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Assessing the Impact of Ridesharing Services on Public Health and Safety Outcomes

Marlon Graf

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EXECUTIVE SUMMARY

The rise of the sharing economy presents both unprecedented challenges and opportunities for policymakers at all levels. On the one hand, companies such as Uber and Airbnb have been criticized sharply as they disrupt many traditional industries such as the hospitality and transportation sectors. On the other hand, these companies have also been credited with filling gaps in transportation networks and creating jobs. To inform policy in the face of these new developments, academic researchers have conducted studies on the effects of the sharing economy on the labor markets and revenues of various industrial sectors.[1]

[1] Cramer, Judd and Alan B. Krueger. 2016. "Disruptive change in the taxi business: The case of Uber." *The American Economic Review 106 (5): 177-182*; Hall, Jonathan V. and Alan B. Krueger. 2016. "An analysis of the labor market for Uber's driver-partners in the United States." *National Bureau of Economic Research: Working Paper No. 22843*; Meyer, Jared. 2015. "Uber positive. the ride-share firm expands transportation options in low-income New York." *Manhattan Institute Issue Brief No. 38*. https://www.manhattan-institute.org/sites/default/files/ib_38.pdf.

This study, however, goes beyond assessing the first-order effects of the sharing economy and estimates the secondary impacts of ridesharing services on public health and safety outcomes. Using data from Google search trends for Uber and Lyft to approximate actual ridership intensity, this analysis applies a random-effects panel regression framework to investigate whether increased ridesharing is associated with lower levels of drunk driving.

The findings suggest that a higher intensity of Google Trends in a specific metro area leads to a reduction in both overall and alcohol-involved traffic fatalities.

Specifically, a 1 percent increase in ridership search intensity on Google Trends translates into saving 2.19 lives per month in the average metro area by reducing overall traffic fatalities and 0.3 lives per month in the average metro area by avoiding alcohol-involved traffic fatalities.

For this study, Google search trends serve as an approximation of actual ridership and usage of Uber and Lyft services across the 22 largest U.S. metropolitan areas—as a high correlation between these two measures has been established by both Cramer and Hall et al.[2] While this means that the results have to be treated with caution and cannot be interpreted directly as the effect of ridesharing services on drunk driving, they are in line with findings from previous studies that suggest reductions in traffic fatalities ranging from 3 to 7 percent[3] and provide further evidence of the positive externalities associated with the sharing economy and ridesharing in particular.

[2] Judd Cramer. 2016. "The effect of Uber on the wages of taxi and limousine drivers." Unpublished Working Paper; Hall, Jonathon D., Craig Palsson, and Joseph Price. 2017. "Is Uber a substitute or complement to public transit?" *University of Toronto: Working Papers*

[3] Dills, Angela K. and Sean E. Mulholland. 2017. "Ride-sharing, fatal crashes, and crime." https://ssrn.com/abstract=2783797; Greenwood, Brad N. and Sunil Wattal. 2015. "Show me the way to go home: an empirical investigation of ride sharing and alcohol related motor vehicle homicide." *Fox School of Business Research Paper No. 15-054*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2557612.

INTRODUCTION

According to data from the Highway Traffic Safety Administration,[4] alcohol is a major factor in roughly one in three traffic fatalities and a separate study conducted by the National Highway Traffic Safety Administration estimates that the total cost stemming from alcohol-related crashes (where at least one of the involved drivers had a blood alcohol content greater than zero) amounts to $44 billion per year.[5] This substantial economic and societal burden inflicted by drunk driving has been a growing concern for policymakers at all levels and has led to increased interest in interventions focused on curbing drunk driving.[6] Among the range of approaches proposed, ignition interlock devices that connect a vehicle's ignition mechanism to a breathalyzer system and prevent cars from starting if drivers fail their breath tests are typically deemed to be the most promising, with the caveat that the effects are limited to the timeframe during which the device is installed.[7] A similar picture emerges when looking at administrative sanctions such as license suspensions and vehicle impoundments. As long as the sanctions are in place, they reduce the prevalence of drunk driving, although those effects vanish quickly once they are lifted.[8]

Thus, there is a need for policy interventions that have a long-run impact on people's drunk-driving behaviors and do not just deter drinking and driving in the short term. In gauging the potential of any alternative programs to achieve this objective, it is critical to assess their impact on people's habits and preferences in their daily lives. In a nutshell, to affect drinking and driving over an extended period, interventions need to be focused on educating the population on the adverse effects of intoxicated driving and to precipitate a voluntary shift in alcohol consumption patterns. This study considers the emergence of ridesharing services as one such intervention.

[4] NHTSA Traffic Safety Fact Sheet, 2015: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812413.

[5] Blincoe, Lawrence J., Ted R. Miller, Eduard Zaloshnja, and Bruce A. Lawrence. 2015. "The economic and societal impact of motor vehicle crashes, 2010." *Report No. DOT HS 812 013*. Washington, DC: National Highway Traffic Safety Administration.

[6] Ecola, Liisa, Benjamin Saul Batorsky, Jeanne Ringel, Johanna Zmud, Kathryn Connor, David Powell, Brian G. Chow, Christina Panis, and Gregory S. Jones. 2015. "Which behavioral interventions are most cost-effective in reducing drunk driving?" Santa Monica, CA: RAND Corporation. https://www.rand.org/pubs/research_briefs/RB9826.html; Marques, Paul R., A. Scott Tippetts, and Robert B. Voas. 2003. "Comparative and joint prediction of DUI recidivism from alcohol ignition interlock and driver records." *Journal of Studies on Alcohol 64 (1): 83-92.*

[7] Kaufman, Elinore J. and Douglas J. Wiebe. 2016. "Impact of state ignition interlock laws on alcohol-involved crash deaths in the United States." *American Journal of Public Health 106 (5): 865-871.*

[8] Fell, James C. and Michael Scherer. 2017. "Administrative license suspension: Does length of suspension matter?" *Traffic Injury Prevention 1-8*; Byrne, Patrick A., Tracey Ma, and Yoassry Elzohairy. 2016. "Vehicle impoundments improve drinking and driving licence suspension outcomes: Large-scale evidence from Ontario." *Accident Analysis & Prevention 95: 125-131.*

INTRODUCTION

Recently, there has been heightened interest in the secondary effects of the sharing economy beyond its primary impact on housing (in the case of Airbnb) and transportation (in the case of Uber and Lyft).[9] Ridesharing companies, in particular, have emphasized the potential of their services to contribute to public safety, especially concerning drunk driving. The two companies and their competitors argue that ridesharing services fill gaps in existing transportation networks by providing cheaper, on-demand alternatives to taxis and public transportation in traditionally underserved, often dangerous neighborhoods. Moreover, as online-based services in the so-called gig economy are extremely popular among younger populations, they have become a key mode of transportation on nights and weekends, where alcohol consumption is highest, thus potentially preventing people from driving while drunk or drowsy.

[9] For a broad overview of research on the sharing economy, see Research Roundup from the Harvard Kennedy School's Shorenstein Center on Media, Politics, and Public Policy: https://journalistsresource.org/studies/economics/business/airbnb-lyft-uber-bike-share-sharing-economy-research-roundup.

BACKGROUND

UNDERSTANDING THE RISE OF RIDESHARING SERVICES

Prior to investigating the impact of ridesharing on drunk driving and other aspects of public health and public safety, it is critical to understand the background and rise of these types of sharing economy services.

The core business idea behind Uber, Lyft, and other companies of the sharing economy such as Airbnb, is to exploit market inefficiencies through the sharing of privately owned and operated resources. In the case of ridesharing, this means developing and maintaining a smartphone application to connect people in need of transportation to those who have a car and are willing to provide rides for a service fee.

Since its inception and early days as a ridesharing service in San Francisco at the start of 2010, Uber has experienced substantial growth in size and ridership as documented by Meyer for New York City.10 Specifically, the ridesharing service has been very successful in supplying excess transportation options in areas that were previously underserved by the existing taxi and public transit networks, such as the outer boroughs in New York's periphery.

