

Study Protocol with Statistical Analysis Plan

Official Title: Impacts of Subsidized Ridesharing on Drunk Driving, Alcohol Consumption, and Mobility

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Background

Alcohol-related road crashes have been shown to be preventable and reductions in traffic crash deaths, especially from alcohol, are one of the great public health achievements of the twentieth century.¹ Between 1982 and 1999, the proportion of fatal crashes involving a driver with a blood alcohol concentration 0.08 g/mL fell from 35% to 20%,² credited largely to key interventions introduced during that period (e.g. raising the minimum legal drinking age from 18 to 21 years; limiting blood alcohol concentrations for licensed drivers to 0.08 g/mL). After this sustained reduction, the incidence of alcohol-related crashes has remained roughly constant for the last two decades, and upwards of 12,000 deaths are attributable to alcohol-related crashes each year.³

Achieving further reductions requires concerted efforts to implement evidence-based strategies. One intervention that could theoretically reduce alcohol-related motor vehicle crashes is access to ridesharing services, such as Uber and Lyft. Ridesharing is a mobile technology that enables prospective passengers to summon private owner-operator drivers to specific locations on demand. Key advantages of ridesharing over traditional taxi services are their accessibility (Lyft and Uber often operate in places taxis do not), ease of payment (users keep their payment source on file within the app), transparency (you can track the car's location and arrival time), and safety (your ride is tracked via the app and can be shared with friends or family).

Prospect theory provides a clear mechanism by which this technology will affect alcohol-related motor vehicle crashes. This theory of behavioral economics states that individuals make discrete choices based on probabilistic assessment of risk.⁴ A prospective impaired driver will weigh the unknown costs of driving after drinking (e.g. crashing, DUI) against the known financial and convenience costs associated with using an alternative form of transportation (e.g. public transportation, taxis, ridesharing).⁵⁻⁷ Improved access to alternative transportation, including ridesharing, will make impaired driving less attractive. Fewer impaired drivers will lead to fewer alcohol-related motor vehicle crashes.

The few published studies in this area mostly support the hypothesis that ridesharing will reduce alcohol-related motor vehicle crashes. Three studies, including our own contribution, identify that locations where ridesharing services are available have fewer alcohol-related crashes and fewer DUI arrests.⁸⁻¹⁰ However, another difference-in-difference analysis conducted in the 100 most-populous US counties found no association between ridesharing and alcohol-related road crash fatalities or all road crash fatalities.¹¹ Despite this sparse and somewhat mixed evidence, municipalities have already deployed ridesharing as an intervention to reduce alcohol-related motor vehicle crashes. These programs aim to reduce crashes by subsidizing rideshare trips at times and places when impaired driving is most common. For example, the Townships of Evesham and Voorhees, NJ, provide free trips up to \$30 from 21 local bars.¹² Our analyses identify that this intervention averted 268 (95% CI: 147, 451) alcohol-related crashes and 3 deaths (95% CI: 2, 5) from 2016 to 2018.

The goal of the current study is to examine ridesharing as a strategy to reduce risks for drunk driving among high-risk individuals (e.g. people who go to bars). For this study, we will recruit a sample of participants through Facebook advertisements. We will follow the participants for two weeks using 3 weekly surveys to assess differential risks for drunk driving for the intervention vs. control group.

Objectives

The long-term goal of this research is to inform environmental strategies to reduce alcohol-involved motor vehicle crashes, while minimizing unintended negative consequences, including increased alcohol consumption. The broad objective of this intervention study is to test the effects of access to subsidized ridesharing on alcohol consumption and risks for drunk driving.

The specific aims of this study are:

1. Aim 1 (Intended Impacts). To test whether access to subsidized rideshare trips reduces individuals' risks for drunk driving.
2. Aim 2 (Side Effect). To test whether access to subsidized rideshare trips affects individuals' alcohol consumption.
3. Aim 3 (Mechanism). To test whether access to ridesharing affects individuals' mobility, including access to alcohol.

