The Demand for Mobility: Evidence from an Experiment with Uber Riders

Peter Christensen and Adam Osman*

Current Draft: October 2021

Abstract

Optimal transportation policies depend on demand elasticities that interact across modes and vary across the population, but understanding how and why these elasticities vary has been an empirical challenge. Using an experiment with Uber in Egypt, we randomly assign large price discounts for transport services over a 3 month period to examine: (1) the demand for ride-hailing services and (2) the demand for total mobility (km/week). A 50% discount more than quadruples Uber usage and induces an increase of nearly 49% in total mobility. These effects are stronger for women, who are less mobile at baseline and perceive public transit as unsafe. Technology-induced reductions in the price of ride-hailing services could generate substantial consumer surplus through combined mobility effects ($12 Billion PPP) but would be accompanied by considerable increases in external costs ($3.2 Billion PPP) resulting from increases in private vehicle travel.

*Christensen: Department of Agricultural and Consumer Economics, University of Illinois (email: pchrist@illinois.edu); Osman: Department of Economics, University of Illinois, (email: aosman@illinois.edu). We thank Santosh Rao Danda for support in implementing the experiment, as well as others at Uber including Ahmed Aly, Rana Kortam, and Ian Muir. We thank Esther Duflo and John List for their support in the development of this project. We thank Treb Allen, Michael Anderson, David Atkin, Gharad Bryan, Benjamin Faber, Erica Field, Marco Gonzalez-Navarro, Jonathan Hall, Amit Khandelwal, Florence Kondylis, Gabriel Kreindler, David Phillips, Nick Tsivanidis, Kate Vyborny and seminar participants at Cornell, UC Berkeley, UC Santa Barbara, University of Chicago, the Advances with Field Experiments Workshop, the Cities and Development Workshop, the Urban Economics Association Meeting and the American Economics Association Annual Meeting for excellent comments. We thank Rahma Ali, Norhan Muhab, Sarah Saeed, Mahmoud El Bably, Ahmed Abdelsalam for research assistance in Egypt, as well as Abdelrahman Nagy and Nagla Rizk for implementation support. We also thank Gustavo Nino, Keshi Shen, Felipe Diaz, and student assistants in the University of Illinois Big Data and Environmental Economics and Policy (BDEEP) Group. We acknowledge generous support from the University of Illinois Department of Economics (RIFDC) and Office of International Programs. University of Illinois IRB 19102, AEARCTR-0004966. Authors retained full intellectual freedom throughout all stages of this project (more details in the Ethics Appendix). All views expressed here, and all remaining errors are our own and do not reflect the views of Uber B.V. and/or any affiliates.

1 Introduction

The introduction and expansion of ride-hailing services represents one of the most dramatic changes in global transportation markets in decades. This is especially true in the developing world, where the high fixed costs of car ownership and low levels of reliability/safety of taxi services limit private transit use. While previous work has found substantial consumer surplus from ride-hailing services (Cohen et al., 2016, Alvarez and Argente, 2020a), it has been challenging to properly account for the associated external costs (Hall et al., 2018, Tirachini and Gomez-Lobo, 2020). It is well-understood that shifts from mass transit to the same travel in private vehicles involves considerably higher congestion and emissions externalities (FTA, 2010, FHA 2018). Credible estimates of how changes to private travel affect external costs requires exogenous variation in prices *and* comprehensive micro-data that can capture total mobility and substitution behavior on all available transportation choices.

To overcome these challenges, we implement a demand-side experiment on the Uber platform.[1] The study randomizes large, sustained changes to the prices facing Uber riders in Cairo, Egypt and introduces a new method for collecting comprehensive data on participants' mobility patterns using Google Maps' *Timeline* software. We randomly assign 1,373 Uber riders into three groups: (1) participants who face prices that are reduced by 50% for the 3-month study period, (2) participants who face prices that are reduced by 25% for the 3-month study period, and (3) a control group. We use individual-level data collected from Google Maps' Timeline to estimate the demand for *total mobility (km/day)*. We combine this with data collected in follow-up phone surveys to examine how impacts on total mobility are split across private and public modes of transport, each of which contribute differently to economy-wide transport externalities.[2]

We find evidence of a strong demand response to the price reductions, with those receiving a 25% price reduction more than doubling their Uber utilization and those receiving a 50% reduction more than quadrupling it. We find that these effects also translate into large increases in overall mobility – participants receiving the 50% treatment increase their vehicle kilometers traveled (VKT) by 49%, an increase of 1,211 km over the 12-week period. This increase in total travel understates the increase in private vehicle kilometers traveled (PVKT) due to substitution behavior. Using direct evidence on transport mode-switching, we find that the proportion of trips taken by public transport declines by approximately 10%. Combining the effects on distance traveled with the substitution from public to private vehicles, we estimate that a 50% price reduction in ride-hailing can result in a 74% increase in private vehicle kilometers traveled.

We then examine impacts by subgroup and find that these average effects mask impor-

[1] Individuals volunteered to join the research program, as outlined in section 2.2 below.

[2] We focus on kilometers traveled as opposed to number of trips taken because that is the relevant metric for assessing congestion and emission externalities. We also report impacts on trips which are similar.

tant heterogeneity by gender. Point estimates indicate that the price elasticity of demand for mobility is substantially higher among women (-1.46) relative to men (-0.59). Female participants, who are less mobile at baseline but have higher baseline Uber utilization, respond to the 50% treatment by expanding their Uber usage as well as their overall mobility more than men. We use data on transport mode use and safety perceptions to examine key mechanisms underlying these differences. We find that women feel more unsafe than men on all modes of transit aside from private cars and ride-hailing, where all participants tend to report feeling safe. While men primarily use Uber to increase their overall travel, a substantial portion of Uber use among women involves substitution away from public buses – the least safe travel option reported by female participants in our study. This substitution pattern is particularly strong among the subset of women who reported the public bus as an unsafe mode at baseline. The price treatment on Uber leads to important increases in safety experienced in recent travel for female participants but not for male participants.

Researchers have predicted that costs in ride-hailing markets could fall by 40-80% as connected and autonomous vehicle (CAV) technologies improve (Narayanan et al., 2020). Given the strong reduced-form evidence that price reductions affect travel on close complements and substitutes in our sample, we hypothesize that the demand response on Uber alone may understate the full welfare effects and external costs associated with technology-induced price reductions for ride-hailing services. We interrogate this question by first comparing estimates of consumer surplus using the experimentally-identified demand elasticities for Uber services (CS^{Uber}) to those obtained using mobile phone and survey-based measures of total travel (CS^{Travel}) that capture the full set of mobility responses. A 50% reduction in the price of ride-hailing services generates considerable surplus to Uber riders (156 EGP per week), which is equivalent to 13% of the income of the average participant in our sample. The comparable consumer surplus estimate calculated from the Uber demand elasticity understates by half the estimate obtained when accounting for extensive margin and substitution responses on all modes. The benefits from overall mobility are demonstrated both using total travel measured on Google Timeline as well as total trips reported in participant surveys.

We then turn to the external costs associated with changes in private vehicle travel (PVKT) that could result from market-level price reductions on ride-hailing services. We utilize our experimental parameters and a simple model to: (1) recover an estimate of the elasticity of private vehicle travel (PVKT), which is a function of the extensive margin response and the substitution response (from mass transit to private modes) and then (2) adjust the PVKT elasticity to reflect an equilibrium where price reductions endogenously affect average travel times through induced congestion. We estimate that the partial equilibrium price elasticity of demand for private vehicle kilometers traveled (PVKT) is -1.48 in Cairo. This is driven in large part by substitution from buses. Induced congestion effects attenuate the price effect, yielding an equilibrium PVKT elasticity of -1.32. Using this equilibrium elasticity estimate, we find that a 50% price reduction would result in an 27% increase in the external costs attributable to Cairo's transportation sector, equivalent to \$3.2 Billion PPP per year. We adjust our estimates for consumer surplus to also utilize equilibrium elasticities and estimate that total consumer surplus would be \$11.5 Billion PPP.[3] This increase in benefits would be concentrated among users of ride-hailing services, who have higher incomes relative to Cairo's overall population, while the external costs are borne by the full population.

A new database identifies more than 45 cities within Brazil, China, India and Mexico alone that have implemented uniform tax instruments to address externalities in the ride-hailing market and to redistribute the surplus (World Resources Institute, 2020). Our elasticity estimates suggest that taxes are likely to have strong effects on ride-hailing behavior in developing country cities like Cairo, but that implementing a *uniform* tax to more equitably address the regressive nature of imbalance between consumer surplus and external costs would have a disproportionate impact on women. Our estimates indicate that a uniform tax would reduce female mobility by 46% more than the reduction in male mobility. Earlier work has shown how transport accessibility and safety concerns can affect a variety of downstream outcomes for women including education and labor market choices (Kondylis et al., 2020, Kreindler, 2020, Anderson, 2014, Bryan et al., 2014, Desmet and Rossi-Hansberg, 2013). This suggests that policymakers must carefully consider heterogeneity in price elasticities when utilizing price instruments.

We highlight three important caveats to consider when interpreting our results. First, as with any experimental study implemented on a particular sample, we must be careful to consider the extent to which these results will generalize to other markets and to non-experimental settings. We run two auxiliary experiments to test the importance of key features of our experimental design – the salience and length of the price reductions. We recover consistent elasticities when varying these features in independent experimental samples, providing strong evidence that they do not affect the interpretation of our results. A second caveat relates to the potential income effects that our subsidies provide. By discounting the cost of Uber rides, individuals in treatment are receiving an implicit transfer that they could then use to buy more transport services. While this is a discount and not a credit (all participants face prices on every trip), we find that individuals with lower incomes (whose marginal value of income is higher) do not respond more to our treatments. Third, our experimental design does not allow us to assess the full range of general equilibrium effects of large reductions in the price of ride-hailing services. Making personalized travel more accessible could have wide ranging impacts on outcomes and on

[3] In the absence of a technology-induced price reduction, a government could consider a direct subsidy program. However, this would cost nearly \$25.2 Billion PPP, which would yield a negative marginal value of public funds.

timescales that fall outside the scope of this particular study.

This paper contributes to a large empirical literature on the impact of transportation services on commuting patterns and economic activity in cities (Bryan et al., 2019, Campante and Yanagizawa-Drott, 2017, Asher and Novosad, 2018, Hanna et al., 2017, Duranton and Turner, 2011). A primary challenge in this literature is that the provision and prices of transportation services are almost never randomly assigned. As a result, empirical efforts have focused on settings characterized by exogenous shocks in service provision (Gupta et al., 2020, Gorback, 2020, Yang et al., 2020, Tsivanidis, 2018, Gonzalez-Navarro and Turner, 2018, Ahlfeldt et al., 2015, Anderson, 2014), available instruments (Severen, 2018, Baum-Snow et al., 2017, Duranton and Turner, 2011, Baum-Snow, 2007), and structural approaches (Heblich et al., 2020, Allen and Arkolakis, 2019, Redding and Rossi-Hansberg, 2017). Recent studies have demonstrated the benefits of high-frequency price variation in estimating price elasticities for gasoline or private transportation services (Levin et al., 2017, Cohen et al., 2016), though it remains difficult to study sustained changes in the price of transport services (Schaal and Fajgelbaum, 2020, Ahlfeldt et al., 2016). We contribute to this literature by randomizing the price of a transport service for a 3-month period and collecting comprehensive travel data, allowing us to provide a novel experimental estimate of the demand for mobility. We use this and other experimental parameters to provide a more complete picture of the benefits and external costs associated with reductions in the price of personalized transport.

An important feature of our research design is the measurement of overall mobility patterns using a mobile app, which helps to avoid recall/reporting biases. We combine these data with information from follow-up surveys to examine the mechanisms through which price reductions in transport services affect mobility, including substitution across modes, changes in the geography of travel, and learning. There is growing interest in using digital technologies to measure transportation decisions and map physical movements (Kreindler and Miyauchi, 2021, Kreindler, 2020, Martin and Thornton, 2017, Glaeser et al., 2018). Advances in data collection on mobile devices will facilitate direct observation of mobility patterns in future research, though these sources also involve important measurement challenges. We combine data from mobile phones with trip-level data on Uber travel and a trip survey, allowing us to evaluate the robustness of our central findings and perform validation tests that can inform future work on individual mobility patterns.

Our paper also builds on a growing set of economic studies of the impacts of ride-hailing markets. The current paper combines a field experiment with an extensive data collection effort that allows us to characterize the relationship between the demand for ride-hailing services and the demand for mobility in a developing country city. Studies of complement/substitute transport technologies have relied mainly upon stated preference methods (Leard and Xing, 2020, Young and Farber, 2019) or observational methods using aggregate behavior on outside modes (Hall et al., 2018).[4] Consistent with recent work on consumer behavior in retail markets (Atkin et al., 2018), our micro-level evidence on consumer surplus demonstrates that an important fraction of the consumer surplus associated with price reductions operates through impacts on substitutes/complements. While the economics literature has largely focused on the benefits of ride-hailing markets to participants (riders/drivers) (Buchholz et al., 2020, Alvarez and Argente, 2020b, Goldszmidt et al., 2020, Castillo, 2019, Moskatel and Slusky, 2019, Cohen et al., 2016), the present study uses sustained price changes to provide estimates of external costs, which are considerable in magnitude and critical for optimal policy.

Finally, we contribute to a strand of research that demonstrates that reducing the monetary cost of transportation can improve the economic outcomes of mobility-constrained populations (Franklin, 2018, Bryan et al., 2014, Phillips, 2014). We identify key sources of heterogeneity by gender and safety perceptions in Cairo's transport market, linking to the growing literature on the importance of female safety in transportation. There is evidence that perceived safety levels can affect educational attainment and earnings in developing country settings (Kondylis et al., 2020, Jayachandran, 2019, Velásquez, 2019, Borker, 2018). These safety considerations are also relevant in high income countries, for example Kaufman et al. (2018) find that 54% of women are concerned about being harassed while using public transportation in New York City. Liu and Su (2020) show that the spatial distribution of jobs in the US contributes to the gender wage gap due to differential preferences by gender about commuting. We find that subsidies for ride-hailing services result in disproportionate effects on women in several outcomes: Uber utilization, total mobility, substitution away from less safe options (buses), and self-reported safety in recent trips. Our results suggest the need for attention to the benefits of safety improvements and the safety of outside options when designing pricing instruments for ride-hailing services, which are becoming widespread.

The paper proceeds as follows: Section 2 describes the setting and experimental design, Section 3 provides details on the data we collect and Section 4 reports the impacts on Uber Utilization. Section 5 reports the impacts on total mobility and presents robustness checks. Section 6 estimates effects on consumer surplus and external costs and discusses policy implications. Section 7 discusses study limitations and Section 8 concludes.

2 Study Setting & Experimental Design

Cairo is a city of approximately 20 million inhabitants and is expected to continue to grow in the coming years. As with many other developing country cities, Cairo suffers from high levels of traffic congestion and underinvestment in public transit services (Nakat et al., 2014). The city has also become infamous for dangerous travel as a result of

[4] An important exception is Alvarez and Argente (2020a), who use experiments to estimate how demand for Uber changes based on riders' payment method, cash or credit.

accident and harassment risk (Parry and Timilsina, 2015).

The primary modes of travel in Cairo include: private cars and taxis, private and public buses (though no official bus map exists for the city), a metro line that runs through the heart of the city, and other small transport vehicles such as mini-buses (private vans) and auto-rickshaws (locally called tuktuks).[5] Ride-hailing services are also well-established in Cairo. Egypt is one of Uber's larger markets, with over 4 million users (Reuters, 2018), where it launched in 2014. The ride-hailing market also includes another option in "Careem," which provides services that are similar to Uber.[6] At the time of the study, the market was considered competitive, with promotions and subsidies used regularly to attract both riders and drivers to the platform. Promotions usually take the form of coupons for 5-10% off of a set number of upcoming rides.

Cairo's residents spend between 5-10% of their income on transportation-related expenses.[7] Household expenditure on transportation services differs across the income distribution. At the lower end of the income distribution, individuals tend to spend less of their income on transport and rely upon low cost options, while those in the highest quintile spend closer to 10% of their income.[8] This is because there are large price differences between public and private options. A typical bus ticket costs 5 EGP, and a typical metro fare is also 5 EGP, for trips that can be as long as 40km. Ride-hailing services on the other hand can cost 6 EGP per kilometer traveled, as is also true of the costs of taxis.

2.1 Experimental Design

We study the demand response to experimental variation in the price of ride-hailing services in Cairo. The experiment applied discounts that reduced the price[9] of Uber mobility services over a period of 12 weeks for two randomly-assigned groups of individuals that opted in: (1) a 50% reduction or (2) a 25% reduction to the price of Uber services. Participants in the control group continued to face standard market prices on the Uber app. The experiment reduced the prices on five of Uber's services, including the most common-UberX which provides a private car on demand based on the individual's requested start location and time. Participants also received a price adjustment on UberXL (similar to UberX but with larger cars), Uber Pool (rides shared with other passengers that are

[5]Auto-rickshaws are not allowed on the highways, but otherwise there are no restrictions on type of vehicles allowed on the road network. i.e. there are no bus-only lanes/roads.

[6]Uber acquired Careem in 2019, but regulators approved the purchase conditional on Careem continuing to operate as an independent brand with independent management (Saba, 2019).

[7]This estimate comes from Egypt's Household Income, Consumption and Expenditure Survey of 2015 (Economic Research Forum, 2015).

[8]For comparison, this is somewhat lower than the share of income spent on transport in Latin American cities, where households spend between 12-15% of income on transport (Gandelman et al., 2019).

[9]Any time we reference a "price reduction" in this paper, we refer to changes to the price faced by the consumer due to the researchers providing a discount and not through any changes in the market price of Uber services.

less expensive but may take longer to complete), Uber Scooter (rides on a two-wheeled motorcycle that are significantly cheaper than the car-based services, but potentially less safe/comfortable), and Uber Bus (a newer, high-occupancy service provided along a dynamic path across certain zones of the city).[10] See Appendix L for a discussion of ethical considerations regarding the experimental design.

2.2 Recruitment

To recruit the study sample, Uber's engineering team sent text messages to a random subset of riders who had taken at least one ride in Cairo over the past 4 weeks. The text message informed riders that researchers at the University of Illinois were conducting a study on mobility patterns and participants had a chance to receive discounts on their future Uber rides. Interested individuals were given a link to a registration page that provided more detailed information about the study and the opportunity to enroll.[11] Upon enrollment, participants received a phone call to confirm their understanding of the study and to implement the baseline survey that is outlined in section 3.1 below. Recruitment occurred in batches, with a group of messages sent out every 2-3 weeks, allowing for the surveyors to complete data collection on the existing cohort before sending recruitment messages to a new one.

2.3 Randomization and Enrollment

After successful completion of the baseline survey, participants were randomized into one of the two treatment groups or the control group. The randomization was conducted at the individual level and was stratified by gender and whether individuals were looking for a job. Each cohort was randomized separately (cohort fixed effects are included in all regressions). After randomization, individuals were sent an email to welcome them into the study and to inform them about their treatment status.[12] The first cohorts were enrolled in July 2019, with the final cohorts enrolled in December 2019.[13] During the study period, all participants were sequestered from other incentives that Uber provides on the basis of recent ridership. Those in the two treatment groups were told that they

[10]Participants were informed that price reductions would not apply to rides on Uber Select, which is a service that provides on-demand rides in luxury cars and is Uber's most expensive option. This restriction was implemented to safeguard against the potential depletion of funds on services that were not commonly used and less relevant for the study.

[11]The response rate to the text message was about 2%, which is typical of these types of solicitations (Allcott et al., 2020, 2021).

[12]We do not have data regarding whether the participants had read the enrollment email but the results below will show that individuals respond to the subsidies within the first week (see Figure 1), providing evidence that the emails were seen in a timely fashion. Individuals were also cross-randomized into an information treatment. The entirety of treatment was two additional sentences in the enrollment email. One group was informed about a popular online job board that includes thousands of vacancies, and another was informed about a website that provided data on harassment risk around the city. We control for these additional treatments in our regressions, but their impacts are outside the scope of this paper.

[13]As discussed in Appendix K, we exclude the final cohort which was affected by COVID-19. Including them in our estimates does not qualitatively change any of our results.

were provided their respective price reduction for 12 weeks and informed that they could apply it to any service except "Uber Select." Participants were also informed that the discounts could not be transferred to another person.[14] Subsidy treatments were applied directly to a participant's account and were applied to prices displayed to participants whenever they used the app, such that participants in each of the different groups faced different prices directly and in real-time in the context of a trip decision. For those assigned to treatment groups, the Uber App would display the reduced fare and below that, a smaller display of the original fare with a strike-through (an example can be found in Figure A.1).[15]

3 Data Collection & Sample Characteristics

3.1 Baseline Survey

Prior to their enrollment in the study, participants were asked to complete a baseline phone survey to collect individual characteristics such as gender, age, education, marital status and employment information. Appendix Table B1 reports the characteristics of the experimental sample of 1,373 participants at baseline. The sample is composed of 47% women (53% men), approximately half of whom are married. Participants in the control group make an average of 4,655 EGP in monthly income. 78% of the sample is currently working, though 48% of participants are looking for work at baseline. About a quarter of the sample owns a car. We compare our participants to a representative sample of Cairo residents in Appendix Table B2. We find that our sample is younger, more educated, and has a higher income than the average Cairene, which is not surprising given that selection depends on utilization of Uber.

We also collect data on overall transport behavior through the survey and Google Maps Timeline (which we detail below). We ask respondents to report the number of trips they took on a variety of transport modes during the day before the survey.[16] This includes trips on the metro, on the bus, on taxis, in private cars as well as ride-hailing services (we group Uber and Careem in this question). Furthermore, in an effort to better understand baseline travel behavior and perceptions of available options, we collected detailed data on a participants' longest trip (in distance for a single direction of travel) taken the day before the survey. We began by collecting information on the mode of travel used for that trip. Figure B1 plots the fraction of trips on the 6 primary

[14]It is possible for Uber engineers to identify whether people were utilizing their account to provide discounted rides for other people. There were a negligible number of rides that fit that criteria in our sample.

[15]The 'discount display' (strike-through) was a requirement of the Uber engineering team. While not prominent on the screen, it could possibly affect the behavioral responses of participants.

[16]To simplify comparisons across our different measures we adjust all of our variables so that they are reported over a 7-day period. For example, while we only ask about the number of trips taken across modes in the day before our survey, we multiply these estimates by 7 and report it as the number of trips taken on that mode weekly.

modes that participants use for their longest trips on a given day. The 3 primary modes of transit are bus, ride-hailing services, and private car, which together constitute more than 85% of trips. While these three modes are the primary modes used by both genders, men report the greatest reliance on bus services whereas women report the greatest reliance on Uber services for long trips.

Survey enumerators asked participants to report the perceived duration, cost, and level of personal safety for the longest trip they took yesterday. They then asked them to imagine taking the exact same trip using each of the 5 other primary modes available to them: private car, taxi, ride-hail (i.e. Uber or Careem), public buses (including private mini-buses), private bus (Swvl), and metro.[17] Participants were then asked to report their expectations about the duration, cost, level of safety, and likelihood of on-time arrival on each counterfactual mode. Figure B2 plots these counterfactual perceptions on each mode relative to ride-hailing services. Not surprisingly, ride-hailing is considered a more expensive option than all but taxi services. Ride-hailing is also considered to offer a faster trip from origin to destination than bus and taxi's but not substantially different from metro services or transport by private car. Interestingly, ride-hailing services are also considered to be substantially safer than all options aside from private car.

3.2 Google Timeline Data

To complete enrollment in the study, we asked individuals to adjust the settings on their mobile phones during the baseline survey to allow Google Maps to record their locations as they travel. Google uses this information to generate a "Timeline" of travel. This option is available for all mobile devices that have access to Google services (i.e. Android and iPhone devices), but is turned off by default. Some participants in our sample already had this service turned on at the time of recruitment, but the majority did not. When turned on, Google then uses the location data to generate summary statistics on mobility patterns, including daily reports that provide the distance and time spent traveling on different transport modes (as shown in Figure A.2). Participants who had it off received guided instruction on how to turn on their Google Timeline and a follow-up call (4-7 days later) to confirm functionality and report to us the summary statistics for their travel on each of the past three days, which is then included in their baseline data.[18]

To our knowledge, this is the first case of researchers using Google's Timeline feature to collect data on the mobility behavior (total km traveled) of participants in an experiment. Digital and mobile-based technologies provide distinct advantages over earlier methods

[17] We ask about ride-hailing as a whole to capture the overall effects on ride-hailing services, which include substitution from Careem to Uber. A few companies in Cairo (such as *Swvl*) now provide private bus services that people reserve in advance. Mini-buses in Cairo are vehicles that are about the size of a large van and can hold about a dozen passengers. They are usually the cheapest form of transit and follow varied routes usually starting and ending at well known landmarks.

