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## Uber and Metropolitan Traffic Fatalities in the United States

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**Abstract:** Uber and similar rideshare services are rapidly dispersing in cities across the United States and beyond. Given the convenience and low cost, Uber has been characterized as a potential countermeasure for reducing the estimated 121 million episodes of drunk driving and the 10,000 resulting traffic fatalities that occur annually in the United States. We exploit differences in the timing of the deployment of Uber in US metropolitan counties from 2005 to 2014 to test the association between Uber's rideshare services and total, drunk driving-related, and weekend and holiday-specific traffic fatalities in the 100 most populated metropolitan areas in the United States using Negative Binomial and Poisson regression models. We found that the deployment of Uber services in a given metropolitan county had no association with the number of subsequent traffic fatalities, whether measured in aggregate or specific to drunk driving fatalities or fatalities during weekends and holidays.

**Keywords:** traffic fatalities; drunk driving; Uber; rideshare; mortality

**Abbreviations:** TNC, transportation network company; VMT, Vehicle miles traveled

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Traffic fatalities are one of the leading causes of death in the United States, particularly for teenagers and young adults, with nearly 33,000 people dying from motor vehicle crashes in 2014 and another 2.3 million individuals injured (1). A primary culprit of the magnitude of traffic fatalities in the United States is drunk driving. Data from the National Highway Traffic Safety Administration reveal that nearly 10,000 people died in 2014 in the United States in a crash involving an alcohol-impaired driver (defined as a driver with a blood alcohol concentration of .08 or more), accounting for nearly one-third of all traffic fatalities (2). Common strategies for reducing drunk driving, such as reduced illegal thresholds for blood alcohol concentration and increased taxes on alcohol, center on the assumption that would-be drunk drivers will be deterred by the added cost and penalty of engaging in drunk driving (3-6). Being arrested, having a license revoked and a car impounded, and being sanctioned and stigmatized by the criminal justice system can surely be costly endeavors, but only if one is caught. A mere 1.1 million arrests for driving under the influence were made by US law enforcement in 2014 relative to the roughly 121 million incidents of drunk driving ( $< 1\%$ ) (3,7).

Yet some would argue that the phenomenal rise of Uber (Uber Technologies Inc., San Francisco, CA) and its ridesharing competitors is a sign of a worldwide transportation revolution, potentially with ramifications for curtailing the extensive volume of drunk driving that occurs in the United States (8). Ridesharing connects passengers with owner-operator drivers through a smartphone app, which also calculates and processes costs, provides real-time tracking of drivers, and feeds the passenger's destination information into the driver's navigational software, offering a service that can be more convenient than taxis and public transit (9). Uber is by far the highest valued of

the so-called transportation network companies (TNCs). As of late 2015, Uber exceeded \$62 billion in value (10). By April 2016, Uber was operating in more than 60 countries and 400 cities worldwide. Uber's closest competitor among TNCs in the United States is Lyft (Lyft Inc., San Francisco, CA), which is valued at \$5.5 billion and, as of April 2016, operated in just over 200 US cities (11). In the vast majority of US metropolitan areas, Uber was the first TNC to the market. In the few major markets where Lyft service launched before Uber, Uber's launch usually followed quickly.

Uber's model is designed to ensure that the supply of Uber drivers keeps up with the demand for rides. When demand increases, the cost of a ride increases — known as surge pricing — in order to encourage more drivers to become available. In this sense, Uber at least reduces the challenges of finding a sober ride, although whether Uber is cheaper than a taxi service depends upon the prevailing demand at a given time.

If would-be drunk drivers are rational, then lowering the difficulty of finding as well as the cost of alternate transportation options should, in theory, reduce the number of drunk driving occurrences and fatalities. This is the promise of Uber and other TNCs, particularly in terms of increasing the supply of transportation options. Indeed, Uber claimed that it provides "more than just a convenient transportation option. The choice, reliability and flexibility it affords also make [it] a powerful tool in the quest to protect families from drunk driving" (12). Uber has further asserted, "A city with Uber has...fewer drunk drivers on the streets" (<https://www.uber.com/>). Given these broad claims and the significant challenges remaining in curbing drunk driving and associated fatalities, the implications of this so-called transportation revolution for traffic fatalities warrant empirical study.

In the lone piece of academic research we could find on the relationship between Uber services and drunk driving, the authors used a similar difference-in-differences methodology that we employ in this paper to examine the association between quarterly county-level alcohol-related fatalities and the deployment of Uber's low-cost UberX and luxury UberBlack services in California from 2009 to 2013 (13). They concluded that the deployment of UberX, but not UberBlack, yields a significant reduction in traffic-related fatalities. Moreover, the study reported that there is no association of Uber on fatalities when Uber's surge pricing is in effect, suggesting that Uber is only a substitute for drunk driving when the cost of a Uber ride is relatively reasonable. However, the authors noted that their analysis is limited by its sole geographic focus on California as well as the possibility that confounding factors influenced the results.

Although there are theoretical reasons to suggest that the introduction of Uber in a market will lead to a reduction in drunk driving, there are alternate positions as well. First, because drivers are unlikely to get caught drinking and driving, paying for a rideshare service may still be far more costly than driving drunk for many individuals. Second, individuals inclined to drink and drive may not be very rational. Third, while Uber's growth in terms of markets and drivers has been unprecedented, the number of Uber drivers in a market may still be too small to have much of an influence on the 121 million incidents of drunk driving that take place each year in the United States (3). Based on these counter perspectives as well as the inconclusiveness of research to-date, we examine the relationship between the deployment of Uber and subsequent traffic fatalities within the 100 largest metropolitan areas across the United States from 2005 to

2014, using a research strategy designed to minimize the possibility of confounding influences.

## MATERIALS AND METHODS

### Sample

We employed an observational panel study design to examine within-county changes in monthly motor vehicle fatalities after Uber entry for the period 2005-2014. The analytic sample contains monthly observations for the most populated county in the 100 most populated metropolitan areas in the United States (see Web Table 1 for the list of counties) (*14*). To determine the top 100 most populated metropolitan areas in the country, we used the latest delineation of metropolitan areas as defined by the US Census Bureau (*15*). We then used 2010 US Census population counts by metropolitan area to rank order these metropolitan areas, and constructed our sample based on the top 100 most populated areas (*14*).

Because traffic fatality data are available by county, we used a Census geographic crosswalk to identify the most populated county within the top 100 metropolitan areas in the country, and this county represents our geographic unit (*16*). The exception is the New York metropolitan area. Given the population size of the New York metropolitan area, we included the five separate counties in our dataset that correspond to the five boroughs of New York City (Bronx, Kings, New York, Queens, and Richmond).

Dependent variable: Traffic fatalities

We examined the association between Uber deployment and three types of traffic fatalities: total, drunk driving-related, and weekend/holiday-specific. We examined fatalities occurring during the weekend — that is, traffic fatalities between 5pm on a Friday and 5am on the following Sunday — and major US holidays because alcohol consumption is likely greater during these days, potentially increasing demand for rideshare services (17). County monthly traffic fatality data come from the Fatality Analysis Reporting System, which is produced by the National Highway Traffic Safety Administration. The data represent a census of all fatal injuries resulting from motor vehicle accidents in the United States. Information on the details of each accident and whether alcohol was involved comes from a variety of sources including police reports, driver licensing files, vehicle registration files, state highway department data, emergency medical service records, medical examiner reports, toxicology reports and death certificates. Information on drunk driving-related fatalities are available only from 2009 to 2014.

### Independent variable: Uber deployment

Our measure of Uber deployment is a binary indicator for whether, in a given month and year, Uber had established services in a county. Uber was founded in 2009, and began pilot testing its service in January 2010 (18). Uber service officially launched on May 31, 2010, in San Francisco. In 2011, Uber was introduced in six more metropolitan areas and rapidly dispersed thereafter. Figure 1 shows the number and timing of the deployment of Uber services within the principal counties of the top 100

metropolitan areas in the United States *through 2014* (see Web Table 1 for county deployment dates).