Cramer and Krueger further expand on this idea by estimating the effects of Uber's ridesharing services on the taxi industry as a whole. To do so, the authors compare the capacity utilization rates of Ubers and taxi cabs, defined as the share of driving time and miles driven with a passenger on board out of the total time and miles driven for work purposes. Using data on Uber and taxi trips in Boston, New York, San Francisco, Seattle and Los Angeles between 2013 and 2015, the study finds that on average, Ubers are driving fully occupied about half the time and mileage, while taxis are only

[10] Meyer, "Uber positive."

occupied about one-third of the time and mileage throughout their work shift. In order to explain these differences, Cramer and Krueger point to the higher level of efficiency of Uber's matching algorithm between drivers and riders and the resulting lower transaction costs, a claim which is likewise supported by an intercept survey conducted among ridesharing customers in San Francisco in 2014, finding that ridesharing customers experienced substantially lower wait times than taxi customers.[11] Also, they reference the fact that Uber's highly flexible work schedule and labor supply model allows the service to quickly adjust to sudden shifts in transportation demand.[12]

To illustrate these effects, Uber's research team developed a case study to explain the effects of its surge pricing algorithm. Using data on ride requests following a crowded concert in New York City, the study shows that the pricing multiplier used by Uber functions as a way to balance supply and demand by incentivizing more drivers to offer their services and by driving away people that are looking to hail a ride (both due to inflated prices).[13] In a way, the surge pricing algorithm therefore acts as a dynamic adjustment that helps to clear the market of riders and drivers. This adjustment, in turn, enhances the efficiency of the overall transportation market and leads to the effects described above by Cramer and Krueger.[14]

In another study published by Uber's research team, Chen and Sheldon set out to quantify the elasticity of supply for Uber drivers, defined as their willingness to work extra hours in a dynamic pricing regime. Given the fact that many workers in the taxi industry are perceived to operate under an income targeting model and frequently stop working once they hit a daily income objective, it is crucial to understand whether Uber drivers behave in similar ways or can be incentivized to work longer and more extreme hours through the service's surge pricing mechanism. Applying a regression discontinuity approach, the authors find that while cumulative time driven, total number of trips in a day, cumulative

[11] Rayle, Lisa, Susan Shaheen, Nelson Chan, Danielle Dai, and Robert Cervero. 2014. "App-based, on-demand ride services: Comparing taxi and ridesourcing trips and user characteristics in San Francisco." *University of California Transportation Center (UCTC): Working Papers.*

[12] Cramer, Judd and Alan B. Krueger. 2016. "Disruptive change in the taxi business: The case of Uber." *The American Economic Review 106 (5): 177-182.*

[13] Hall, Jonathan, Cory Kendrick, and Chris Nosko. 2015. "The effects of Uber's surge pricing: A case study." The University of Chicago Booth School of Business. https://drive.google.com/file/

[14] Cramer and Krueger, "Disruptive change in the taxi business."

distance driven and total fare earned are all associated with a higher probability of stopping service for the day, surge multipliers and corresponding higher marginal prices are indeed associated with a higher probability of remaining active and in service.[15] This finding provides additional underpinnings for the notion that ridesharing services are well positioned to satisfy excess demand at unconventional times and later hours. According to an analysis of Uber's drivers conducted by Hall and Krueger, it is precisely this high degree of flexibility, paired with the ability to dictate their own working hours and supplement regular income, that attracts workers to the ridesharing platform.[16] Lastly, the fact that many taxi drivers face additional constraints with regards to workday limits and geographic zones further exacerbates these ideas.

[15] Chen, M. Keith and Michael Sheldon. 2015. "Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform." *UCLA Anderson School of Management Working Papers*. http://www.anderson.ucla.edu/faculty/keith.chen/papers/SurgeAndFlexibleWork_WorkingPaper.pdf.

[16] Hall and Krueger, "An analysis of the labor market."

[17] Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. 2016. "Using big data to estimate consumer surplus: The case of Uber." *National Bureau of Economic Research: Working Paper No. w22627*.

[18] Dills and Mulholland, "Ride-sharing, fatal crashes, and crime."

RIDESHARING, PUBLIC HEALTH, AND PUBLIC SAFETY

In addition to Uber's effect on cities' transportation systems, the impact of ridesharing services on drunk driving has also received a lot of attention from policymakers and the wider public and has become the primary research focus of a number of research studies in the area of public health. Notably, in a widely publicized study, a team of researchers from Uber and the University of Chicago attempted to measure the consumer surplus and societal welfare derived from the ridesharing service. Using a series of regression discontinuity designs to measure the effect of jumps in market prices that are generated by Uber's surge multiplier, Cohen et al. find that the total consumer surplus generated by charging consumers less than the value of the benefit that they get for rides ranges between \$2.88 and \$6.76 billion per year. The authors take this result as evidence of the tremendous societal value provided by the rise of ridesharing services.[17]

However, as Dills and Mulholland point out, trying to measure the impact of ridesharing on drunk driving and other measures of public safety is a complex and difficult undertaking.[18] Ex-ante, the hypothesis that young people are swayed to opt for Uber or Lyft instead of driving while intoxicated appears sensible, but the overall impact of ridesharing may not be as straightforward to assess. While ridesharing has the potential to take people off the road, it also introduces an entirely new group of fee-for-hire Uber drivers into the transportation network in a particular city to compete with the existing stock of taxi drivers, thus making it difficult to predict the effect of ridesharing on traffic congestion. Furthermore, as suggested by Richtel, ridesharing services rely on smartphone applications as a primary means of communication, therefore distracting the drivers and increasing their risk of accidents.[19]

Along those same lines, a major argument presented in opposition to ridesharing companies' claims about their positive impact on public safety is the fact that licensing and training protocols, as well as vehicle inspection protocols, are not as stringent as they would be for professional personal transportation services such as taxi companies. On the other side, however, it could also be argued that the far higher percentage of vehicle ownership among ridesharing drivers compared to taxi drivers incentivizes greater care, thus making up for the lack of professional licensing. In summary, the impact of ridesharing services on public health and public safety is a hot topic for debate in academic literature and the broader media.[20] Due to the rich information available on alcohol consumption, the initial focus of much of this work has been on drunk driving.

In a research collaboration between Uber and Mothers Against Drunk Driving, the authors posit that ridesharing provides reliable access to safe transportation, particularly at times when alternative options are not readily available. Specifically, the authors point to a spike in ridership on nights and weekends, which are also associated with increases in alcohol consumption and drunk-driving incidents. Based on this observation, the authors suggest that due to various aspects specific to ridesharing such as the flexible labor supply described above and the fact that drivers are not bound to specific

[19] Richtel, Matt. 2014. "Distracted driving and the risks of ride-hailing services like Uber." *The New York Times*. https://bits.blogs.nytimes.com/2014/12/21/distracted-driving-and-the-risks-of-ride-hailing-services-like-uber/?mcubz=3.

[20] Fortin, Jacey. 2017. "Does Uber really prevent drunken driving? It depends on the study." *The New York Times*. https://www.nytimes.com/2017/04/07/business/uber-drunk-driving-prevention.html?_r=0.

times and geographic boundaries, it is uniquely positioned to curb drunk driving and alcohol-related incidents.[21]

To further investigate this hypothesis, Brazil and Kirk use data on monthly traffic fatalities for the 100 largest metropolitan regions in the United States between 2005 and 2015 to assess the impact of Uber on drunk driving.[22] Controlling for presence and restrictiveness of various medical marijuana and driving laws, beer taxes, unemployment and employment rates in the taxi sector, the authors apply a difference-in-difference strategy to estimate the effect of Uber market presence in each metro area on the monthly number of alcohol-involved traffic fatalities where at least one of the drivers showed a blood alcohol content (BAC) greater than zero. Due to the discrete nature of its traffic fatalities outcome measure, the study presents findings from both fixed-effects Poisson and negative binomial panel regression models, but fails to show any association between the market presence of Uber and subsequent alcohol-involved traffic fatalities or traffic fatalities occurring on weekends and holidays.

Faced with these results, the authors suggest several aspects that could curb the effect of ridesharing on drunk driving, including the fact that rational drinkers might weigh the costs of ridesharing against the low probability of getting caught while driving under the influence. This notion is in line with the idea that most drunk-driving offenders are habitual offenders and are thus unlikely to be affected by the emergence of a new mode of transportation. Furthermore, while Uber ridership is growing across the country, it remains at a small scale compared to the total number of drivers on the road.

In a similar study, Greenwood and Wattal exploit the variation in Uber market entry dates across counties in California to assess the ridesharing service's impact on alcohol-related fatalities through a location and time fixed effects difference-in-difference setup, controlling for a range of demographic and socioeconomic factors, as well as the number of law enforcement employees.[23] While their

[21] Uber Technologies and Mothers Against Drunk Driving. 2015. "More options. Shifting mindsets. Driving better choices."