[18] We adjust these data by multiplying the values by $\frac{7}{3}$ so that the values reported in the tables represent a weekly time period. This allows for easier comparisons across measures.

that depend exclusively upon respondent recall (Kreindler, 2020, Martin and Thornton, 2017). Google Timeline records the places an individual has been, how long it took to get there and how long they stayed there. Users can access both the summary of their travel and more detailed data which breaks the day into separate trips including information on the exact locations and exact times of their travel. Depending on the city, Google Timeline can differentiate between modes of travel including private car, bus, train, as well as plane, motorcycle and walking. In Cairo, Google's mode algorithm is unable to differentiate between car and bus travel since the two modes use the same routes and travel at similar speeds. We use the Timeline data to measure the total daily travel for each participant in the study – participants read their summary statistics to enumerators over the phone. We utilized this method to avoid participant concerns about potential violations of privacy.

The daily travel measurements on the Timeline app rely upon GPS measurements and a proprietary algorithm that is designed to detect and minimize error for a given set of measurements. While the large user base and importance of accurate trace data for many of Google's products may yield a more robust set of measurements than those collected from other available trace-retrieval applications (and their correction algorithms), little work has been done on the accuracy of the daily travel measurements from the Timeline app. Most prior studies that have used GPS data have relied exclusively on the single source, making it difficult to understand the magnitude or implications of measurement error. In Appendix C, we provide an analysis of measurement error in total daily travel using trip logs conducted by our research team prior to the experiment as well as using Uber administrative data and additional survey information for participants during the study.

3.3 Follow-Up Surveys and Uber Administrative Data

Upon completion of the baseline survey (including reporting on their total daily distance traveled from Google Timeline), we randomized individuals into the different treatment groups. We then implemented multiple rounds of follow-up phone surveys with each participant in the sample, with four attempts per participant. Follow-up surveys mirror the baseline survey in collecting data on recent travel, counterfactual expectations about a participant's longest trip using alternate modes, and Google Timeline data over the past three days using the summary feature in the mobile application. Individuals were informed that for each successfully completed survey they will receive 25 EGP in Uber credit on their account. This is distinct from the subsidized prices shown only to participants in treatment.[19]

[19] These one-time credits have the potential to have differential impacts due to their interaction with reduced prices. On average, 1 km of travel on Uber costs approximately 6 EGP, so those in the 50% treatment could travel an additional 4 km on each credit relative to control. A conservative upper bound estimate of this impact would be 20 km over the study period. By comparison, our impact estimates

All participants consented to allow Uber to share trip-level Uber utilization data with the research team, including the 3-month period preceding the study, the study period, and the 3-months following the completion of the study.[20] For each trip, this dataset records the Uber service used (e.g. UberX, Uber Bus, etc.), the time of the trip (rounded to the nearest hour), the start and end locations of the trip (rounded to the 4th digit latitude/longitude), the distance and duration of the trip, the fare (both before and after the application of the price treatment, if appropriate), and any credits applied for payment of a trip (including the 25 EGP credits obtained after the completion of each survey).

4 Impacts on Uber Utilization

We use the following specification to estimate the impact of price treatments on outcomes:

$$Y_{it} = \beta_1 T_{1i} + \beta_2 T_{2i} + \beta_0 Y_{0i_{DPL}} + \delta_C + \gamma_t + \lambda_S + \varepsilon_{it} \tag{1}$$

where Y_i is the outcome of interest (e.g. weekly kilometers on Uber), T_1 and T_2 are indicators for the 25% treatment and 50% treatment respectively, $Y_{0_{DPL}}$ represents the set of baseline controls chosen using the double post-lasso procedure outlined in Belloni et al. (2014), δ_C are randomization cohort fixed effects, γ_t represents fixed effects for each round of follow-up surveys, and λ_S represents randomization strata fixed effects.[21] Standard errors are clustered at the individual level.

For continuous variables, we measure outcomes using the Inverse Hyperbolic Sine (IHS) transformation, which confers three primary advantages: (1) our outcome data follow a log normal distribution, which lends itself to the IHS form; (2) it allows us to interpret the coefficients as percentage changes. To properly translate the coefficients into percentage change, we can calculate "$exp(\beta) - 1$," which for small values of β are approximately equal to β. As described below, several estimates that we report are quite large and the values can differ as a result (Bellemare and Wichman, 2020). We therefore report both the IHS coefficient in the tables and the corresponding percentage change in the text; (3) The IHS transformation dampens the effects of outliers, while retaining realizations in outcomes that have a value of zero.[22]

are equivalent to an increase of over 700 km in distance traveled on Uber in the 50% group relative to control during the study period.

[20] We analyze the post-treatment impacts of the subsidies in Appendix F.

[21] In addition to results with baseline controls chosen with the double post-lasso (preferred specifications), we also report our main results while controlling only for the baseline value of the outcome variable in Appendix G. We find no substantial differences in the two specifications, aside from increased precision in our preferred estimates. We list all controls provided to the lasso in Appendix G. We also control for two additional information treatments that were cross-randomized on the sample which are outside the scope of this paper.

[22] A recent paper discusses the potential for the scale of the dependent variable to affect estimated elasticities (Aïhounton and Henningsen, 2020). When we implement the procedure from Aïhounton and Henningsen (2020), we find that kilometers is close to the optimal level of scaling and provides slightly more conservative estimates. Our elasticity estimates are also very similar to the estimates generated using nominal levels instead of the IHS transformation.

4.1 Effects on Uber Usage

Table 1 reports estimates of the effects of the price reduction on the utilization of Uber services for transportation in the three experimental groups: control, 25% price reduction treatment, and 50% price reduction treatment. Column 1 reports effects on weekly distance traveled, which are estimated using the IHS transformation. Relative to the mean of 13.6 km per week for the control group, we estimate that the utilization of Uber services increases by 1.01 IHS points (approx. 23.7 km or 175% per week) for participants who receive the 25% price reduction and by 1.70 IHS points (approx. 60.8 km or 447% per week) for participants who receive the 50% price reduction.

Average effects mask important differences between male and female participants. In Column 2, we include an interaction term for male riders. These estimates indicate that female participants are more price elastic than their male counterparts. Weekly distance traveled on Uber in the 25% treatment group increases by 1.11 IHS points among female riders and by 0.93 IHS points among male riders. A similar difference is found in the 50% treatment group, where Uber utilization increases by 1.85 IHS points among female riders and by 1.58 IHS points among male riders. These estimates imply that women in the 50% (25%) group traveled an additional 849 km (322 km) on Uber over the course of the study relative to the control group, and men in the 50% (25%) group traveled an additional 652 km (259 km) relative to control over the 12 weeks.

Columns 3 and 4 report effects on the average number of trips taken in a week.[23] Estimates in column 3 indicate that relative to the mean of 1.5 trips per week for the control group, participants who receive a 25% reduction increase their Uber trips by 1.8 trips per week (to 3.3) and participants who receive a 50% reduction increase trips by 3.7 per week (to 5.2). Estimates in column 4 indicate that the differential effect on trips for female participants in the two treatment groups parallels the findings on distance. In the low treatment group, the number of trips increases by 131% (from 1.5 to 3.5 trips per week) for women, and 100% for men (from 1.6 to 3.2 trips per week). The 50% price treatment increases trips by 274% for women (from 1.6 to 5.7 trips per week) and by 205% for men (from 1.5 to 4.8 trips per week).

Figure 1 plots average kilometers traveled on Uber across the 12 weeks of the study by gender and treatment group. While the initial increase in utilization for the 25% group levels off, the (larger) initial increase for the 50% group continues to grow over time. One explanation for this result is that changes in the price of ride-hailing services can induce learning and experimentation at lower price points that may not occur for a 25% reduction.

We plot the results from quantile regressions of the treatment effect in Figure B3. We do not interpret these as quantile treatment effects, as that would require a strong

[23] Since the number of trips in a week is usually small we analyze this variable using levels instead of IHS.

rank-preservation assumption. On the other hand, it provides suggestive evidence that our estimates of average treatment effects are not driven by a small group of "super-users." Panel A presents the estimates on total distance traveled. We find that they are relatively evenly distributed across quantiles. In both the 25% and 50% price treatments, there are a small fraction of riders that do not respond to the treatment, a large increase in the middle of the distribution, and a moderate increase at the top of the distribution. Panel B presents the estimates for trips taken, which illustrate a steady increase over the distribution, with larger increases for women relative to men. In each of the quantile regressions, we utilize bootstrapped standard errors with 1,000 repetitions, clustered at the individual level.

4.2 Price Elasticity of Demand for Uber

In Panel B of Table 1, we explicitly estimate price elasticities of demand for both distance traveled and trips per week. Demand elasticities for total Uber kilometers average -9.5 for women and -6.8 for men. Elasticities estimated based on the number of trips taken are more similar across genders, with women averaging -5.1 and men averaging -4.4. The confidence intervals for these elasticity estimates generally overlap between genders.

Our estimates are larger than recent private travel elasticities from the United States gasoline market, which are larger than had been found in prior studies with aggregate data and cross-sectional designs Levin et al. (2017). They are also larger than those found in the United States taxi market (Rose and Hensher, 2014) However, they are consistent with recent estimates from ride-hail services in Prague (Buchholz et al., 2020). Our estimates may differ with the earlier literature for a few potential reasons: (1) Prior studies have typically examined the effects of short-run price changes. As far as we are aware, this price treatment was the largest and longest that Uber has provided to riders. We will test the importance of this in the following subsection. (2) Whereas prior studies have typically focused on transport markets with higher-quality substitutes, this study specifically focuses on a transit-constrained city. The large price changes examined in this study may induce significant substitution across different modes of travel, including other ride-hailing services; We assess the importance of substitution across modes in Section 5.2. (3) The experimental elasticities in Table 1 isolate the response to a change in price alone, while studies of market-wide price changes examine responses to changes in monetary costs as well as endogenous increases in time cost related to congestion effects. We examine differences between the effects of monetary price changes in our sample and the equilibrium effects of market-level price reductions in Section 6.

Experiments on the Salience and Length of Treatment

It is possible that our pre-announced price reductions affected the salience of discounted Uber services, leading to increased utilization due to the attention our study brings to travel as opposed to the price effects alone. In order to better disentangle the experimental effect of the price change from the salience and length of announced discounts, we implemented two separate 1-week experiments with additional waves of participants.

In the first auxiliary experiment, we split the sample into 3 treatment groups (50% price reduction, 10% price reduction, control) and held all elements of the experimental protocol constant aside from the length of the intervention.[24] Participants were sent an email telling them that they were enrolled in the study, and that they would get a *1 week* subsidy based on their treatment group (as opposed to the 3 months in the main experiment).

In the second auxiliary experiment, we split a different sample into 3 treatment groups (50% price reduction, 10% price reduction, control) but instead of informing the participants of their impending discount we simply applied the discount to their accounts automatically for 1 week. These individuals did not know in advance that they would have a price reduction during this time, nor did they know how long the price reduction would continue for. This experiment deviates from the main experiment in two ways: (1) in the length of the subsidy (i.e. 1 week vs 3 months) and (2) in the salience of the subsidy (pre-announced vs unannounced).

Table 2 reports the results of these two experiments alongside estimates of effects from the first week of the main experiment. We assess the importance of salience by comparing impacts on Uber utilization for the 10% treatment group in columns 3 & 4 versus columns 5 & 6. If it were the case that prior knowledge of the discount was leading to strategic overuse of Uber during the 1 week of the discount (e.g. moving up travel they were planning to take in the future to benefit from the discount), we would expect greater increases among participants in the pre-announced experiment relative to those in the unannounced experiment. Instead, we find that the effects on weekly kilometers are nearly the same across the two experiments, while the number of trips is somewhat smaller but not statistically different in the pre-announced experiment. Even without strategic overuse, bringing attention to the subsidy could have led to additional utilization due to salience effects. We do not find any evidence to support this hypothesis.

We evaluate the effect of knowledge of the 3-month experimental treatment by comparing the impacts from the 1-week experiments to the impacts from the first week of our main experiment. The point estimate for weekly kilometers from the 50% price reduction is 0.65 in the main experiment versus 0.77 in the 1-week experiment. These estimates are statistically equivalent. Hence, it does not appear that intervention length has an important impact on the findings reported in our main experiment.

[24] We reduced the treatment in the low group from 25% to 10% as a result of implementation costs. We also note that due to an implementation error in this experiment, the 50% group was provided a one-time price change instead of a week-long price change and so we omit them from the table.

4.3 Effects on the Geography of Uber Utilization

We use Uber administrative data on the origin and destination locations of trips taken by study participants to examine the effects of price changes on the geography of travel behavior. We begin by estimating differences in the number of unique locations visited using Uber services during the intervention, noting that this captures the effect of treatment on changes in how participants use Uber services but not their travel outside the platform (which we consider in Section 5). We do this by dividing the Cairo Metropolitan Region into 1x1 km grid cells and then computing the total number of unique grid cells that a participant travels to (origins or destinations) across the 12-week study period.

Columns 1 & 2 in Table 4 report the average number of locations visited for participants in the study. We find that the average participant in the control group travels to 8.9 unique grid cells during the study period. This increases by 5 grid cells for participants in the 25% treatment group, an increase of 64%. Participants in the 50% treatment group more than double their Uber travel to unique destinations (to 18.7 grid cells). We do not find evidence of strong differences by gender. These results indicate that price reductions induce both groups to increase their consumption of Uber services and also to use Uber services to travel to locations that they did not previously visit using Uber.

We dig deeper into effects on Uber travel behavior by testing for increased travel to major universities, hospitals and metro stops throughout Cairo.[25] Table 4 reports differences for each of the treatment groups. We find that the 25% price reduction increases the number of trips to universities by 88%, trips to hospitals by 141% and to metro stations by 237%. In the 50% price reduction trips to universities increase by 265%, to hospitals by 240%, and to metro stations by 251%. We find some evidence that the effects on travel to universities are stronger for women in the 50% treatment group, though this difference is marginally significant.

5 Effects on Overall Mobility and Substitution

5.1 Effects on Overall Mobility

The estimates reported in the prior section demonstrate that price reductions on Uber services dramatically increase Uber utilization and that subsidies increase Uber travel to an expanded set of locations in Cairo. However, these estimates alone are not sufficient for determining to what extent the price treatments increase mobility (total travel) versus inducing substitution from other modes. To our knowledge, no prior study has measured effects on total mobility or fully accounted for substitution behavior in the context of reductions in the cost of private transport services. This is likely to be especially important in many transport markets in developing country cities, where travel is not dominated

[25] We define a trip to these points of interest using buffers of 100 meters, 175 meters, or 250 meters around the buildings using OpenStreetMap. These locations and boundaries are illustrated in Appendix E.

by a single transit mode (such as private car travel).

To test for effects on total mobility, we estimate differences in *total distance traveled* by participants during the intervention using data from each participant's Google Maps Timeline (described in section 3.2 above).[26] Table 4 reports estimates for each of the treatment groups. Columns 1 and 2 report effects on total distance traveled during the week before the survey, as reported on a participant's Google Timeline during follow-up surveys.[27] Relative to the mean of 205 km per week for the control group, point estimates suggest that total mobility increases by 0.10 IHS points (approx. 22 km or 10.5% of the control mean) for participants who receive a 25% price reduction, though this effect is not statistically significant. Total mobility increases by 0.4 IHS points (approx. 101 km or 49% of the control mean) among participants who receive a 50% reduction.[28]

The average male participant in the control group travels nearly twice as much as the average female participant (261 km vs. 145 km per week). Column 2 reports effects on overall mobility for female versus male riders. Among female riders, our estimates suggest a larger (but non-significant) increase of 0.18 IHS points (approx. 29 km or 19.7% of the control mean) in the low treatment group. In the high treatment group, we estimate an increase of 0.55 IHS points (approx. 106 km or 73% of the control mean). Differences by gender are not statistically significant, but suggest much smaller effects for men in both treatment groups. These estimates imply that women in the 50% (25%) group traveled an additional 1,272 km (342 km) overall over the course of the study relative to the control group, and men in the 50% (25%) group traveled an additional 930 km (161 km) relative to control over the 12 weeks.

Price Elasticity of Demand for Mobility

In Panel B of Table 4, we report estimates of the price elasticity of demand for mobility (total travel). The estimated elasticities for the full sample are -0.44 for the low subsidy and -0.99 for the high subsidy. The average elasticity for women is -1.32, and for men it is -0.38. These estimates are consistent with other estimates of price elasticity of travel demand. Power calculations conducted prior to the experiment suggested that treatment effects on total travel could be difficult to detect for the 25% group and indeed we cannot rule out an elasticity of 0 in the 25% group. Hence, another possible interpretation of our results is that moderate changes in cost of Uber may not change overall mobility, but large price changes do. Figure B3 includes results from quantile regressions of total distance traveled by treatment and gender in Panel C. We find that the results are rather evenly distributed across all quantiles, providing evidence that our average treatment effects are not driven by a small subset of users who dramatically increase their overall

[26]We describe a battery of test to assess the accuracy of these data in Appendix C.

[27]As mentioned above, we collect the three days of data prior to our follow-up survey from Google Timeline. We multiply this by $\frac{7}{3}$ to simplify comparison across measures.

[28]The estimated impacts for the two treatment groups are statistically different at the 1% level.

mobility.[29]

5.2 Is Uber a Substitute or a Complement to Other Modes?

Cities around the world are interested in the extent to which travelers use ride-hailing services as a substitute or complement to public transit. Empirical studies have produced mixed results, with some concluding that ride-hailing services increase private vehicle kilometers traveled (PVKT) (Tirachini and Gomez-Lobo, 2020) and others indicating that they increase public transit use (Hall et al., 2018).[30] The literature has thus far been unable to reconcile these results, which is critical for developing optimal transport policies.

Our research design allows us to evaluate how transport mode choice responds to changes in Uber usage at the individual level. Table 5 reports effects on the number of trips taken on each the 5 main modes of transportation on the day before our survey.[31] The bottom panel reports corresponding effects on mode choice probabilities.[32] The estimates reveal evidence of *substitution* away from the primary transit mode used by the Cairo sample: the public bus. The 50% fare reduction reduces the number of weekly bus trips by 1.51 and the probability of taking a bus trip by 10 percentage points. We also observe a smaller shift away from taxis, which are perceived as less safe and more costly than ride-hailing services. We find suggestive evidence of small increases in the number of trips taken by metro and private car in the 50% treatment, although these differences are not statistically significant.

Our survey collects data on the total number of ride-hailing trips, including Uber as well as other services such as Careem. By comparing the treatment effects estimated using Uber admin data to treatment effects on total ride-hailing trips from the survey, we can evaluate the magnitude of substitution between Uber and other ride-hailing services in response to the price change. While those in the 50% group take an extra 3.66 trips on Uber (based on our estimate in Table 1), they only take an additional 2.32 trips on any ride-hailing service. Assuming the self-reported trip data are perfectly comparable to the Uber administrative data, this implies a substitution effect of approximately 1.34 weekly trips from Careem to Uber, which is about a third of the increase in Uber utilization. The same substitution behavior occurs in the 25% treatment group, about half as often.

Overall, our results indicate that price reductions on Uber induce substitution away from bus trips, taxi trips and other ride hailing services. Nonetheless, a reduction in the

[29]The quantile regressions utilize bootstrapped standard errors with 1,000 repetitions, clustered at the individual level.

[30]Using variation in entry timing and growth of Uber services across metropolitan areas, Hall et al. (2018) suggest that within 2 years of entry, Uber services *increased* public transit use by 5% for the average transit agency in the U.S.

[31]We multiply the number of trips by 7 to simplify comparison with the weekly time period used in the other tables in the paper.

[32]We compare effects on mode choice probabilities for all trips to those for longest trips in Appendix Table C7 and find that they are highly consistent.

proportion of travel taken on public bus doesn't necessarily imply a decrease in the total travel taken on public transit. While we do not directly measure changes in the distances traveled for each trip taken by each mode for each individual, results in Appendix Table B3 indicate that the average length of Uber trips increases substantially for those in treatment.[33] In Appendix Table B4, we estimate the total distance travelled separately by public and private modes under the assumption that total distance traveled on a mode is proportional to the rate of utilization of that mode. Under this assumption, we find no evidence of a significant decrease in total distance traveled on public transit, with point estimates consistent with a potential increase. This suggests that ride-hailing could serve as a complement to public transit in certain contexts.

The findings above illustrate the importance of understanding multi-margin responses to shifts in the price of transport services. As participants become more mobile, they may increase their use of other modes in multi-part journeys or for return trips. Our micro-level findings indicate that price reductions have considerable effects on trip substitution, though these substituation effects may not convert into large reductions in the kilometers traveled using public buses use when accompanied by strong increases in total travel. The implication for metro use, where point estimates suggest an increase in the 50% group that is not statistically significant, is that the 50% price reduction may have induced a net increase through complementarity. This is corroborated by the finding (from Table 4) that price reductions increased Uber travel to and from metro stations.

5.3 Safety Concerns Help Explain Heterogeneity by Gender

Our baseline survey reveals important gender disparities in baseline mobility levels and in expectations regarding safety on public transit. In the presence of large fare reductions for ride-hailing services, women may benefit from shifting existing trips away from modes where they feel less safe, which could help explain why we find greater substitution behavior by women relative to men. We explore this below using two different pieces of information: (1) self-reported levels of safety on recent trips and (2) heterogeneity in effects on Uber use and total mobility among safety-conscious riders.

In Table 6, we report the estimated effects of the treatments on the reported *safety* of the longest trip that a participant took on the day prior to the survey. We find significant increases in the perceived safety of recent trips among participants in the high treatment group. However, they appear to be entirely driven by female participants,

[33]Estimates reported in Appendix Table B3 indicate an increase of 0.17 IHS-points in the length of trips on Uber in the 50% treatment group, which corresponds to an 18.5% increase. The results from Table 5 indicate participants in the 50% group take 1.2 additional trips per week (across all modes of transport), a statistically significant 6% increase relative to control. Combining these two estimates produces a calculated increase in total mobility of 26%, which lies within the confidence interval of our estimates of the impact of the 50% price reduction on total mobility using the Google Maps Timeline measure, providing additional evidence of consistency in the estimated effects obtained using the different data sources.

who report a 0.2 point increase in the safety of yesterday's trip from an average baseline rating of 4 out of 5. We find no impact on perceived safety among men.[34] To assist interpretation, estimates in Columns 3 & 4 standardize the outcome variable. Perceived safety increases by 0.17 standard deviations in the 50% group, which is considered large in other literatures with hard-to-interpret outcomes (e.g. test scores in education (Evans and Yuan, 2020)).

Panel A of Table 7 reports the results of tests for differences in the effects of the price interventions on mobility for individuals who used the bus at baseline. These tests suggest important gender differences that also vary across the two treatment groups. Whereas our estimates suggest that the intervention may have had somewhat *smaller* effects among male bus riders in both groups, we find *substantially larger* effects for female bus riders in the 50% treatment group (Columns 2 & 3). The intervention increases Uber utilization by 2.29 IHS points for this group. Our point estimate becomes even larger when we examine effects for female bus riders who perceive public transit as unsafe (at baseline) (Column 5). For this group, the 50% price reduction increases Uber utilization by 2.93 IHS points.

In Panel B, we report effects on total mobility for the same groups. These estimates indicate that while female bus riders increase their Uber usage relative to non-bus riders, they do not increase their overall mobility relative to non-bus riders. This result holds for women who perceived the bus as unsafe at baseline. Appendix Table D3 helps explain this by showing how women who took the bus at baseline substitute away from the bus more, while men don't. Taken together, these results indicate that price reductions on Uber lead to important differences in travel by gender and baseline behavior and perceptions. In particular, women substitute away from using the bus for long trips and subsequently report feeling more safe on their recent trips. This result is stronger for women who perceived the bus as an unsafe mode of transit at baseline.

5.4 Robustness Tests

We consider three main types of robustness tests: (1) income effects from reduced transport prices, (2) survey response rates, and (3) sensitivity to controls.

One underlying concern in our experimental design is that the price intervention also serves as an implicit income transfer. By making these trips cheaper, the overall budget constraint for participants has changed and it is possible that participants use Uber more because they have more income to spend on travel. We examine heterogeneity in effects by income level to consider the potential importance of this effect in interpreting our estimates. We do this by identifying individuals in the top 25% of baseline income and classify them as "high income," while also identifying those in the bottom 25% of income

[34] Table D2 in the appendix shows that nighttime travel on Uber is similar across both genders, implying that these safety gains are more due to adaptations to the general safety environment as opposed to specifically unsafe times of day.

and classifying them as "low income" within our sample. We then interact indicators for high/low income with treatment indicators. Appendix Table D4 reports the results of these regressions.

We find that individuals in the high income group are likely to increase their utilization of Uber more than the rest of the sample. At the same time, we find that those in the low income group utilize Uber less than those in the rest of the sample. If income effects were a primary driver of our results, we would expect to find the opposite. The marginal value of the income effect should be larger for participants in the lower income quartile, increasing their responsiveness to treatment.

Second, Appendix Tables B5 - B7 provide information about survey response rates. Column 1 shows that 94% of the control group responded to at least 1 follow-up survey, with 96% of the low treatment group responding to at least one and 97% of the high treatment group. Columns 2-5 provide information about response rates for each survey. The first two follow-up surveys indicate that control group response rates fall in the 80% range while the latter two suggest much lower response rates. Treatment assignment does lead to a statistically significant increase in response rates. Reassuringly, Appendix Tables B6 & B7 illustrate that there is no differential response based on observable characteristics. In other words, individuals who are responding to the surveys in the treatment groups are observationally equivalent to those who respond to the surveys in the control group. This is true both for whether they respond to any follow-up survey, as well as for their response rates for all follow-up surveys. We also estimate lee bounds for both our "Total Mobility" and "Safety" outcomes in Appendix Tables B8 & B9 (we have no attrition in the Uber admin data by design).