We determined the location and timing of Uber's services using a combination of sources. First, we used information published on Uber's website, specifically an up-to-date listing of service locations as well a “newsroom” section that publicizes the launch of services in new markets. As a for-profit company, Uber has a vested interest in advertising where it has service in order to attract consumers and drivers and thus the information contained in these sections are regularly maintained. Second, we searched local media outlets for further information about the timing of implementation and any suspensions of services. For any locations in the top 100 metropolitan areas not listed as a location on the Uber website, we searched local media outlets online to confirm that Uber had not yet been launched.

#### Control variables

We controlled for factors associated with crash risk. Previous studies provide evidence that state-level traffic related policies influence driver fatalities (19-23). We included binary indicators for whether the following policies were present in a county's state in a given month and year: legalization of medical marijuana; the decriminalization of marijuana use; a graduated driver-licensing law, which forces young drivers to safely gain experience before obtaining full driving privileges; Per se administrative license revocation, which allows states to revoke driving privileges before court action related to drunk driving; cell phone texting bans and hands free driving regulations; and primary seatbelt laws. We obtained information on implementation dates of primary seat belt and

graduated driver-licensing laws from the Insurance Institute for Highway Safety (24). Drug per se dates were obtained from previous studies and updated using information from the National Conference of State Legislatures (19,25). We obtained information on effective dates for texting and handheld bans, the legalization of medical marijuana and the decriminalization of marijuana use from previous studies and updated using LexisNexis (26-28).

We also controlled for state by year beer tax rates in 2014 US dollars per gallon, which have been linked to alcohol consumption and traffic fatalities (29, 30). Because economic conditions influence factors associated with crash risk, such as alcohol consumption and the number of miles driven, we controlled for county monthly unemployment rates, which measure the percentage of the labor force 16 years and older that is unemployed (31, 32). Lastly, because the availability of taxis may influence the demand for Uber, we controlled for the yearly number of taxi drivers per 100,000 population employed in a county's metropolitan area weighted by the county's proportion of its metropolitan area's total population. We obtained data on beer taxes from the Beer Institute's Brewers Almanac and unemployment rates and the number of taxi drivers from the Bureau of Labor Statistics.

### Statistical Analyses

We used a difference-in-differences strategy with county, month, and year dummy variables to assess the relationship between the presence of Uber and traffic fatalities across the principal counties of the 100 largest metropolitan areas. Because some counties in our study had Uber and some did not, our empirical strategy compared



the changes in fatality counts within Uber counties with the contemporaneous changes in fatality counts in non-Uber counties.

We examined the relationship between traffic fatalities and Uber entry using Negative Binomial regression models. We used a Negative Binomial specification to account for the extreme skewness of the traffic fatality data, with many observations containing few or no fatalities. Our measure of exposure is the number of vehicle miles traveled (VMT) in a county month, which we estimated by multiplying the state-month-year VMT by the county's proportion of its state's total roadway mileage. VMT is a common measure of crash fatality risk because it captures time and persons exposed to driving (33). We obtained VMT and roadway length data from the Federal Highway Administration. Negative Binomial models for drunk driving-related fatalities failed to converge; we instead report results from Poisson models, which have the same distributional assumptions but do not correct for overdispersion. Results from Poisson and Negative Binomial models for total and weekend/holiday-specific fatalities did not significantly differ.

We included individual county, month and year fixed effects in our models. County fixed effects controlled for all time-invariant county-specific factors that are potentially correlated with traffic fatalities, such as land area and geographic location. The month fixed effects controlled for factors that vary month to month but are county and year invariant, such as travel patterns. The year fixed effects controlled for factors that affected all counties in all months in a given year, such as changes in national car safety standards. We adjusted standard errors for clustering at the county level.

## Sensitivity Analyses

We ran a set of additional models to test the robustness of our main results (Web Appendix 1). First, we tested the sensitivity of our results to the measure of crash risk by replacing VMT with another popular measure of exposure: county yearly Census population (Web Tables 2 and 3). Second, in order to test whether findings are sensitive to distributional assumptions, we fitted Poisson models to go along with the Negative Binomial models presented in the main analysis (Web Table 4). Third, because prior evidence revealed that Uber's association with traffic fatalities becomes stable after nine months (13), we tested for a lagged association by replacing the binary Uber indicator from the main analysis with a variable categorizing observations into no Uber service present, Uber present less than nine months, and Uber present nine months or longer (Web Tables 5 and 6). Fourth, we accounted for the presence of Lyft, Uber's largest competitor, by testing a variable that indicates whether either company was present in a county (Web Tables 7 and 8). We also tested the number of rideshare services by including a variable that categorizes counties as having neither Uber nor Lyft, either Uber or Lyft, or both Uber and Lyft (Web Tables 9 and 10). Lyft is present in 65 counties in our sample, with 60 of these counties also having Uber by the end of 2014. Although other TNCs exist, Uber and Lyft capture the bulk of the market in the United States, with Uber as the market leader by a considerable margin (34, 35). Finally, we tested whether the results are sensitive to the dramatic decline in traffic fatalities that occurred between 2007 and 2008, which has been attributed to the Great Recession and improved air bag standards (36), by limiting the time period to 2009-2014 (Web Tables 11 and 12). Results for these robustness tests are consistent with the main results, particularly for the final

models including fixed effects and control variables. We conducted all analyses in Stata version 14 (StataCorp, College Station, TX).

## RESULTS

Table 1 presents the descriptive statistics for our sample of 12,480 county months disaggregated by Uber presence. Uber was present in 10% of the total county-month observations. Counties experienced slightly higher traffic fatalities during months when Uber was present (8.75 vs. 6.93). Differences are much smaller for drunk driving (2.22 vs. 1.80) and weekend and holiday-specific (2.88 vs. 2.23) fatalities.

Results from Negative Binomial models of Uber's association with total fatalities are shown in Table 2. The table presents coefficients as incidence rate ratios. An incidence rate ratio less than one indicates a reduction in traffic fatalities after Uber entry, while a ratio greater than one suggests an increase. Model 1 presents results for an unconditional model with the measure of Uber service as the sole predictor. This model shows that on average, the presence of Uber was associated with a 2.0% (95% Confidence Interval: 0.98, 1.06) increase in traffic fatalities among all drivers; however, this association is not statistically significant at conventional levels.

Model 2 in Table 2 introduces county, month and year fixed effects. This model shows no statistical association between the presence of Uber and crash-related fatalities. We found a similar result in Model 3, which includes control variables. Consistent with prior evidence (29-32), county unemployment rates and state beer tax rates were associated with decreases in traffic fatalities. The presence of Uber, however, had no statistically significant association.

The first three columns in Table 3 present results for Poisson regression models on drunk driving-related fatalities. There is no significant association between Uber deployment and drunk driving-related fatalities in any of the three models. Columns 4-6 in Table 3 present results for Negative Binomial regression models on traffic fatalities occurring during the weekend and major US holidays. Similar to the total and drunk driving results, Uber had no statistically significant association with weekend and holiday-specific fatalities across all modelling specifications.

## DISCUSSION

### Findings

Findings reveal that the deployment of Uber services in a given metropolitan county has no association with the number of subsequent traffic fatalities, whether measured in aggregate or specific to drunk driving fatalities or fatalities during weekends and holidays. We undertook a variety of robustness checks, and found similar results across a number of different model specifications.

There are several explanations for the apparent lack of reduction in traffic fatalities following the implementation of Uber. First, Uber may have no association with traffic fatalities because it represents a relatively small share of transportation usage in the United States. If the share of total vehicle miles traveled by Uber drivers increases, then perhaps there will be a greater possibility for an association with traffic fatalities in the future (whether positive or negative). Indeed, the number of active Uber drivers in a given month increased exponentially between January 2013 and April 2016, from a few thousand drivers to 450,000 monthly drivers (37,38). However, given that there are 210

million licensed drivers in the United States (39), as well as an estimated 4.2 million adults driving impaired by alcohol in a given month (3), it is hard to conceive of Uber making a substantial change in aggregate traffic fatalities when its users make up such a minimal share of total drivers.

Second, Uber may be a substitute for taxis and other forms of public transportation but not a substitute for drunk driving. Accordingly, Uber passengers may have formerly been taxi and public transit users and thus the number of at-risk drivers on the road would not substantially change. Prior evidence has suggested this substitutability (40, 41).