[22] Brazil, Noli and David S. Kirk. 2016. "Uber and metropolitan traffic fatalities in the United States." *American Journal of Epidemiology 184 (3): 192-198*.

[23] Greenwood and Wattal, "Show me the way to go home."

approach is very similar to the one undertaken by Brazil and Kirk, the singular focus on counties within California allows the authors to conclude that Uber market entry leads to a 3.6 to 5.6 percent decrease in alcohol-involved fatalities per quarter (or about one to two percent per month).[24] Given the fact that both Uber and Lyft (the main ridesharing companies in the U.S.) originated in the San Francisco Bay Area and that Los Angeles was among the first major metro areas to adopt the services after that, these cities are logical choices. It is likely that the effects of ridesharing on public health would be more pronounced in these cities given their longer track record and higher ridership usage.

The study further expands on these findings to investigate pathways through which ridesharing might affect drunk driving by testing both an availability and a cost hypothesis. Under the availability hypothesis, the main reason for Uber's effect on drunk driving would be the fact that Ubers are more readily available than taxis and can be ordered on an on-demand basis. In effect, this argument concerns the superior matching algorithm between drivers and riders compared to traditional taxi cabs and the resulting minimal transaction costs in hailing a ride. The second hypothesis is developed around the pricing of ridesharing services compared to traditional taxi cabs. If ridesharing is indeed cheaper, it is conceivable that some would-be drunk drivers could be convinced to order a ride. To shed light on the relative importance of these alternative pathways, the study explores the differences in effects of Uber's lower cost service, UberX, and its premium product, UberBlack. Given that only regression models employing market entry of UberX as an independent variable are displaying a negative and statistically significant effect on alcohol-involved traffic fatalities, the authors conclude that price rather than availability is the dominant mechanism through which ridesharing affects drunk driving. Furthermore, as part of their robustness and sensitivity analyses, the authors uncover that effects are strongest in larger cities and take time to materialize and solidify.[25]

[24] Brazil and Kirk, "Uber and metropolitan traffic fatalities."

[25] Greenwood and Wattal, "Show me the way to go home."

In a separate study on drunk driving in New York City, Peck uses a difference-in-difference approach to show a 25 to 35 percent decrease in alcohol-related collision rates across four of the city's inner boroughs, compared to a matched control group of 62 counties across New York state. For her study, the author obtained crash data from the New York Department of Motor Vehicles, following the argument that crashes occur at a much higher and more frequent rate than fatalities, thus enabling the detection of smaller effects through a larger sample size.[26]

The argument that alcohol-involved fatalities alone are too rare of an occurrence to serve as an outcome to gauge the effect of ridesharing services on public health and drunk driving is further expanded by Dills and Mulholland. Combining data from the FBI's Uniform Crime Reporting database (FBI-UCR) and the Fatality Analysis Reporting System (FARS) from 2007 to 2014, the authors investigate whether the availability of ridesharing services decreases alcohol-involved fatalities as well as arrests due to aggravated assault, vehicle theft, disorderly conduct, drunk driving, and drunkenness. Throughout their analyses, the authors find that DUI arrests across U.S. counties decrease by six to 27 percent after Uber market entry, while alcohol-involved fatalities decrease by roughly seven percent.[27] In addition, the study lends further evidence to Greenwood and Wattal's earlier suggestion that effects magnify over time, with each additional month of Uber in a county leading to a 2.8 to 3.4 percent decline in DUI arrests.[28]

[26] Peck, Jessica L. 2017. "New York City drunk driving after Uber." *CUNY Economics Working Papers GC-WP013*. http://wfs.gc.cuny.edu/Economics/RePEc/cgc/wpaper/CUNYGC-WP013.pdf.

[27] Dills and Mulholland, "Ride-sharing, fatal crashes, and crime."

[28] Greenwood and Wattal, "Show me the way to go home."

DATA

MARKET LAUNCH

[10] Meyer, "Uber positive."

All the studies referenced above use a single treatment variable to estimate the effect of ridesharing applications on a variety of different outcomes, ranging from drunk driving to usage of public transit and taxis. Typically, this single treatment variable is the market entry date for Uber Technologies in each metro area, allowing for a pre-post comparison or difference-in-difference analysis. This study follows this idea and extends the treatment to include market entry dates for Lyft, Uber's largest competitor. Metro-specific market launch dates for each service were obtained through a targeted search of company announcements and news reports from local markets and are shown below in Table 1.

Table 1. Uber/Lyft Market Launch Dates by U.S. Metropolitan Area

Metro Area	Uber Launch	Lyft Launch	Metro Area	Uber Launch	Lyft Launch
Atlanta	Aug. 2012	Sept. 2013	New York	May 2011	Jul 2014
Baltimore	Feb. 2013	Oct 2013	Philadelphia	June 2012	Feb. 2015
Boston	Sept. 2012	May 2013	Phoenix	Nov. 2012	Sept. 2013
Chicago	Sept. 2011	May 2013	Pittsburgh	March 2014	Feb. 2014
Dallas–Ft. Worth	Sept. 2012	May 2013	Portland	Dec. 2014	April 2015
Denver	Sept. 2012	Sept. 2013	San Diego	June 2012	July 2013
Detroit	March 2013	Sept. 2013	San Francisco-Oakland-San Jose	March 2010	Aug. 2012
Houston	Feb. 2014	Feb. 2014	Seattle–Tacoma	Aug. 2011	April 2013
Los Angeles	March 2012	Jan. 2013	St. Louis	Sept. 2015	April 2014
Miami–Ft. Lauderdale	June 2014	May 2014	Tampa–St. Petersburg	April 2014	April 2014
Minneapolis-St. Paul	Oct. 2012	Feb. 2014	Washington, DC	Dec. 2015	Aug. 2013

Source: Milken Institute.

While it is relatively easy to find market launch dates for both companies, making it a convenient treatment variable for the research undertaking at hand, it might be difficult to detect nuanced or small effects when relying on such a crude measure. Rather, econometric studies tend to prefer intensity or frequency measures over a simple binary market entry treatment indicating whether Uber or Lyft are operating in a metro area. However, relying on a binary treatment often is the only choice available to researchers because proprietary ridership and usage data from companies such as Uber and Lyft are hard to obtain.[29]

RIDESHARING INTENSITY

To cope with the fact that a binary market launch treatment is unlikely to accurately reflect any nuanced effect that ridesharing applications might have on the public health and safety measures described in detail below, this study relies on a concept first outlined and introduced by Hall et al.[30] and uses data from Google Trends[31] to approximate usage of Uber and Lyft across U.S. metropolitan areas.

To assess whether ridesharing services such as Uber act as a complement or substitute to public transportation, the authors first employ a difference-in-difference approach and exploit the lag time in Uber market entry dates between metropolitan areas across the United States. This approach is very similar to the ones described above, albeit with the intent to show whether Uber, in fact, fills existing gaps in the public transportation network or deters people from using public transit altogether. However, the most interesting component of their work for this study is the second set of difference-in-difference regression models, using Google Trends search index data at the MSA-level to approximate actual market penetration of Uber instead of simple market presence. To validate this approach, the authors point to an unpublished manuscript by Cramer, which "uses data on the number of Uber drivers in 18 MSAs (Metropolitan Statistical Areas) from Hall and Krueger[32] to show that Google searches for 'Uber' are strongly correlated with the number of drivers in each market."[33]

To complete their investigation of Uber's relationship to public transit, Hall et al. then proceed to implement a series of regression models to look at both market entry and market penetration of Uber

[29] The author of this white paper requested monthly ridership data for the 25 largest metropolitan regions and was unsuccessful in reaching Uber.

[30] Hall, Palsson, and Price, "Is Uber a substitute?"

[31] To conduct this study, Google Trends data were obtained for each of the 22 metropolitan areas considered and then normalized and weighted against the average U.S. search intensity index as reported by Google Trends, allowing for comparisons of historical trends within each metro area as well as across different metros. For the general trend of Uber searches, see https://trends.google.com/trends/explore?q=Uber

[32] Hall and Krueger, "An analysis of the labor market."