Third, our main results utilize the double-post lasso procedure outlined in Belloni et al. (2014). This procedure allows us to maximize statistical power while remaining agnostic regarding which controls to include in our regressions. In Appendix G we redo our main tables using the ANCOVA specifications that were previously standard in the experimental literature (McKenzie, 2012). Those tables include the results from regressions of the outcome variable on treatment indicators and control for the baseline value of the outcome variable when available (as well as all relevant strata and survey round fixed effects). We find no meaningful differences between both sets of results.

6 Consumer Surplus and External Costs

6.1 Consumer Surplus from Increased Mobility

Our research design allows us to recover estimates of the consumer surplus associated with mobility impacts from price reductions on ride-hailing services in Cairo. Results in prior sections indicate that reductions in the price of private transport changes the amount of travel and the modes used, such that the demand response on Uber alone may not yield a comprehensive measure of surplus. Using the experimentally-identified demand elasticities for travel on Uber services (Table 1) and those for total travel (Table 4), we can compare the benefits from the utilization of Uber services CS^{Uber} and those estimated using total travel $CS^{Mobility}$. We also compare these estimates to those obtained using the demand for Uber trips and total trips as measured in our surveys.

We compute the consumer surplus from a 50% price reduction using the following equation, which evaluates demand across the intervals that correspond to each of the two experimental treatments: (1) from $P_{1.0}$ (baseline) to $P_{0.75}$ and (2) from $P_{0.75}$ to $P_{0.50}$.

$$CS_{Experiment} = \int_{Q_{1.0}}^{Q_{0.75}} P_{0.75}(Q)\, dQ + \int_{Q_{0.75}}^{Q_{0.5}} P_{0.50}(Q)\, dQ \tag{2}$$

For estimates of consumer surplus using the Uber-specific response, we measure kilometers traveled on Uber ($Q_{1.0}^{Uber}$) using the mean in the control group and use the demand elasticity estimates from Table 1 to measure the points $Q_{0.75}^{Uber}$ and $Q_{0.5}^{Uber}$. We recover the price of a kilometer in the control group $P_{1.0}^{Uber}$ using the average price in our administrative data and obtain $P_{0.75}^{Uber}$ and $P_{0.5}^{Uber}$ using information from each treatment group. We use equivalent trip-level administrative data from Uber to obtain trip prices ($P^{UberTrips}$) and estimates from the right panel of Table 1 to obtain the quantity of trips demanded at each price level ($Q^{UberTrips}$).

For estimates of consumer surplus from the total mobility response, we measure the baseline level of kilometers traveled $Q_{1.0}^{TotalKm}$ using the control mean and measure $Q_{0.75}^{TotalKm}$ and $Q_{0.5}^{TotalKm}$ using demand elasticity estimates from Table 4. We generate the price per kilometer of travel as the composite price for all transport services used by participants at a given price level. Since we do not have prices for each trip on each mode, we use the within-trip relative prices reported across different modes in our survey, and weigh them by the mode share used in each experimental group. The composite price of mobility therefore captures changes in the price of Uber as well as shifts in the composition of modes used as participants optimize transport choices in response to the experimentally induced price reductions of Uber services. We replicate this procedure using the number of trips and their composite price.[35]

The top two rows of Table 8 (Panel A) report estimates of consumer surplus using the demand response on Uber ($CS_{0.5}^{UberKm}$) and the demand response for total mobility ($CS_{0.5}^{TotalKm}$). In the left panel, we report consumer surplus estimates computed using two points on the demand curve ($Q_{0.75}$, $Q_{0.5}$), as in Equation 2. In the right column, we include a variant estimated with a single point ($Q_{0.5}$). The magnitudes are very similar. The consumer surplus estimate from the demand response on Uber ($CS_{0.5}^{UberKm}$) indicates that the average participant receives 88 EGP per week from the price reductions.

[35]See Appendix J for details on composite price calculations and sensitivity analysis of CS results to reporting bias in the relative prices of different modes.

The benefits are 19% larger for women than men. The consumer surplus from total mobility ($CS_{0.5}^{TotalKm}$) impacts induced by the same 50% price reduction on Uber indicate substantially larger benefits of 156 EGP per week for the average participant in our sample. Accounting for the total mobility impacts of a price reduction on ride-hailing services results in benefits that are nearly twice as high than those estimated when considering mode-specific demand for Uber services alone.

Rows 3 and 4 of Table 8 (Panel A) report consumer surplus estimates that correspond to the demand for trips observed using Uber administrative data and the trip survey. These estimates are substantially smaller than those estimated using distance traveled, providing evidence of non-trivial benefits from increases in the length of trips taken in response to reductions in the price of ride-hailing services. Results in Table B3 illustrate a 17% increase in the length of Uber trips in the 50% treatment group. A comparison of the estimates in row 3 to those in row 4 reinforces the key finding above, which is consistent across transport measures and data sources. A large fraction of the benefits from price reductions on ride-hailing services owe to impacts on total mobility, which capture extensive margin effects as well as effects on complements/substitutes.

The results above contribute three novel findings to the literature on the welfare impacts of reductions in the cost of transportation: (1) Several recent studies have indicated that reducing the monetary cost of transportation can improve the economic outcomes of mobility-constrained populations (Franklin, 2018, Bryan et al., 2014, Phillips, 2014). The estimates above provide a measure of surplus based directly on participant demand for total mobility ($CS_{0.5}^{TotalKm}$) and suggest benefits that are equivalent to 13% of the monthly income of the average participant in our sample. (2) Every available measure of surplus reported above indicates that benefits accrue disproportionately to women in our Cairo sample. The same women report feeling unsafe on the primary mode of public transportation and have lower baseline levels of mobility than their male counterparts. This provides further evidence to support the general finding that safe, low-cost transportation services dramatically improve the welfare of mobility-constrained populations and the body of emerging evidence on the specific importance of mobility for women in developing countries (Kondylis et al., 2020, Jayachandran, 2019, Velásquez, 2019, Borker, 2018). Finally, the results above provide strong evidence that the benefits from reductions in the price of a given technology can operate through complements/substitutes in the transport market, such that the total welfare effects in Cairo are approximately double those estimated when considering Uber-specific effects.

6.2 Equilibrium Responses to Market-Level Price Reductions

Our experiment provides a unique opportunity to isolate the price elasticity of travel demand in the absence of changes in congestion that we would expect from a market-level price change. Understanding behavioral responses to market-level reductions is also important for considering optimal policy design, as governments grapple with how to respond to advances in transport technologies and growth in transport demand. Some researchers have estimated that innovations in ride-hailing and other technologies could reduce the cost of these services by 40-80% (Narayanan et al., 2020). In this section, we estimate how market-wide price reductions may affect our estimated elasticities and compare consumer surplus and external costs in equilibrium.

We focus on estimating the impacts of a *market level* reduction in the price of ride-hailing services on private kilometers traveled (PVKT) by considering the combined impact of extensive margin and substitution effects in a model with endogenous congestion. This simple model is motivated by theoretical and empirical findings indicating that a market-level price reduction would increase congestion, which would increase the effective price of travel (through added time cost) and exert downward pressure on demand. We use the demand elasticities estimated from the experiment and estimates of rider value of time (VOT) to inform a simple model of transport supply and demand in Cairo. We use this model to estimate equilibrium demand elasticities and then study the implications of market-level price reductions on external costs and consumer surplus.[36]

A Simple Continuous Supply and Demand Framework for Mobility

In our simple model, equilibrium travel in Cairo is given by the following demand and supply equations:

$$\Delta X_{PVKT} = f(\Delta P_U) = \varepsilon_{Eq} * \Delta P_U \tag{3}$$

$$\Delta P_E = \Delta P_U + g(\Delta X_{PVKT}, PR_U) * (C_{VOT}) \tag{4}$$

The demand equation defines the change in private vehicle kilometers traveled (X_{PVKT}) as a function of the change in the price per kilometer of Uber travel. We are interested in recovering ε_{Eq}, which is the equilibrium elasticity of private vehicle kilometers traveled with respect to the price of Uber. Our experimental results above are consistent with a price elasticity of travel demand that is approximately linear, and so we assume here that the $f(.)$ function is also linear.

The supply equation states that the change in the effective price of Uber ΔP_E is equal to the change in the price of Uber plus the change in the cost of time due to an increase in congestion resulting from induced demand. The $g(.)$ function converts changes in private kilometers traveled into changes in congestion, conditional on five basic assumptions: (1) congestion is a function of the change in private kilometers traveled and the proportion of the population that uses ride-hailing services (PR_U), (2) the congestion function is linear, which is consistent with recent work by Kreindler (2020) in a similar developing country setting, (3) the value of time on Uber is 75% of the hourly wage in

[36] Changing the market-level price of Uber could potentially affect passenger levels on different modes of transport and their safety, though we assume that the net effects of multiple possible adjustments would be small.

the sample, consistent with recent estimates from the ride-hailing market (Goldszmidt et al., 2020), (4) increases in aggregate demand for Uber don't affect the baseline Uber price, and (5) labor supply in the ride-hailing market is perfectly elastic, such that drivers face no frictions in responding to increased demand. The final two assumptions allow us to focus specifically on the effects of price variation from the experiment, but are also generally consistent with recent evidence from other low income settings (Alvarez and Argente, 2020b).[37] Solving the model generates the following expressions:

$$\varepsilon_{Eq} = \varepsilon_{PVKT} * \gamma \tag{5}$$

$$\gamma = 1/(1 - \varepsilon_{PVKT} * PR_U * C_{VOT}) \tag{6}$$

Equation 5 defines the equilibrium elasticity of PVKT as the product of the partial equilibrium elasticity of PVKT (ε_{PVKT}) and an adjustment parameter (γ). The adjustment parameter captures the impact of price reductions on aggregate travel demand (congestion), which by increasing the time cost of travel, attenuates impacts of ride-hailing price changes on demand for private transit. Equation 6 illustrates that the magnitude of this attenuating effect depends on the interaction between the price elasticity of private travel demand ε_{PVKT}, the size of the ride-sharing market in Cairo (PR_U), and the normalized cost of an additional minute of travel (C_{VOT}).

Elasticity of Private Vehicle Kilometers Traveled

As illustrated in Section 5, riders respond to reductions in the price of private transport services by changing how much they travel, as well as the modes they use for travel. To account for both of these changes we use the following general formula:

$$\varepsilon_{PVKT} = f(\varepsilon_{ext}, \varepsilon_{sub}) \tag{7}$$

That is, the elasticity of private vehicle kilometers traveled (ε_{PVKT}) is a function of how riders respond in their demand on the extensive margin of distance (ε_{ext}) and how they respond by substituting between public and private transportation options (ε_{sub}).

We measure ε_{ext} using elasticity estimates from Table 4, which indicate that for the average participant in our study, a 50% reduction in the price of ride-hailing services induces a 49% increase in total VKT. This translates to an average elasticity of -0.98, which is higher for women than men (-1.46 vs -0.59) in Cairo.[38] We measure ε_{sub} using estimates of substitution from Panel B of Table 5, which indicate that a 50% price reduction in Uber services induces a 10 percentage point shift away from public transport to private transport (calculated on base of 40% public and 60% private vehicle utilization). If we assume that the average proportion of trips taken on public transport in each

[37]Other papers consider a more complete supply side model in ride-hailing and taxi markets (Buchholz et al., 2020, Frechette et al., 2019, Castillo, 2019, Shapiro, 2018)

[38]As shown in Table D1, virtually all of the additional travel on Uber services is made using UberX single-occupancy services.

treatment is indicative of the proportion of total kilometers taken on public transport, we can estimate the effects of a 50% price reduction on VKT in private vehicles.[39]

The average person in the control group travels 205 km in a typical week. 60% (123 km) of this is done in private vehicles. Treatment leads to a 49% increase in overall kilometers traveled (an additional 101 km, for a total of 306 km traveled) and a 10 percentage point shift in travel by private modes (to 70%). Treated individuals travel 214 km in private vehicles, leading to a 74% overall increase in private vehicle kilometers traveled. This implies that the price elasticity of demand for private travel ε_{PVKT} = -1.48, in contrast the -0.98 elasticity estimate that would be generated by a naive model that does not account for substitution from public transit. The elasticity of PVKT estimates by gender are -2.06 for women, and -1.02 for men. In both cases, failing to account for substitution yields underestimates of the private vehicle elasticities.

Equilibrium Elasticity of Private Travel Demand

We now use the behavioral parameter (ε_{PVKT}) and equations 1 & 7 to estimate the equilibrium elasticity of PVKT (ε_{Eq}). Publicly available estimates of size of the Uber market in Cairo suggest that 20% of the population uses ride-hailing services (Reuters, 2018). We will assume that this increases to 40% in response to a permanent decrease in the price for our calculations. We evaluate the sensitivity of our results to a range of alternate values in Appendix J.[40] We use 75% of the hourly wage, as estimated in Goldszmidt et al. (2020), for the normalized value of time in the ride-hailing market. We multiply this by average minutes per kilometer in our data (3.1 minutes) and then divide by the average cost per kilometer (6.2 EGP). Together this provides a value of γ of 0.89 for the full sample. Hence, accounting for the dampening effect of congestion, the demand response to a change in the price of Uber is only 89% as large as the behavioral elasticity alone would suggest. This yields an equilibrium PVKT elasticity of -1.32. Our findings indicate that women in Cairo have a higher demand elasticity than their male counterparts, but with a slightly lower value of time. An analysis done separately by gender produces an adjustment parameter of 0.86 for women and 0.92 for men, which results in an equilibrium elasticity of -1.78 for women and -0.93 for men.

6.3 Consumer Surplus and External Costs in Equilibrium

We use the equilibrium elasticity of private vehicle kilometers traveled to estimate the external costs associated with the change in travel behavior using the following expression:

[39] Results reported in Appendix Table C7 indicate that changes in mode use are consistent across measures of changes in all trips versus changes in the longest trip taken yesterday. We think it is more likely that people take long trips using bus or metro services as a result of the "first/last" mile problem, which reduces the probability of short trips on bus/metro services.

[40] Ridehailing in the US has already reached nearly 40% penetration without a 50% decrease in price (Jiang, 2019).

$$\alpha_{eq} = \alpha_0 * h(\Delta P_U, PR_U) \tag{8}$$

External costs from the price reduction are a function of baseline external costs in the transport sector (α_0) and changes in private travel induced by a change in the price of Uber (from equation 5, $f(\Delta P_U) = \Delta X_{PVKT}$). A comprehensive World Bank study of transport externalities in Cairo estimates a total current cost that is equivalent to 47 billion EGP ($10.9B PPP), which was 3.6% of Cairo's GDP in 2010 (Nakat et al., 2014, 2013). The report carefully characterizes 10 different dimensions of congestion costs including travel time delay, reliability, excess fuel consumption, excess CO_2 emissions, road safety, and suppressed demand. Using the equilibrium elasticity of PVKT from section 6.2, the 0.4 estimate of the share of the Cairo population using ride-hailing services, and assuming a linear relationship between travel demand and congestion as suggested by Kreindler (2020), we estimate that a 50% reduction in the price of Uber services would result in a 68% increase in private kilometers traveled for Uber users and a 27.1% increase in external costs in the transport sector. This is equivalent to 0.98% of Cairo GDP, or $3.2 Billion PPP per year.[41]

In Panel B of Table 8, we report the consumer surplus utilizing the equilibrium elasticities. When scaled to the population of Uber users, we estimate that the total equilibrium consumer surplus is 3.5% of GDP. Comparing this estimate to the external costs (0.98% of GDP) suggests the potential for considerable increases in welfare and also substantial external cost from a technology-induced price change.[42] If the price-reduction was implemented through a government subsidy, however, it would no longer be welfare enhancing. The total cost of a ride-hailing subsidy program would be equivalent to $25.2 billion PPP, or 7.6% of Cairo's GDP.[43] While the consumer surplus from a technology-induced price reduction is greater than the external costs, the surplus would be concentrated in the segment of the higher-income, higher-educated population that uses Uber.[44] The external costs, however, would be more evenly distributed across the population given general effects on road users (including bus riders) and residents affected by pollution exposures. Hence, a technology-induced price reduction may be distributionally regressive.

[41] If we instead assumed that 30% of the population used Uber after the price change, then external costs would be equivalent to 0.76% of Cairo's GDP.

[42] The ratio of consumer surplus to external costs stays close to 3.5 as we change the proportion of the population who utilizes Uber. This is primarily due to the assumption of the linear congestion function as in Kreindler (2020). A convex congestion function would increase the estimates of external costs more as the proportion of the population increases.

[43] This calculation is made in the following way: the average elasticity of Uber KM traveled is -8.96, the equilibrium adjustment parameter is 0.89, the average KM traveled in a week for baseline is 13.6, the average cost of a kilometer is 6.2 EGP, the penetration rate is 0.4, the population of Cairo is 15.56 million, and the PPP conversion rate is 4.32.

[44] Appendix Table B2 shows that Uber riders are likely to have higher incomes than the average Cairo resident.

6.4 Impacts and Incidence of a Uniform Tax on Ride-hailing

Governments around the world have begun using tax instruments to address the effects of ride-hailing services on society (World Resources Institute, 2020). As the demand for private transport increases in a context of technology-induced price reductions, taxation strategies will become even more important. Policy concern about (regressive) external costs may result in taxes on ride-hailing services. Our results point to a potential unintended consequence of standard taxation strategies. Suppose that a government were to place a uniform pigovian tax on ride-hailing services in response to a technology-induced price reduction. A tax of this sort would reduce the mobility of female riders at a rate that is more than twice that of men (2.45x). If we assume that responses to price increases in the current pricing environment are symmetric to the responses to price reductions, then the implied incidence of a uniform tax would disproportionately reduce the welfare of female riders. Importantly, the present findings also suggest that the disparity in tax incidence could be managed through improvements in the safety of public transit services, since safety concerns help explain the differences between the demand elasticities of women and men. The combination of evidence across our treatments and data sources clarifies the need to address transport externalities while carefully considering distributional impacts by gender, and more generally by different subgroups of the population.

7 Study Limitations

We identify five main study limitations: (1) sample size, (2) incomplete data on all travel locations during the study period, (3) measurement of longer-run impacts, (4) general equilibrium effects, and (5) generalizability.

While our study and data collection procedures were designed to ensure sufficient power to detect impacts on mobility, downstream impacts such as labor market outcomes are noisier and likely require larger sample sizes for precision. Future studies could secure and invest the additional funds necessary to provide subsidies to a larger sample.

We are also limited in our ability to fully characterize certain mobility choices. For instance, our overall mobility data cannot help determine whether price reductions lead to travel to new places or to the same places more often. Using trip-level data from Uber, we find that participants in treatment increase their Uber travel to new locations, but this does not guarantee that a participant would not have otherwise traveled to that location using a different mode of transportation. Future research designs might focus more on the geographic effects of price reductions by collecting detailed data on participant location during all times of the study. Of course, this comes at a cost to participant anonymity.

As is true of many studies of transportation behavior, the 3-month study period limits our analysis of impacts on margins that involve longer-run adjustments such as vehicle purchase decisions and residential location decisions.[45] Our experimental design also does not permit a comprehensive examination of the general equilibrium effects from price reductions on ride-hailing services for the full population of Cairo. A broader examination of effects that includes adjacent sectors like housing, education, and the labor market is an important area for additional research.

Finally, as with any study of a particular intervention or policy, we are limited in how broadly our results will generalize to other contexts. We design and implement a set of auxiliary experiments that test the importance of certain features of our experimental design. These experiments provide support for the conclusion that our estimated effects are driven by strong demand for mobility in Cairo. Future research could test the external validity of our estimates by implementing similar experiments in other settings.

8 Conclusion

Ride-hailing services will continue to transform the transportation option set in cities around the world. When paired with careful data collection methods, digital platforms provide an opportunity for researchers and policymakers to more rigorously examine complex behavioral responses to shifts in the transportation sector and develop a basis for the design of evidence-based policy instruments. The present study provides evidence that in developing country cities like Cairo, individuals travel substantially more when the cost of ride-hailing services falls and they are not close to satiating their demand for mobility. These findings have important implications for researchers and policymakers, as they imply that improvements in transportation services could substantially increase urban mobility. They reinforce prior results from Duranton and Turner (2011), who find that expanding road capacity leads to a commensurate increase in travel.

Our estimates suggest that technology-induced price changes would yield large welfare effects as well as substantial external costs from increases in private vehicle kilometers. They also provide important evidence that the benefits of cheaper ride-hailing services may be pronounced for groups that face safety/harassment risk on outside options such as public buses. These benefits are concentrated among higher-income individuals that use ride-hailing services, while external costs would be borne by everyone who uses public roads or is affected by associated pollution. Tax instruments could be used to redistribute the gains more equally across society, though a uniform tax could reduce female mobility much more than it would reduce male mobility. Policymakers therefore need to anticipate the potential for substantial increases in utilization while also considering the

[45] We planned to follow up with the participants in our study 6 months after the onset of treatment to examine effects on longer-run outcomes from the 3 month treatment. While our 12-week treatments were effectively complete before the onset of the COVID-19 crisis (see Appendix K), the pandemic resulted in significant disruptions to travel behavior and survey capacity. We paused data collection for longer-term 6-month follow-ups that coincided with COVID-19, which was true for the majority of our sample, limiting what we can say about longer-run impacts on mobility.

nuanced distributional implications of price changes on population subgroups.

References

ABEBE, G., A. S. CARIA, M. FAFCHAMPS, P. FALCO, S. FRANKLIN, AND S. QUINN (2021a): "Anonymity or distance? Job search and labour market exclusion in a growing African city," *The Review of Economic Studies*, 88, 1279–1310.

ABEBE, G., A. S. CARIA, AND E. ORTIZ-OSPINA (2021b): "The selection of talent: Experimental and structural evidence from ethiopia," *American Economic Review*, 111, 1757–1806.

AHLFELDT, G. M., S. J. REDDING, AND S. DM (2016): "A Quantitative Framework for Evaluating the Impact of Urban Transport Improvements," Working Paper.

AHLFELDT, G. M., S. J. REDDING, D. M. STURM, AND N. WOLF (2015): "The Economics of Density: Evidence from the Berlin Wall," *Econometrica*, 83, 2127–2189.

AÏHOUNTON, G. B. AND A. HENNINGSEN (2020): "Units of Measurement and the Inverse Hyperbolic Sine Transformation," *The Econometrics Journal*.

ALLCOTT, H., L. BRAGHIERI, S. EICHMEYER, AND M. GENTZKOW (2020): "The welfare effects of social media," *American Economic Review*, 110, 629–76.

ALLCOTT, H., M. GENTZKOW, AND L. SONG (2021): "Digital Additiction," Working Paper.

ALLEN, T. AND C. ARKOLAKIS (2019): "The Welfare Effects of Transportation Infrastructure Improvements," Working Paper.

ALVAREZ, F. AND D. ARGENTE (2020a): "Consumer surplus of alternative payment methods: Paying uber with cash," Working Paper.

——— (2020b): "On the Effects of the Availability of Means of Payments: The Case of Uber," Working Paper.

ANDERSON, M. L. (2014): "Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion," *American Economic Review*, 104, 2763–96.

ASHER, S. AND P. NOVOSAD (2018): "Rural Roads and Local Economic Development," *The American Economic Review*.

ASIEDU, E., D. KARLAN, M. P. LAMBON-QUAYEFIO, AND C. R. UDRY (2021): "A Call for structured ethics Appendices in social science papers," Tech. rep., National Bureau of Economic Research.

ATKIN, D., B. FABER, AND M. GONZALEZ-NAVARRO (2018): "Retail globalization and Household Welfare: Evidence from Mexico," *Journal of Political Economy*, 126, 1–73.

BAUM-SNOW, N. (2007): "Did Highways Cause Suburbanization?" *The Quarterly Journal of Economics*, 122, 775–805.

BAUM-SNOW, N., L. BRANDT, J. V. HENDERSON, M. A. TURNER, AND Q. ZHANG (2017): "Roads, Railroads, and Decentralization of Chinese Cities," *Review of Economics and Statistics*, 99, 435–448.

Bellemare, M. F. and C. J. Wichman (2020): "Elasticities and the Inverse Hyperbolic Sine Transformation," *Oxford Bulletin of Economics and Statistics*, 82, 50–61.

Belloni, A., V. Chernozhukov, and C. Hansen (2014): "Inference on Treatment Effects After Selection Among High-Dimensional Controls," *The Review of Economic Studies*, 81, 608–650.

Borker, G. (2018): "Safety First: Perceived Risk of Street Harassment and Educational Choices of Women," Working Paper.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014): "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, 82, 1671–1748.

Bryan, G., E. Glaeser, and N. Tsivanidis (2019): "Cities in the Developing World," National Bureau of Economic Research.

Buchholz, N., L. Doval, J. Kastl, F. Matějka, and T. Salz (2020): "The Value of Time: Evidence from Auctioned Cab Rides," NBER.

Campante, F. and D. Yanagizawa-Drott (2017): "Long-Range Growth: Economic Development in the Global Network of Air Links," *The Quarterly Journal of Economics*, 133, 1395–1458.

Castillo, J. C. (2019): "Who Benefits from Surge Pricing?" SSRN Working Paper.

