exceptions are that rates of arrest for aggravated assault and disorderly conduct are higher in the years preceding Uber's entry. The longer Uber remains, the larger the gap in arrests for disorderly conduct. Table

Table 10. Uber Entry and Arrests per 100,000 with Lags and Leads of Uber Entry Sample of Counties Ever Hosting Uber

	(1) Robbery	(2) Aggravated Assault	(3) Other Assaults	(4) Motor vehicle thefts	(5) DUI	(6) Drunk	(7) Disorderly conduct
Panel A: no weights, county-specific trends							
Uber in three years	1.183	3.905	−7.069	2.494	−1.144	0.167	11.73**
	(0.835)	(2.950)	(4.323)	(2.951)	(4.118)	(3.023)	(5.446)
Uber in two years	1.036**	4.738	−9.169	0.928	−1.007	2.215	14.47**
	(0.504)	(3.197)	(6.458)	(1.012)	(6.034)	(5.259)	(6.832)
Uber next year	1.567**	2.539	−7.014	1.911	−2.477	1.722	28.30***
	(0.617)	(2.482)	(8.501)	(1.432)	(7.157)	(6.651)	(10.29)
Uber this year	1.715**	4.763	−12.34	2.948*	−8.485	2.664	23.78**
	(0.706)	(3.241)	(11.04)	(1.704)	(8.742)	(7.841)	(10.91)
Uber last year	0.896	0.411	−21.45	3.734**	−19.38	−4.129	19.49
	(0.930)	(6.335)	(13.72)	(1.757)	(12.16)	(9.912)	(16.70)
Uber two years ago	1.125	2.291	−32.47*	8.560***	−33.39**	1.671	13.88
	(1.337)	(8.029)	(18.94)	(2.939)	(15.36)	(17.67)	(19.07)
Uber three years ago	2.379	1.813	−28.22	8.489**	−39.73**	23.10	18.70
	(1.596)	(10.51)	(23.79)	(3.504)	(19.23)	(21.26)	(23.80)
Uber four+ years ago	5.530**	9.483	2.093	9.609*	−36.74	34.72	33.38
	(2.377)	(15.20)	(30.31)	(5.608)	(25.91)	(32.99)	(27.74)
R-squared	0.643	0.803	0.765	0.181	0.786	0.704	0.820
Panel B: weights, county-specific trends							
Uber in three years	1.483	6.847	−3.478	−0.977	11.07	−4.084	15.95*
	(1.149)	(5.101)	(7.470)	(1.827)	(6.896)	(7.462)	(8.172)
Uber in two years	1.132	13.59*	−0.256	−5.866	27.48**	−1.401	29.72**
	(1.225)	(7.651)	(11.30)	(5.926)	(13.81)	(10.30)	(14.47)
Uber next year	1.638	13.31*	4.051	−12.52	33.04	1.009	48.39**
	(1.708)	(7.229)	(17.09)	(11.98)	(21.66)	(20.49)	(19.98)

Table 10. (*Continued*)

	(1) Robbery	(2) Aggravated Assault	(3) Other Assaults	(4) Motor vehicle thefts	(5) DUI	(6) Drunk	(7) Disorderly conduct
Uber this year	−0.0792	14.69*	0.833	−20.57	38.27	8.752	57.28**
	(3.211)	(8.492)	(24.28)	(19.35)	(31.80)	(28.01)	(24.56)
Uber last year	−3.887	14.30	−3.801	−29.88	35.92	16.11	63.42**
	(5.592)	(10.92)	(31.35)	(28.82)	(47.41)	(39.17)	(30.63)
Uber two years ago	−6.600	16.86	4.904	−40.94	53.51	35.61	78.21**
	(8.530)	(15.03)	(43.91)	(40.84)	(65.04)	(59.26)	(39.07)
Uber three years ago	−8.279	13.84	18.55	−57.07	75.98	69.79	94.28*
	(11.38)	(17.97)	(54.12)	(53.34)	(84.83)	(72.16)	(48.63)
Uber four+ years ago	−7.904	24.38	79.64	−73.91	120.4	107.9	128.4**
	(16.64)	(24.58)	(83.17)	(71.97)	(113.4)	(94.95)	(60.99)
R-squared	0.934	0.973	0.828	0.810	0.927	0.895	0.891

There are 69,228 observations. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. The omitted category is Uber in four years. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