Relatedly, Uber users may not be representative of the average metropolitan driver. For example, the principal consumers of Uber in New York City are upper-income passengers who do not own a vehicle (41). Although cheaper than a taxi ride on average, Uber is still considerably more expensive than public transit (42). Therefore, lower income individuals and those near public transit may be less likely to consider Uber as a practical form of transportation. In this case, Uber may have a greater association in smaller areas where transportation options are limited. Future research should examine whether the association between Uber's presence and traffic fatalities depends upon the availability of alternative transportation options.

Finally, the average inebriated individual contemplating drunk driving may not be sufficiently rational to substitute drinking and driving for a presumably safer Uber ride, or perhaps many drunk drivers rationally conclude that it is too costly to pay for an Uber ride (or taxi) given that the likelihood of getting arrested for drinking and driving is actually quite low.

### Strengths and Limitations

Certain limitations of this study should be acknowledged. First, absent data tracking individual Uber usage and related fatalities, it is not possible to explicitly examine Uber's relationship with traffic fatalities at the individual level. This limitation prevented us from examining traffic fatalities disaggregated by pertinent driver characteristics, specifically gender, race, socioeconomic status, and age. Relatedly, accurate data on Uber usage volume would likely strengthen our multivariate findings by allowing us to capture a more precise measure of Uber presence in an area. Also, given the relative novelty of Uber, we were unable to examine the long-term association with fatalities. Finally, this study did not examine Uber's association with other traffic outcomes, including drunk driving incidences and non-fatal crashes. Future research should investigate these relationships to further expand our understanding of rideshare services.

Despite these limitations, this study adds to the limited empirical knowledge concerning the association of rideshare services with traffic outcomes. We extend previous research, which focused on a single state, by examining multiple counties across the United States. By using panel data on multiple counties with timing differences in Uber deployment, we were able to control for county-, month-, and year-invariant effects, which allowed us to purge any unobserved systematic variation from the analysis.

### Conclusion

In summary, our results suggest that the entry of Uber services into a metropolitan area has no aggregate association with traffic fatalities. Our results should provoke skepticism of broad claims regarding the citywide effects of rideshare services in reducing traffic fatalities. At least through the first five years following the advent of Uber's rideshare services, this transportation revolution has not yet translated into aggregate declines in metro-area traffic fatalities.

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## REFERENCES

1. National Highway Traffic Safety Administration. Traffic Safety Facts 2015. Washington, DC: National Highway Traffic Safety Administration. <http://www-nrd.nhtsa.dot.gov/Pubs/812219.pdf>. Published November 2015. Accessed April 28, 2016.
2. National Highway Traffic Safety Administration. Traffic Safety Facts: Alcohol-Impaired Driving 2014. Washington, DC: National Highway Traffic Safety Administration. <http://www-nrd.nhtsa.dot.gov/Pubs/812231.pdf>. Published December 2015. Accessed April 28, 2016.
3. Centers for Disease Control and Prevention. Alcohol-Impaired Driving Among Adults — United States, 2012. *MMWR Morb Mortal Wkly Rep*. 2015; 64(30):814-817.
4. Clarke RV, Cornish DB. Modeling offenders' decisions: A framework for research and policy. In Tonry M, Morris N, eds. *Crime Justice*. Chicago, IL: University of Chicago Press; 1985:147-185.
5. Eisenberg D. Evaluating the effectiveness of policies related to drunk driving. *J Policy Anal Manag*. 2003;22(2):249-274.
6. Villaveces A, Cummings P, Koepsell T, et al. Association of alcohol-related laws with deaths due to motor vehicle and motorcycle crashes in the United States, 1980–1997. *Am J Epidemiol*. 2003;157(2):131-140.
7. Federal Bureau of Investigation. Uniform Crime Reports. Estimated number of arrests, United States, 2014. <https://www.fbi.gov/about-us/cjis/ucr/crime-in-the->



- u.s/2014/crime-in-the-u.s.-2014/tables/table-29. Published September 2015.  
Accessed April 28, 2016.
8. Uber. Uberdependence Day in SF! <https://newsroom.uber.com/us-california/uberdependence-day-in-sf/>. Published June 30, 2011. Accessed February 9, 2016.
  9. Fahey, M. What's cheaper in your city: Cabs or ride shares? *CNBC*.  
<http://www.cnbc.com/2015/08/31/whats-cheaper-in-your-city-cabs-or-ride-shares.html>. Published August 31, 2015. Accessed April 28, 2016.
  10. Newcomer, E. Uber raises funding at \$62.5 billion valuation. *Bloomberg*.  
<http://www.bloomberg.com/news/articles/2015-12-03/uber-raises-funding-at-62-5-valuation>. Published December 3, 2015. Accessed April 26, 2016.
  11. Newcomer, E. GM invests \$500 million in Lyft. *Bloomberg*.  
<http://www.bloomberg.com/news/articles/2016-01-04/gm-invests-500-million-in-lyft-to-bolster-alliance-against-uber>. Published January 4, 2016. Accessed April 26, 2016.
  12. Uber and Mothers Against Drunk Driving. More options. Shifting mindsets. Driving better choices. <https://newsroom.uber.com/wp-content/uploads/2015/01/UberMADD-Report.pdf>. Published January 27, 2015.  
Accessed May 20, 2016.
  13. Greenwood B, Wattal S. Show me the way to go home: An empirical investigation of ride sharing and motor vehicle homicides. *MIS Quart.* 2016;*In press*.
  14. Bureau of the Census, US Department of Commerce. Census Population and Housing Tables. Washington, DC: Bureau of the Census.

- <http://www.census.gov/population/www/cen2010/cph-t/cph-t-5.html>. Published March 2013. Accessed April 28, 2016.
15. Bureau of the Census, US Department of Commerce. Principal cities of metropolitan and micropolitan statistical areas. Washington, DC: Bureau of the Census. <http://www.census.gov/population/metro/files/lists/2013/List2.xls>. Published February 2013. Accessed April 28, 2016.
  16. Missouri Census Data Center. MABLE/Geocorr12, Version 1.2.: Geographic Correspondence Engine. <http://mcdc.missouri.edu/websas/geocorr12.html>. Published March 18, 1998. Modified January 27, 2016. Accessed April 28, 2016.
  17. Anowar S, Yasmin S, Tay R. Comparison of crashes during public holidays and regular weekends. *Accident Anal Prev*. 2013;51:93-97.
  18. Uber. Uber's Founding. <https://newsroom.uber.com/ubers-founding/>. Published December 22, 2010. Accessed April 28, 2016.
  19. Anderson DM, Rees DI. Per se drugged driving laws and traffic fatalities. *Int Rev Law Econ*. 2015;42:122-134.
  20. Neeley GW, Richardson Jr LE. The effect of state regulations on truck-crash fatalities. *Am J Public Health*. 2009;99(3):408-415.
  21. Ferdinand AO, Menachemi N, Sen B, et al. Impact of Texting Laws on Motor Vehicle Fatalities in the United States. *Am J Public Health*. 2014;104(8):1370-1377.
  22. Shults RA, Elder RW, Sleet DA, et al. Reviews of evidence regarding interventions to reduce alcohol-impaired driving. *Am J Prev Med*. 2001;21(4):66-88.
  23. Cohen A, Einav L. The effects of mandatory seat belt laws on driving behavior and traffic fatalities. *Rev Econ Stat*. 2003;85(4):828-843.

24. Insurance Institute for Highway Safety Highway Loss Data Institute. Safety belts.  
<http://www.iihs.org/iihs/topics/laws/safetybeltuse?topicName=safety-belts>. Accessed April 23, 2016.
25. National Conference of State Legislatures. Drugged Driving Per Se Laws.  
<http://www.ncsl.org/documents/transportation/persechartOct2015.pdf>. Published October 2015. Accessed April 28, 2016.
26. Cheng C. Do cell phone bans change driver behavior? *Econ Inq.* 2015;53(3):1420-1436.
27. Anderson DM, Hansen B, Rees DI. Medical marijuana laws, traffic fatalities, and alcohol consumption. *J Law Econ.* 2013;56(2):333-369.
28. Scott EM. *Marijuana decriminalization*. Connecticut General Assembly, Office of Legislative Research. <https://www.cga.ct.gov/2010/rpt/2010-R-0204.htm>. Published May 5, 2010. Accessed May 20, 2016.
29. Morrissey M, Grabowski D. Gas prices, beer taxes and GDL programmes: effects on auto fatalities among young adults in the US. *App Econ.* 2011;43(25):3645-3654.
30. Chang, K, Wu, CC, Ying YH. The effectiveness of alcohol control policies on alcohol-related traffic fatalities in the United States. *Accid Anal Prev.* 2012; 45(2):406-415.
31. Evans W, Graham JD. Traffic safety and the business cycle. *Alcohol, Drugs, and Driving.* 1988;4(1):31-38.
32. Ruhm, CJ, Black, WE. Does drinking really decrease in bad times? *J Health Econ.* 2002; 21(4):659-678.