Cohen, P., R. Hahn, J. Hall, S. Levitt, and R. Metcalfe (2016): "Using Big Data to Estimate Consumer Surplus: The Case of Uber," NBER.

Desmet, K. and E. Rossi-Hansberg (2013): "Urban accounting and welfare," *American Economic Review*, 103, 2296–2327.

Duranton, G. and M. A. Turner (2011): "The Fundamental Law of Road Congestion: Evidence from US Cities," *American Economic Review*, 101, 2616–52.

Economic Research Forum (2015): "Household Income, Expenditure, and Consumption Survey," http://www.erfdataportal.com/index.php/catalog/129.

Evans, D. K. and F. Yuan (2020): "How big are effect sizes in international education studies," *Center for Global Development, Working Paper*, 545.

Federal Highway Administration (2018): "Average Vehicle Occupancy Factors for Computing Travel Time Reliability Measures and Total Peak Hour Excessive Delay Metrics," Technical Report.

Federal Transit Administration (2010): "Public transportation's role in responding to climate change," Technical Report.

Franklin, S. (2018): "Location, Search Costs and Youth Unemployment: Experimental Evidence from Transport Subsidies," *The Economic Journal*, 128, 2353–2379.

Frechette, G. R., A. Lizzeri, and T. Salz (2019): "Frictions in a competitive, regulated market: Evidence from taxis," *American Economic Review*, 109, 2954–92.

Gandelman, N., T. Serebrisky, and A. Suárez-Alemán (2019): “Household Spending on Transport in Latin America and the Caribbean: A Dimension of Transport Affordability in the Region,” *Journal of Transport Geography*, 79, 102482.

Glaeser, E. L., S. D. Kominers, M. Luca, and N. Naik (2018): “Big Data and Big Cities: The Promises and Limitations of Improved Measures of Urban Life,” *Economic Inquiry*, 56, 114–137.

Goldszmidt, A., J. A. List, R. D. Metcalfe, I. Muir, V. K. Smith, and J. Wang (2020): “The Value of Time in the United States: Estimates from Nationwide Natural Field Experiments,” National Bureau of Economic Research.

Gonzalez-Navarro, M. and M. A. Turner (2018): “Subways and Urban Growth: Evidence from Earth,” *Journal of Urban Economics*, 108, 85–106.

Gorback, C. (2020): “Ridesharing and the Redistribution of Economic Activity,” Working Paper.

Gupta, A., S. Van Nieuwerburgh, and C. E. Kontokosta (2020): “Take the Q Train: Value Capture of Public Infrastructure Projects,” *NBER Working Paper*.

Hall, J. D., C. Palsson, and J. Price (2018): “Is Uber a Substitute or Complement for Public Transit?” *Journal of Urban Economics*, 108, 36–50.

Hanna, R., G. Kreindler, and B. A. Olken (2017): “Citywide Effects of High-Occupancy Vehicle Restrictions: Evidence from ”Three-In-One” in Jakarta,” *Science*, 357, 89–93.

Heblich, S., S. J. Redding, and D. M. Sturm (2020): “The Making of the Modern Metropolis: Evidence from London,” *The Quarterly Journal of Economics*, 135, 2059–2133.

Jayachandran, S. (2019): “Social Norms as a Barrier to Womenâs Employment in Developing Countries,” Working Paper.

Jiang, J. (2019): “More Americans are using ride-hailing apps, Pew Research Center,” *Availabe at https://www. pewresearch. org/fact-tank/2019/01/04/more-americans-areusing-ride-hailing-apps*.

Kaufman, S. M., C. F. Polack, and G. A. Campbell (2018): “The pink tax on transportation: Women‘s challenges in mobility,” .

Kondylis, F., A. Legovini, K. Vyborny, A. M. T. Zwager, and L. Cardoso De Andrade (2020): “Demand for Safe Spaces: Avoiding Harassment and Stigma,” *World Bank Policy Research Working Paper*.

Kreindler, G. E. (2020): “Peak-Hour Road Congestion Pricing: Experimental Evidence and Equilibrium Implications,” Working Paper.

Kreindler, G. E. and Y. Miyauchi (2021): “Measuring commuting and economic activity inside cities with cell phone records,” *Review of Economics and Statistics*.

Leard, B. and J. Xing (2020): “What Does Ridesharing Replace?” RFF WP.

Levin, L., M. S. Lewis, and F. A. Wolak (2017): "High frequency evidence on the demand for gasoline," *American Economic Journal: Economic Policy*, 9, 314–47.

Liu, S. and Y. Su (2020): "The Geography of Jobs and the Gender Wage Gap," *Available at SSRN*.

Martin, L. A. and S. Thornton (2017): "To Drive or Not to Drive? A Field Experiment in Road Pricing," Working Paper.

McKenzie, D. (2012): "Beyond Baseline and Follow-up: The Case for More T in Experiments," *Journal of Development Economics*, 99, 210–221.

Moskatel, L. and D. Slusky (2019): "Did UberX Reduce Ambulance Volume?" *Health Economics*, 28, 817–829.

Nakat, Z., S. Herrera, and Y. Cherkaoui (2013): "Cairo Traffic Congestion Study," *World Bank Final Report*.

——— (2014): "Cairo Traffic Congestion Study Executive Note," *The World Bank Group*, 1–5.

Narayanan, S., E. Chaniotakis, and C. Antoniou (2020): "Shared Autonomous Vehicle Services: A Comprehensive Review," *Transportation Research Part C: Emerging Technologies*, 111, 255–293.

Parry, I. W. and G. R. Timilsina (2015): "Demand Side Instruments to Reduce Road Transportation Externalities in the Greater Cairo Metropolitan Area," *International Journal of Sustainable Transportation*, 9, 203–2016.

Phillips, D. C. (2014): "Getting to Work: Experimental Evidence on Job Search and Transportation Costs," *Labour Economics*, 29, 72–82.

Redding, S. J. and E. Rossi-Hansberg (2017): "Quantitative Spatial Economics," *Annual Review of Economics*, 9, 21–58.

Reuters (2018): "Egypt Passes law Regulating Uber, Careem Ride-Sharing Services," *Reuters*.

Rose, J. M. and D. A. Hensher (2014): "Demand for Taxi Services: New Elasticity Evidence," *Transportation*, 41, 717–743.

Saba, Y. (2019): "Egypt Competition Watchdog Approves Uber Acquisition of Careem with Conditions," *Reuters*.

Schaal, E. and P. Fajgelbaum (2020): "Optimal Transport Networks in Spatial Equilibrium," *Econometrica*, 88, 1411–1452.

Severen, C. (2018): "Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification," Working Paper.

Shapiro, M. H. (2018): "Density of Demand and the Benefit of Uber," .

Tirachini, A. and A. Gomez-Lobo (2020): "Does ride-hailing increase or decrease vehicle kilometers traveled (VKT)? A simulation approach for Santiago de Chile," *International journal of sustainable transportation*, 14, 187–204.

Tsivanidis, N. (2018): "The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá's Transmilenio," *Job Market Paper*.

Velásquez, A. (2019): "The Economic Burden of Crime: Evidence from Mexico," *Journal of Human Resources*, 0716–8072r2.

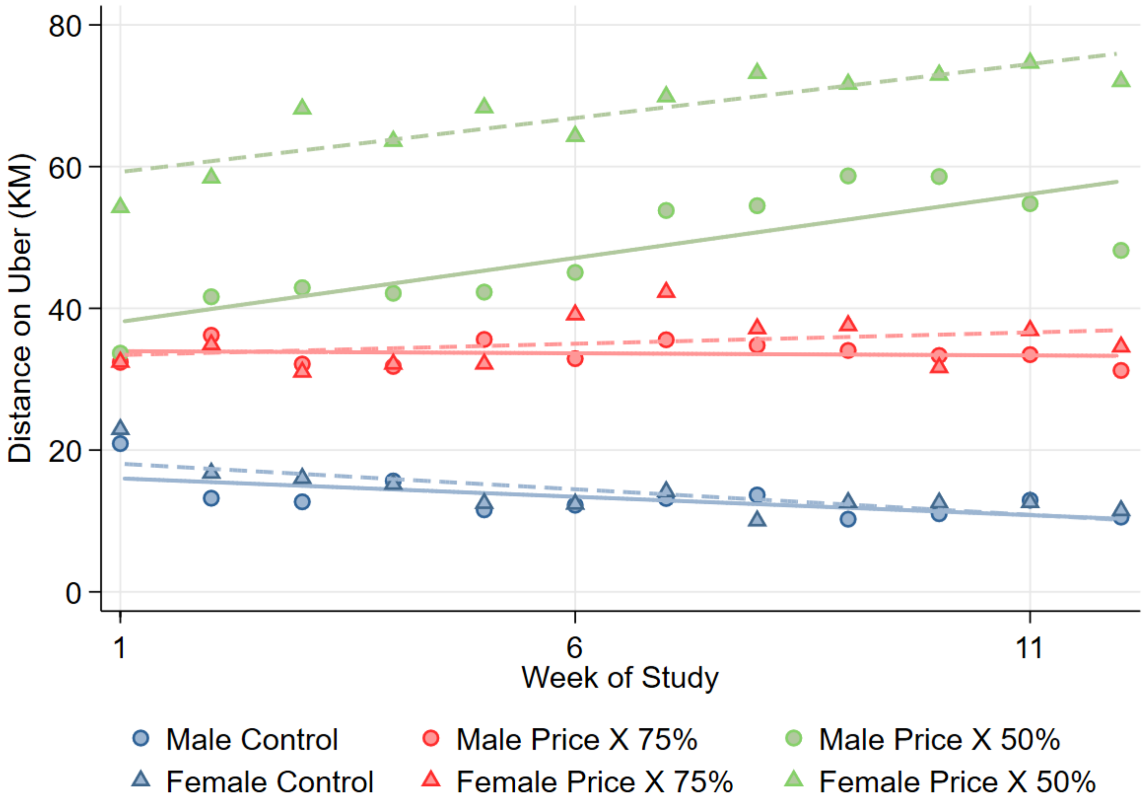
World Resources Institute (2020): "New Sustainable Mobility Database," New Sustainable Mobility Database: https://wrirosscities.org/newmobility.

Yang, J., A. A. Liu, P. Qin, and J. Linn (2020): "The effect of vehicle ownership restrictions on travel behavior: Evidence from the Beijing license plate lottery," *Journal of Environmental Economics and Management*, 99, 102269.

Young, M. and S. Farber (2019): "The Who, Why, and When of Uber and Other Ride-Hailing Trips: An Examination of A Large Sample Household Travel Survey," *Transportation Research Part A: Policy and Practice*, 119, 383–392.

Figures

Figure 1. Uber Usage Over Time



Notes: This figure plots average weekly kilometers traveled on Uber by experiment group, split by gender. The y-axis is reported using nominal kilometers, and the x-axis is the week of the study.

Tables

Table 1. Impacts of Uber Subsidies on Uber Utilization

Panel A: Experimental Impacts				
	Weekly KM on Uber (IHS)		Weekly Trips on Uber	
	(1)	(2)	(3)	(4)
Price X 75%	1.01***	1.11***	1.76***	1.96***
	(0.08)	(0.11)	(0.15)	(0.21)
Price X 75% * Male		-0.18		-0.35
		(0.15)		(0.30)
Price X 50%	1.70***	1.85***	3.66***	4.12***
	(0.08)	(0.12)	(0.20)	(0.31)
Price X 50% * Male		-0.27*		-0.84**
		(0.16)		(0.41)
Observations	16440	16440	16440	16440
Control Group Mean Levels	13.6	14.1	1.5	1.6
Control Group Mean Levels (Male)		13.2		1.5

Panel B: Estimated Elasticity						
	Weekly KM on Uber (IHS)			Weekly Trips on Uber		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Price X 75%	-7.03	-8.17	-6.04	-4.65	-4.93	-4.26
	[-8.67 , -5.38]	[-10.89 , -5.45]	[-8.05 , -4.02]	[-5.43 , -3.86]	[-5.98 , -3.87]	[-5.41 , -3.12]
Price X 50%	-8.96	-10.74	-7.63	-4.85	-5.20	-4.49
	[-10.67 , -7.23]	[-13.65 , -7.83]	[-9.67 , -5.58]	[-5.37 , -4.33]	[-5.94 , -4.46]	[-5.19 , -3.80]

Notes: Panel A: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of weekly kilometers traveled on Uber. Column (2) reports the results from a specification that interacts a dummy variable for men, showcasing the differential impact the treatments have for that subgroup. Columns (3) & (4) report the estimates from a regression on the weekly number of trips taken on Uber (in levels). The bottom rows of Panel A report the control means in levels for each group in Columns (1) & (3), and split the means by gender in columns (2) & (4). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01. Panel B: Elasticities are calculated using the standard transformation of the coefficients estimated in Panel A. Values in brackets are the 95% confidence intervals of the estimated elasticities.

Table 2. Experiments on the Length and Salience of the Price Reduction

	Long Experiment 1st Week		Preannounced Short Experiment		Unannounced Short Experiment	
	(1) Weekly KM	(2) Trips	(3) Weekly KM	(4) Trips	(5) Weekly KM	(6) Trips
Price X 90%			0.41*	0.38	0.44*	0.51
			(0.19)	(0.24)	(0.18)	(0.32)
Price X 90% * Male			-0.24	-0.21	-0.46	-0.35
			(0.25)	(0.33)	(0.26)	(0.45)
Price X 75%	0.29*	0.86***				
	(0.17)	(0.30)				
Price X 75% * Male	0.01	-0.12				
	(0.24)	(0.42)				
Price X 50%	0.65***	2.11***			0.77***	1.45***
	(0.17)	(0.37)			(0.19)	(0.36)
Price X 50% * Male	-0.07	-0.80*			0.04	0.79
	(0.24)	(0.47)			(0.27)	(0.56)
Observations	1370	1370	1000	1000	1500	1500
Control Group Mean Levels	22.9	2.6	13.4	2.0	20.4	2.2
Control Group Mean Levels (Male)	20.9	2.2	18.7	2.2	21.4	2.1

Notes: Columns (1), (3), & (5) report the impacts of the two treatment arms and their interactions with a male dummy variable, on the inverse hyperbolic sine of weekly kilometers traveled on Uber during the first week of the experiment, the pre-announced experiment and the unannounced experiment respectively.Columns (2), (4), & (6) report the same but with number of trips as the outcome variable. The bottom rows report the control means in levels and split by gender. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure in columns (1) and (2). Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table 3. Trips to University, Hospital and Metro

	Unique Location Visited		University Trips		Hospital Trips		Metro Trips	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price X 75%	4.99***	4.81***	4.62**	8.42**	10.19***	10.85**	11.18***	4.92***
	(0.43)	(0.64)	(2.01)	(4.12)	(2.95)	(4.38)	(4.04)	(1.53)
Price X 75% * Male		0.25		-5.67		0.87		11.29
		(0.88)		(4.44)		(6.07)		(7.29)
Price X 50%	9.80***	10.61***	14.07***	21.20***	17.28***	23.81***	11.82***	13.59***
	(0.53)	(0.79)	(3.15)	(6.20)	(3.26)	(5.01)	(1.81)	(3.01)
Price X 50% * Male		-1.48		-11.97*		-10.23		-3.17
		(1.07)		(6.85)		(6.68)		(3.70)
Observations	1404	1404	16452	16452	16452	16452	16452	16452
Control Group Mean Levels	8.9	8.8	5.3	5.6	7.2	6.1	4.7	4.8
Control Group Mean Levels (Male)		8.9		5.0		8.1		4.7

Notes: Column (1) reports the impacts of the two treatment arms on the unique weekly number of grids visited in the start and finish locations on Uber trips. Columns (3), (5), & (7) report the impacts on the weekly number of trips that started or end close to an university, hospital and metro station (multiplied by 100 to make coefficients easier to read). Columns (2), (4), (6), & (8) do the same but include an interaction term for men. The bottom rows report the control means in levels, split the means by gender in even numbered columns. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table 4. Impacts on Total Mobility

Panel A: Experimental Impacts		
	Total KM Past Week (IHS)	
	(1)	(2)
Price X 75%	0.10	0.18
	(0.10)	(0.16)
Price X 75% * Male		-0.13
		(0.21)
Price X 50%	0.40***	0.55***
	(0.09)	(0.14)
Price X 50% * Male		-0.29
		(0.18)
Observations	3476	3476
Control Group Mean Levels	205.2	144.6
Control Group Mean Levels (Male)		261.0

Panel B: Elasticity Estimation			
	Total KM Past Week (IHS)		
	(1) Overall	(2) Female	(3) Male
Price X 75%	-0.44	-0.84	-0.15
	[-1.33 , 0.46]	[-2.3 , 0.67]	[-1.22 , 0.92]
Price X 50%	-0.99	-1.47	-0.60
	[-1.52 , -0.46]	[-2.40 , -0.55]	[-1.21 , 0.02]

Notes: Panel A: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of total kilometers traveled in the three days prior to our follow-up survey as reported by Google Maps' "Timeline" feature. Column (2) reports the results from a specification that interacts treatment with a dummy variable for men. The bottom rows of Panel A report the control means in levels and split by gender in Column (2). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01. Panel B: Elasticities are calculated using the standard transformation of the coefficients estimated in Panel A. Values in brackets are the 95% confidence intervals of the estimated elasticities.

Table 5. Impacts on Trips by Mode of Travel

Panel A: Number of Trips	All Modes		Metro		Bus		Taxi		Uber/Careem		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Price X 75%	1.00	1.19	-0.05	-0.06	-0.15	-0.31	-0.09	-0.20	1.11***	1.11**	-0.11	0.54
	(0.68)	(0.89)	(0.21)	(0.29)	(0.52)	(0.71)	(0.13)	(0.20)	(0.35)	(0.52)	(0.52)	(0.61)
Price X 75% * Male		-0.40	0.04		0.35		0.16		0.06		-1.00	
		(1.35)		(0.44)		(1.04)		(0.27)		(0.70)		(1.03)
Price X 50%	1.35**	1.50*	0.13	0.20	-1.51***	-1.80***	-0.30**	-0.34*	2.32***	2.42***	0.54	0.67
	(0.62)	(0.79)	(0.21)	(0.29)	(0.47)	(0.67)	(0.11)	(0.18)	(0.36)	(0.54)	(0.51)	(0.59)
Price X 50% * Male		-0.29		-0.12		0.48		0.08		-0.32		-0.21
		(1.22)		(0.42)		(0.95)		(0.23)		(0.72)		(0.99)
Observations	3465	3463	3463	3463	3463	3463	3463	3463	3465	3463	3463	3463
Control Group Mean	18.57	16.94	1.29	1.03	6.72	5.45	0.65	0.79	3.97	4.62	5.96	5.06
Control Group Mean (Male)		20.07		1.53		7.90		0.53		3.38		6.79

Panel B: Proportion of Trips	Metro		Bus		Taxi		Uber/Careem		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price X 75%	-0.00	-0.02	-0.03	-0.04	-0.01	-0.02*	0.06***	0.06*	-0.02	0.01
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
Price X 75% * Male		0.02		0.02		0.02		-0.00		-0.04
		(0.02)		(0.04)		(0.01)		(0.04)		(0.04)
Price X 50%	0.00	0.00	-0.10***	-0.11***	-0.02**	-0.02*	0.12***	0.12***	-0.01	0.00
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
Price X 50% * Male		0.00		0.02		0.01		-0.01		-0.01
		(0.02)		(0.04)		(0.01)		(0.04)		(0.04)
Observations	3133	3133	3133	3133	3133	3133	3133	3133	3133	3133
Control Group Mean	0.06	0.06	0.34	0.29	0.04	0.05	0.24	0.29	0.32	0.31
Control Group Mean (Male)		0.06		0.39		0.03		0.19		0.33

Notes: Panel A shows the coefficients from 5 regressions on the number of trips taken the previous day of our follow-up survey. Even numbered columns report the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels, split by gender in even numbered columns. Panel B shows the coefficients from 5 regressions on a continuous outcome that show the proportion of trips taken the previous day of our follow-up survey. Proportion of observations decline in panel B because we do not use observations where individuals report not taking any trips. Even numbered columns report the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels, split by gender in even numbered columns. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table 6. Impacts on Reported Safety on Recent Trips

	Feeling on Longest Trip Yesterday 5=Very Safe, 1=Very Unsafe		Feeling on Longest Trip Yesterday Standardized Variable	
	(1)	(2)	(3)	(4)
Price X 75%	0.06	0.17*	0.05	0.15*
	(0.06)	(0.09)	(0.05)	(0.08)
Price X 75% * Male		-0.22*		-0.19*
		(0.12)		(0.10)
Price X 50%	0.09*	0.20**	0.08*	0.17**
	(0.05)	(0.08)	(0.05)	(0.07)
Price X 50% * Male		-0.19*		-0.16*
		(0.11)		(0.10)
Observations	3182	3182	3182	3182
Control Group Mean	3.98	3.90	-0.04	-0.12
Control Group Mean (Male)		4.06		0.03

Notes: Column (1) reports the impacts of the two treatment arms on the reported level of safety felt during the longest trip taken by the individual during the day prior to the follow-up survey. Column (2) reports the results from a specification that interacts treatment with a dummy variable for men. Column (3) reports the impacts of the two treatment arms on the standardized reported level of safety felt during the longest trip taken by the individual during the day prior to the follow-up survey. Column (2) reports the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels, split by gender in Column (2) & (4). The bottom rows report the control means in levels, split by gender in even numbered columns. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table 7. Effect on Baseline Bus Riders

Panel A:Weekly Uber Usage (KM)	Weekly KM on Uber (IHS)			Weekly KM on Uber (IHS) Perceive Bus as Unsafe		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Price X 75%	1.10***	1.11***	1.08***	1.03***	1.20***	0.81***
	(0.09)	(0.14)	(0.12)	(0.15)	(0.20)	(0.22)
Price X 75% * Bus User	-0.32**	-0.08	-0.47**	-0.39	-0.44	-0.07
	(0.16)	(0.23)	(0.22)	(0.34)	(0.41)	(0.48)
Price X 50%	1.70***	1.69***	1.70***	1.55***	1.67***	1.28***
	(0.10)	(0.14)	(0.13)	(0.14)	(0.19)	(0.21)
Price X 50% * Bus User	0.02	0.60***	-0.36	0.04	1.26***	-0.49
	(0.17)	(0.23)	(0.22)	(0.31)	(0.47)	(0.40)
Observations	16440	7272	9168	6012	3336	2676
Control Group Mean Levels	25.5	25.7	25.4	25.9	27.5	23.5
Control Group Mean Levels (Bus User)	13.4	14.0	13.1	12.6	6.2	15.6

Panel B:Total Mobility (KM)	Total Mobility (KM) in Past Week (IHS)			Total Mobility (KM) in Past Week (IHS) Perceive Bus as Unsafe		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Price X 75%	0.09	0.20	-0.05	-0.01	-0.03	0.09
	(0.12)	(0.19)	(0.16)	(0.18)	(0.25)	(0.25)
Price X 75% * Bus User	0.09	0.09	0.06	0.84*	0.44	0.70
	(0.22)	(0.35)	(0.28)	(0.36)	(0.72)	(0.44)
Price X 50%	0.37***	0.59***	0.16	0.28	0.47*	-0.13
	(0.11)	(0.16)	(0.16)	(0.16)	(0.20)	(0.27)
Price X 50% * Bus User	0.03	-0.18	0.16	0.62	0.33	0.55
	(0.20)	(0.31)	(0.24)	(0.34)	(0.70)	(0.42)
Observations	3476	1666	1810	1313	780	533
Control Group Mean Levels	218.8	142.3	303.7	223.4	158.3	333.5
Control Group Mean Levels (Bus User)	176.3	151.3	191.7	147.3	122.6	160.2

Notes: Panel A: Columns (1), (2), & (3) report impacts on the inverse hyperbolic sine of weekly kilometers traveled on Uber in a specification that interacts the treatment with a dummy variable that takes the value of 1 if the individual reports at baseline that the longest trip took in the previous day was using a bus and 0 otherwise. Columns (4), (5), & (6) in panel A report the result for a specification that includes only people who perceived the bus as unsafe in the baseline survey. Panel B reproduces the same regressions but with total kilometers traveled as the outcome variable. The bottom rows in each panel report the control means in levels, split by if they were bus users at baseline. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table 8. Consumer Surplus

Panel A:	Consumer Surplus using with Two Points in the Demand Curve			Consumer Surplus with One Point in the Demand curve		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
$CS_{Experiment}(UberKm)$	88	95	80	88	109	67
	[70 , 106]	[76 , 115]	[64 , 96]	[71 , 105]	[88 , 131]	[55 , 78]
$CS_{Experiment}(TotalKm)$	156	160	153	158	165	152
	[131 , 194]	[131 , 199]	[132 , 189]	[135 , 182]	[137 , 193]	[132 , 172]
$CS_{Experiment}(UberTrips)$	34	36	31	27	28	25
	[30 , 38]	[32 , 40]	[28 , 35]	[25 , 29]	[26 , 31]	[23 , 27]
$CS_{Experiment}(TotalTrips)$	84	102	66	83	101	64
	[80 , 91]	[98 , 111]	[62 , 71]	[80 , 87]	[98 , 106]	[62 , 67]

Panel B:	Consumer Surplus with Two Points in the Demand Curve			Consumer Surplus with One Point in the Demand curve		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
$CS_{Equilibrium}(Pop. = 40\%)$	153	156	151	154	159	150
	[131 , 189]	[129 , 193]	[132 , 184]	[133 , 176]	[135 , 185]	[132 , 167]

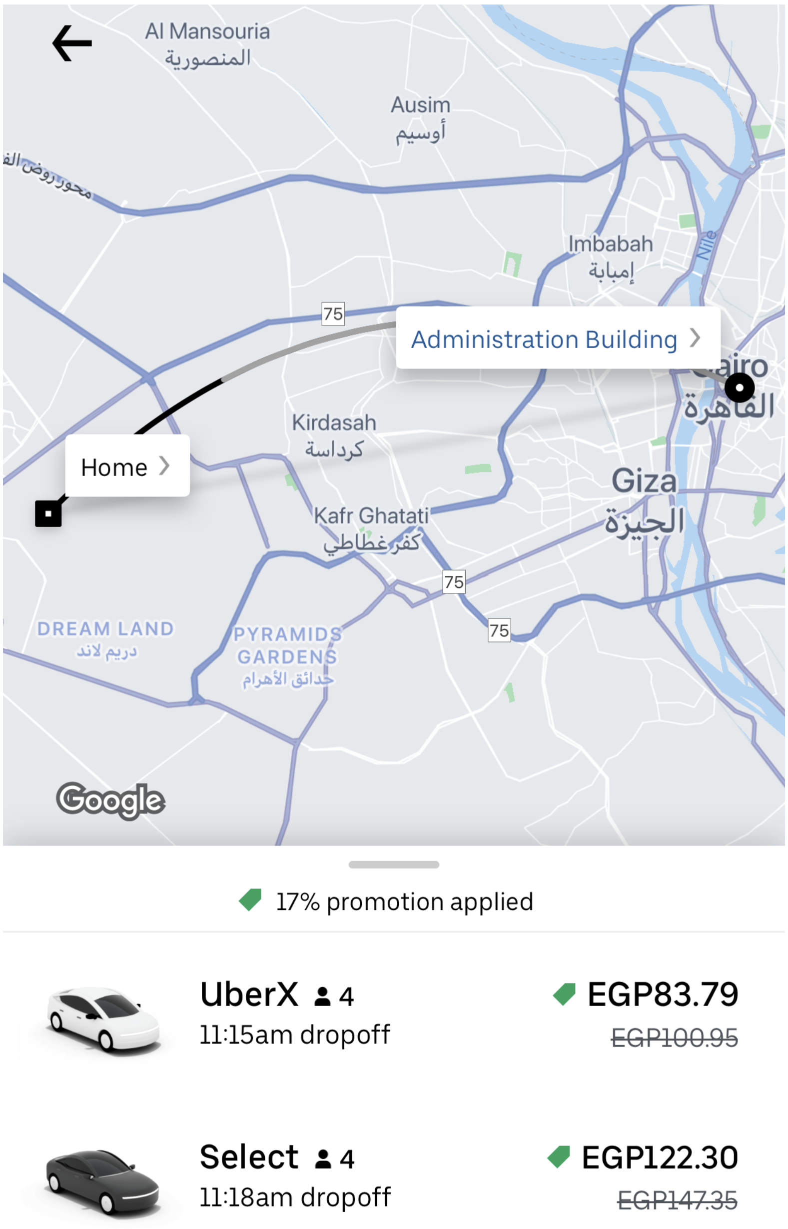
Notes: Columns (1), (2) & (3) report the consumer surplus estimates calculated with two points from the approximation of the elasticity of a reduction of 25% in Uber price and the reduction of 50%. Columns (4), (5) & (6) report the consumer surplus with one point from the approximation of the elasticity of a reduction of 50% of the price of Uber. 95% confidence intervals reported in brackets below.