Table 11. Uber Entry and Arrests per 100,000, Placebo Test Crimes: Differences-in-Differences Estimates

	Full sample			Ever Uber sample		
	(1) Liquor law violations	(2) Forgery	(3) Embezzlement	(4) Liquor law violations	(5) Forgery	(6) Embezzlement
Panel A: with linear county trends (unweighted)						
Uber	19.41	−3.034	−0.444	3.690	−2.692	−0.454
	(18.69)	(3.142)	(0.776)	(5.912)	(3.089)	(0.778)
R-squared	0.025	0.127	0.075	0.512	0.123	0.067
Panel B: with linear county trends (weighted)						
Uber	0.476	−0.632	0.128	−1.801	−0.752	0.0231
	(6.147)	(1.098)	(0.302)	(2.903)	(1.128)	(0.307)
R-squared	0.034	0.479	0.129	0.514	0.533	0.126
Panel C: with linear county trends, postentry trend (unweighted)						
Uber	22.01	−2.284	−0.352	8.745	−1.866	−0.287
	(15.14)	(2.435)	(0.606)	(6.719)	(2.238)	(0.572)
Uber*trend	−0.345	−0.0997	−0.0122	−0.791	−0.129	−0.0261
	(0.924)	(0.103)	(0.0278)	(0.741)	(0.141)	(0.0370)
R-squared	0.025	0.127	0.075	0.512	0.123	0.067
Panel D: with linear county trends, postentry trend (weighted)						
Uber	3.269	−0.462	0.178	0.790	−0.472	0.0886
	(5.615)	(0.944)	(0.286)	(4.357)	(0.952)	(0.292)
Uber*trend	−0.479	−0.0290	−0.00860	−0.645	−0.0696	−0.0163
	(0.808)	(0.0492)	(0.0147)	(0.755)	(0.0629)	(0.0155)
R-squared	0.034	0.479	0.129	0.514	0.533	0.126

There are 311,652 observations in the full sample and 69,012 in the ever-Uber sample. All specifications include month-by-year fixed effects, county fixed effects, and county-specific linear trends. We also control for whether marijuana is decriminalized, medicalized, or legalized; population density; the percent of the population who are black, aged 20 to 24, aged 25to 34, aged 35 to 54, and aged 55 and over; indicators for whether the state has a graduated drivers licensing law, zero tolerance law, maximum legal blood alcohol concentration of 0.08; state real per capita personal income, and the state maximum welfare benefit for a family of three. Standard errors are clustered by county.

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

10 limits the sample to the ever-Uber counties. In the unweighted sample, we observe some differences prior to Uber's entry. Arrests for robbery are higher prior to Uber's entry but this gap increases as Uber remains. There are no differences in arrests for other assaults before Uber's entry; arrests for other assaults fall once Uber enters. There are no differences in arrests for motor vehicle thefts before Uber's entry; arrests for motor vehicle thefts increase once Uber enters. Arrests for disorderly conduct are higher prior to Uber's entry and stay higher once Uber enters. These estimates are sensitive to the use of population weights. In Panel B, we estimate no significant effects on arrests for robbery, other assaults, motor vehicle thefts, DUI, or drunkenness. We observe rates of arrests for aggravated assaults that are higher before Uber's entry and increase over time, although not statistically significantly. We observe rates of arrests for disorderly conduct that are higher prior to Uber's entry and increase over time.

To investigate whether any findings may be spurious, we analyze a number of crimes that are unlikely to be associated with ride-sharing: liquor law violations, fraud, and embezzlement.[20] Table 11 presents these estimates for the specifications and samples in Tables 7 and 8. As expected, we find no relationship between Uber on the arrest rates for liquor law violations, fraud, or embezzlement.

We find evidence that Uber's entry leads to lower rates of DUIs and, likely, lower rates of assault and disorderly conduct. We also observe increases in the rate of motor vehicle thefts following Uber's entry into a county.

6. Conclusion

When Austin, Texas began requiring figure-printed background checks for ride-sharing drivers in 2015, the Mayor, Steven Adler, and Councilwoman and mobility committee chair, Ann Kitchen, were motivated by the "slew of serious sexual assaults by on-demand drivers in Austin" (Bowles 2016). Many other community leaders have sought greater government oversight and limits on the entry of ride-sharing services in the name of consumer protection (for example Moore 2016 and O'Sullivan 2016). Websites such as whosdrivingyou.org serve as a repository for articles about rider and driver safety (whosdrivingyou.org 2016). Yet few studies have investigated the net effect of ridesharing on vehicle crashes and arrest rates.