Methods

Study Design

This study is a two-arm, parallel-group randomized controlled trial (RCT) to test the effects of subsidized ridesharing on self-reported alcohol-impaired driving across 156 US cities.

Participants are blinded to the overall goal of the study, to the nature of the treatment and control conditions, and to their assignment to the treatment and control conditions. This will be accomplished through study materials that refer to the study with a generic name (“SafeNights Study”) and the nature of the study as examining alcohol consumption and alcohol-related harms, without mention of alcohol-impaired driving.

Participants

Eligible participants:

1. Reside in a study city;
2. Are aged 21 years or older;
3. Have a driver’s license;
4. Have access to a motor vehicle;
5. Consumed alcohol at a bar, pub, or nightclub in the past 30 days;
6. Own a smartphone;
7. Speak English

Recruitment:

A two-step approach will be used to recruit the target enrollment of 7,560 participants. First, we will randomly select 70 US cities. Eligible cities are census designated places with a population over 100,000 and access to Uber ridesharing services. Each eligible city is assigned a randomly generated number and then arranged in descending order. Cities are selected for inclusion by assessing first- and second-order adjacency. Cities are excluded if they are adjacent to a previously included city or its immediate neighbors. This process is repeated until 70 cities are selected. In the second step, up to 108 eligible participants are recruited from each city.

After the first year of recruitment, based on enrollment rates, we will estimate progress towards the target enrollment. If enrollment rates are too low to reach the target enrollment, we will include additional cities. Using the same randomly generated number and adjacency eligibility criteria as the original 70 study cities, 86 cities will be added to the sample frame, resulting in 156 total selected cities. **Appendix A** contains a list of the randomly selected cities.

While the cities are selected based on shared criteria, we will employ a two-arm, parallel-group RCT design where the individual is the unit of randomization. To increase the likelihood of balance within cities, we will utilize stratified randomization, using the city of residence as the stratification factor.

Enrollment

Participants will be recruited via social media advertisements placed through the Meta platform on Facebook and Instagram. Advertisements will be displayed on Mondays, Tuesdays, and

Wednesdays. We will display an advertisement to social media users who (i) are aged 21 years or older and (ii) “have expressed an interest in or have liked pages related to ‘bars’ AND ‘alcohol.’” Eligible individuals who click on the social media advertisement will proceed to the SafeNights Study website for screening, informed consent, and an enrollment (Wave 1) survey.

The survey website contains an initial screening form that confirms participants are eligible to participate in the study.

GPS Sub-Sample. After completing the Wave 1 survey, participants who indicate that they have an Android smartphone in the screening form will be invited to join a sub-sample that will be followed using GPS tracking data collection.

Informed Consent

Eligible participants will provide remote e-consent to enroll in the study, using the study website. The first page will ask participants to provide remote e-consent to participate in the research. The page will be designed so that participants can navigate forwards and backwards, although participants who have not e-signed the consent form will not be able to proceed to the enrollment survey. If participants do not wish to electronically sign the informed consent form, they will be directed to a termination screen that provides information about how to enroll if they change their minds. Participants who provide electronically signed informed consent will proceed to the enrollment questionnaire. There are several features that we will use in the consenting procedure. The first is including the study email address for potential participants who have questions before proceeding with the consenting procedure. The system has an embedded digital copy (i.e., a PDF) of the consent form in the questionnaire. And, we will add a PDF including the Consent Form text, the participant's e-signature, and the signature date that participants will be able to download and save.

Enrollment Data Collection

After providing informed consent, enrolled participants will complete a brief enrollment survey asking about their alcohol consumption, risks for drunk driving, and demographic characteristics. After completing and submitting the baseline survey, project staff will receive the questionnaire data via the secure study website.

Pre- and Post-Intervention Data Collection

Participants will receive text messages with links to pre-intervention and post-intervention surveys on Mondays, Tuesdays and Wednesdays one week (pre-intervention: Days 8 to 10) and two weeks (post-intervention: Days 15 to 17) after they complete the enrollment survey. The pre- and post-intervention surveys are identical and are designed to be brief versions of the enrollment survey. Participants will be asked questions regarding their risks for drunk driving over the previous week and alcohol consumption.