Appendices

A Experimental Design

A1. Price Information for Treated Riders

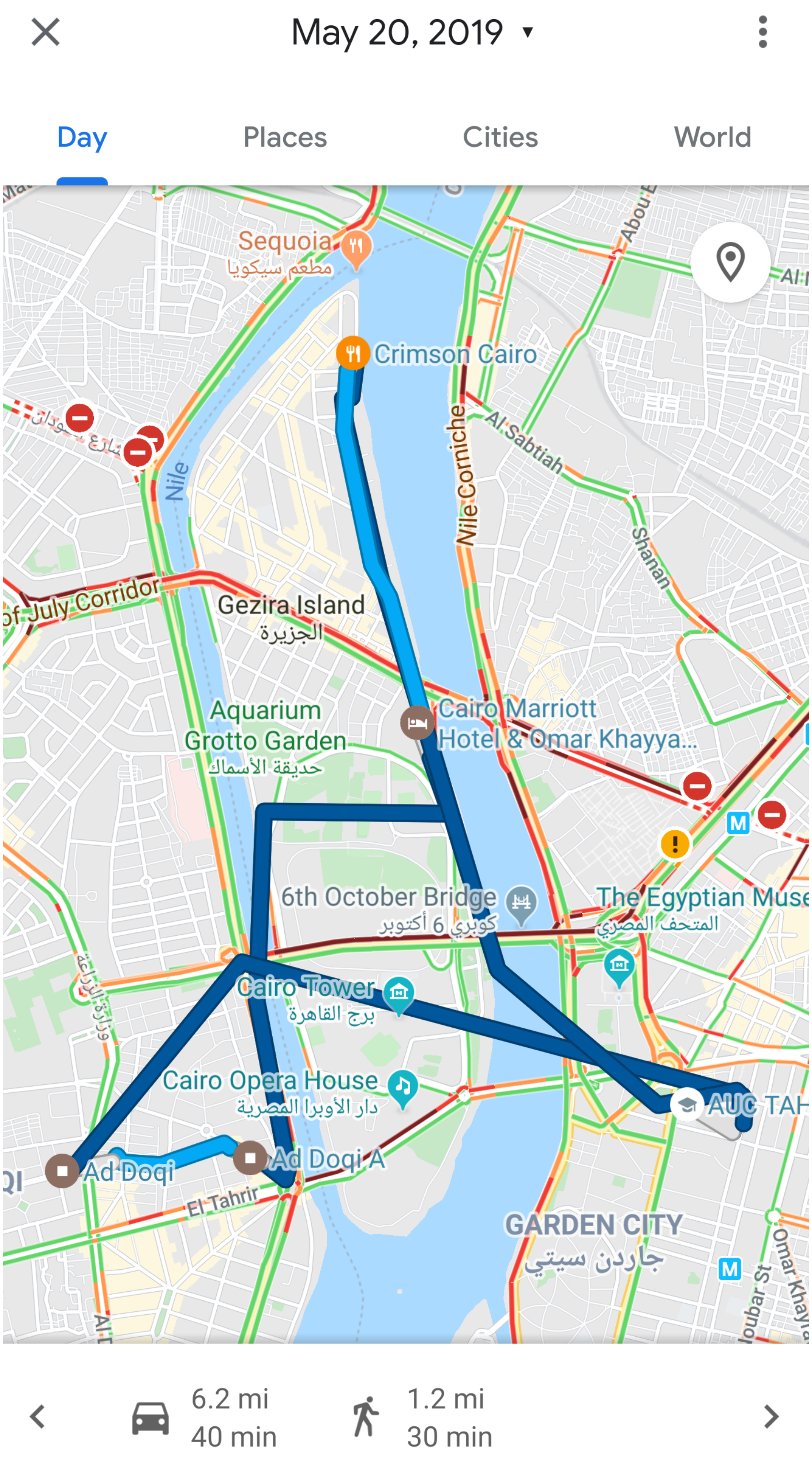
Figure A.1. Uber Price Information



Notes: The figure illustrates an example of a price change represented within the Uber application on a mobile device in the Cairo market. Users receive price information in the process of requesting a given trip and are charged upon completion of a trip.

A2. Google Timeline Platform

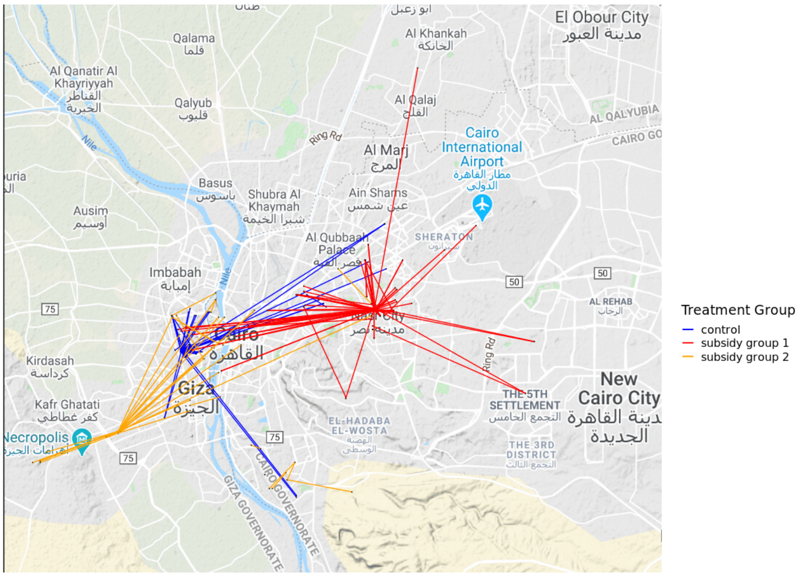
Figure A.2. Google Timeline Platform

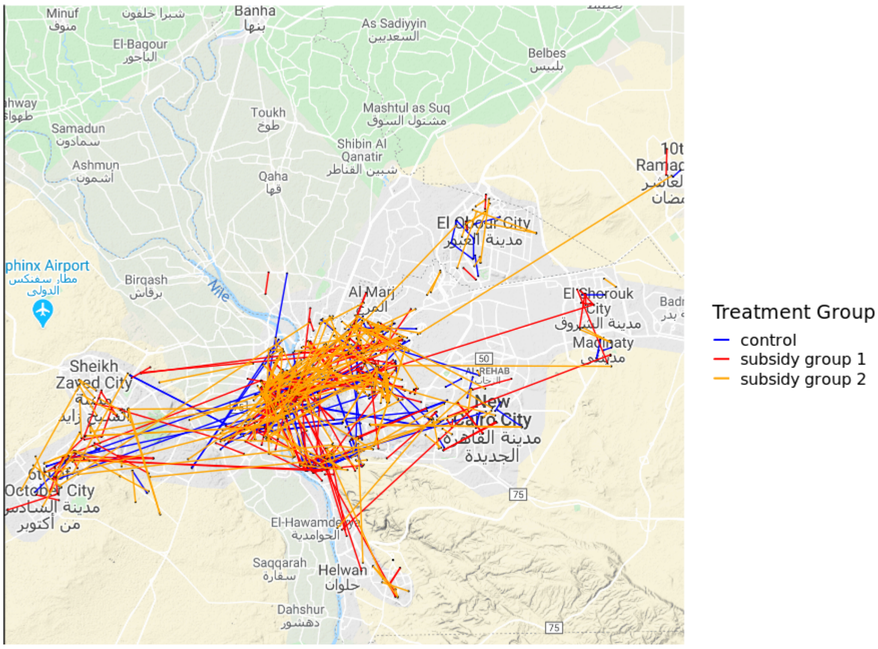


Notes: The figure illustrates the location and travel information displayed to participants on the Google Timeline application. The application provides total travel data for each date after the application is enabled.

A3. Uber Administrative Data

The figure below illustrates the geographic features (origins/destinations) of the Uber administrative data. The top panel maps a sample of trips for 3 randomly drawn participants in the study. The bottom panel maps the full set of trips for a single randomly drawn day. Trips in the control group are shown in blue, trips in the 25% group are shown in red, and trips in the 50% group are shown in orange.





Notes: The figures illustrate the origin/destination information obtained for trips recorded in Uber administrative data. The application provides total travel data for each date after the application is enabled. The top panel maps a sample of trips for 3 randomly drawn participants in the study. The bottom panel maps the full set of trips for a single randomly drawn day. Trips in the control group are shown in blue, trips in the 25% group are shown in red, and trips in the 50% group are shown in orange.

B Sample Characteristics and Attrition

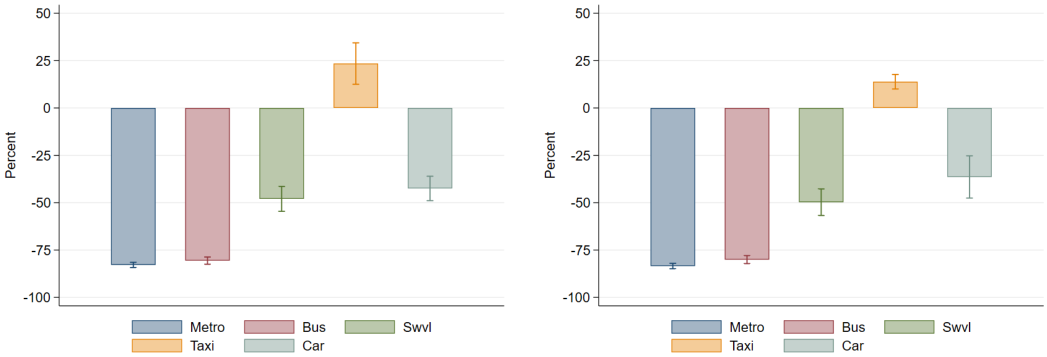
This appendix includes figures and tables that provide additional detail and insights from the experiment. The two figures describe baseline travel behavior and beliefs, split by gender. Table B1 reports baseline characteristics and balance tests for baseline covariates. Table B2 compares baseline characteristics for the sample to a representative sample of the Cairo population. The experimental sample is younger, more educated, and has higher incomes than the average Cairo resident. Tables B5-B6 analyze attrition throughout the study and test for differential response rates by baseline characteristics across treatment groups.

Figure B1. Baseline Transport Behavior

Notes: The figure illustrates mode use from baseline surveys for male (green) and female (yellow) respondents. Survey question asks participants to recall the mode of travel used for their longest trip on the day prior to a phone survey.

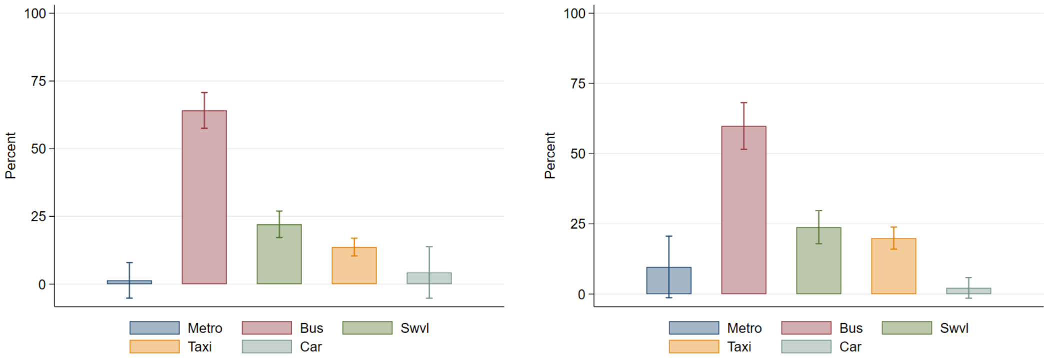
Figure B2. Perceived Cost, Duration, and Safety of Outside Options

Relative Cost Compared to Uber



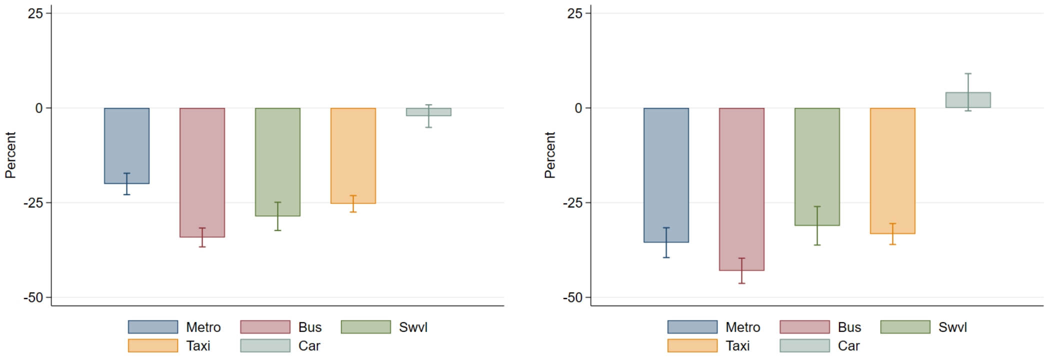
Males Females

Relative Duration Compared to Uber



Males Females

Relative Safety Compared to Uber



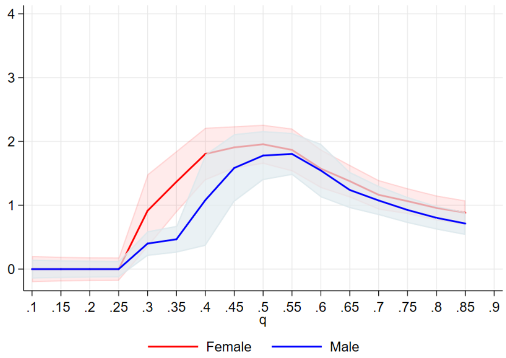
Males Females

Notes: The figure illustrates mode use from baseline surveys for male (left) and female (right) respondents. Survey asks participants to provide expectations for cost, duration, and safety for all possible modes that could have been used for their longest trip on the day prior to a phone survey.

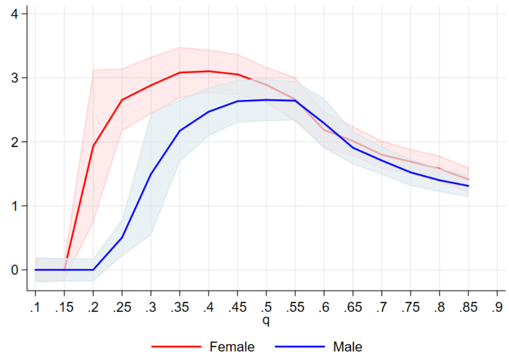
Figure B3. Quantile Regressions

Panel A: Total Weekly Uber Distance (IHS)

25% Price Reduction

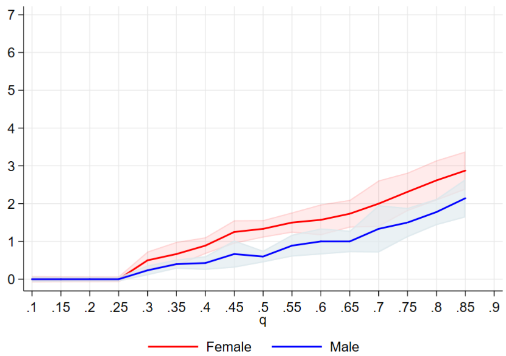


50% Price Reduction

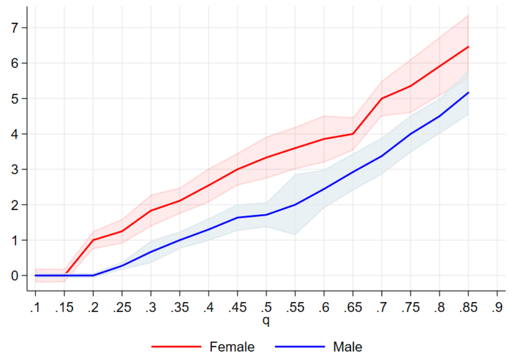


Panel B: Number of Weekly Uber Trips

25% Price Reduction

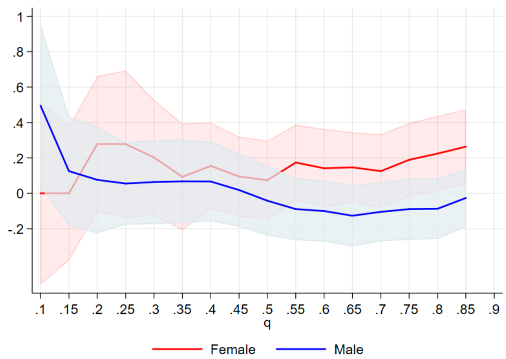


50% Price Reduction

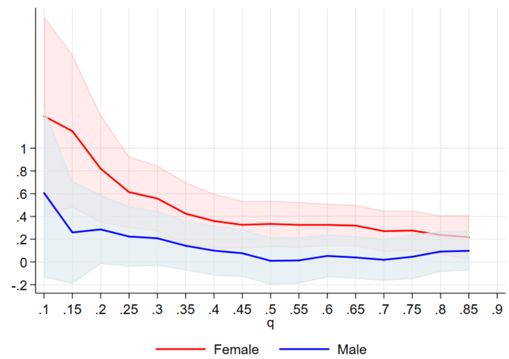


Panel C: Total Distance (IHS)

25% Price Reduction



50% Price Reduction



Notes: This figure plots the results of quantile regressions of the impacts of the treatment split by gender. Panel A reports impacts on weekly distance kilometers traveled on Uber, Panel B reports impacts on the average number of weekly Uber trips, and Panel C reports impacts on the total distance using data from Google Maps' Timeline. The panels on the left show the impacts for the 25% group, while the panels on the right show the impacts for the 50% group. Bootstrapped standard errors with 1,000 repetitions are clustered at the individual level.

Table B1. Baseline Characteristics

Variables	Control Mean	75% vs Control	50% vs Control	50% vs 75%
Female	0.47	0.00	0.00	-0.00
	(0.50)	(0.03)	(0.03)	(0.03)
Age	31.36	-0.29	-0.96	-0.67
	(10.65)	(0.72)	(0.80)	(0.77)
Married	0.50	-0.00	-0.06*	-0.05
	(0.50)	(0.03)	(0.03)	(0.03)
Monthly Income	4,655	-192	-419	-226
	(6,803)	(430)	(423)	(314)
Currently Working	0.78	0.00	0.01	0.00
	(0.41)	(0.03)	(0.03)	(0.03)
Hours Worked (hours/week)	44.54	-0.88	0.32	1.20
	(15.61)	(1.24)	(1.16)	(1.22)
Looking for Work	0.48	0.00	-0.01	-0.01
	(0.50)	(0.03)	(0.03)	(0.03)
Car Owner	0.26	0.01	-0.05	-0.05*
	(0.44)	(0.03)	(0.03)	(0.03)
Total Weekly Trips	20.83	1.26	-0.04	-1.30
	(13.66)	(0.90)	(0.88)	(0.86)
Total Mobility (km/week)	86.33	-12.59	-0.66	11.93
	(200.24)	(11.39)	(12.29)	(9.63)
Total Time in Transit (min/week)	604.72	-59.98	-28.86	31.12
	(2,698.80)	(144.62)	(146.43)	(87.86)
Velocity (km/hour)	25.64	-5.12	10.33	15.45
	(143.54)	(7.65)	(14.24)	(12.77)
Observations	455	954	958	960
Joint F-test (p-value)		0.80	0.61	0.72

Notes: Column (1) reports the mean and standard deviation of the control group for a given outcome variable, Column (2) reports the average difference between each variable for those in the Price X 75% treatment group relative to control, Column (3) reports the average difference between each variable for those in the Price X 50% treatment group relative to control, and Column (4) reports the average difference between each variable for those in the Price X 75% treatment group relative to those in the Price X 50% treatment group. The last row in each panel reports the p-value for the F-test from a regression of the treatment dummy on all baseline balance variables. Significance: *.10; **.05; ***.01.

Table B2. Comparing Experiment Sample to Representative Sample of Cairo

	Overall		Female		Male	
	(1) Population	(2) Sample	(3) Population	(4) Sample	(5) Population	(6) Sample
Gender	0.49	0.53	0	0	1	1
	(0.5)	(0.50)	(0.0)	(0.0)	(0.0)	(0.0)
Age	35.89	30.92	36.42	29.95	35.33	31.77
	(13.81)	(9.54)	(14.11)	(9.89)	(13.47)	(9.15)
Married	0.60	0.49	0.63	0.45	0.57	0.52
	(0.49)	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)
Hours Worked (hours/week)	20.67	44.47	6.76	39.05	35.20	48.15
	(26.98)	(16.17)	(16.69)	(28.00)	(17.08)	(16.44)
Currently Working	0.44	0.79	0.17	0.68	0.73	0.88
	(0.50)	(0.41)	(0.37)	(0.47)	(0.44)	(0.32)
Monthly Income	1026	4403	305	3434	1778	5060
	(2990)	(5274)	(1415)	(3813)	(3882)	(5987)
College Education	0.27	0.88	0.25	0.90	0.29	0.86
	(0.44)	(0.32)	(0.43)	(0.30)	(0.45)	(0.34)
High School	0.33	0.09	0.29	0.08	0.35	0.10
	(0.47)	(0.28)	(0.46)	(0.27)	(0.48)	(0.30)
Less than High School	0.40	0.01	0.46	0.01	0.36	0.01
	(0.49)	(0.08)	(0.50)	(0.08)	(0.48)	(0.08)
Car Owner	0.13	0.25	0.13	0.20	0.12	0.29
	(0.33)	(0.43)	(0.34)	(0.40)	(0.32)	(0.46)
Looking for Work	0.03	0.49	0.03	0.33	0.04	0.63
	(0.18)	(0.50)	(0.17)	(0.47)	(0.19)	(0.48)

Notes: Columns (1), (3), & (5) report the average values for a representative sample of Cairo residents, taken from the 2018 Egypt Labor Market Panel Survey. Columns (2), (4), & (6) report the values for individuals in our sample. Standard deviations reported in parentheses.