We investigate and find that many of these concerns are, at least on net, unwarranted. Using a differences-in-differences specification and controlling for county-specific linear trends, we find that the entry of ride-sharing tends to *decrease* fatal vehicular crashes. Our (unweighted) estimated 0.2% decline in vehicle fatalities for each additional quarter is smaller than those found by Greenwood and Wattal (2017). Once Uber has operated in a county for four or more years, we find that fatal crashes have declined by 17 to 40%.

Moreover, none of our results support the safety concern often cited by regulatory agents. We find that residents are no more or less likely to become victims of robbery, assault, or

---

[20] Liquor law violations are "The violation of state or local laws or ordinances prohibiting the manufacture, sale, purchase, transportation, possession, or use of alcoholic beverages, not including driving under the influence and drunkenness. Federal violations are excluded." (US DoJ September 2010 "Offense Definitions" accessed Feb. 1, 2016 https://www2.fbi.gov/ucr/cius2009/about/offense_definitions.html). In results not reported here, we examine effects on arrests for family violations and curfew/loitering violations. These two crimes may be less clearly counterfactuals as family violations may be correlated with alcohol consumption and curfew/loitering may be affected by the availability of transportation. Nonetheless, we estimate no effects of Uber on these arrest rates.

drunkenness after Uber's entry. However, we do find weak evidence that DUIs arrests rates decline for the first three years that Uber is available. We also discover a decline in disorderly conduct arrests for each additional month Uber operates in a location. The big adverse effect we observe is an increase in the arrest rate for motor vehicle thefts that coincides with Uber's arrival.

Acknowledgments

We would like to thank the editor, anonymous referees, Reynaldo Hernandez-Julian, Christopher Schilling, Luke Sherry, E. Frank Stephenson, seminar participants at Creighton University and Texas Tech University, and session participants at the 2016 Public Choice Society Meetings and the 2016 Association for Private Enterprise Meetings for their valuable comments and suggestions. All errors are most assuredly ours alone.

References

Anderson, D. Mark, Benjamin Hansen, and Daniel I. Rees. 2013. Medical marijuana laws, traffic fatalities, and alcohol consumption. *The Journal of Law and Economics* 56(2):333–69.

Bhuiyan, Johana. 2017. Though demand for UberBlack has dropped, Lyft launched its own luxury service in SF, LA and NY. *Recode*. May 25, 2017. Accessed 13 November 2017. Available https://www.recode.net/2017/5/25/15692884/lyft-lux-uber-black-supply-demand-drivers

Bowles, Nellie. 2016. 'We're just getting started': inside Austin's contentious clash with Uber and Lyft. *The Guardian*. Accessed 11 October 2017. Available https://www.theguardian.com/technology/2016/mar/10/uber-lyft-austin-ann-kitchen-sxsw-texas.

Bradley, Ryan. 2015. Lyft's Search for a New Mode of Transport. *MIT Technology Review*. October 13, 2015. Accessed 22 February 2016. Available https://www.technologyreview.com/s/541791/lyfts-search-for-a-new-mode-of-transport/.

Brazil, Noli and David Kirk. 2016. Uber and metropolitan traffic fatalities in the United States. *American Journal of Epidemiology* 184(3):192–8

Carpenter, Christopher and Carlos Dobkin. 2015. The minimum legal drinking age and crime. *The Review of Economics and Statistics* 97(2):521–4.

Chang, Dow. 2008. Comparison of crash fatalities by sex and age group. *Traffic Safety Facts Research Note* July, DOT HS 810 853. Accessed 11 December 2017. Available http://www-nrd.nhtsa.dot.gov/Pubs/810853.pdf

Chen, L. H., Baker, S. P., Braver, E. R., and Li, G. 2000. Carrying passengers as a risk factor for crashes fatal to 16-and 17-year-old drivers. *JAMA* 283(12):1578–82

Carney, Cher, Dan McGehee, Karisa Harland, Madonna Weiss, and Mireille Raby. 2015. Using naturalistic driving data to assess the prevalence of environmental factors and driver behaviors in teen driver crashes. AAA Foundation for Traffic Safety. March 2015.