33. Braver, ER. Race, Hispanic origin, and socioeconomic status in relation to motor vehicle occupant death rates and risk factors among adults. *Accid Anal Prev.* 2003; 35(3):295-309.
34. Lien, T. Lyft defies predictions by continuing to grow as a rival to Uber. *Los Angeles Times*. <http://www.latimes.com/business/technology/la-fi-0105-lyft-growth-20160105-story.html>. Published January 5, 2016. Accessed April 20, 2016.
35. Gelles, D, Isaac, M. Challenging Uber, Lyft bets on a road wide enough for two. *New York Times*. <http://www.nytimes.com/2016/01/10/technology/challenging-uber-lyft-bets-on-a-road-wide-enough-for-two.html>. Published January 9, 2016. Accessed April 20, 2016.
36. Sivak M, Schoettle B. Toward understanding the recent large reductions in US road fatalities. *Traffic injury prevention.* 2010;11(6):561-566.
37. Wong, JC. Uber reaches \$100m settlement in fight with drivers, who will stay contractors. *The Guardian*. <https://www.theguardian.com/technology/2016/apr/21/uber-driver-settlement-labor-dispute-california-massachusetts>. Published April 21, 2016. Accessed April 26, 2016.
38. Hall JV, Krueger AB. An analysis of the labor market for Uber's driver-partners in the United States. Princeton University Industrial Relations Section working paper 587. <http://dataspace.princeton.edu/jspui/bitstream/88435/dsp010z708z67d/5/587.pdf>. Published January 22, 2015. Accessed May 19, 2016.

39. Federal Highway Administration, US Department of Transportation. Our Nation's Highways: 2011.  
<https://www.fhwa.dot.gov/policyinformation/pubs/hf/pl11028/chapter4.cfm>.  
Published May 2010. Modified November 7, 2014. Accessed April 28, 2016.
40. Silver, N, Fischer-Baum, R. Public transit should be Uber's new best friend. *FiveThirtyEight*. <http://fivethirtyeight.com/features/public-transit-should-be-ubers-new-best-friend/>. Published August 28, 2015. Accessed April 23, 2016.
41. The Economist Staff. Taxis v Uber: A tale of two cities. *The Economist*.  
<http://www.economist.com/news/united-states/21661016-does-uber-substitute-cabs-or-attract-new-riders-it-depends-where-you-live-tale>. Published August 13, 2015.  
Accessed April 23, 2016.
42. Silverstein, S. These animated charts tell you everything about Uber prices in 21 cities. *Business Insider*. <http://www.businessinsider.com/uber-vs-taxi-pricing-by-city-2014-10>. Published October 16, 2014. Accessed April 23, 2016.

Table 1. Descriptive Statistics for County-Month Sample, Principal Counties of the Top 100 US Metropolitan Areas, 2005-2014.

	County-year-months with Uber (N = 1,218)	County-year-months without Uber (N = 11,262)
Variable	Mean (SD)	Mean (SD)
<i>Traffic fatality counts</i>		
Total	8.75 (10.44)	6.93 (7.80)
Drunk-driving <sup>a</sup>	2.22 (3.02)	1.80 (2.21)
Weekends and Holidays	2.88 (3.81)	2.23 (2.86)
County unemployment rate, %	7.07 (2.14)	7.04 (2.62)
State beer tax, 2014 dollars/gal.	0.23 (0.18)	0.26 (0.19)
Taxi drivers per 100,000 population	25.23 (21.87)	34.78 (54.18)
<i>State laws</i>		
Marijuana decriminalization	0.55 (0.50)	0.38 (0.49)
Medical marijuana legalization	0.30 (0.46)	0.17 (0.38)
Graduated driver licensing law	0.99 (0.12)	0.97 (0.18)
Hands free driving	0.46 (0.50)	0.18 (0.38)
Cell phone texting ban	0.69 (0.46)	0.27 (0.45)
Drug per se	0.37 (0.48)	0.33 (0.47)
Seat belt law, primary enforcement	0.80 (0.40)	0.62 (0.48)

Abbreviations: SD, standard deviation.

<sup>a</sup>From 2009-2014.

Table 2. Incidence Rate Ratios for the Number of Total Traffic Fatalities Regressed on Uber Deployment from Negative Binomial Models<sup>a</sup>, Principal Counties of the Top 100 US Metropolitan Areas, 2005-2014.

Variable	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active	1.06	0.93, 1.21	1.01	0.97, 1.06	1.02	0.98, 1.06
County unemployment rate, %					0.97 <sup>c</sup>	0.95, 0.98
State beer tax, 2014 dollars/gal.					0.73 <sup>d</sup>	0.60, 0.89
Taxi drivers per 100,000 population					1.00	1.00, 1.00
Marijuana decriminalization					1.04	0.94, 1.15
Medical marijuana legalization					1.00	0.82, 1.22
Graduated driver licensing law					0.92	0.82, 1.04
Hands free driving					0.95	0.89, 1.01
Cell phone texting ban					0.98	0.94, 1.03
Drug per se					1.03	0.98, 1.09
Seat belt law, primary enforcement					0.97	0.92, 1.03
N	12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05

Table 3. Incidence Rate Ratios for the Number of Drunk Driving-Related Traffic Fatalities from Poisson Models, 2009-2014, and Weekend and Holiday-Related Traffic Fatalities from Negative Binomial Models, 2005-2014, Regressed on Uber Deployment, Principal Counties of the Top 100 US Metropolitan Areas.

Variable	Drunk Driving <sup>a</sup>						Weekends and Holidays <sup>a</sup>					
	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>		Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active	0.96	0.83, 1.10	1.03	0.97, 1.10	1.03	0.97, 1.10	1.07	0.95, 1.21	1.05	0.98, 1.12	1.05	0.99, 1.12
County unemployment rate, %					0.96 <sup>d</sup>	0.94, 0.99					0.97 <sup>d</sup>	0.95, 0.99
State beer tax, 2014 dollars/gal.					1.08	0.83, 1.39					1.06	0.83, 1.37
Taxi drivers per 100,000 population					1.00	1.00, 1.00					1.00	1.00, 1.00
Marijuana decriminalization					0.93	0.78, 1.10					1.09	0.94, 1.26
Medical marijuana legalization					0.79 <sup>c</sup>	0.75, 0.82					0.97	0.77, 1.22
Graduated driver licensing law					1.22 <sup>e</sup>	1.03, 1.45					0.91	0.75, 1.10
Hands free driving					0.88	0.76, 1.03					0.95	0.88, 1.03
Cell phone texting ban					1.00	0.94, 1.07					0.95	0.90, 1.01
Drug per se					1.02	0.79, 1.31					1.04	0.94, 1.16
Seat belt law, primary enforcement					0.95	0.78, 1.15					0.95	0.88, 1.03
N	7,488		7,488		7,488		12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