Table B3. Impact of Treatment on Length of Uber Trips

	Total KM per Trip (IHS)	
	(1)	(2)
Price X 75%	0.09*	0.11
	(0.05)	(0.08)
Price X 75% * Male		-0.04
		(0.11)
Price X 50%	0.17***	0.23***
	(0.05)	(0.07)
Price X 75% * Male		-0.11
		(0.10)
Observations	56802	56718
Control Group Mean	9.0	8.9
Control Group Mean (Male)		9.1

Notes: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of total kilometers traveled in the uber trip. Column (2) reports the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels and split by gender in Column (2). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table B4. Travel on Private vs. Public Transportation

	Total Weekly KM Public (IHS)		Total Weekly KM Private (IHS)	
	(1)	(2)	(3)	(4)
Price X 75%	0.12	0.39	0.37**	0.07
	(0.19)	(0.26)	(0.18)	(0.25)
Price X 75% * Male		-0.54		0.61*
		(0.37)		(0.36)
Price X 50%	0.22	0.27	0.47***	0.39
	(0.19)	(0.26)	(0.18)	(0.24)
Price X 50% * Male		-0.08		0.15
		(0.37)		(0.36)
Observations	3352	3352	3352	3352
Control Group Mean Levels	74.5	38.9	127.7	106.6
Control Group Mean Levels (Male)		108.0		147.7

Notes: Notes: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of total kilometers on public transportation (bus & metro). Column (2) reports the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels and split by gender in Column (2). Columns (3) & (4) report impacts on on private travel (i.e. taxi, Uber, and private car). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table B5. Response Rates

	(1) Any Follow-Up	(2) Follow-Up 1	(3) Follow-Up 2	(4) Follow-Up 3	(5) Follow-Up 4
Price X 75%	0.02	-0.01	0.05*	0.04	0.02
	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
Price X 50%	0.03**	0.02	0.08***	0.06*	0.08**
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)
Control Group Response Rate	0.94***	0.82***	0.78***	0.40***	0.38***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	1373	1373	1373	1373	1373

Notes: Columns (1) & (2) report the coefficients from a regression on a binary outcome that takes the value 1 if the individual reported to answer any follow-up survey and 0 otherwise. Columns (2), (3), (4), & (5) report the result for each follow-up. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table B6. Impacts of Observable Characteristics on Response Rates (All Follow-Ups)

	Dependent variable: Response to Follow-Up	
	(1) Price X 75%	(2) Price X 50%
treatment	-0.09 (0.11)	-0.13 (0.11)
Car	-0.06** (0.03)	-0.06** (0.03)
Education	-0.02 (0.02)	-0.02 (0.02)
Married	-0.02 (0.02)	-0.02 (0.02)
Female	0.09*** (0.02)	0.09*** (0.02)
Looking for work	0.00 (0.00)	0.00 (0.00)
Total distance	0.00 (0.00)	-0.00 (0.00)
Treatment * Car	0.03 (0.04)	0.08** (0.04)
Treatment * Education	0.03 (0.02)	0.03 (0.02)
Treatment * Married	-0.01 (0.03)	-0.02 (0.03)
Treatment * Female	-0.04 (0.03)	0.03 (0.03)
Treatment * Looking for work	0.00 (0.00)	0.00 (0.00)
Treatment * Total distance	0.00 (0.00)	0.00 (0.00)
Constant	0.67*** (0.08)	0.67*** (0.08)
Observations	3632	3644
F-Test (P Value)	0.71 (0.64)	1.30 (0.25)

Notes: Columns (1) reports the coefficients from a regression on a binary outcome that takes the value 1 if the individual reported to answer any follow-up survey and 0 otherwise given the 25% treatment group, some control variables and the interaction of the treatment with the controls. Column (2) reports the same estimation for the 50% treatment group. The F-Test shows joint significance for the control variables when interacted with the treatments. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table B7. Impacts of Observable Characteristics on Response Rates (1 Follow-Up Min.)

	Dependent variable: Response to Follow-Up	
	(1) Price X 75%	(2) Price X 50%
Treatment	-0.01	-0.13
	(0.10)	(0.09)
Car	-0.04*	-0.04**
	(0.02)	(0.02)
Education	-0.01	-0.01
	(0.01)	(0.01)
Married	-0.01	-0.01
	(0.02)	(0.02)
Female	0.00	0.00
	(0.02)	(0.02)
Looking for work	0.00	0.00
	(0.00)	(0.00)
Distance	0.00	0.00
	(0.00)	(0.00)
Treatment * Car	0.03	0.04
	(0.03)	(0.03)
Treatment * Education	0.01	0.03*
	(0.02)	(0.02)
Treatment * Married	0.00	-0.02
	(0.03)	(0.03)
Treatment * Female	-0.03	0.01
	(0.03)	(0.03)
Treatment * Look For Work	0.00	0.00
	(0.00)	(0.00)
Treatment * Total Distance	0.00**	0.00
	(0.00)	(0.00)
Constant	1.01***	1.01***
	(0.07)	(0.06)
Observations	908	911
F-Test	1.17	0.91
(P Value)	(0.32)	(0.49)

Notes: Columns (1) reports the coefficients from a regression on a binary outcome that takes the value 1 if the individual reported to answer at least 1 follow-up survey and 0 otherwise given the 25% treatment group, some control variables and the interaction of the treatment with the controls. Column (2) reports the same estimation for the 50% treatment group. The F-Test shows joint significance for the control variables when interacted with the treatments. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table B8. Lee Bounds for Total Mobility

	Overall			Female			Male		
	(1) Lower	(2) Higher	(3) Main Estimate	(4) Lower	(5) Higher	(6) Main Estimate	(7) Lower	(8) Higher	(9) Main Estimate
Price X 75%	-0.01	0.5***	0.1	0.11	0.65***	0.18	-0.11	0.38***	0.03
	(0.00)	(0.08)	(0.09)	(0.14)	(0.12)	(0.14)	(0.12)	(0.10)	(0.12)
Price X 50%	0.11	0.74***	0.35***	0.24*	0.90***	0.49***	0.02	0.58***	0.23**
	(0.08)	(0.07)	(0.08)	(0.12)	(0.11)	(0.12)	(0.11)	(0.10)	(0.11)

Notes: Columns (1), (4) & (7) report the lower Lee Bounds from regressions of total mobility on treatment. To generate the lower lee bounds we compare the proportion in treatment and control groups who respond to the surveys and trim the excess respondents with the highest values in the group with more respondents. For columns (2), (5) & (8) we repeat this process but remove the lowest values. In columns (3), (6), & (9) we reproduce the main results. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table B9. Lee Bounds for Safety

	Overall			Female			Male		
	(1) Lower	(2) Higher	(3) Main Estimate	(4) Lower	(5) Higher	(6) Main Estimate	(7) Lower	(8) Higher	(9) Main Estimate
Price X 75%	-0.71***	0.39***	0.06	-0.62***	0.31***	0.19***	-0.78***	0.32***	0.05
	(0.06)	(0.05)	(0.06)	(0.10)	(0.09)	(0.10)	(0.08)	(0.06)	(0.08)
Price X 50%	-0.77***	0.44***	0.09*	-0.69***	0.76***	0.22***	-0.85***	0.33***	0.01
	(0.06)	(0.05)	(0.06)	(0.10)	(0.07)	(0.09)	(0.08)	(0.06)	(0.08)

Notes: Columns (1), (4) & (7) report the lower Lee Bounds from regressions of total mobility on treatment. To generate the lower lee bounds we compare the proportion in treatment and control groups who respond to the surveys and trim the excess respondents with the highest values in the group with more respondents. For columns (2), (5) & (8) we repeat this process but remove the lowest values. In columns (3), (6), & (9) we reproduce the main results. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

C Measuring Mobility

This appendix provides additional detail on the measurement of mobility across the three data sources used in the study: (1) Uber administrative data on trips, (2) trip surveys, and (3) total travel using Google Timeline.

C.1 Measuring Total Travel with Google Timeline

As described in Section 3.2, 'jumps' and 'drift' can affect the accuracy of Google Timeline data. In this section, we evaluate the consistency of measurements across different data sources and report results from a set of validation exercises that evaluated differences in distance measurements between a manually constructed daily travel log, Uber administrative data, and Google Timeline data prior to the study.

Google Timeline Validation

Over a 5-day period prior to the study, we conducted a validation exercise to evaluate measurement error in Google Timeline data. As depicted in Figure C1, we created a manual trip log that records the distances of travel taken by Uber and private car. We then compared the distances recorded in the log to the distance measurements collected on the Uber platform and in our Google Timeline.

Figure C1. Comparison of Manual Travel Log, Google Timeline, Uber Admin

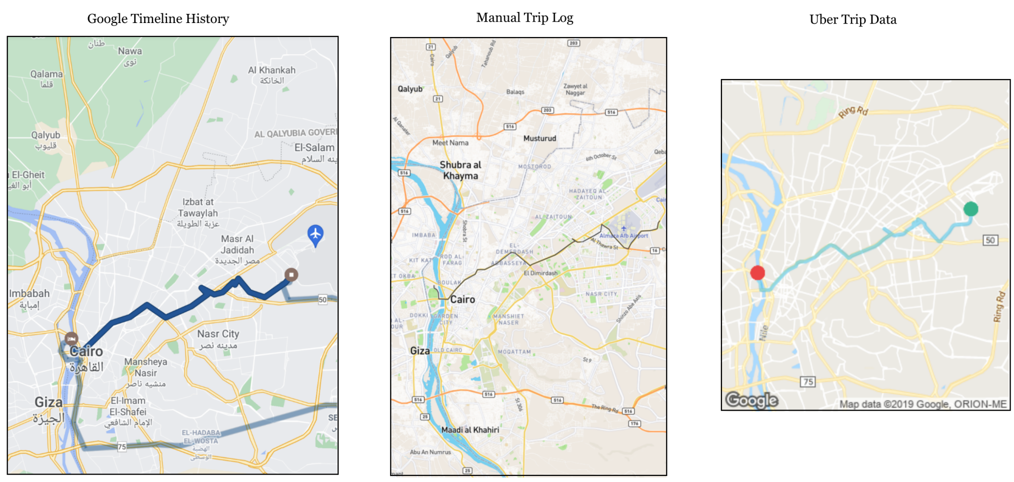


Table C1 reports the results from the validation exercise, which indicates that Timeline understates total travel by about 12.5% relative to the manual log. In our analysis, we report our results in percentage terms using an IHS transformation and restrict all comparisons between data sources to comparisons of percentage effects, further helping to correct for any uniform underestimate of overall distance measured on Google Timeline. The difference is 12.6% when taking an Uber trip and by 12% when not taking an Uber trip, providing some evidence that GPS functionality when an individual is taking an Uber trip does not result in differences in Timeline measurements of total travel. When we compare data from Uber's administrative data to manual logs, we find that the administrative data understates total travel by 2.9%. This is likely because Uber's log utilizes data from an application on the *driver's* phone, which is built to collect more accurate data (but is much more battery intensive).

Table C1. Comparison of Manual Travel Log, Google Timeline, Uber Admin

Category	# of trips	Log Distance	Uber Distance	Timeline Distance	Log-Timeline (%)	Log-Uber (%)
Uber Trips	11	169.30	174.20	147.90	12.62%	2.89%
Non-Uber Trips	3	33.70	-	29.70	11.94%	-
All Vehicle Trips	14	202.90	-	177.60	12.51%	-

Notes: All distances are reported in kilometers.

GPS tracking on Uber vs. Non-Uber Trips

The validation exercise above suggests that measurement error in Google Timeline measurements is similar across Uber and non-Uber trips. It is possible that participants disable their GPS while using modes other than Uber. While this would require that a participant fully disables navigation services during travel, participants may do this in certain cases to preserve battery life. A benefit of the Timeline app is that it is optimized for battery life, potentially reducing participant concerns about battery use. Either of these issues could bias our experimental results if they differentially affect the measurement of total travel for the treated group (who use Uber more).

Using data from the baseline survey, Table C2 reports the results of a regression of total travel on the number of trips taken using each mode for the same period. While disentangling mode-specific measurement error from mode-specific differences in trip lengths would require independent measurements of distances traveled in each of the recorded trips, these correlations do not suggest that Uber trips have an outsized influence in the the total distance measurement.

Table C2. Previous Day Km on Trips (Baseline)

	(1) Total KM Previous Day (IHS)
Metro Trips	0.21***
	(0.06)
Bus Trips	0.23***
	(0.03)
Taxi Trips	0.17**
	(0.07)
Uber Trips	0.31***
	(0.05)
Car Trips	0.27***
	(0.03)
Observations	1373

Notes:

We then compare the coefficient of variation in total distance traveled on days that include Uber trips and those that do not. If the use of Uber makes Google Timeline more precise, then we would expect less variation in the data collected on days when Uber trips are taken. Directly comparing the variance would not be appropriate because as distance travelled increases, the overall variance will also increase. For this reason, we utilize the coefficient of variation (the standard deviation divided by the mean), which provides a scale invariant measure. Table C3 reports the results of this analysis. We find that the coefficient of variation are very similar on days with and without an Uber, suggesting that this potential bias is not a first-order concern for our analysis.

Table C3. Coefficient of Variation

	Overall (1)	Control (2)	Subsidy 25% (3)	Subsidy 50% (4)
Day With Uber	1.41 [1.19, 1.47]	1.32 [1.12, 1.36]	1.47 [1.27, 1.68]	1.44 [1.24, 1.68]
Day Without Uber	1.52 [1.23,1.59]	1.42 [1.33,1.80]	1.55 [1.36, 1.70]	1.59 [1.53, 1.95]

Notes: This table reports the coefficient of variation of distance reported on Google Timeline separated by days in which an individual took an Uber ride and days in which they did not take an Uber ride. 95% confidence intervals reported in brackets.

Uber Travel (Administrative Data) vs Total Travel (Timeline)

Next, we examine the robustness of our results by utilizing Uber's administrative data to identify instances of measurement error in the Google Timeline. Figure C2 plots the total distance traveled from a participant's Timeline against the distance recorded on Uber over the same period. During the average 3-day period with no Uber travel, a participant's total travel is 77 km. For each additional 1 km of Uber travel, the total travel increases by 0.26 km on average. Table B7 reports these estimates by treatment group. We do not find any evidence of systematic differences in the relationships between Uber and Timeline measurements across the groups.

Figure C2. Total Travel (Timeline) vs Uber Travel (Uber Admin. Data) (3 days)

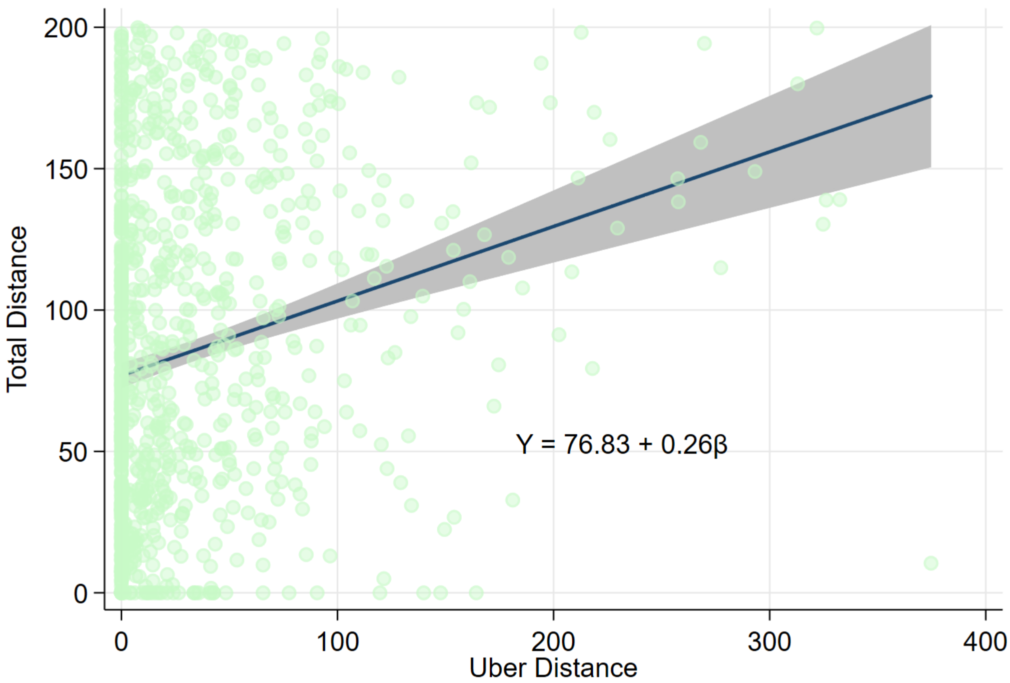


Table C4. Total Distance vs Uber Distance Regression

	Overall (1)	Control (2)	Subsidy 25% (3)	Subsidy 50% (4)
Beta Estimator	0.27*** (0.04)	0.24* (0.14)	0.20** (0.07)	0.29*** (0.05)

Notes: Column (1) reports the beta estimator of the regression of Total distance on Uber distance for the same period. Columns (2), (3) & (4) report the beta estimators of the regression of Total distance on Uber distance by treatment group. Standard errors in parentheses. Significance: *.10; **.05; ***.01.

Since a participant's Uber travel should be captured in their total daily distance, we expect to see that $TotalDistance > UberDistance$. In Table C5, we identify observations where the measurement of Uber travel exceeds the measurement of total travel, which indicates measurement error that could occur during intervals when a GPS is not collecting data or battery failure. This occurs in 13.6% of the observations in the sample.

Table C5. Total Travel (Timeline) vs Uber Travel (Administrative Data)

3 Days	Distance Fraction	Average Total Distance (km)
Total Distance $\geq Uberdistance$	86.37%	98.25
Uber distance $\geq TotalDistance$	13.63%	68.57

To examine the effects of these observations on our results on the effects of price reductions on total mobility, we produce a version of Table 4 that omits the 13.6% of observations where Uber travel exceeds total travel. We view this set of inconsistent observations as instances of likely under-reporting of total travel by Google Timeline. We find that removing these observations slightly increases our estimates of effects of treatment on total mobility, likely due to the fact that these observations fall at the low end of the distribution of observations of total travel, at the upper end of the distribution of observations of Uber travel (which are more likely to be found in the treatment groups). However, the estimates are not different from estimates produced with the full sample. Whereas the point estimate for the effect of a 50% price reduction was 0.40 IHS points in Table 4, the effects in this restricted sample are 0.53 IHS points.

Table C6. Impacts in Total Mobility (Sample: $TotalDistance > UberDistance$)

	Total KM Past Week (IHS)	
	(1)	(2)
Price X 75%	0.13	0.22
	(0.11)	(0.18)
Price X 75% * Male		-0.19
		(0.23)
Price X 50%	0.53***	0.67***
	(0.10)	(0.15)
Price X 50% * Male		-0.27
		(0.20)
Observations	3073	3071
Control Group Mean	212.95	151.16
Control Group Mean (Male)		267.29

Notes: Table reports estimates from Table 4, restricting the sample to observations where $TotalDistance > UberDistance$. Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of total kilometers traveled in the three days prior to our follow-up survey as reported by Google Maps' "Timeline" feature. Column (2) reports the results from a specification that interacts treatment with a dummy variable for men. The bottom rows of report the control means in levels and split by gender in Column (2). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

C.2 Mode Choice

We measure mode choice using two different survey questions: (1) total number of trips taken on each mode on the day before the survey, and (2) mode used for the longest trip (in distance) on the day before the survey. Table C7 reports treatment effects across the two measures. Panel A reports effects on the mode share for all trips while Panel B reports effects on the mode share for longest trips. We find that these two measures are highly consistent, indicating that treatment effects on mode substitution on longest trips are reflective of overall effects.

Table C7. Travel Mode Choice

Panel A: Longest Trip	Metro		Bus		Taxi		Uber/Careem		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price X 75%	0.00 (0.01)	-0.02 (0.02)	-0.03 (0.02)	-0.05 (0.04)	-0.02** (0.01)	-0.03** (0.01)	0.07*** (0.02)	0.09*** (0.03)	-0.02 (0.02)	0.01 (0.03)
Price X 75% * Male		0.03 (0.03)		0.02 (0.05)		0.02 (0.01)		-0.04 (0.04)		-0.04 (0.05)
Price X 50%	0.00 (0.01)	-0.01 (0.02)	-0.09*** (0.02)	-0.11*** (0.03)	-0.02** (0.01)	-0.03** (0.01)	0.11*** (0.02)	0.12*** (0.03)	0.00 (0.02)	0.03 (0.03)
Price X 50% * Male		0.02 (0.03)		0.03 (0.05)		0.02 (0.01)		-0.02 (0.04)		-0.06 (0.05)
Observations	3186	3186	3186	3186	3186	3186	3186	3186	3186	3186
Control Group Mean	0.06	0.06	0.33	0.36	0.03	0.02	0.21	0.16	0.32	0.34
Control Group Mean (Male)		0.07		0.29		0.04		0.26		0.29

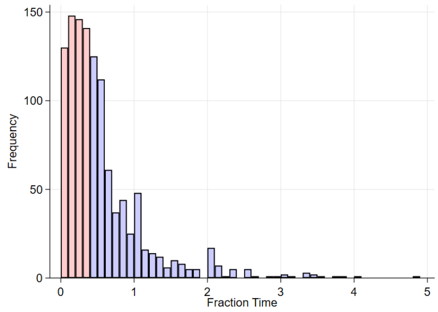
Panel B: Proportion of Trips	Metro		Bus		Taxi		Uber/Careem		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price X 75%	-0.00 (0.01)	-0.02 (0.01)	-0.03 (0.02)	-0.04 (0.03)	-0.01 (0.01)	-0.02* (0.01)	0.06*** (0.02)	0.06* (0.03)	-0.02 (0.02)	0.01 (0.03)
Price X 75% * Male		0.02 (0.02)		0.02 (0.04)		0.02 (0.01)		-0.00 (0.04)		-0.04 (0.04)
Price X 50%	0.00 (0.01)	0.00 (0.02)	-0.10*** (0.02)	-0.11*** (0.03)	-0.02** (0.01)	-0.02* (0.01)	0.12*** (0.02)	0.12*** (0.03)	-0.01 (0.02)	0.00 (0.03)
Price X 50% * Male		0.00 (0.02)		0.02 (0.04)		0.01 (0.01)		-0.01 (0.04)		-0.01 (0.04)
Observations	3133	3133	3133	3133	3133	3133	3133	3133	3133	3133
Control Group Mean	0.06	0.06	0.34	0.29	0.04	0.05	0.24	0.29	0.32	0.31
Control Group Mean (Male)		0.06		0.39		0.03		0.19		0.33

Notes: Panel A reports the coefficients from 5 discrete regressions of each mode on a binary outcome that takes the value 1 if the individual reported taking that mode of transportation for their longest trip the day our follow-up survey. Even numbered columns report the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels, split by gender in even numbered columns. Panel B reports the coefficients from 5 regressions on the proportion of trips taken the previous day of our follow-up survey. Even numbered columns report the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels, split by gender in even numbered columns. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

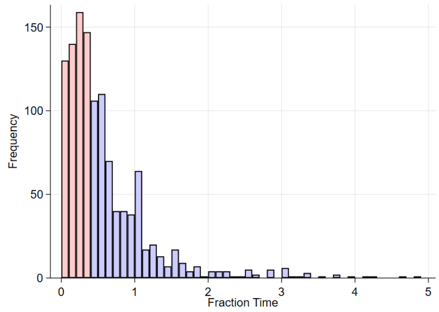
C.3 Robustness: Time Spent on Different Modes

Figure C3 plots histograms of the fraction of time spent on a participants' longest trip (self-reported) relative to time recorded in travel by Google Timeline. We note that on 14% of trips, participants report spending more time on their longest trip than the total recorded travel. This does not vary by treatment group – Control Group: 13.58%; 25% Treatment Group: 15.44%; 50% Treatment Group: 13.21%. We split the sample using this histogram into two groups: (1) participant-days where the longest trip is a large fraction of total travel and (2) participant-days where the longest trip is a small fraction of total travel.

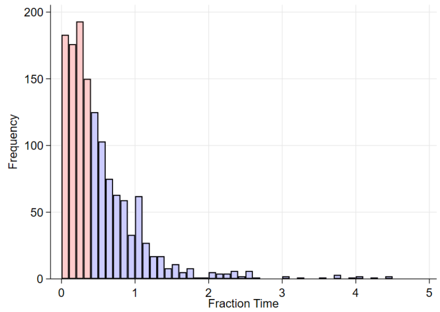
Figure C3. Longest Trip as Fraction of Time Spent Daily Travel Histograms



Control Group



Subsidy 25%



Subsidy 50%

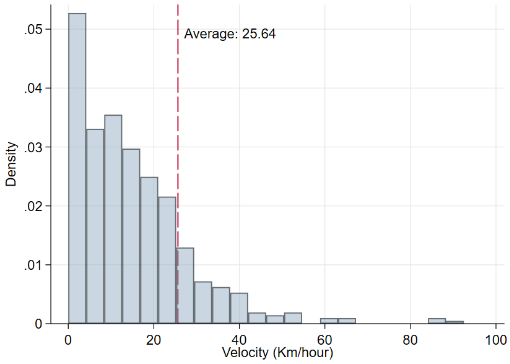
Notes: The figure illustrates longest trip as fraction of time spent daily travel histograms. Bars in red color represent frequencies below the median, bars in blue color represent frequencies above the median.