[33] Cramer, "The effect of Uber."

as key treatment measures across all U.S. metro areas between 2008 and 2012, controlling for various demographic and socioeconomic characteristics and public transit-specific contextual variables. Ultimately, study findings appear to be slightly more consistent when using the Google Trends approximation of ridesharing intensity compared to the simple market entry treatment. The authors find that on average, Uber and public transit agencies are complements, though there appears to be considerable variation between different metro areas.[34]

[34] Hall, Palsson, and Price, "Is Uber a substitute?"

The present study builds on the idea of using Google Trends as a stand-in for actual ridership intensity and expands on previous research on the effect of ridesharing services on public health outcomes. In addition to search trends for Uber, a comparable panel was generated for Lyft, along with an average intensity variable denoted as ridesharing search intensity in Figure A.1 in the appendix.

While Hall et al. present a panel that is normalized to market entry dates between metro areas, the trends generated for this study suggest that the overall industry trend over time is dominant over both metro-specific and company-specific trends, thus creating a viable treatment variable for the subsequent regression models that references concurrent, real-time changes of search trends for Uber, Lyft, and overall ridesharing.

To assess the impact of ridesharing applications such as Uber, Lyft, and others on public health and safety outcomes, this study relies on a comprehensive, metropolitan-level dataset of covariates and public safety outcomes that was compiled from a range of sources as follows.

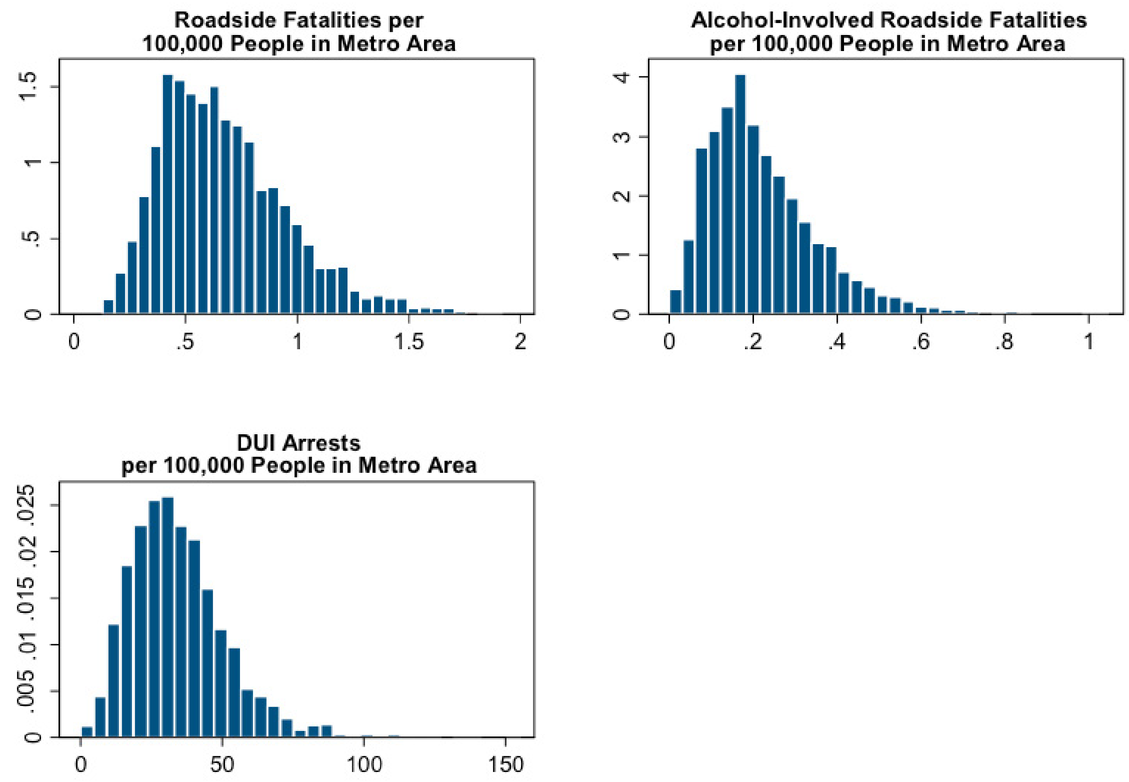
PUBLIC HEALTH AND PUBLIC SAFETY OUTCOMES

Most studies concerned with road safety primarily rely on traffic fatalities or a variant thereof, presumably because the necessary information is readily available at most geographic levels in the U.S. through the Fatality Analysis Reporting System (FARS). Consequently, this study also employs monthly counts of traffic fatalities and alcohol-involved traffic fatalities. A fatality was categorized as alcohol-involved if one of the drivers involved was reported to have blood alcohol content (BAC) greater than zero. In addition, as FARS data is reported at the county level, all counties were aggregated to the metropolitan level based on the U.S. Census classification of metropolitan statistical areas (MSAs). Nevertheless, while traffic fatalities present a convenient measure of public safety and are thus frequently used as key outcome measures, they might not be directly affected by an intervention like ridesharing. To a certain extent, a traffic fatality presents a low-probability, high-cost event and any effect might be hard to detect due to low overall numbers.

Accordingly, relying on DUI arrests as a key outcome variable could provide more immediate information and potentially paint a clearer image of the true impact that anti-drunk-driving interventions such as ridesharing apps may have. A reason why DUI arrests are not used as often as roadside fatalities is the fact that the data are not as accessible and far more fragmented. For this study, DUI arrest data were obtained from the Federal Bureau of Investigation's Uniform Crime Reporting Database (UCR). However, since data on DUI arrests were only available through 2012 from this source, the remaining gaps up to 2015 were filled by local and state law enforcement databases. In addition, as DUI arrests were not available on a monthly basis, the month-by-month variation of alcohol-involved traffic fatalities in FARS for each metropolitan area was used to distribute annual counts of DUI arrests into the twelve months of each year. While this is only an approximation of the monthly pattern of DUI arrests, it seems safe to assume that the seasonality of drunk driving incidents is shared by alcohol-involved deaths and DUI arrests.

The distributions of all three of these public health and safety outcome variables are displayed as histograms in Figure 1.

Figure 1. Distribution of Public Health and Safety Outcome Variables



CONTROL VARIABLES

To account for factors aside from ridesharing that could affect the key outcome measures described above, the analyses conducted as part of this study also account for an extensive set of metropolitan-level control variables, including each metro's socioeconomic and demographic composition, people's drinking behaviors, and proxies for traffic volume and density over the 10-year study period between January 2005 and December 2015.

Demographic covariates include age, gender, and race/ethnicity, while socioeconomic characteristics are composed of median household income and educational attainment, all compiled using data from the American Community Survey (ACS)'s Annual survey files. For simplicity, the distribution of demographic and socioeconomic measures is presumed to be constant within each study year and variable across years. As with the DUI arrest data above, information was gathered at the county level and aggregated up to the metropolitan level.

In addition to these population covariates, the average number of daily vehicle miles traveled (VMT) was obtained from the Federal Highway Authority (FHWA) to adjust for traffic volume in each metro, and the extent of the road network was taken to compute a VMT-per-mile measure, indicating traffic density since it appears logical to assume that higher density, rather than higher mileage driven, leads to higher rates of traffic incidents. While data from FHWA are available at the metro level and therefore did not require any geographic adjustment, they are only available on an annual basis and therefore require a seasonal adjustment to impute monthly measures. Similar to the procedure used to distribute annual DUI arrest counts across months in a given year, the monthly distribution of total traffic fatalities was used to estimate monthly traffic variables, with the implicit assumption that the seasonal variation in traffic mimics the seasonal variation in overall fatalities.

Lastly, to effectively estimate the impact of ridesharing applications on drunk driving, it is important to account for overall trends in alcohol consumption, both over time and including seasonal variation within a given year. Using data from the Behavioral Risk Factor Surveillance System (BRFSS), this study controls for time trends in drinking levels, measured by the share of people in each metro that drank any alcoholic drink in the past month; binge drinking, measured by the share of men drinking more than five drinks and women drinking more than four drinks on a single occasion in the past month; and heavy drinking, measured by the share of men who consume more than 14 and women who consume more than seven drinks per week. It is critical to include these patterns in drinking habits in any research inquiry concerning alcohol consumption, as overall period and time effects can have a strong impact on people's consumption preferences and, by extension, any consequences of excessive drinking such as alcohol-involved fatalities and DUI arrests.[35]

While BRFSS alcohol consumption is reported by U.S. metropolitan areas, data could only be obtained on an annual basis. To reflect the widely documented seasonality of alcohol consumption, for example the annual increase in drinking observed around major holidays such as the Fourth of July or New Year's Eve, monthly weights from Cho et al. were applied to apportion annual average percentages of people falling into each drinking category to the monthly level.[36] While the monthly weights from Cho et al. are generated from a small set of states, present a selective average of U.S. regions that do not fully overlap with the sample of metros here, and only reflect a single year of data, it is the most detailed such study to date and thus serves as a sensible basis for the seasonal adjustment of alcohol consumption covariates in this study.[37] Provided that overall trends in consumption quantity are captured in annual totals, it is likely that the relative month-by-month variation in consumption remains relatively stable over the years.