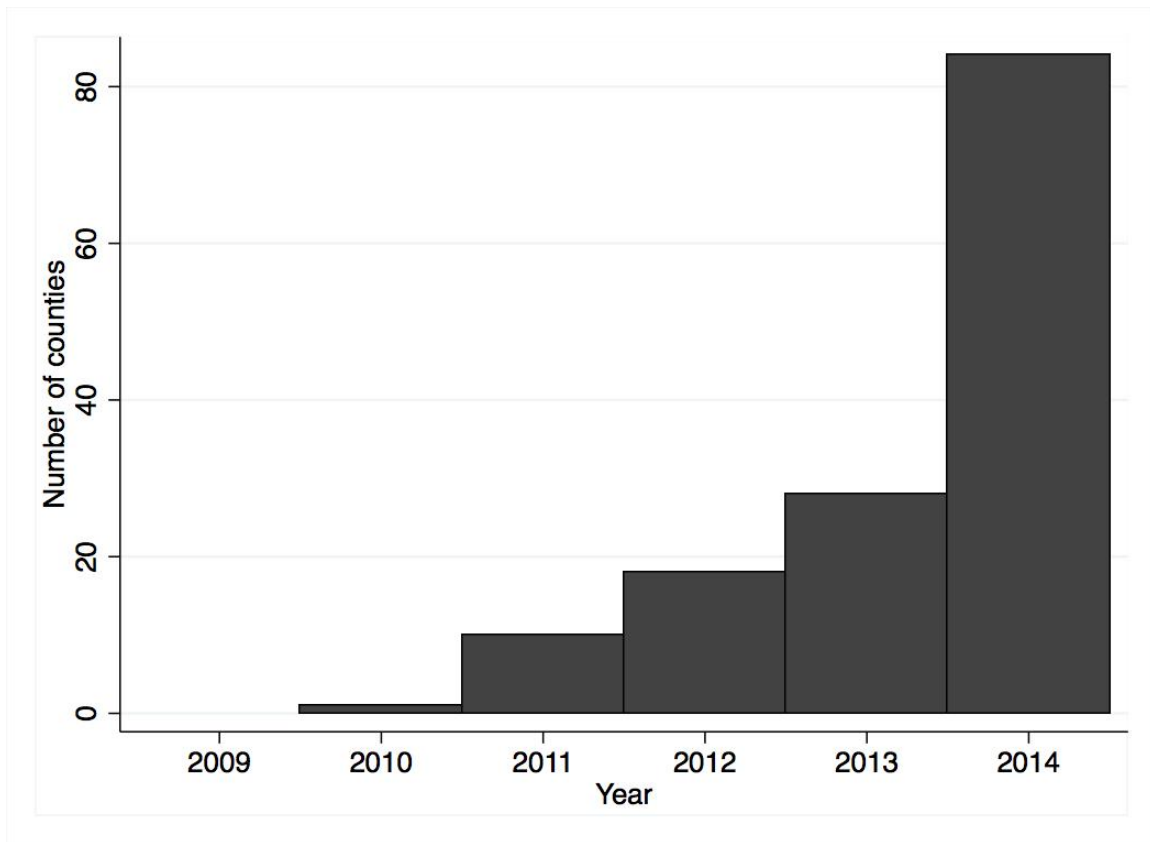
<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05



Figure 1. Number of the Most Populated Counties in the Top 100 Metropolitan Areas in the United States with Uber Services, 2009-2014 (N = 84).



**Web Appendix 1**

Our analytic sample contains month by year observations for the most populated county in the 100 most populated metropolitan areas in the United States (see Web Table 1). For the main analysis presented in the paper, we examined the relationship between traffic fatalities and Uber entry using Negative Binomial regression models. Our measure of exposure is the number of vehicle miles traveled (VMT) in a county month. Because county monthly VMT data are not available, we estimated these values by multiplying the state-month-year VMT by the county's proportion of its state's total roadway mileage. County roadway mileage data are not available for all years in our observation period. However, for the years that data are available, county mileage is highly stable. Therefore, we use the county's roadway mileage proportion in 2008, which is approximately midway through the observation period. Although county monthly VMT data are not available, yearly VMT data are available for some years, which allowed us to test the validity of our estimation method by comparing estimated and actual VMT yearly totals. The correlation between estimated and actual yearly VMT values was large ( $\rho = 0.9$ ).

We ran a set of additional models to test the robustness of our main results. First, we replaced VMT with county yearly Census population estimates as the measure of exposure (Web Tables 2 and 3). Although population as an exposure variable has its limitations, specifically it often overestimates the true population at risk of traffic fatalities because it does not account for changes in the number of vehicles, instances of driving, and distance traveled, it is a popular measure of crash risk. Second, in order to test whether findings are sensitive to distributional assumptions, we fitted Poisson models

(Web Table 4) to go along with the Negative Binomial models presented in the main analysis. Third, because prior evidence revealed that Uber's association with traffic fatalities becomes stable after nine months (*1*), we tested for a lagged association by replacing the binary Uber indicator from the main analysis with a variable categorizing observations into no Uber service present, Uber present less than nine months, and Uber present nine months or longer (Web Tables 5 and 6). We also tested whether our results are sensitive to the use of a nine-month threshold for a lagged association versus a different threshold, and therefore reran analyses with a lag of six months. This model yielded similar results as the model with the nine-month lag and therefore its results are not reported in the tables to follow. Fourth, we accounted for the presence of Lyft, Uber's largest US competitor, by testing a variable that indicates whether either company is present in a county (Web Tables 7 and 8). We also examined the association between the number of rideshare services and traffic fatalities by including a variable that categorizes counties as having neither Uber nor Lyft presence (reference group), either Uber or Lyft, or both Uber and Lyft (Web Tables 9 and 10). Lyft is present in 65 counties in our sample through the end of 2014, with Uber also present in 60 of these counties. Although other rideshare companies exist, Uber and Lyft capture the bulk of the market in the United States, with Uber as the market leader by a considerable margin (*2,3*). Finally, traffic fatalities dramatically declined in the United States between 2007 and 2008, which has been attributed to the Great Recession and improved air bag standards (*4*). In order to test whether results are sensitive to this decline, we ran analyses limited to just the 2009-2014 period (Web Tables 11 and 12). Results for these robustness tests, which are consistent with the main results, are provided on the following pages.

As in the main analysis, we start with a baseline model with just the independent variable of interest. We then add county, month, and year fixed effects in Model 2 and assorted control variables in Model 3. In Web Tables 2 and 3, we find in the unconditional model that there is a significant association between Uber and traffic fatalities. This association disappears when we add county, month, and year fixed effects to the model. Conceptually when we include the county fixed effects, we are using each county as its own control and estimating what happened to traffic fatalities once Uber was launched. Results reveal that the number of traffic fatalities in a given county did not significantly change once Uber was implemented.

## References

1. Greenwood B, Wattal S. Show me the way to go home: An empirical investigation of ride sharing and motor vehicle homicides. *MIS Quart.* 2016; *In press*.
2. Lien, T. Lyft defies predictions by continuing to grow as a rival to Uber. *Los Angeles Times*. <http://www.latimes.com/business/technology/la-fi-0105-lyft-growth-20160105-story.html>. Published January 5, 2016. Accessed April 20, 2016.
3. Gelles, D, Isaac, M. Challenging Uber, Lyft bets on a road wide enough for two. *New York Times*. <http://www.nytimes.com/2016/01/10/technology/challenging-uber-lyft-bets-on-a-road-wide-enough-for-two.html>. Published January 9, 2016. Accessed April 20, 2016.
4. Sivak M, Schoettle B. Toward understanding the recent large reductions in US road fatalities. *Traffic injury prevention*. 2010;11(6):561-566.

Web Table 1. Uber Deployment Dates for Principal Counties in Top 100 Metropolitan Areas in the United States, through 2014.

State	County	Metropolitan Statistical Area	2010 MSA population	Uber Deployed	
				Month	Year
New York	Bronx	New York-Wayne-White Plains	19,599,534	5	2011
New York	Kings	New York-Wayne-White Plains	19,599,534	5	2011
New York	New York	New York-Wayne-White Plains	19,599,534	5	2011
New York	Queens	New York-Wayne-White Plains	19,599,534	5	2011
New York	Richmond	New York-Wayne-White Plains	19,599,534	5	2011
California	Los Angeles	Los Angeles-Long Beach-Santa Ana	12,845,311	3	2012
Illinois	Cook	Chicago-Naperville-Joliet	9,470,069	9	2011
Texas	Dallas	Dallas-Plano-Irving	6,452,725	9	2012
Pennsylvania	Philadelphia	Philadelphia	5,971,276	6	2012
Texas	Harris	Houston-Baytown-Sugar Land	5,949,076	2	2014
District of Columbia	District of Columbia	Washington-Arlington-Alexandria	5,665,931	12	2011
Florida	Miami-Dade	Miami-Miami Beach-Kendall	5,586,506	6	2014
Georgia	Fulton	Atlanta-Sandy Springs-Marietta	5,304,207	8	2012
Massachusetts	Suffolk	Boston-Quincy	4,564,659	10	2011
California	San Francisco	San Francisco-San Mateo-Redwood City	4,345,179	5	2010
Michigan	Wayne	Detroit-Livonia-Dearborn	4,291,176	3	2013
California	Riverside	Riverside-San Bernardino-Ontario	4,244,242	5	2014
Arizona	Maricopa	Phoenix-Mesa-Scottsdale	4,209,347	11	2012
Washington	King	Seattle-Bellevue-Everett	3,448,234	8	2011
Minnesota	Hennepin	Minneapolis-St. Paul-Bloomington	3,355,105	10	2012
California	San Diego	San Diego-Carlsbad-San Marcos	3,104,543	6	2012
Missouri	St. Louis	St. Louis	2,789,886	10	2014
Florida	Hillsborough	Tampa-St. Petersburg-Clearwater	2,789,334	3	2014