Table **??** examines evidence of substitution behavior for those whose longest trip is a large or small fraction of total travel, as measured by time spent on a trip. For each participant-day, we compute the fraction of time spent on the longest trip relative to the total time in transit reported by that participant that day. We split the sample using this fraction to examine the robustness of our main estimates on longest trips. The estimates are largely consistent across the tables and with our main findings using all reported trips.

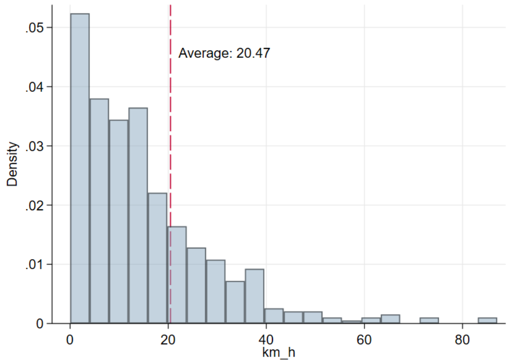
C.4 Velocity

Figure C4 describes the average speed of all movements (km/hour) recorded on participant mobile devices using measurements of distance and time spent traveling. On average velocities range from 20-26 km/hour.

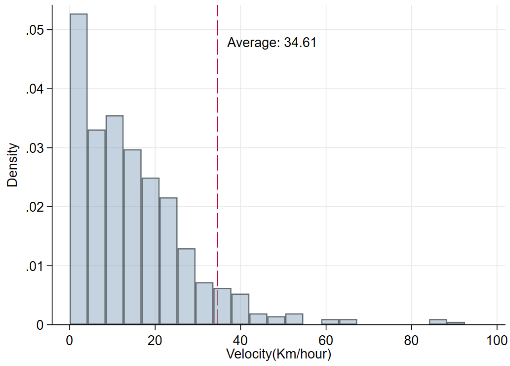
Figure C4. Velocity Histograms by Group



Control Group



Subsidy 25%



Subsidy 50%

Notes: The figure illustrates velocity histograms calculated as total distance (Km) in past 3 days divided by total time (Hours) in past 3 days.

D Additional Heterogeneity in Effects

This appendix includes figures and tables that provide insights from additional analysis of heterogeneity in experimental effects by other characteristics. Table D1 estimates effects on Uber usage, disaggregated by Uber's 4 services. These effects demonstrate that nearly all effects come through increased consumption of UberX services. Table D2 tests for effects on rides taken during at night – effects on both rides and distance traveled are lower than the average effects. Table D3 tests for effects on mode substitution (on longest trips) for the subset of riders that use bus at baseline. While imprecisely estimates, the results provide suggestive evidence of even stronger substitution away from buses among women who ride bus at baseline. The same difference is not observed for men. Among men, the results indicate that effects on additional Uber usage come almost exclusively from men who do *not* ride bus at baseline. Table D4 reports tests of effects for the bottom/top of the income distribution (at baseline), providing some evidence that effects are stronger for higher-income riders.

Table D1. Impacts by Uber Service

	Black		Moto		Shared		Uber X	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price X 75%	0.01**	0.01	0.04	0.01	-0.02	-0.04	1.07***	1.18***
	(0.00)	(0.00)	(0.04)	(0.02)	(0.04)	(0.05)	(0.08)	(0.11)
Price X 75% * Male		0.01		0.09		0.04		-0.22
		(0.01)		(0.08)		(0.07)		(0.15)
Price X 50%	0.01**	0.02***	-0.02	-0.02	-0.03	-0.07	1.84***	1.96***
	(0.00)	(0.01)	(0.04)	(0.01)	(0.04)	(0.05)	(0.08)	(0.11)
Price X 50% * Male		-0.02**		0.00		0.07		-0.22
		(0.01)		(0.07)		(0.07)		(0.16)
Observations	16452	16452	16452	16452	16452	16452	16452	16452

Notes: Columns (1), (3), (5), & (7) report the impacts of the two treatment arms on the inverse hyperbolic sine of weekly kilometers traveled on Uber for each kind of service. Columns (2), (4), (6), & (8) report the results from a specification that interacts a dummy variable for men, showcasing the differential impact the treatments have for that subgroup. The bottom rows report the control means in levels for each group in Columns (1), (3), (5), & (7), and split the means by gender in columns (2), (4), (6), & (8). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table D2. Impacts of Uber Subsidies on Uber Utilization at Night

	Weekly KM on Uber (IHS)		Weekly Trips on Uber	
	(1)	(2)	(3)	(4)
Price X 75%	0.57***	0.54***	0.51***	0.35***
	(0.05)	(0.08)	(0.06)	(0.06)
Price X 75% * Male		0.07		0.29**
		(0.11)		(0.12)
Price X 50%	1.13***	1.18***	0.99***	0.96***
	(0.06)	(0.10)	(0.07)	(0.11)
Price X 50% * Male		-0.10		0.06
		(0.13)		(0.15)
Observations	16440	16440	16440	16440
Control Group Mean Levels	2.7	3.4	0.32	0.28
Control Group Mean Levels (Male)		2.5		0.33

Notes: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of weekly kilometers traveled on Uber at night. Column (2) reports the results from a specification that interacts a dummy variable for men, showcasing the differential impact the treatments have for that subgroup. Columns (3) (4) report the estimates from a regression on the weekly number of trips taken on Uber (in levels) at night. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table D3. Impacts on Mode Used by Bus User (Longest Trip)

Panel A: Impacts on Mode Used

	Metro			Bus			Taxi		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male	(7) Overall	(8) Female	(9) Male
Price X 75%	0.00	-0.02	0.01	-0.02	-0.02	-0.02	-0.01	-0.04**	0.01
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)
Price X 75% * Bus User	-0.01	0.00	-0.02	-0.06	-0.12	-0.02	-0.01	0.04*	-0.04*
	(0.03)	(0.04)	(0.04)	(0.05)	(0.09)	(0.07)	(0.01)	(0.02)	(0.02)
Price X 50%	0.01	0.00	0.01	-0.08***	-0.09***	-0.08**	-0.02*	-0.03**	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)
Price X 50% * Bus User	-0.03	-0.05	-0.01	-0.03	-0.10	0.02	0.00	0.03*	-0.02
	(0.03)	(0.04)	(0.04)	(0.05)	(0.08)	(0.07)	(0.01)	(0.02)	(0.02)
Observations	3186	1503	1683	3188	1503	1683	3188	1503	1683
Control Group Mean Levels	0.07	0.07	0.08	0.57	0.54	0.62	0.03	0.04	0.01
Control Group Mean Levels (No Bus User)	0.06	0.05	0.07	0.22	0.25	0.19	0.03	0.02	0.05

Panel B: Impacts on Mode Used

	Uber			Car		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Price X 75%	0.09***	0.10**	0.08**	-0.03	0.00	-0.04
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
Price X 75% * Bus User	-0.06	-0.02	-0.09*	0.05	0.08	0.07
	(0.04)	(0.07)	(0.06)	(0.05)	(0.06)	(0.07)
Price X 50%	0.13***	0.12***	0.14***	-0.02	0.01	-0.06
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
Price X 50% * Bus User	-0.05	0.01	-0.12**	0.07	0.09*	0.09
	(0.04)	(0.08)	(0.05)	(0.05)	(0.06)	(0.07)
Observations	3186	1503	1683	3188	1503	1683
Control Group Mean Levels	0.13	0.11	0.17	0.18	0.23	0.09
Control Group Mean Levels (No Bus User)	0.24	0.19	0.29	0.39	0.42	0.36

Notes: Panel A reports the coefficients from a regression on a binary outcome that takes the value 1 if the individual reported taking that mode of transportation for their longest trip the day our follow-up survey in a specification that interacts the treatment with a dummy variable that takes the value of 1 if the individual reports at baseline that the longest trip took in the previous day was using a bus and 0 otherwise. Panel B reproduces the same regression but with Uber and Car modes. The bottom rows in each panel report the control means in levels, split by if they were bus users at baseline. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01

Table D4. Treatment Heterogeneity by Income

	Weekly KM on Uber (IHS)	
	(1) Low Income Quartile	(2) High Income Quartile
Price X 75%	1.06*** (0.08)	0.86*** (0.11)
Price X 75% * Interaction	-0.39* (0.21)	0.30* (0.15)
Price X 50%	1.81*** (0.09)	1.60*** (0.11)
Price X 50% * Interaction	-0.82*** (0.24)	0.20 (0.16)
Observations	16440	16440
Control Group Mean Levels	15.2	13.9
Control Group Mean Levels (Interacted group)	13.3	13.1

Notes: Column(1) report impacts on the inverse hyperbolic sine of weekly kilometers traveled on Uber in a specification that interacts the treatment with a dummy variable that takes the value of 1 if the individual falls in the bottom quartile of the income distribution at baseline and 0 otherwise. Column (2) reports the results from a specification that interacts the treatment with a dummy variable that takes the value of 1 if the individual falls in the top quartile of the income distribution at baseline and 0 otherwise .The bottom rows in each panel report the control means in levels, split by gender. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

E Geography of Travel

This section describes the procedure used to estimate effects of price reductions on Uber travel to unique locations, hospitals, universities, and metro stations discussed in Section 4.3. Unique locations were defined using the grid and origins/destinations (shown for one trip in red) mapped below in figure E.1. The exact location and extent of hospitals, universities, and metro stations was obtained using geographically explicit data obtained from OpenStreetMap. Using the latitude/longitude information for trips in the Uber sample, we identify all trips for participants in treatment and control within origins/destinations falling within 100 meters of each feature type. The locations and extents of each feature and associated trips are mapped below in blue and red, respectively, along with the coordinates of all trips in grey.

If the origin/destination of a trip falls within 100 meters, we attribute that feature with the purpose of the trip. The tests reported in table of Section 4.3 depend upon the assumption that differences in the frequency of trips that originate or end within a tight radius around each of these types of features (between treatment and control) provide evidence of the impacts of the intervention on the use of Uber to access universities, hospitals, and metro stations. It is possible, of course, that they provide evidence of the impacts of the intervention on access to other places that are located within close proximity to the associated feature. Tables G.3, E.2, E.3 provide an analysis of the sensitivity to the choice of 100 meter, 175 meter, or 250 meter thresholds for distances around buildings using OpenStreetMap. These tests suggest little difference in the estimated effects (percent difference relative to control).

Figure E.1. Uber Travel to Unique Locations: Cairo Grid

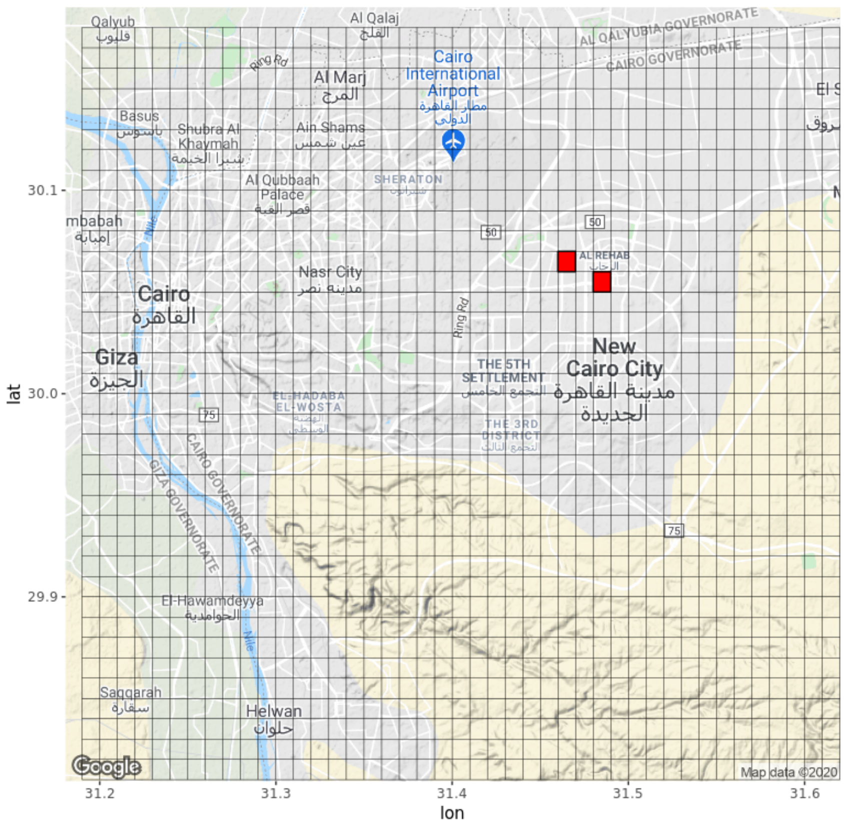


Figure E.2. Trips to Hospitals

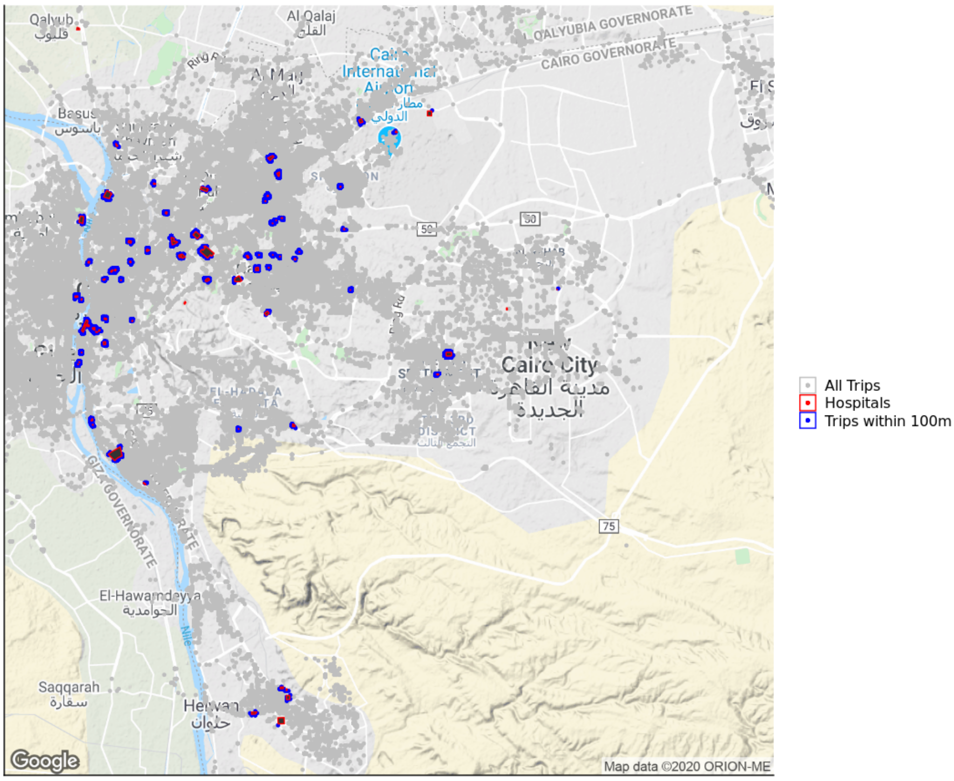


Table E.1. Trips to Hospitals

	Hospital 100			Hospital 175			Hospital 250		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male	(7) Overall	(8) Female	(9) Male
Price X 75%	11.31***	10.71**	11.73***	21.45***	15.85**	25.91***	28.83***	26.15***	31.13***
	(3.05)	(4.40)	(4.20)	(4.94)	(7.12)	(6.84)	(5.96)	(9.23)	(7.79)
Price X 50%	18.13***	23.67***	13.49***	32.87***	37.11***	29.35***	50.55***	52.98***	48.54***
	(3.34)	(5.00)	(4.41)	(5.07)	(7.38)	(6.89)	(6.31)	(9.05)	(8.69)
Constant	7.21***	6.16***	8.08***	13.62***	14.49***	12.94***	19.31***	21.40***	17.62***
	(1.50)	(1.66)	(2.35)	(2.40)	(3.99)	(2.92)	(2.74)	(4.56)	(3.35)
Observations	16452	7272	9168	16452	7272	9168	16452	7272	9168

Notes: The table reports the impacts of the two treatment arms on the weekly number of trips times 100 that started or finished close to a hospital taken on Uber. Columns (1), (2), & (3) report trips that are taken in a range of 100 meters from a hospital. Columns (4), (5), & (6) report trips that are taken in a range of 175 meters. Columns (7), (8), & (9) report trips that are taken in a range of 250 meters. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10;**.05; ***.01.

Figure E.3. Trips to Universities

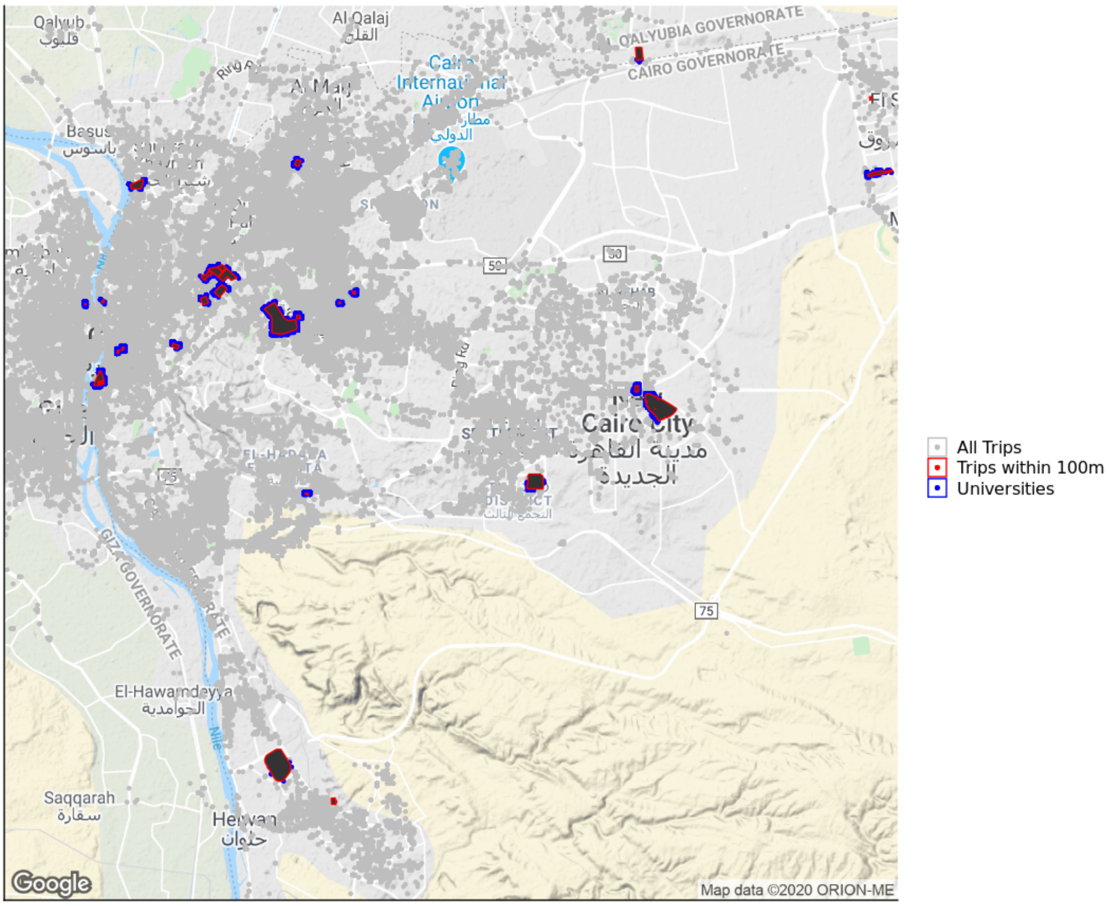


Table E.2. Trips to Universities

	University 100			University 175			University 250		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male	(7) Overall	(8) Female	(9) Male
Price X 75%	5.27**	8.33**	2.80*	10.74***	11.90**	9.86***	14.72***	13.88**	15.48***
	(2.06)	(4.12)	(1.63)	(3.01)	(5.27)	(3.34)	(3.72)	(6.04)	(4.55)
Price X 50%	14.60***	21.49***	9.14***	24.25***	26.85***	22.25***	34.76***	38.97***	31.56***
	(3.22)	(6.25)	(2.91)	(4.58)	(7.03)	(5.98)	(5.53)	(8.66)	(7.12)
Constant	5.22***	5.59***	4.96***	7.73***	9.23***	6.54***	10.55***	12.59***	8.91***
	(0.88)	(1.33)	(1.19)	(1.18)	(2.03)	(1.42)	(1.49)	(2.45)	(1.83)
Observations	16452	7272	9168	16452	7272	9168	16452	7272	9168

Notes: The table reports the impacts of the two treatment arms on the weekly number of trips times 100 that started or finished close to a university taken on Uber. Columns (1), (2), & (3) report trips that are taken in a range of 100 meters from an university. Columns (4), (5), & (6) report trips that are taken in a range of 175 meters. Columns (7), (8), & (9) report trips that are taken in a range of 250 meters. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10;**.05; ***.01.

Figure E.4. Trips to Metro Stations

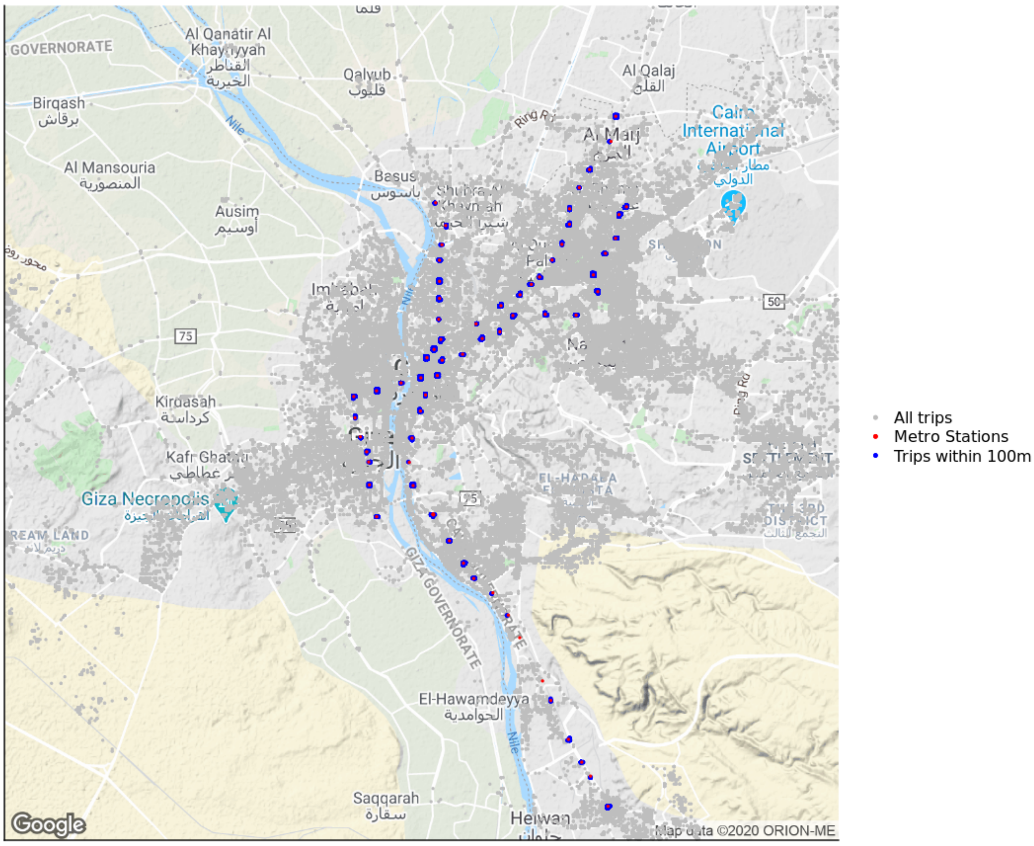


Table E.3. Trips to Metro Stations

	Metro 100			Metro 175			Metro 250		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male	(7) Overall	(8) Female	(9) Male
Price X 75%	11.17***	4.80***	16.23**	18.19***	10.77***	24.00***	30.71***	25.27***	34.82***
	(4.03)	(1.49)	(7.15)	(4.63)	(3.01)	(7.94)	(6.27)	(6.55)	(9.94)
Price X 50%	11.86***	13.74***	10.36***	22.70***	21.68***	22.83***	37.12***	37.97***	35.73***
	(1.81)	(3.05)	(2.18)	(3.11)	(3.81)	(4.64)	(4.80)	(5.49)	(7.42)
Constant	4.72***	4.77***	4.69***	8.81***	8.44***	9.14***	15.73***	12.22***	18.64***
	(0.65)	(0.87)	(0.98)	(0.99)	(1.23)	(1.55)	(2.20)	(1.76)	(3.77)
Observations	16452	7272	9168	16452	7272	9168	16452	7272	9168

Notes: The table reports the impacts of the two treatment arms on the weekly number of trips times 100 that started or finished close to a metro station taken on Uber. Columns (1), (2), & (3) report trips that are taken in a range of 100 meters from a metro station. Columns (4), (5), & (6) report trips that are taken in a range of 175 meters. Columns (7), (8), & (9) report trips that are taken in a range of 250 meters. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10;**.05; ***.01.