[35] Kerr, William C., Thomas K. Greenfield, Jason Bond, Yu Ye, and Jürgen Rehm. 2004. "Age, period and cohort influences on beer, wine and spirits consumption trends in the US National Alcohol Surveys." *Addiction 99 (9): 1111-1120*; Kerr, William C., Thomas K. Greenfield, Jason Bond, Yu Ye, and Jürgen Rehm. 2009. "Age–period–cohort modelling of alcohol volume and heavy drinking days in the US National Alcohol Surveys: divergence in younger and older adult trends." *Addiction 104 (1): 27-37.*

[36] Apportionment was conducted according to the following formula: DM(i,t) = DM(y)/12 * W(t), where DM reflects the drinking measure of interest (current drinking, binge drinking, and heavy drinking), i represents the specific metropolitan region, t represents the specific month of interest, y represents a specific year, and W presents the monthly weight obtained from Cho et al.

[37] Cho, Young Ik, Timothy P. Johnson, and Michael Fendrich. 2001. "Monthly variations in self-reports of alcohol consumption." *Journal of Studies on Alcohol 62 (2): 268-272.*

Mean values and standard deviations of all variables included in the study are displayed in Table 2.

Table 2. Descriptive Statistics of Key Variables

Variable	Mean	Standard Deviation	Source[1]
Public Health and Public Safety Outcome Variables			
Roadside fatalities	0.67	0.28	FARS
Alcohol-involved roadside fatalities	0.22	0.13	FARS
DUI arrests	34.55	17.46	FBI-UCR and state-level data
Population Control Variables			
Total population	5,453,865	3,951,278	ACS
Median household income	$60,161.24	$10,201.21	ACS
Age: under 15	19.81%	1.93%	ACS
Age: 15-24	13.30%	0.85%	ACS
Age: 25-34	14.10%	1.30%	ACS
Age: 35-49	21.81%	1.58%	ACS
Age: 50-64	18.64%	1.56%	ACS
Age: 65 and older	12.35%	2.57%	ACS
Education: less than 9 years	5.66%	2.55%	ACS
Education: 9-12 years of education	7.20%	1.62%	ACS
Education: high school degree	24.84%	4.42%	ACS
Education: some college, but no degree	20.34%	2.91%	ACS
Education: associate's degree	7.55%	1.17%	ACS
Education: bachelor's degree	21.31%	2.96%	ACS
Education: graduate degree	13.10%	3.35%	ACS
Race: mixed	5.44%	2.17%	ACS
Race: White	70.20%	10.02%	ACS
Race: Black	14.21%	8.63%	ACS
Race: American Indian/Alaskan Native	0.49%	0.44%	ACS
Race: Asian	6.78%	4.87%	ACS
Race: Pacific Islander/Hawaiian	0.16%	0.22%	ACS
Race: Hispanic	5.44%	4.48%	ACS
Traffic Control Variables			
Average daily vehicle miles traveled	104,410.90	70,095.32	FHWA
Traffic density (VMT/miles of road in metro)	6.71	2.44	FHWA
Alcohol Consumption Control Variables			
Past-month drinkers[2]	58.29%	7.33%	BRFSS
Past-month binge drinkers[3]	16.97%	3.10%	BRFSS
Past-month heavy drinkers[4]	5.87%	1.50%	BRFSS

n = 2,376

[1] *FARS = Fatality Analysis Reporting System, FBI-UCR = FBI Uniform Crime Reporting Database, ACS = American Community Survey, FHWA = Federal Highway Authority, BRFSS = Behavioral Risk Factor Surveillance System*

[2] *current drinking = people who consumed at least one alcoholic drink in the past month*

[3] *binge = male residents with 5+ drinks/occasion, female residents with 4+ drinks/occasion*

[4] *heavy = male residents with 14+ drinks/week, female residents with 7+ drinks/week*

METHODOLOGICAL APPROACH

This study uses data from the 22 largest metropolitan areas in the United States between 2009 and 2015 to assess the impact of ridesharing search intensity on a series of public health and safety outcomes, including traffic fatalities, alcohol-involved traffic fatalities, and DUI arrests. Both within- and between-metro variations in key variables are explored using a random effects approach, which controls for factors that are unique to each metro over time.

$$d_{mt} = \beta_1 \mathrm{Rideshare}_{mt} + \beta_2 X_{mt} + \delta_t + \eta_m + \epsilon_{mt}$$

In the model outlined above, specific public health and safety outcomes d in metro m at month t depend on the intensity of Google Trends searches for ridesharing and a set of control variables X_{mt}. In addition, this random-effects specification includes month-fixed effects δ_t and a metro-level random effects parameter η_m that accounts for covariance across estimates by metropolitan area. Given the high level of heterogeneity in both ridesharing search intensity and public health and safety outcomes, allowing for metro-specific intercepts in the regression model appears to be a better fit than a traditional fixed effects model, as it takes into account both variation within metros and across metros over time. Finally, ϵ_{mt} is the error term. The results presented below are outcomes of a log-log panel regression framework.

The main objective of this study is to show how changes in the search intensity of ridesharing across metropolitan areas over time affect various public health and public safety outcomes, including traffic fatalities, alcohol-involved traffic fatalities, and DUI arrests. Furthermore, the results ought to highlight the role of metro-specific demographic and socioeconomic factors, propensities for risky health behaviors, and control variables that approximate a

[10] Meyer, “Uber positive.”

metropolitan region's traffic patterns.

To specify the set of covariates and the underlying functional form used for this study, various sensitivity and robustness checks were performed using the model robustness package in STATA 14, developed and explained in detail by Young and Holsteen as well as Young and Kroeger. In effect, the authors follow an idea first presented by Leamer in outlining the dangers of model selection. Taking account of the fact that most regression models are highly sensitive to various specifications, they suggest running several alternative models to assess the validity of the specific econometric approach chosen. As explained by Young, one needs to distinguish between sampling error and modeling error when performing econometric analyses. While most studies are highly aware of sampling error and pay close attention to irregular results stemming from issues with the study data at hand, very few take into account the problems that emerge from misspecified functional forms.[38]

In response, this study systematically varied the set of control variables included in regression models, along with the underlying functional form and model specification. Results of these robustness checks are presented in Table A.1 and Figure A.2 in the appendix. When examining the results of these tests, two insights emerge: First, it seems that longitudinal panel models which account for both within- and between-metro variation are substantially more likely to show a negative effect of ridesharing search intensity on public health and public safety outcomes. Given that ridesharing trends across metropolitan areas are highly heterogeneous, it thus appears sensible to apply a longitudinal model. Second, coefficients for any model that fail to account for age and education are substantially different from those that do. Therefore, age groups need to be separately accounted for—as the effect of ridesharing on public health and safety varies substantially by age group. Consequently, the final regression model presented in Table 3 includes interaction terms between age groups and the market presence of either Lyft

[38] Young, Cristobal and Katherine Holsteen. 2017. "Model uncertainty and robustness: A computational framework for multimodel analysis." *Sociological Methods & Research 46 (1): 3-40*; Young, Cristobal and Kathy Kroeger. 2013. "Uncertainty program manual." https://web.stanford.edu/~cy10/public/UncertaintyProgramManual-v1.0.pdf; Leamer, Edward E. 1983. "Let's take the con out of econometrics." *The American Economic Review 73 (1): 31-43*; Leamer, Edward E. 1985. "Sensitivity analyses would help." *The American Economic Review 75 (3): 308-313*; Young, Cristobal. 2009. "Model uncertainty in sociological research: An application to religion and economic growth." *American Sociological Review 74 (3): 380-397*.

or Uber.[39] Once these interaction terms for age enter the regression model, education-related coefficients behave more consistently, suggesting that model specification issues stemming from the education variables are likely due to the relationship between education and age.