Cohen, A., and Einav, Liran. 2003. The effects of mandatory seatbelt laws on driving behavior and traffic fatalities. *Review of Economics and Statistics* 85(4):828–43

Dee, T., Grabowski, D.C., and Morrisey, M.A. 2005. Graduated driver licensing and teen traffic fatalities. *Journal of Health Economics* 24(3):571–89

Dee, T.S. 1999. State alcohol policies, teen drinking and traffic fatalities. *Journal of Public Economics* 72:289–315

Dee, T.S. 2001. Does setting limits save lives? The case of 0.08 BAC laws. *Journal of Policy Analysis and Management* 20(1):111–28

Department of Transportation (US). 2015. National highway traffic safety administration (NHTSA). Traffic Safety Facts 2014 data: alcohol-impaired driving. Washington, DC: NHTSA. Accessed 26 May 2017 Available http://www-nrd.nhtsa.dot.gov/Pubs/812231.pdf.

Dills, Angela K. 2010. Social host liability for minors and underage drunk-driving accidents. *Journal of Health Economics* 29:241–9.

Dills, Angela K., Sietse Goffard, and Jeffrey A. Miron. 2017. The effects of marijuana liberalizations: Evidence from monitoring the future. NBER WP No. 23779.

Doherty, S. T., Andrey, J. C., and MacGregor, C. 1998. The situational risks of young drivers: The influence of passengers, time of day and day of week on accident rates. *Accident Analysis & Prevention* 30(1):45–52

Eisenberg, Daniel. 2003. Evaluating the Effectiveness of Policies Related to Drunk Driving. *Journal of Policy Analysis and Management* 22(2):249–74

Greenville Online. 2015. "Uber Launches Service in Clemson area." Accessed 11 December 2017. Available http://www.greenvilleonline.com/story/money/business/2015/09/10/uber-clemson-south-carolina-market/72023272/

Greenwood, Brad N. and Wattal, Sunil. 2017. Show me the way to go home: an empirical investigation of ride sharing and alcohol related motor vehicle homicide. *MIS Quarterly* 41(1):163–97

Henkel, Dieter. 2011. Unemployment and substance use: A review of the literature (1990–2010). *Current Drug Abuse Reviews* 4(1):4–27

Jackson and Owens. 2011. One for the road: Public transportation, alcohol consumption, and intoxicated driving. *Journal of Public Economics* 95:106–21

Kiplinger, Lisa. 2016. Kalamazoo shooting: A look at Uber background checks. *USA Today. EST February 22, 2016*. Accessed 29 February 2016. Available http://www.whosdrivingyou.org/rideshare-incidents#deaths.

Martin-Buck, Frank. 2016. Driving safety: An empirical analysis of ridesharing's impact on drunk driving and alcohol-related crime. Accessed 17 November 2016. Available http://www.frankmartinbuck.com/Ridesharing%20and%20Alcohol-Related%20Crime%20by%20Frank%20Martin-Buck.pdf

Mayhew, D. R., Simpson, H. M., and Pak, A. 2003. Changes in collision rates among novice drivers during the first months of driving. *Accident Analysis & Prevention* 35(5):683–91

Miller, Dennis. 2015. Lyft vs. Uber: Just how dominant is Uber in the ridesharing business? Accessed February 2016. Available http://www.fool.com/investing/general/2015/05/24/lyft-vs-uber-just-how-dominant-is-uber-ridesharing.aspx.

Miron, J.A., and Tetelbaum, E. 2009. Does the minimum legal drinking age save lives? *Economic Inquiry* 47(2):317–36

Moore, Daniel. 2016. Lobbying efforts intensify as ride-sharing bill enters final stretch Pittsburgh Post-Gazette. Accessed February 2016. Available http://www.post-gazette.com/business/tech-news/2016/01/18/Uber-Yellow-Cab-Lyft-ride-sharing-permanent-regulated-Pennsylvania/stories/201601140004.

National Highway Traffic Safety Administration's (NHTSA). 2016. Fatality analysis reporting system (FARS). Accessed February 2016. Available http://www.nhtsa.gov/FARS.

National Highway Transportation Safety Administration (NHTSA). 2014. Traffic Safety Facts, Distracted Driving 2012, DOT HS 812 012. April 2014.