State	County	Metropolitan Statistical Area	2010 MSA population	Uber Deployed	
				Month	Year
Maryland	Baltimore	Baltimore-Towson	2,715,625	2	2013
Colorado	Denver	Denver-Aurora	2,554,335	9	2012
Pennsylvania	Allegheny	Pittsburgh	2,356,678	3	2014
Oregon	Multnomah	Portland-Vancouver-Beaverton	2,232,079		
North Carolina	Mecklenburg	Charlotte-Gastonia-Concord	2,223,894	9	2013
California	Sacramento	Sacramento--Arden-Arcade--Roseville	2,154,382	2	2013
Texas	Bexar	San Antonio	2,153,255	3	2014
Florida	Orange	Orlando	2,139,686	6	2014
Ohio	Hamilton	Cincinnati-Middletown	2,117,863	3	2014
Ohio	Cuyahoga	Cleveland-Elyria-Mentor	2,075,558	4	2014
Missouri	Jackson	Kansas City	2,013,651	5	2014
Nevada	Clark	Las Vegas-Paradise	1,953,263		
Ohio	Franklin	Columbus	1,906,177	12	2013
Indiana	Marion	Indianapolis	1,892,508	6	2014
California	Santa Clara	San Jose-Sunnyvale-Santa Clara	1,842,462		
Texas	Travis	Austin-Round Rock	1,727,743	6	2014
Virginia	Virginia Beach	Virginia Beach-Norfolk-Newport News	1,680,110	5	2014
Tennessee	Davidson	Nashville-Davidson--Murfreesboro	1,675,913	12	2013
Rhode Island	Providence	Providence-New Bedford-Fall River	1,602,154	7	2013
Wisconsin	Milwaukee	Milwaukee-Waukesha-West Allis	1,556,535	4	2014
Florida	Duval	Jacksonville	1,349,137	1	2014
Tennessee	Shelby	Memphis	1,326,580	4	2014
Oklahoma	Oklahoma	Oklahoma City	1,257,888	10	2013
Kentucky	Jefferson	Louisville	1,237,778	4	2014
Connecticut	Hartford	Hartford-West Hartford-East Hartford	1,214,021	4	2014

State	County	Metropolitan Statistical Area	2010 MSA population	Uber Deployed	
				Month	Year
Virginia	Richmond	Richmond	1,210,063	8	2014
Louisiana	Orleans	New Orleans-Metairie-Kenner	1,195,794		
North Carolina	Wake	Raleigh-Cary	1,137,346	6	2014
New York	Erie	Buffalo-Niagara Falls	1,135,342		
Alabama	Jefferson	Birmingham-Hoover	1,129,034		
Utah	Salt Lake	Salt Lake City	1,091,432	5	2014
New York	Monroe	Rochester	1,080,082		
Michigan	Kent	Grand Rapids-Wyoming	989,205	7	2014
Arizona	Pima	Tucson	981,935	10	2013
Hawaii	Honolulu	Honolulu	956,336	8	2013
Oklahoma	Tulsa	Tulsa	939,858	3	2014
California	Fresno	Fresno	932,642	2	2014
Connecticut	Fairfield	Bridgeport-Stamford-Norwalk	919,506	4	2014
Massachusetts	Worcester	Worcester	918,791	10	2014
New Mexico	Bernalillo	Albuquerque	889,649	4	2014
New York	Albany	Albany-Schenectady-Troy	870,954		
Nebraska	Douglas	Omaha-Council Bluffs	868,113	5	2014
Connecticut	New Haven	New Haven-Milford	863,367	4	2014
California	Kern	Bakersfield	841,762	6	2014
Tennessee	Knox	Knoxville	838,687	8	2014
South Carolina	Greenville	Greenville	825,765	7	2014
California	Ventura	Oxnard-Thousand Oaks-Ventura	825,353	7	2014
Pennsylvania	Lehigh	Allentown-Bethlehem-Easton	822,083		
Texas	El Paso	El Paso	807,089	6	2014
Louisiana	East Baton Rouge	Baton Rouge	804,491	7	2014



State	County	Metropolitan Statistical Area	2010 MSA population	Uber Deployed	
				Month	Year
Ohio	Montgomery	Dayton	800,245	8	2014
Texas	Hidalgo	McAllen-Edinburg-Pharr	779,194		
South Carolina	Richland	Columbia	769,661	7	2014
North Carolina	Guilford	Greensboro-High Point	725,040	6	2014
Florida	Sarasota	Sarasota-Bradenton-Venice	703,462	12	2014
Ohio	Summit	Akron	702,967	8	2014
Arkansas	Pulaski	Little Rock-North Little Rock	702,305	11	2014
California	San Joaquin	Stockton	687,513	5	2014
South Carolina	Charleston	Charleston-North Charleston	667,724	7	2014
New York	Onondaga	Syracuse	662,976		
Colorado	El Paso	Colorado Springs	650,351	5	2014
North Carolina	Forsyth	Winston-Salem	641,351	6	2014
Kansas	Sedgwick	Wichita	631,936	8	2014
Massachusetts	Hampden	Springfield	623,426		
Florida	Lee	Cape Coral-Fort Myers	620,521	12	2014
Idaho	Ada	Boise City-Nampa	617,923		
Ohio	Lucas	Toledo	610,201	6	2014
Wisconsin	Dane	Madison	606,409	3	2014
Florida	Polk	Lakeland	603,359	12	2014
Utah	Weber	Ogden-Clearfield	599,569		
Florida	Volusia	Deltona-Daytona Beach-Ormond Beach	590,678	12	2014
Iowa	Polk	Des Moines	571,883		
Mississippi	Hinds	Jackson	568,905	12	2014
Georgia	Richmond	Augusta-Richmond	566,683		
Ohio	Mahoning	Youngstown-Warren-Boardman	564,874		

State	County	Metropolitan Statistical Area	2010 MSA population	Uber Deployed	
				Month	Year
Pennsylvania	Lackawanna	Scranton--Wilkes-Barre	563,655		
Pennsylvania	Dauphin	Harrisburg-Carlisle	550,258		
Florida	Brevard	Palm Bay-Melbourne-Titusville	544,029	12	2014
Utah	Utah	Provo-Orem	529,830		
Tennessee	Hamilton	Chattanooga	529,103	11	2014
North Carolina	Durham	Durham	508,063	6	2014

Abbreviations: MSA, Metropolitan Statistical Area.

Web Table 2. Incidence Rate Ratios for the Number of Total Traffic Fatalities Regressed on Uber Deployment from Negative Binomial Models<sup>a</sup> using County Yearly Population as Exposure, Principal Counties of the Top 100 US Metropolitan Areas, 2005-2014.

Variable	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active	0.69 <sup>c</sup>	0.62, 0.77	1.01	0.97, 1.05	1.01	0.97, 1.06
County unemployment rate, %					0.96 <sup>c</sup>	0.95, 0.98
State beer tax rate, 2014 dollars/gal.					0.72 <sup>d</sup>	0.59, 0.89
Taxi drivers per 100,000 population					1.00	1.00, 1.00
Marijuana decriminalization					1.07	0.97, 1.18
Medical marijuana legalization					1.03	0.81, 1.31
Graduated driver licensing law					0.93	0.81, 1.05
Hands free driving					0.95	0.88, 1.03
Cell phone texting ban					1.00	0.96, 1.04
Drug per se					1.06 <sup>e</sup>	1.00, 1.12
Seat belt law, primary enforcement					0.95	0.90, 1.01
N	12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county yearly population.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05

Web Table 3. Incidence Rate Ratios for the Number of Drunk Driving-Related Traffic Fatalities from Poisson Models, 2009-2014, and Weekend and Holiday-Related Traffic Fatalities from Negative Binomial Models, 2005-2014, Regressed on Uber Deployment using County Yearly Population as Exposure, Principal Counties of the Top 100 US Metropolitan Areas.