[39] Market presence is defined as having either Uber, Lyft, or both ridesharing services operating in a particular metro area at a specific time. The measure is set to be a binary variable that assumes 1 in case at least one ridesharing service is present and zero otherwise.

RESULTS

As described previously, the primary regression model presented below is a log-log panel model of the relationship between public safety outcomes and ridesharing search intensities, controlling for month fixed effects, along with a set of covariates including age-ridesharing interactions, each metro's population size, median income, age and racial distributions, alcohol consumption patterns, and traffic volume. In addition to time fixed effects, the random effects nature of this regression allows coefficients to randomly vary at the metro-level, accounting for the fact that ridesharing trends differ vastly across metropolitan regions in the study sample.

As seen in Table 3, ridesharing search intensities are indeed associated with a lower level of fatalities, both overall and alcohol-involved. As the regression models are presented in a log-log format, coefficients can be easily interpreted as elasticities, prompting the following statements about top-level findings:

- If ridesharing search intensity on Google Trends increases by 1 percent, the number of roadside fatalities drops by 6 percent. Ultimately, this amounts to a reduction of 0.0402 fatalities per 100,000 residents[40] or a total of 2.19 lives saved per month in the average metro.[41]

- If ridesharing search intensity on Google Trends increases by 1 percent, the number of alcohol-involved roadside fatalities drops by 2.5 percent. Ultimately, this amounts to a reduction of 0.0055 alcohol-involved fatalities per 100,000 residents[42] or a total of 0.3 lives saved per month in the average metro.[43]

While these results are very encouraging and suggest a substantial impact of ridesharing services on traffic fatalities, they have to be

[40] 0.67 average metro fatalities* (-0.06) = -0.0402 fatalities per 100,000 residents

[41] (0.0402 fatalities avoided / 100,000) * 5,453,865 average metro population = 2.19 lives saved per month in the average metro area

[42] 0.22 average metro alcohol-involved fatalities * (-0.025) = -0.0055 alcohol-involved fatalities per 100,000 residents

[43] (0.0055 alcohol-involved fatalities avoided / 100,000) * 5,453,865 average metro population = 0.3 lives saved per month in the average metro area

interpreted with caution. The first caveat to be considered is the fact that the treatment variable does not necessarily reflect actual ridesharing usage across metropolitan regions in the U.S., but rather uses Google search trends data as an approximation.

Table 3. Google Search Intensity Log-Log Panel Model with Random Effects

Variables	Roadside Fatalities			Alcohol-Involved Roadside Fatalities			DUI Arrests		
	Coef.	95% CI		Coef.	95% CI		Coef.	95% CI	
Constant	-63.1459***	-68.1206	-58.1713	-31.0937***	-37.3957	-24.7917	-59.8706**	-107.961	-11.78
Ridesharing search intensity	-6.0254***	-7.8033	-4.2476	-2.4935**	-4.7457	-0.2413	11.8981	-14.103	37.8993
Total population	10.1427***	9.3612	10.9242	4.8578***	3.8678	5.8478	9.6719**	2.0714	17.2724
Median income	-0.0473***	-0.0784	-0.0161	0.0399**	0.0005	0.0794	-0.3157**	-0.6172	-0.0143
Age: under 15	-1.5728***	-1.7562	-1.3893	-0.8288***	-1.0612	-0.5964	-0.1884	-1.9854	1.6085
Age: 15-24	-1.2985***	-1.4175	-1.1795	-0.3788***	-0.5296	-0.228	-0.5523	-1.6713	0.5668
Age: 25-34	-1.4051***	-1.5421	-1.2681	-0.5604***	-0.7339	-0.3868	0.6787	-0.5897	1.947
Age: 35-49	-2.1091***	-2.3182	-1.9	-1.3651***	-1.63	-1.1002	-2.9205***	-4.8918	-0.9492
Age: 50-64	-2.2775***	-2.4601	-2.0949	-0.7536***	-0.9849	-0.5222	0.3312	-1.4472	2.1095
Age: 65 and older	-0.8642***	-0.9605	-0.7678	-0.4373***	-0.5594	-0.3152	-0.7472	-1.6496	0.1551
Education: less than 9 years	-0.0739***	-0.0965	-0.0513	-0.0252*	-0.0538	0.0034	-1.0747***	-1.3089	-0.8404
Education: 9-12 years of education	0.0144	-0.0181	0.0469	-0.0491**	-0.0903	-0.0079	-0.1400	-0.4548	0.1748
Education: high school degree	0.0123	-0.0521	0.0768	-0.1059**	-0.1876	-0.0242	-1.4869***	-2.1136	-0.8602
Education: some college, but no degree	-0.0855***	-0.1474	-0.0236	0.0010	-0.0774	0.0794	-0.7799**	-1.3816	-0.1781
Education: associate's degree	-0.2774***	-0.3203	-0.2344	-0.2711***	-0.3255	-0.2167	-0.9027***	-1.3112	-0.4941
Education: bachelor's degree	-0.0274	-0.0874	0.0325	-0.0106	-0.0866	0.0654	-0.2435	-0.7846	0.2976
Education: graduate degree	-0.1710***	-0.2178	-0.1241	-0.1633***	-0.2227	-0.104	-1.4795***	-1.9312	-1.0278
Average daily vehicle miles traveled	0.3340***	0.3142	0.3537	0.2025***	0.1775	0.2275	0.2513***	0.0625	0.4401
Traffic density (VMT/miles)	0.0116	-0.0117	0.0349	-0.0671***	-0.0966	-0.0376	0.8358***	0.612	1.0596
Race: White	-0.3417***	-0.4098	-0.2737	-0.1595***	-0.2457	-0.0733	-0.7248*	-1.4967	0.047
Race: Black	-0.0004	-0.0105	0.0096	0.0013	-0.0114	0.014	-0.0525	-0.1545	0.0495
Race: American Indian/ Alaskan Native	0.0288***	0.0215	0.0361	0.0255***	0.0163	0.0348	0.0953***	0.0266	0.164
Race: Asian	0.0252***	0.0139	0.0366	0.0184**	0.0039	0.0328	0.1771***	0.069	0.2852
Race: Pacific Islander/ Hawaiian	0.0094***	0.0044	0.0143	0.0012	-0.0051	0.0074	-0.0066	-0.0581	0.0449
Race: Hispanic	-0.0678***	-0.0756	-0.06	-0.0379***	-0.0478	-0.028	-0.1588***	-0.2356	-0.082
Past-month drinkers[1]	-0.0991***	-0.1381	-0.0602	-0.0294	-0.0787	0.02	0.0761	-0.2799	0.4321
Past-month binge drinkers[2]	0.0131	-0.0107	0.037	0.0046	-0.0256	0.0348	0.2333**	0.0074	0.4592
Past-month heavy drinkers[3]	0.0313***	0.0169	0.0457	0.0412***	0.023	0.0594	0.0825	-0.0511	0.2161
Mean dependent variable	0.67			0.22			34.55		
Metro-month observations	2,304			2,304			1,920		
Chi-squared	23,700***			3,696***			1,794***		

[1] current drinking = people who consumed at least one alcoholic drink in the past month

[2] binge = male residents with 5+ drinks/occasion, female residents with 4+ drinks/occasion

[3] heavy = male residents with 14+ drinks/week, female residents with 7+ drinks/week

** p<0.1, ** p<0.05, *** p<0.01*

Note: Errors are clustered on individual metropolitan areas, controlling for month FE and age-ridesharing interactions

Concerning Google Trends, Stocking and Matsa note that while they present a rich and novel source of data on the popularity of specific issues, it is difficult to establish a definitive causal mechanism between search trends and the underlying phenomenon of interest.[44] As an example, search trends could be easily influenced by news or events affecting the issue and causing a spike in public attention. There is thus a risk that news about Uber or Lyft could cause a temporary spike in Google searches, while actual rides may remain unaffected. In this particular instance, however, on aggregate, there do not seem to be enough temporary spikes in public interest to lead trends to diverge substantially from ridership as indicated by the time series graphs in Figure A.1 in the appendix.

[44] Stocking, Galen and Katerina Eva Matsa. 2017. "Using Google Trends data for research? Here are 6 questions to ask." Pew Research Center. https://medium.com/@pewresearch/using-google-trends-data-for-research-here-are-6-questions-to-ask-a7097f5fb526.