NYC Taxi & Limousine Commission. 2014. 2014 *Taxicab Fact Book*. Office of Policy and External Affairs.

O'Sullivan, Jim. 2016. Uber, Lyft would face new rules under state bill. Boston Globe. March 04, 2016. Accessed March 2016. Available https://www.bostonglobe.com/metro/2016/03/04/uber-lyft-would-face-new-rules-under-state-bill/VyS7ciSX6pDmN9ldSll0HO/story.html.

Peck, Jessica. 2017. New York city drunk driving after Uber. CUNY graduate center PhD program in economics. Working Paper Series No. 13.

Phillips, David C. and Danielle Sandler. 2015. Does public transit spread crime? Evidence from temporary rail closures. *Regional Science and Urban Economics* 52:13–26

Rayle, Lisa, Shaheen, Susan, Chan, Nelson, Dai, Danielle, and Cervero, Robert. 2016. App-based, on-demand ride services: comparing taxi and ridesourcing trips and user characteristics in San Francisco. *Transport Policy* 45(C):168–78

Richtel, Matt. December 2014. "Distracted Driving and the Risks of Ride-Hailing Services Like Uber." *New York Times*. Accessed February 2016. Available http://bits.blogs.nytimes.com/2014/12/21/distracted-driving-and-the-risks-of-ride-hailing-services-like-uber/.

Rogers, Brishen. 2015. The social costs of Uber. *University of Chicago Law Review Dialogue* 82(1):85–102

Saffer, H., and Grossman, M. 1987. Beer taxes, the legal drinking age, and youth motor vehicle fatalities. *Journal of Legal Studies* 16(2):

Silverstein, Sara. 2014. "These Animated Charts Tell You Everything about Uber Prices in 21 Cities." *Business Insider*, October 16. Accessed November 2017. Available http://www.businessinsider.com/uber-vs-taxi-pricing-by-city-2014-10.

Smith, Aaron. 2012. "46% of American Adults are Smartphone Owners." *PewInternet*. Accessed April 2016. Available http://www.niu.edu/facdev/m/twti/2012/Smartphone_ownership_2012.pdf.

Snyder, Howard N., Michael R. Rand, and William J. Sabol. 2010. Alcohol and Crime: Data from 2002 to 2008. *Bureau of Justice Statistics*. Accessed May 2017. Available https://www.bjs.gov/index.cfm?ty=pbdetail&iid=5884.

Solon, Gary, Steven J. Haider, and Jeffrey W. Wooldridge. 2015. What are we weighting for? *Journal of Human Resources* 50(2):301–16

Stromberg, Joseph. 2015. We don't say "plane accident." We shouldn't say "car accident" either. *Vox*. Accessed May 2016. Available http://www.vox.com/2015/7/20/8995151/crash-not-accident.

Uber. 2014. Uber blog. Accessed February 2015. Available https://www.uber.com/blog/south-carolina/south-carolina-your-uberx-is-arriving-now/.

Uber. 2015. Uber Blog. Accessed February 2015. Previously Available at http://blog.uber.com.

Uber. 2017. Uber moves Greenville, SC. Accessed September 2017. Available at https://www.uber.com/cities/greenville-sc/

WBAL TV. 2015. "Uber driver unwittingly becomes getaway driver in Parkville armed robbery." WBAL. Accessed May 2016. Available at http://www.wbaltv.com/news/uber-driver-unwittingly-becomes-getaway-driver-in-parkville-armed-robbery/35746542.

United States Department of Justice, Federal Bureau of Investigation. Crime in the United States, 2007–2014. Accessed January 2016. Available at https://www.fbi.gov/about-us/cjis/ucr.

Who's Driving You? Accessed February 2016. Available http://www.whosdrivingyou.org/rideshare-incidents.

Williams, A. F. 2003. Teenage drivers: Patterns of risk. *Journal of Safety Research* 34(1):5–15

Williams, A. F., Ferguson, S. A., and McCartt, A. T. 2007. Passenger effects on teenage driving and opportunities for reducing the risks of such travel. *Journal of Safety Research* 38(4):381–90

Wolfers, Justin. 2006. Did unilateral divorce laws raise divorce rates? A reconciliation and new results. *American Economic Review* 96(5):1802–20

Supporting Information

Additional Supporting Information may be found in the online version of this article.