Variable	Drunk Driving <sup>a</sup>						Weekends and Holidays <sup>a</sup>					
	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>		Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active	0.68 <sup>c</sup>	0.60, 0.78	1.03	0.97, 1.10	1.03	0.97, 1.10	0.72 <sup>d</sup>	0.64, 0.82	1.05	0.98, 1.12	1.05	0.98, 1.12
County unemployment rate, %					0.96 <sup>c</sup>	0.93, 0.98					0.97 <sup>c</sup>	0.95, 0.98
State beer tax rate, 2014 dollars/gal.					1.09	0.82, 1.45					1.05	0.85, 1.31
Taxi drivers per 100,000 population					1.00	1.00, 1.00					1.00	1.00, 1.00
Marijuana decriminalization					0.95	0.80, 1.12					1.13	0.97, 1.31
Medical marijuana legalization					0.74 <sup>c</sup>	0.71, 0.78					1.01	0.77, 1.31
Graduated driver licensing law					1.26 <sup>d</sup>	1.07, 1.49					0.91	0.75, 1.11
Hands free driving					0.94	0.78, 1.14					0.95	0.87, 1.05
Cell phone texting ban					1.01	0.95, 1.08					0.97	0.92, 1.02
Drug per se					1.01	0.78, 1.32					1.07	0.96, 1.19
Seat belt law, primary enforcement					0.91	0.76, 1.10					0.93	0.86, 1.01
N	7,488		7,488		7,488		12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county yearly population.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05

Web Table 4. Incidence Rate Ratios for the Number of Total and Holiday-Related Traffic Fatalities Traffic Fatalities Regressed on Uber Deployment from Poisson Models, Principal Counties of the Top 100 US Metropolitan Areas, 2005-2014.

Variable	Total <sup>a</sup>						Weekends and Holidays <sup>a</sup>					
	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>		Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active	1.00	0.89, 1.13	1.01	0.97, 1.06	1.02	0.98, 1.06	1.03	0.91, 1.16	1.05	0.98, 1.12	1.05	0.99, 1.12
County unemployment rate, %					0.97 <sup>c</sup>	0.95, 0.98					0.97 <sup>d</sup>	0.95, 0.99
State beer tax rate, 2014 dollars/gal.					0.71 <sup>c</sup>	0.58, 0.87					1.06	0.81, 1.38
Taxi drivers per 100,000 population					1.00	1.00, 1.00					1.00	1.00, 1.00
Marijuana decriminalization					1.05	0.95, 1.16					1.09	0.94, 1.27
Medical marijuana legalization					1.02	0.84, 1.24					0.97	0.78, 1.22
Graduated driver licensing law					0.90	0.80, 1.00					0.90	0.75, 1.08
Hands free driving					0.96	0.90, 1.02					0.95	0.88, 1.03
Cell phone texting ban					0.97	0.93, 1.02					0.95	0.90, 1.00
Drug per se					1.03	0.98, 1.09					1.04	0.94, 1.16
Seat belt law, primary enforcement					0.98	0.92, 1.03					0.95	0.88, 1.03
N	12,480		12,480		12,480		12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05

Web Table 5. Incidence Rate Ratios for the Number of Total Traffic Fatalities Regressed on the Timing of Uber Deployment from Negative Binomial Models<sup>a</sup>, Principal Counties of the Top 100 US Metropolitan Areas, 2005-2014.

Variable	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber < active 9 mos. <sup>c</sup>	0.99	0.91, 1.07	1.00	0.96, 1.05	1.01	0.96, 1.05
Uber ≥ active 9 mos. <sup>c</sup>	1.13	0.93, 1.38	1.03	0.97, 1.09	1.04	0.98, 1.09
County unemployment rate, %					0.97 <sup>d</sup>	0.95, 0.98
State beer tax rate, 2014 dollars/gal.					0.73 <sup>d</sup>	0.60, 0.88
Taxi drivers per 100,000 population					1.00	1.00, 1.00
Marijuana decriminalization					1.04	0.94, 1.15
Medical marijuana legalization					1.00	0.82, 1.22
Graduated driver licensing law					0.92	0.82, 1.04
Hands free driving					0.95	0.89, 1.01
Cell phone texting ban					0.98	0.94, 1.03
Drug per se					1.03	0.97, 1.09
Seat belt law, primary enforcement					0.97	0.92, 1.03
N	12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>Reference group is no Uber present.

<sup>d</sup>*P* value ≤ 0.001, <sup>e</sup>*P* value ≤ 0.01, <sup>f</sup>*P* value ≤ 0.05

Web Table 6. Incidence Rate Ratios for the Number of Drunk Driving-Related Traffic Fatalities from Poisson Models, 2009-2014, and Weekend and Holiday-Related Traffic Fatalities from Negative Binomial Models, 2005-2014, Regressed on the Timing of Uber Deployment, Principal Counties of the Top 100 US Metropolitan Areas.

Variable	Drunk Driving <sup>a</sup>						Weekends and Holidays <sup>a</sup>					
	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>		Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active < 9 mos. <sup>c</sup>	0.99	0.90, 1.08	1.02	0.95, 1.11	1.02	0.95, 1.11	1.03	0.93, 1.13	1.05	0.97, 1.13	1.05	0.98, 1.12
Uber active ≥ 9 mos. <sup>c</sup>	0.93	0.76, 1.15	1.04	0.96, 1.13	1.05	0.97, 1.13	1.12	0.92, 1.35	1.05	0.96, 1.14	1.06	0.97, 1.16
County unemployment rate, %					0.96 <sup>e</sup>	0.94, 0.99					0.97 <sup>e</sup>	0.95, 0.99
State beer tax rate, 2014 dollars/gal.					1.08	0.84, 1.39					1.06	0.82, 1.38
Taxi drivers per 100,000 population					1.00	1.00, 1.00					1.00	1.00, 1.00
Marijuana decriminalization					0.93	0.78, 1.10					1.09	0.94, 1.26
Medical marijuana legalization					0.78 <sup>d</sup>	0.75, 0.82					0.97	0.77, 1.22
Graduated driver licensing law					1.22 <sup>f</sup>	1.03, 1.45					0.91	0.75, 1.10
Hands free driving					0.88	0.76, 1.03					0.95	0.88, 1.02
Cell phone texting ban					1.00	0.94, 1.07					0.95	0.90, 1.00
Drug per se					1.02	0.78, 1.32					1.04	0.94, 1.16
Seat belt law, primary enforcement					0.95	0.78, 1.15					0.95	0.88, 1.03
N	7,488		7,488		7,488		12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>Reference group is no Uber present.

<sup>d</sup> $P$  value ≤ 0.001, <sup>e</sup> $P$  value ≤ 0.01, <sup>f</sup> $P$  value ≤ 0.05

Web Table 7. Incidence Rate Ratios for the Number of Total Traffic Fatalities Regressed on Uber or Lyft Deployment from Negative Binomial Models<sup>a</sup>, Principal Counties of the Top 100 US Metropolitan Areas, 2005-2014.

Variable	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber or Lyft active	1.04	0.92, 1.18	1.02	0.97, 1.06	1.02	0.98, 1.06
County unemployment rate, %					0.97 <sup>c</sup>	0.95, 0.98
State beer tax rate, 2014 dollars/gal.					0.73 <sup>d</sup>	0.60, 0.89
Taxi drivers per 100,000 population					1.00	1.00, 1.00
Marijuana decriminalization					1.04	0.94, 1.15
Medical marijuana legalization					1.00	0.82, 1.22
Graduated driver licensing law					0.92	0.82, 1.04
Hands free driving					0.95	0.89, 1.01
Cell phone texting ban					0.98	0.94, 1.03
Drug per se					1.03	0.98, 1.09
Seat belt law, primary enforcement					0.97	0.92, 1.03
N	12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05



Web Table 8. Incidence Rate Ratios for the Number of Drunk Driving-Related Traffic Fatalities from Poisson Models, 2009-2014, and Weekend and Holiday-Related Traffic Fatalities from Negative Binomial Models, 2005-2014, Regressed on Uber or Lyft Deployment, Principal Counties of the Top 100 US Metropolitan Areas.