Nonetheless, without actual ridership data as a means of comparison, it is hard to draw any conclusions about the impact of ridesharing services on traffic fatalities beyond their proxy of Google Trends. Given the actual correlation between ridership in a metro area and intensity of Google Trends for a specific ridesharing service in a metro area, it would be possible to infer the impact of ridesharing services on drunk driving, but in the absence thereof, the results of this study remain exploratory in nature.

The second point of contention is the fact that a single coefficient of ridesharing services on fatality measures likely does not exist. Rather, effects appear to be very heterogeneous and to differ substantively by metro area and region of the country. Thus, coefficients reported above are likely to underestimate the impact for some metro areas and overestimating the effects for others. While some of these metro-specific factors (such as market tenure for ridesharing services) are easily identified, other unobservable factors are hard to capture and control for. Thus, a possible extension of this study would be to perform a clustered analysis, looking at impacts on groups of metropolitan regions, rather than individual metro areas.

Lastly, the estimates of the impact of ridesharing search intensities on DUI arrests are not statistically significant at conventional levels and fail to show the anticipated magnitude and directionality. Ex ante, it would be reasonable to expect ridesharing services to have a stronger effect on drunk driving and DUI arrests due to the fact that DUI arrests occur far more frequently and present a more immediate drunk-driving outcome than fatalities. However, the present analysis does not support this image. Instead, traffic fatalities and its subset of alcohol-involved fatalities prove to be far more responsive to the ridesharing treatment. To some extent, this could be explained by the notion that a vast majority of DUI arrestees are repeat offenders and are unlikely to change their behaviors due to the availability of a new mode of transportation such as Uber or Lyft.[45] Furthermore, repeat DUI offenders have a higher likelihood of being involved in fatal car crashes and have a fivefold chance of suffering from alcohol dependence or abuse, compared to the general U.S. population.[46]

[45] Schell, Terry L., Kitty S. Chan, and Andrew R. Morral. 2006. "Predicting DUI recidivism: Personality, attitudinal, and behavioral risk factors." *Drug and Alcohol Dependence 82 (1): 33-40*; Watkins, Katherine E., Beau Kilmer, Karen Chan Osilla, and Marlon Graf. 2015. "Driving under the influence of alcohol: Could California do more to prevent it?" Santa Monica, CA: RAND Corporation. https://www.rand.org/pubs/perspectives/PE162.html.

[46] Lapham, Sandra C., Robert Stout, Georgia Laxton, and Betty J. Skipper. 2011. "Persistence of addictive disorders in a first-offender driving while impaired population." *Archives of General Psychiatry 68 (11): 1151-1157.*

DISCUSSION AND CONCLUSIONS

The analyses presented suggest that ridesharing services could be highly promising interventions to curb drunk-driving behaviors and thus positively affect public health outcomes in major metropolitan areas in the U.S. By providing alternative and often cheaper, more readily available means of transportation that might be more convenient than alternative public transit options, these newly emerging services may deter people from driving after consuming alcohol. However, it should be noted that while ridesharing services might prevent drunk driving, they merely possess the potential to combat the symptoms of the underlying problem of excessive alcohol consumption, rather than the root itself. Thus, while ridesharing could provide a welcomed transportation alternative to more traditional transportation options and deter some people from using their cars while intoxicated, it is unlikely to have an impact on broader alcohol consumption trends and unlikely to induce a deeper learning effect. Given that repeat offenses represent a substantial share of DUI arrests in the United States,[47] there is a natural limit to the effectiveness of driving- and transportation-related interventions. Nonetheless, while ridesharing services may only appeal to a smaller portion of the overall population of drunk drivers, they could have the potential to reduce the overall burden of alcohol-involved traffic incidents and therefore warrant a closer look.

While the objective of this research is to assess the impact of ridesharing services on drunk driving specifically, there are additional potential positive impacts of ridesharing on public health and safety. As pointed out by both Dills and Mulholland and Greenwood and Wattal, the effect of ridesharing on traffic congestion and crime remains an important, yet unanswered question.[48]

This study expands on existing academic research concerning the

[47] Schell et al., "Predicting DUI recidivism."

[48] Dills and Mulholland, "Ride-sharing, fatal crashes, and crime;" Greenwood and Wattal, "Show me the way to go home."

issue of ridesharing and drunk driving by introducing a novel data source in Google Trends, and by moving beyond a simple binary measurement of market presence for Uber. Also, this study combines searches for both Uber and Lyft and shows that overall industry and time trends appear to trump company-specific trends, suggesting that consumers may not perceive a meaningful difference between the two major ridesharing companies. In consequence, the idea that Uber and Lyft might in fact be complements could be a subject of future research that warrants further investigation.

Despite the uncertainties surrounding the findings of this study, it is very interesting to see that the results are in line with the findings from other ridesharing studies, which report that the presence of ridesharing services in a metro area is associated with decreases in alcohol-involved traffic fatalities in the range of 1 to 7 percent,[49] compared to the impact of 2.9 percent found here.

The fast rise of the sharing economy and its two key players in Uber and Lyft has created several new regulatory challenges for policymakers at all levels.[50] However, it also presents a range of new opportunities, both from economic and societal perspectives. As laid out above, the results of this study lend further credence to the claims of ridesharing services as a useful and impactful intervention to curb drunk driving and related incidents and as a way to enhance public health and safety. However, further research is needed to definitively prove that there exists a positive impact and to estimate its magnitude. To do so, it will be instrumental to obtain and use actual usage data from ridesharing services and to gain a better understanding of the underlying causal mechanisms.

[49] Ibid.

[50] Dudley, Geoffrey, David Banister, and Tim Schwanen. 2017. "The rise of uber and regulating the disruptive innovator." *The Political Quarterly.*

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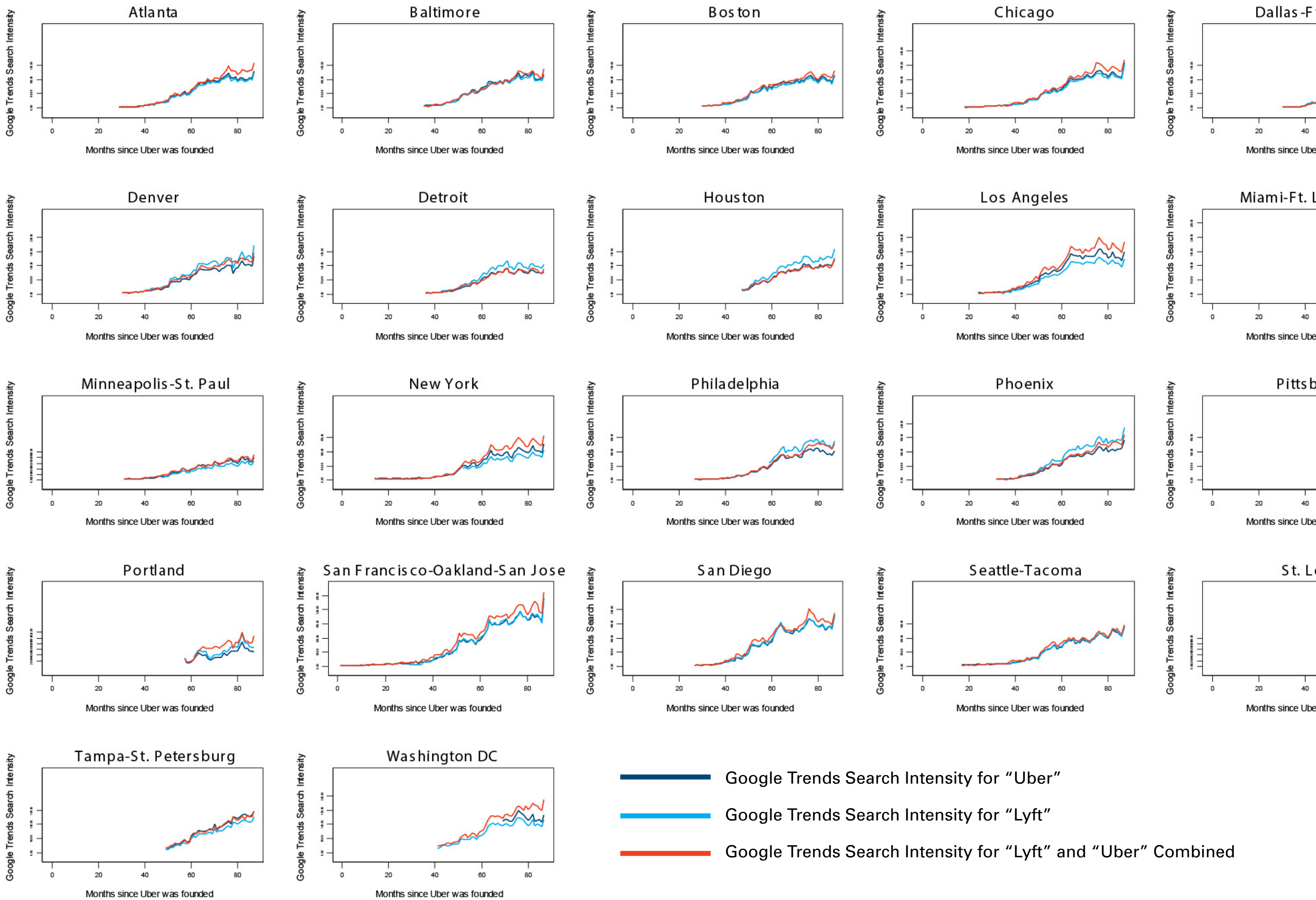
APPENDIX