Random Allocation

Randomization will occur at the individual level. To increase the likelihood of balance within cities, stratified randomization will allocate participants to the treatment or control conditions within cities, allowing for equal numbers of participants to be assigned to the treatment and control groups within each selected city. After randomization, participants randomly assigned to the treatment condition receive a \$35 Uber voucher, and participants randomly assigned to the control condition received a \$35 Amazon voucher. The compensation for the pre-intervention

survey serves as the intervention being tested. The randomization procedure is performed using computer generated random numbers.

Incentives

Participants will receive online shopping vouchers for the completion of each survey.

Participants who complete the enrollment survey receive a \$5 Amazon voucher sent via text (SMS). Compensation for the pre-intervention survey will follow the procedures described above for Random Allocation. For the post-intervention survey, participants not in the GPS sub-sample will receive an additional \$40 Amazon voucher for completing the survey; participants in the GPS sub-sample will receive an additional \$80 for completing the post-intervention survey. The value of the total available incentives are \$80 for the non-GPS sub-sample and \$120 for the GPS sub-sample.

GPS Sub-Sample

Immediately after completing the enrollment survey, participants who indicate on the screener that they have an Android smartphone will be invited to join a sub-sample that will be followed using GPS tracking data collection. We will cap participation in the GPS sub-sample at 2,000 participants (i.e. 40 from each city). Participants in the GPS sub-sample will be asked to download a custom smartphone application through the Google Play app store and will be sent a unique passcode by text and email. After downloading the application, participants will enter the unique passcode and will complete a further informed consent form that describes the procedures for the GPS data collection. GPS tracking will be activated following informed consent procedures and will be deactivated immediately after completion of the Wave 3 survey.

Statistical Analysis Plan

We will compare participant characteristics, including demographics and baseline alcohol consumption, between the treatment and control groups. All models will be fitted among participants who have at least one outcome measurement in the pre- or post-intervention surveys.

Aim 1

We will conduct an intention-to-treat analysis using generalized estimating equations (GEEs) with a logit link to estimate the ratio of odds ratios for alcohol-impaired driving, comparing changes from pre- to post-intervention between the intervention and control groups. Separate models will be fit for two binary alcohol-impaired driving outcomes: (1) any driving after drinking and (2) any driving after drinking “too much.” Each model will include an indicator for time (pre- vs. post-intervention), intervention group, and their interaction. To address missing data, Multivariate Imputation by Chained Equations (MICE)¹³ will be used to generate multiple imputed datasets. Analyses will be conducted with and without multiple imputation, and results will be compared to assess the robustness of the findings.

Aim 2

We will conduct an intent-to-treat analysis to evaluate the effect of the intervention on changes in alcohol consumption. Consumption outcomes will include the frequency (defined as the number of drinking days) and continued volume (defined as the number of drinks consumed after 1 drink on a drinking day) of drinking per week. We will fit Poisson GEEs to estimate the ratio of rate ratio comparing changes in alcohol consumption from pre- to post-intervention between the intervention and control groups. Each model will include an indicator for time (pre- vs. post-intervention), intervention group, and their interaction. We will also examine differences in alcohol consumption between licensed venues (bars, pubs, clubs, or restaurants) and other locations (e.g., home or friends’ homes). Missing data in alcohol consumption will be addressed using MICE. Results from the analyses with and without multiple imputation will be reported.

Aim 3

Using records from the GPS sub-sample, we will calculate participants’ exposure to alcohol outlets and mobility. We will first clean the GPS data by removing any records that are obtained from cell phone towers and that are clearly erroneous (e.g. where individuals travelled > 100 miles/hour between readings). We will use the GPS data to calculate the following measures:

1. Time spent near an alcohol outlet is calculated as the sum of the time elapsed between GPS records when the participant is within a buffer distance of an alcohol outlet. The main measures will use a buffer of 50 meters. Additional measures for use in sensitivity analyses will be calculated within buffers of 100 meters and 200 meters. The average amount of time spent near an alcohol outlet will provide the average duration of trips to an alcohol outlet.
2. Trips to an alcohol outlet are calculated as the count of times participant is within a buffer distance of an alcohol outlet. The main measures will use a buffer of 50 meters. Additional measures for use in sensitivity analyses will be calculated within buffers of 100 meters and 200 meters. The average number of trips to an alcohol outlet will provide the average frequency of trips to an alcohol outlet.