Variable	Drunk Driving <sup>a</sup>						Weekends and Holidays <sup>a</sup>					
	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>		Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber or Lyft active	0.94	0.83, 1.07	1.03	0.97, 1.10	1.03	0.97, 1.10	1.05	0.93, 1.17	1.04	0.98, 1.11	1.05	0.98, 1.12
County unemployment rate, %					0.96 <sup>d</sup>	0.94, 0.99					0.97 <sup>d</sup>	0.95, 0.99
State beer tax rate, 2014 dollars/gal.					1.08	0.83, 1.39					1.07	0.83, 1.38
Taxi drivers per 100,000 population					1.00	1.00, 1.00					1.00	1.00, 1.00
Marijuana decriminalization					0.93	0.78, 1.10					1.09	0.94, 1.26
Medical marijuana legalization					0.79 <sup>c</sup>	0.75, 0.82					0.97	0.77, 1.22
Graduated driver licensing law					1.22 <sup>c</sup>	1.03, 1.45					0.91	0.75, 1.10
Hands free driving					0.88	0.76, 1.03					0.95	0.88, 1.03
Cell phone texting ban					1.00	0.94, 1.07					0.95	0.90, 1.00
Drug per se					1.02	0.79, 1.31					1.04	0.94, 1.16
Seat belt law, primary enforcement					0.95	0.78, 1.15					0.95	0.88, 1.03
N	7,488		7,488		7,488		12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05

Web Table 9. Incidence Rate Ratios for the Number of Total Traffic Fatalities Regressed on Uber/Lyft Presence from Negative Binomial Models<sup>a</sup>, Principal Counties of the Top 100 US Metropolitan Areas, 2005-2014.

Variable	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI
Either Uber or Lyft <sup>c</sup>	1.14	0.93, 1.39	1.01	0.97, 1.06	1.02	0.98, 1.06
Both Uber and Lyft <sup>c</sup>	0.96	0.87, 1.06	1.02	0.97, 1.08	1.02	0.97, 1.08
County unemployment rate, %					0.97 <sup>d</sup>	0.95, 0.98
State beer tax rate, 2014 dollars/gal.					0.73 <sup>e</sup>	0.60, 0.89
Taxi drivers per 100,000 population					1.00	1.00, 1.00
Marijuana decriminalization					1.04	0.94, 1.15
Medical marijuana legalization					1.00	0.82, 1.22
Graduated driver licensing law					0.92	0.82, 1.04
Hands free driving					0.95	0.89, 1.01
Cell phone texting ban					0.98	0.94, 1.03
Drug per se					1.03	0.98, 1.09
Seat belt law, primary enforcement					0.97	0.92, 1.03
N	12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>Reference group is neither Uber nor Lyft present.

<sup>d</sup>*P* value ≤ 0.001, <sup>e</sup>*P* value ≤ 0.01, <sup>f</sup>*P* value ≤ 0.05

Web Table 10. Incidence Rate Ratios for the Number of Drunk Driving-Related Traffic Fatalities from Poisson Models, 2009-2014, and Weekend and Holiday-Related Traffic Fatalities from Negative Binomial Models, 2005-2014, Regressed on Uber/Lyft Presence, Principal Counties of the Top 100 US Metropolitan Areas.

Variable	Drunk Driving <sup>a</sup>						Weekends and Holidays <sup>a</sup>					
	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>		Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Either Uber or Lyft <sup>c</sup>	0.96	0.82, 1.14	1.03	0.96, 1.11	1.03	0.96, 1.11	1.14	0.95, 1.37	1.05	0.97, 1.14	1.06	0.99, 1.14
Both Uber and Lyft <sup>c</sup>	0.92	0.81, 1.05	1.04	0.97, 1.12	1.04	0.97, 1.11	0.98	0.87, 1.10	1.03	0.95, 1.11	1.03	0.95, 1.13
County unemployment rate, %					0.96 <sup>e</sup>	0.94, 0.99					0.97 <sup>e</sup>	0.95, 0.99
State beer tax rate, 2014 dollars/gal.					1.08	0.83, 1.39					1.07	0.83, 1.38
Taxi drivers per 100,000 population					1.00	1.00, 1.00					1.00	1.00, 1.00
Marijuana decriminalization					0.93	0.78, 1.10					1.09	0.95, 1.26
Medical marijuana legalization					0.79 <sup>d</sup>	0.75, 0.82					0.97	0.77, 1.22
Graduated driver licensing law					1.22	1.03, 1.45					0.91	0.75, 1.10
Hands free driving					0.88	0.76, 1.03					0.95	0.88, 1.03
Cell phone texting ban					1.00	0.94, 1.07					0.95	0.90, 1.00
Drug per se					1.02	0.79, 1.32					1.04	0.94, 1.16
Seat belt law, primary enforcement					0.95	0.78, 1.15					0.95	0.88, 1.03
N	7,488		7,488		7,488		12,480		12,480		12,480	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>Reference group is neither Uber nor Lyft present.

<sup>d</sup> $P$  value  $\leq 0.001$ , <sup>e</sup> $P$  value  $\leq 0.01$ , <sup>f</sup> $P$  value  $\leq 0.05$

Web Table 11. Incidence Rate Ratios for the Number of Total Traffic Fatalities Regressed on Uber Deployment from Negative Binomial Models<sup>a</sup>, Principal Counties of the Top 100 US Metropolitan Areas, 2009-2014.

Variable	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active	1.17 <sup>e</sup>	1.01, 1.35	1.03	0.99, 1.07	1.03	0.99, 1.06
County unemployment rate, %					0.99	0.97, 1.00
State beer tax rate, 2014 dollars/gal.					0.78 <sup>c</sup>	0.70, 0.87
Taxi drivers per 100,000 population					1.00	1.00, 1.00
Marijuana decriminalization					1.05	0.96, 1.16
Medical marijuana legalization					0.70 <sup>c</sup>	0.67, 0.73
Graduated driver licensing law					1.12 <sup>e</sup>	1.00, 1.25
Hands free driving					0.92	0.82, 1.04
Cell phone texting ban					0.99	0.94, 1.04
Drug per se					1.05	0.94, 1.18
Seat belt law, primary enforcement					0.93	0.83, 1.04
N	7,488		7,488		7,488	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup> $P$  value  $\leq 0.001$ , <sup>d</sup> $P$  value  $\leq 0.01$ , <sup>e</sup> $P$  value  $\leq 0.05$

Web Table 12. Incidence Rate Ratios for the Number of Weekend and Holiday-Related Traffic Fatalities Regressed on Uber Deployment from Negative Binomial Models<sup>a</sup>, Principal Counties of the Top 100 US Metropolitan Areas, 2009-2014.

Variable	Model 1		Model 2 <sup>b</sup>		Model 3 <sup>b</sup>	
	IRR	95% CI	IRR	95% CI	IRR	95% CI
Uber active	1.19 <sup>d</sup>	1.05, 1.36	1.08 <sup>e</sup>	1.01, 1.15	1.08 <sup>e</sup>	1.01, 1.15
County unemployment rate, %					0.98	0.96, 1.00
State beer tax rate, 2014 dollars/gal.					1.18	0.88, 1.60
Taxi drivers per 100,000 population					1.00 <sup>d</sup>	1.00, 1.01
Marijuana decriminalization					0.99	0.83, 1.20
Medical marijuana legalization					0.52 <sup>c</sup>	0.49, 0.55
Graduated driver licensing law					1.07	0.93, 1.23
Hands free driving					0.87	0.72, 1.05
Cell phone texting ban					0.98	0.91, 1.05
Drug per se					0.99	0.81, 1.20
Seat belt law, primary enforcement					0.91	0.77, 1.07
N	7,488		7,488		7,488	

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.

<sup>a</sup>Each model accounts for county monthly vehicle miles traveled.

<sup>b</sup>Includes county, month and year fixed effects.

<sup>c</sup>*P* value ≤ 0.001, <sup>d</sup>*P* value ≤ 0.01, <sup>e</sup>*P* value ≤ 0.05