Figure 2. Google Search Trends for Ridesharing Services, by U.S. Metropolitan Area



APPENDIX

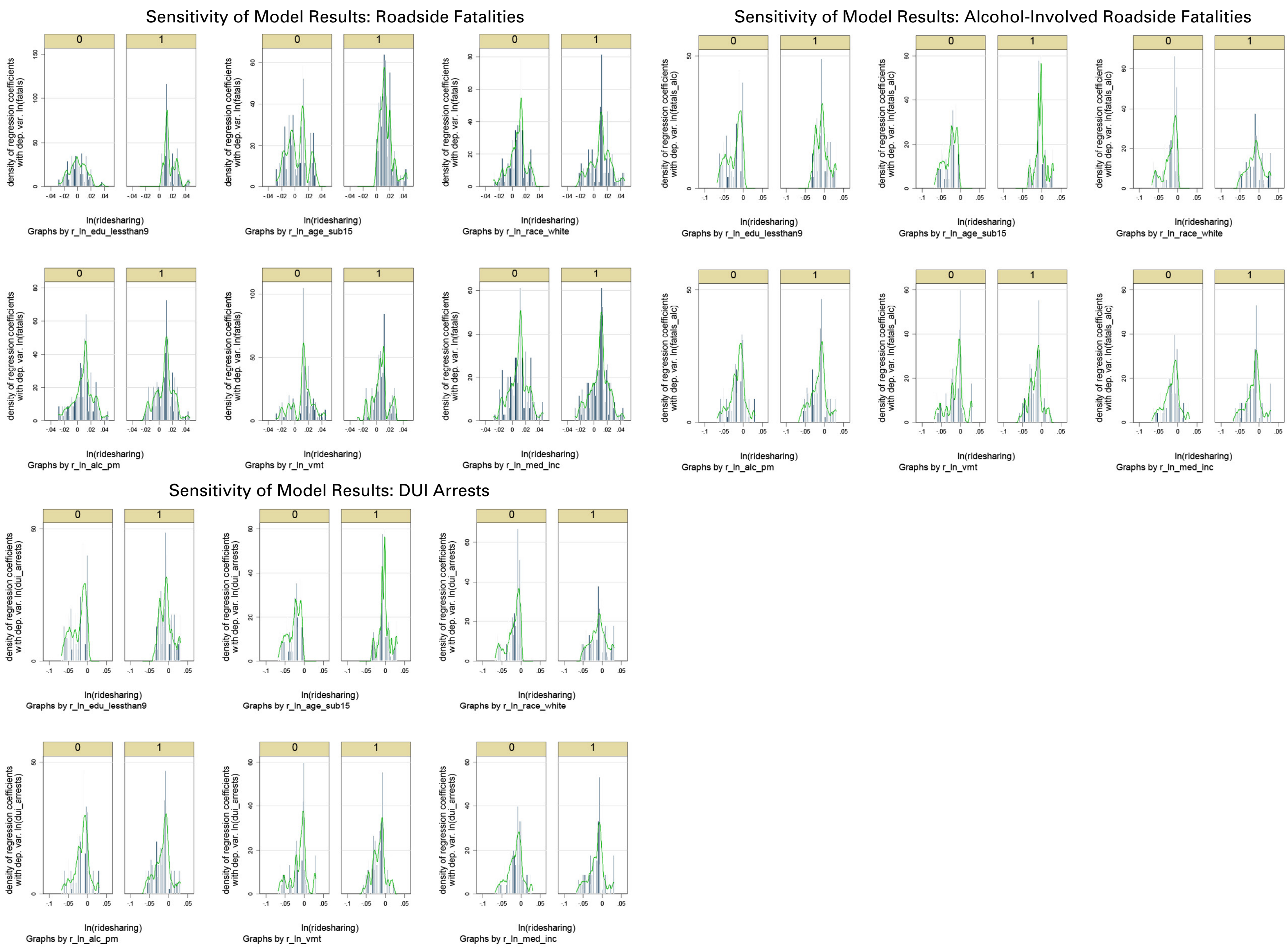
Table 4. Sensitivity Analysis Regression Results

Model Parameters	Roadside Fatalities				Alcohol-Involved Roadside Fatalities				DUI Arrests			
	All models	Log-log	Poisson	Log-log panel	All models	Log-log	Poisson	Log-log panel	All models	Log -log	Poisson	Log-log panel
Number of Models:	384	128	128	128	384	128	128	128	384	128	128	128
Sign Stability	75%	73%	73%	78%	58%	70%	67%	64%	85%	87%	87%	83%
Significance Rate	85%	91%	92%	71%	47%	52%	48%	41%	48%	56%	55%	34%
Positive	75%	73%	73%	78%	42%	30%	33%	64%	15%	13%	13%	17%
Positive and Sig	68%	66%	67%	70%	14%	15%	12%	16%	1%	2%	0%	0%
Negative	25%	27%	27%	22%	58%	70%	67%	36%	85%	87%	87%	83%
Negative and Sig	17%	25%	25%	2%	33%	38%	36%	25%	48%	55%	55%	34%

Variables	Marginal Effect on Significance Probability	Marginal Effect on Positive Probability	Marginal Effect on Significance Probability	Marginal Effect on Positive Probability	Marginal Effect on Significance Probability	Marginal Effect on Positive Probability
Model: Log-log panel	-0.20	0.05	-0.11	0.34	-0.23	0.04
Model: Poisson	0.01	0.00	-0.05	0.02	-0.01	0.00
Note: log-log is the reference model						
Constant	0.86	0.24	0.88	-0.02	1.00	-0.23
Age controls	0.01	0.46	-0.43	0.43	-0.61	0.29
Education controls	0.27	0.50	-0.12	0.48	-0.36	0.24
Traffic controls	-0.16	0.00	-0.09	-0.20	0.19	-0.04
Race controls	0.03	0.00	-0.04	0.06	-0.11	0.26
Drinking controls	-0.02	-0.02	0.08	-0.06	0.06	-0.02
Total population	-0.01	0.04	-0.07	0.02	-0.03	0.00
Median income	-0.02	0.00	-0.04	-0.08	0.00	0.00
Observations	2304		2304		1920	
R-squared	0.61	0.43	0.23	0.58	0.61	0.43

APPENDIX

Figure 3. Sensitivity Graphs of Model Results to Covariates, by Outcome Variables



ABOUT US

ABOUT THE AUTHOR

Dr. Marlon Graf is a health research analyst at the Milken Institute. His work focuses primarily on applied microeconomic analysis of health and substance abuse issues with an emphasis on mixed methods research. His work has been published in peer-reviewed journals and policy reports and has recently been looking at a range of different health policy issues, such as the effects of community health programs on health outcomes, the efficiency and effectiveness of health systems across U.S. states, and the impact of ridesharing services on drunk driving. Before joining the Institute, Graf was an assistant policy analyst at the RAND Corp. and a doctoral fellow at the Pardee RAND Graduate School, where he carried out qualitative and quantitative analyses on a wide range of policy issues, including alcohol and crime control, innovation, technology and economic growth, financial decision-making, and higher education finance. Graf holds a B.S. in business administration from the University of Mannheim (Germany), a master's in public policy from the University of California, Los Angeles, and a Ph.D. in policy analysis from the Pardee RAND Graduate School.

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