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Appendix A. List of randomly selected study cities.

<u>Original Study Cities</u>	
Albuquerque, NM	Lincoln, NE
Aurora, CO	Lowell, MA
Austin, TX	Miramar, FL
Baltimore, MD	Moreno Valley, CA
Birmingham, AL	Nashville, TN
Burbank, CA	New Haven, CT
Charlotte, NC	New Orleans, LA
Chattanooga, TN	New York, NY
Clearwater, FL	North Las Vegas, NV
Cleveland, OH	Oklahoma City, OK
Colorado Springs, CO	Olathe, KS
Columbus, OH	Paterson, NJ
Costa Mesa, CA	Raleigh, NC
El Paso, TX	Rochester, NY
Escondido, CA	Roseville, CA
Everett, WA	Salinas, CA
Fairfield, CA	San Francisco, CA
Flint, MI	Santa Clara, CA
Fontana, CA	Santa Rosa, CA
Fort Wayne, IN	Scottsdale, AZ
Fort Worth, TX	Seattle, WA
Fresno, CA	Springfield, MA
Fullerton, CA	St. Louis, MO
Grand Rapids, MI	St. Paul, MN
Green Bay, WI	St. Petersburg, FL
Hartford, CT	Stamford, CT
Henderson, NV	Stockton, CA
Hialeah, FL	Syracuse, NY
Houston, TX	Tallahassee, FL
Independence, MO	Temecula, CA
Indianapolis, IN	Vallejo, CA
Jacksonville, FL	Vancouver, WA
Joliet, IL	Victorville, CA
Knoxville, TN	Washington D.C., DC
Lexington-Fayette, KY	Westminster, CO
<u>Additional Study Cities</u>	
Akron, OH	Little Rock, AR
Allentown, PA	Long Beach, CA
Anchorage, AK	Louisville, KY

Ann Arbor, MI	Lubbock, TX
Atlanta, GA	Madison, WI
Aurora, IL	Milwaukee, WI
Bakersfield, CA	Modesto, CA
Bellevue, WA	Montgomery, AL
Boise City, ID	Newark, NJ
Bridgeport, CT	Newport News, VA
Buffalo, NY	Norfolk, VA
Cambridge, MA	Norwalk, CA
Cedar Rapids, IA	Oceanside, CA
Chandler, AZ	Omaha, NE
Charleston, SC	Orange, CA
Chicago, IL	Orlando, FL
Chula Vista, CA	Oxnard, CA
Cincinnati, OH	Pasadena, CA
Columbia, SC	Philadelphia, PA
Concord, CA	Pittsburgh, PA
Coral Springs, FL	Plano, TX
Corona, CA	Pomona, CA
Corpus Christi, TX	Providence, RI
Des Moines, IA	Provo, UT
Detroit, MI	Reno, NV
East Los Angeles, CA	Sacramento, CA
El Monte, CA	Salem, OR
Elgin, IL	Salt Lake City, UT
Eugene, OR	San Antonio, TX
Fargo, ND	San Bernardino, CA
Fort Collins, CO	Sioux Falls, SD
Fort Lauderdale, FL	Spokane, WA
Fremont, CA	Spring Valley, NV
Garland, TX	Thousand Oaks, CA
Glendale, AZ	Topeka, KS
Gresham, OR	Torrance, CA
Honolulu, HI	Tucson, AZ
Huntsville, AL	Tulsa, OK
Inglewood, CA	Waterbury, CT
Jackson, MS	West Jordan, UT
Kansas City, KS	Wichita, KS
Lakewood, CO	Wilmington, NC
Lansing, MI	Worcester, MA