F Persistence of Treatment Effects

While the subsidies provided to the participants in our study changed their Uber usage during the 12 weeks of the intervention, it is unclear how their usage would change after discontinuing the subsidies. It is possible that individuals go back to their pre-treatment utilization levels, but it also possible that individuals have learned how to better optimize their mobility choices now that they have additional experience with Uber and decide to use it more than they did before. On the other hand, they may have become used to having access to Uber at a lower price, changing their reference points for acceptable costs, and decrease their Uber usage after the end of the intervention due to the relative increase in price.

Using Uber administrative data, we can estimate the impact of the treatments on rider behavior after the subsidies are removed. Table F1 reports the impacts on total weekly kilometers traveled on Uber and the number of weekly trips taken during the 12 weeks after the end of the intervention (weeks 13-24 after randomization). We find that those in treatment use Uber much more than those in control, an increase of 0.55 IHS-points for the 25% treatment group (a 73% increase), and an increase of 0.60 IHS-points for those in the 50% group (an 82% increase). While this is much smaller than the impact from the actual price reductions, these estimates are both statistically and economically significant. Point estimates suggest that the persistence of effects for participants in the 50% group is *lower* than for those in the 25% group. One possible explanation is that participants anchored their reference point at the 50% price level, making the price increase after the end of the intervention larger compared to those in the 25% group. However, we note that treatment effects are less precisely estimated than effects during the treatment period and that differences between groups are not statistically significant.

Table F1. Persistence of Uber Utilization After Study

	Weekly KM on Uber (IHS)		Weekly Trips on Uber	
	(1)	(2)	(3)	(4)
Price X 75%	0.55***	0.92***	0.77***	1.18***
	(0.13)	(0.24)	(0.23)	(0.40)
Price X 75% * Male		-0.50*		-0.50
		(0.28)		(0.47)
Price X 50%	0.60***	0.75***	0.80***	0.68
	(0.13)	(0.25)	(0.20)	(0.43)
Price X 50% * Male		-0.19		0.04
		(0.29)		(0.48)
Observations	4251	4251	4251	4251
Control Group Mean Levels	12.1	13.9	1.3	1.6
Control Group Mean Levels (Male)		11.4		1.3

Notes: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of weekly kilometers traveled on Uber after the experiment is finished. Column (2) reports the results from a specification that interacts a dummy variable for men, showcasing the differential impact the treatments have for that subgroup. Columns (3) & (4) report the estimates from a regression on the weekly number of trips taken on Uber (in levels). The bottom rows report the control means in both IHS and levels for each group in Columns (1) & (3), and split the means by the interacted and non-interacted groups in columns (2) & (4). Regressions include controls chosen using a double-post-lasso procedure. Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

G Estimates of Treatment Effects Omitting Lasso-Based Controls

In this section, we report estimates for all main tables using regressions that control for the baseline value of the outcome variable instead of the set of controls selected when using the double post-lasso procedure developed by Belloni et al. (2014). We find no evidence of sensitivity to the inclusion of these controls, although the precision of estimates often increases when we utilize the double post-lasso procedure.

We included 26 variables for the lasso to utilize: Gender, travel, marital status, work status, car ownership, motorcycle ownership, aspects of their longest trip in the day before the survey (safety, time, cost), feelings of safety on different modes, education, and an interaction of all of these variables with a dummy variable for male.

Table G.1. Impacts of Uber Subsidies on Uber Utilization

	Weekly KM on Uber (IHS)		Weekly Trips on Uber	
	(1)	(2)	(3)	(4)
Price X 75%	1.00***	1.08***	1.73***	1.98***
	(0.08)	(0.12)	(0.15)	(0.21)
Price X 75% * Male		-0.15		-0.44
		(0.16)		(0.30)
Price X 50%	1.69***	1.84***	3.68***	4.20***
	(0.08)	(0.12)	(0.20)	(0.31)
Price X 50% * Male		-0.27		-0.92**
		(0.16)		(0.41)
Observations	16440	16440	16440	16440
Control Group Mean Levels	13.6	14.1	1.5	1.6
Control Group Mean Levels (Male)		13.2		1.5

Notes: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of weekly kilometers traveled on Uber. Column (2) reports the results from a specification that interacts a dummy variable for men, showcasing the differential impact the treatments have for that subgroup. Columns (3) & (4) report the estimates from a regression on the weekly number of trips taken on Uber (in levels). The bottom rows of Panel A report the control means in levels for each group in Columns (1) & (3), and split the means by gender in columns (2) & (4). Regressions include strata, cohort and follow-up round fixed effects as well as baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table G.2. Experiments on the Length and Salience of the Price Treatment

	Unannounced Short Experiment		Preannounced Short Experiment		Long Experiment 1st Week	
	(1) Weekly KM	(2) Trips	(3) Weekly KM	(4) Trips	(5) Weekly KM	(6) Trips
Price X 90%	0.42**	0.49	0.42**	0.38		
	(0.18)	(0.32)	(0.19)	(0.24)		
Price X 90% * Male	-0.44*	-0.32	-0.25	-0.22		
	(0.26)	(0.45)	(0.25)	(0.33)		
Price X 75%					0.32*	0.88**
					(0.20)	(0.34)
Price X 75% * Male					0.19	0.24
					(0.27)	(0.49)
Price X 50%	0.77***	1.44***			0.84***	2.49***
	(0.19)	(0.36)			(0.20)	(0.43)
Price X 50% * Male	0.04	0.80			-0.23	-1.08**
	(0.27)	(0.56)			(0.27)	(0.55)
Observations	1500	1500	1000	1000	1370	1370
Control Group Mean Levels	20.4	2.2	13.4	2.0	22.9	2.6
Control Group Mean Levels (Male)	21.4	2.1	18.7	2.2	20.9	2.2

Notes: Columns (1), (3), & (5) report the impacts of the two treatment arms and their interactions with a male dummy variable, on the inverse hyperbolic sine of weekly kilometers traveled on Uber during the unannounced experiment respectively , the pre-announced experiment and the first week of the experiment. Columns (2), (4), & (6) report the same but with number of trips as the outcome variable. The bottom rows report the control means in levels and split by gender. Regressions include strata, cohort and follow-up round fixed effects as well as baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table G.3. Trips to University, Hospital and Metro

	Unique Location Visited		University Trips		Hospital Trips		Metro Trips	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price X 75%	5.12***	5.06***	5.27**	8.28**	11.31***	10.72**	11.17***	4.76***
	(0.44)	(0.63)	(2.06)	(4.12)	(3.05)	(4.40)	(4.03)	(1.50)
Price X 75% * Male		0.13		-5.42		1.05		11.51
		(0.87)		(4.43)		(6.10)		(7.39)
Price X 50%	9.96***	10.89***	14.60***	21.35***	18.13***	23.91***	11.86***	13.73***
	(0.54)	(0.81)	(3.22)	(6.23)	(3.34)	(5.04)	(1.81)	(3.04)
Price X 50% * Male		-1.67		-12.15*		-10.38		-3.35
		(1.09)		(6.88)		(6.71)		(3.72)
Observations	1404	1404	16452	16452	16452	16452	16452	16452
Control Group Mean Levels	8.9	8.8	5.3	5.6	7.2	6.1	4.7	4.8
Control Group Mean Levels (Male)		8.9		5.0		8.1		4.7

Notes: Column (1) reports the impacts of the two treatment arms on the unique weekly number of grids visited in the start and finish locations on Uber trips. Columns (3), (5), & (7) report the impacts on the weekly number of trips that started or finished close to an university, hospital and metro station (multiplied by 100 to make coefficients easier to read). Columns (2), (4), (6), & (8) do the same but include an interaction term for men. The bottom rows report the control means in levels, split the means by gender in even numbered columns. Regressions include strata, cohort and follow-up round fixed effects as well as baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table G.4. Impacts in Total Mobility

	Total KM Past 3 Days (IHS)	
	(1)	(2)
Price X 75%	0.10	0.17
	(0.09)	(0.14)
Price X 75% * Male		-0.12
		(0.19)
Price X 50%	0.36***	0.49***
	(0.08)	(0.12)
Price X 50% * Male		-0.26
		(0.17)
Observations	3476	3476
Control Group Mean Levels	88.0	62.0
Control Group Mean Levels (Male)		111.9

Notes: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of total kilometers traveled in the three days prior to our follow-up survey as reported by Google Maps' "Timeline" feature. Column (2) reports the results from a specification that interacts a dummy variable for men, showcasing the differential impact the treatments have for that subgroup. The bottom rows report the control means in levels and split the means by the interacted group, and non-interacted groups in Columns (2).Regressions include strata, cohort and follow-up round fixed effects as well as baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table G.5. Impacts on Mode Used for Longest Trip

	Metro		Bus		Taxi		Uber		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price X 75%	-0.01	-0.02	-0.06**	-0.04	-0.02**	-0.03**	0.10***	0.10***	-0.01	-0.01
	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
Price X 75% * Male		0.03		-0.03		0.02		0.00		-0.01
		(0.03)		(0.05)		(0.01)		(0.05)		(0.05)
Price X 50%	0.00	-0.01	-0.1***	-0.1***	-0.02**	-0.03**	0.13***	0.15***	-0.02	0.00
	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
Price X 50% * Male		0.02		0.02		0.02		-0.03		-0.03
		(0.03)		(0.05)		(0.01)		(0.05)		(0.05)
Observations	3186	3186	3186	3186	3186	3186	3186	3186	3186	3186
Control Group Mean Levels	0.1	0.1	0.3	0.3	0.0	0.0	0.2	0.3	0.3	0.3
Control Group Mean Levels (Male)		0.1		0.4		0.0		0.2		0.3

Notes: This table reports the coefficients from a regression on a binary outcome that takes the value 1 if the individual reported taking that mode of transportation for their longest trip the day our follow-up survey. Even numbered columns report the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels, split by gender in even numbered columns. Regressions include strata, cohort and follow-up round fixed effects as well as baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table G.6. Impacts on Reported Safety on Recent Trips

	Feeling on Longest Trip Yesterday 5=Very Safe, 1=Very Unsafe	
	(1)	(2)
Price X 75%	0.07	0.16*
	(0.06)	(0.09)
Price X 75% * Male		-0.16
		(0.12)
Price X 50%	0.11*	0.20**
	(0.06)	(0.09)
Price X 50% * Male		-0.18
		(0.11)
Observations	3101	3101
Control Group Mean Levels	4.0	3.9
Control Group Mean Levels (Male)		4.1

Notes:Column (1) reports the impacts of the two treatment arms on the reported level of safety felt during the longest trip taken by the individual during the day prior to the follow-up survey. Column (2) reports the results from a specification that interacts treatment with a dummy variable for men. The bottom rows report the control means in levels, split by gender in Column (2). The bottom rows report the control means in levels, split by gender in even numbered columns. Regressions include strata, cohort and follow-up round fixed effects as well as baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table G.7. Effect on Baseline Bus Riders

Panel A:Weekly Uber Usage (KM)	Weekly KM on Uber(IHS)			Weekly KM on Uber(IHS) Perceive Bus as Unsafe		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Price X 75%	1.08***	1.11***	1.06***	1.07***	1.24***	0.90***
	(0.09)	(0.14)	(0.12)	(0.15)	(0.21)	(0.22)
Price X 75% * Bus User	-0.29*	-0.06	-0.43*	-0.36	-0.34	-0.17
	(0.16)	(0.24)	(0.22)	(0.33)	(0.43)	(0.48)
Price X 50%	1.69***	1.70***	1.69***	1.59***	1.77***	1.44***
	(0.10)	(0.14)	(0.13)	(0.15)	(0.19)	(0.22)
Price X 50% * Bus User	-0.02	0.57**	-0.38	-0.03	1.10**	-0.56
	(0.17)	(0.24)	(0.23)	(0.33)	(0.46)	(0.42)
Observations	16440	7272	9168	6012	3336	2676
Control Group Mean Levels	25.5	25.7	25.4	25.9	27.5	23.5
Control Group Mean Levels (Bus User)	13.4	14.0	13.1	12.6	6.2	15.6
Panel B:Total Mobility (KM)	Total Mobility (KM) in past 3 days(IHS)			Total Mobility (KM) in past 3 days(IHS) Perceive Bus as Unsafe		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Price X 75%	0.10	0.18	-0.04	0.03	0.02	0.03
	(0.12)	(0.17)	(0.15)	(0.17)	(0.23)	(0.24)
Price X 75% * Bus User	0.02	0.04	0.15	0.64	0.91	0.72
	(0.21)	(0.32)	(0.26)	(0.35)	(0.60)	(0.41)
Price X 50%	0.37***	0.52***	0.21	0.23	0.43*	-0.12
	(0.11)	(0.15)	(0.14)	(0.15)	(0.18)	(0.25)
Price X 50% * Bus User	-0.04	-0.12	0.12	0.50	0.79	0.62
	(0.18)	(0.29)	(0.22)	(0.31)	(0.57)	(0.36)
Observations	3476	1666	1810	1313	780	533
Control Group Mean Levels	93.8	61.0	130.2	95.7	67.8	142.9
Control Group Mean Levels (Bus User)	75.6	64.8	82.1	63.1	52.6	68.6

Notes: Panel A: Columns (1), (2), & (3) report impacts on the inverse hyperbolic sine of weekly kilometers traveled on Uber in a specification that interacts the treatment with a dummy variable that takes the value of 1 if the individual reports at baseline that the longest trip took in the previous day was using a bus and 0 otherwise. Columns (4), (5), & (6) in panel A report the result for a specification that includes only people who perceived the bus as unsafe in the baseline survey. Panel B reproduces the same regressions but with total kilometers traveled as the outcome variable. The bottom rows in each panel report the control means in levels, split by if they were bus users at baseline. Regressions include strata, cohort and follow-up round fixed effects as well as baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

H Effects on Short-Term Labor Market Outcomes

This section reports on the impacts of reductions in the cost of ride-hailing services on labor market impacts. A price decrease could improve the ability of job seekers to better match with existing vacancies. Previous studies, such as Abebe et al. (2021a), Franklin (2018), Abebe et al. (2021b), Bryan et al. (2014) and Phillips (2014), provide evidence that travel subsidies can improve employment outcomes. Other work has shown the importance of safety on female education and labor market choices in developing country cities (Kondylis et al., 2020, Borker, 2018, Jayachandran, 2019).

Table H.1 reports impacts on job search and work status. We stratified our sample by job search status and interact search status with treatment in this table. The main effects are reported for individuals who were searching for a job at baseline. Overall, we find little evidence that these subsidies had substantial effects on search behavior or employment for either gender across the 3-month study period. We find that among individuals who were searching for a job at baseline, there is a one percentage point decrease in whether those in the 25% treatment group are currently working relative to control, and a three percentage point decrease in the 50% subsidy group. These null effects are precisely estimated, with standard errors of 3 percentage points.

These results contribute to a growing literature on the labor market impacts of transport subsidies, much of which has found that transport frictions are an important part of the reason why job seekers are not matching with employers. The present study provides larger subsidies, over a longer period, and delivers transport services using a highly flexible ride-hailing platform. The intervention generates large effects on mobility yet we can rule out large labor market effects (in the short-run). Our findings reflect effects on a higher income sample than the earlier studies, implying that transport frictions in the job search phase may interact in important ways with capital constraints in low income countries.

Table H.1. Labor Market Impacts

	Searching			Apply			Currently Working		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male	(7) Overall	(8) Female	(9) Male
Price X 75%	-0.03	0.02	-0.04	-0.47**	-0.32	-0.50*	-0.01	0.02	-0.01
	(0.04)	(0.08)	(0.05)	(0.23)	(0.34)	(0.30)	(0.03)	(0.07)	(0.04)
Price X 75% * Not Searching	0.08	0.02	0.10	0.60**	0.39	0.67**	-0.06	-0.09	
	(0.05)	(0.08)	(0.06)	(0.25)	(0.36)	(0.32)	(0.06)	(0.08)	
Price X 50%	0.02	-0.04	0.05	-0.01	0.60	-0.20	-0.03	-0.01	-0.01
	(0.04)	(0.07)	(0.05)	(0.30)	(0.68)	(0.32)	(0.03)	(0.08)	(0.03)
Price X 50% * Not Searching	-0.01	0.02	-0.01	0.07	-0.63	0.34	0.03	0.01	
	(0.04)	(0.08)	(0.06)	(0.30)	(0.70)	(0.33)	(0.05)	(0.09)	
Observations	3195	1501	1692	3193	1500	1691	1643	959	684
Control Group Mean Levels	0.50	0.43	0.52	1.28	0.94	1.43	0.80	0.69	0.85
Control Group Mean Levels (N.S.)	0.07	0.08	0.07	0.08	0.09	0.05	0.66	0.66	1.00

Notes: Columns (1), (2), & (3) report the impact of treatments on a binary variable that is equal to 1 if the individual reports that they are searching for work during the follow-up survey. The regression specification includes treatment interacted with a dummy equal to 1 if the individual was not searching for work at baseline. Columns (4), (5), & (6) estimate the impacts on the number of jobs applied to, while columns (7), (8), & (9) estimate the impacts on if the individuals are currently working at the time of the follow-up survey. The bottom rows report the control means in levels, split by if they were searching for a job at baseline (N.S. = "Not Searching"). There is no variation in responses for men who were not searching for a job at baseline in column 9 and so those interaction cells are intentionally left empty (they are all currently working). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure.Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

I Model of Supply and Demand for PVKT

This section provides additional details about the model of supply and demand for private vehicle kilometers traveled from Section 6.2. As described in the main text, equilibrium travel in Cairo is given by the following demand and supply equations:

$$\Delta X_{PVKT} = f(\Delta P_U) = \varepsilon_{Eq} * \Delta P_U \tag{1}$$

$$\Delta P_E = \Delta P_U + g(\Delta X_{PVKT}, PR_U) * (C_{VOT}) \tag{2}$$

The demand equation defines the change in private vehicle kilometers traveled (X_{PVKT}) as a function of the change in the price of Uber. We are interested in recovering ε_{Eq}, which is the equilibrium elasticity of private vehicle kilometers traveled with respect to the price of Uber. We know from our experimental results above that the price elasticity of travel demand is approximately linear, and so we assume here that the $f(.)$ function is also linear.

The supply equation states that the change in the effective price of Uber ΔP_E is equal to the change in the price of Uber plus the change in the cost of time due to an increase in congestion resulting from induced demand. The $g(.)$ function converts changes in private kilometers traveled into changes in congestion. We assume that congestion is a linear function of the change in kilometers traveled as shown by Kreindler (2020), and so we simply multiply the change in kilometers traveled by the proportion of the population that is induced to change their travel by the change in the price of Uber.

Here we illustrate how Eq. 1 and Eq. 2 are used to derive Eq. 6 in Section 6.2. First, we define a γ parameter that describes how the price of Uber and the *effective* price of Uber are related.

$$\varepsilon_{Eq} = \varepsilon_{PVKT} * \gamma \tag{3}$$

Inserting the expression for ΔX_{PVKT} in the supply equation, we obtain:

$$\Delta P_E = \Delta P_U + g(\varepsilon_{Eq} * \Delta P_U, PR_U) * (C_{VOT}) \tag{4}$$

$$\Delta P_E = \Delta P_U + \varepsilon_{PVKT} * \gamma * \Delta P_U * PR_U * (C_{VOT}) \tag{5}$$

Noting that $\Delta P_E = \Delta P_U * \gamma$, we then get:

$$\Delta P_U * \gamma = \Delta P_U + \varepsilon_{PVKT} * \gamma * \Delta P_U * PR_U * (C_{VOT}) \tag{6}$$

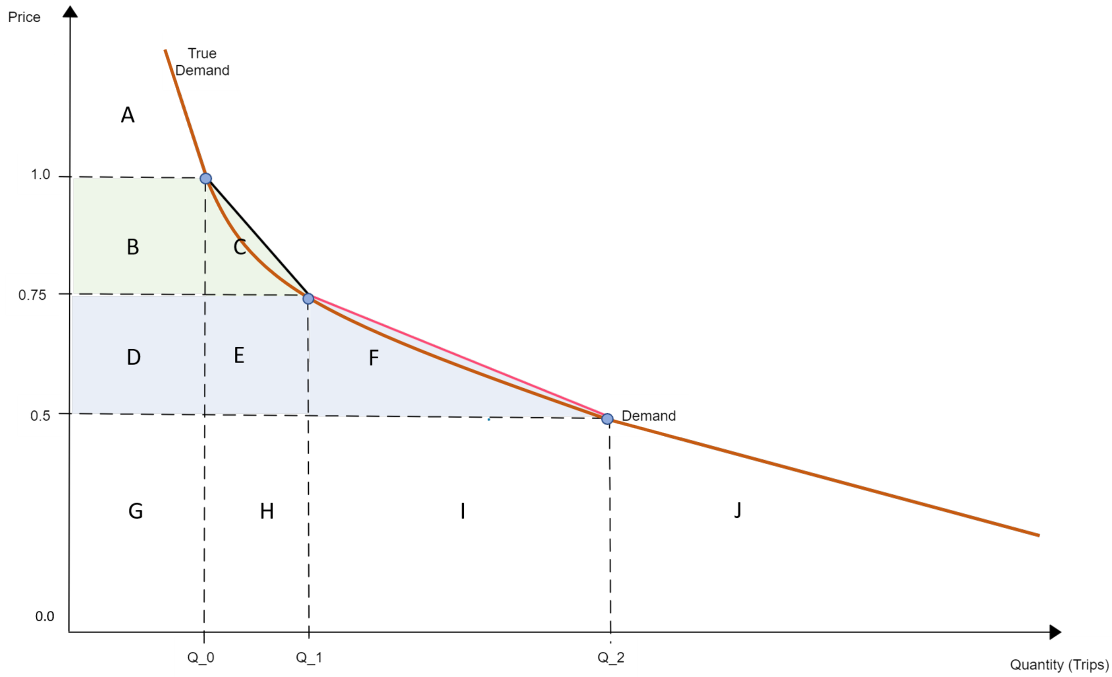
Re-arranging terms, we recover the following expression for gamma:

$$\gamma = 1/(1 - \varepsilon_{PVKT} * PR_U * C_{VOT}) \tag{7}$$

J Consumer Surplus

In this section, we provide details on the procedure that we use to compute the consumer surplus using different elasticities from the experiment.

Figure J.1. Consumer Surplus from Transport Cost Reductions



Price per Kilometer of Travel (All Modes): $P_{1.0}^{TotalKm}, P_{0.75}^{TotalKm}, P_{0.5}^{TotalKm}$

To compute the consumer surplus for each level of price on Uber services, we need to estimate the impacts on quantity consumed and changes in the corresponding prices of a kilometer of travel. We do this for two sets of outcomes: (1) changes in *Uber* mobility and prices, and (2) changes in *total mobility* and prices. Changes in the quantity of travel are estimated directly from our experiment. The change in the price of Uber is observed directly in Uber administrative data. We describe changes in the price of total travel below.

We construct a composite price of overall travel using the average price of travel on each mode, weighted by the proportion of trips taken using that mode. We use the shares for each treatment group (by gender) to account for changes in the effective price of each kilometer of travel as participants optimize travel across different modes in response to experimental changes in the price of Uber. We do not directly measure the price of a kilometer of travel on each modes. In our follow up survey, we ask respondents to report the cost of the longest trip they took on the day before the survey and to estimate the cost of that same trip if they took it on different modes. We use these within-trip relative prices to compute the relative price of the average trip taken on Uber vs each of the 4 other modes ($\frac{Price_m}{Price_{Uber}}$). We estimate the composite price using the relative price of each mode, the probability that a given mode is used at each level of Uber price treatment ($Prob(m)_{0.5,0.75}$), and the baseline Uber price per kilometer for the average trip in the control group:

$$\overline{Price}^{TotalKm}_{0.5,0.75} = \sum_{i=1}^{5} Prob(m)_{0.5,0.75} * \frac{Price_m}{Price_{Uber}} * \overline{\frac{Price}{Km}}_{Uber}$$

To estimate the composite price *per trip* ($\overline{Price}^{TotalTrips}_{0.5,0.75}$), we use the baseline Uber price for the average trip in the control group as the numeraire $(\overline{\frac{Price}{Trip}})_{Uber}$:

$$\overline{Price}^{TotalTrips}_{0.5,0.75} = \sum_{i=1}^{5} Prob(m)_{0.5,0.75} * \frac{Price_m}{Price_{Uber}} * \overline{\frac{Price}{Trip}}_{Uber}$$

The estimated price ratios for each transportation mode are:

Variable	Uber	Metro	Bus	Taxi	Car
Mode Cost Ratio: All	1	0.17	0.21	1.17	0.69
Mode Cost Ratio: Female	1	0.16	0.19	1.13	0.71
Mode Cost Ratio: Male	1	0.19	0.23	1.21	0.69

The probabilities that a trip is taken on each available mode using trip counts from follow-up surveys are reported in below, in line with estimates from Table 5.

All	Metro	Bus	Taxi	Uber	Car
Control	0.060	0.345	0.037	0.239	0.319
Price x 75%	0.053	0.287	0.027	0.326	0.306
Price x 50%	0.062	0.240	0.020	0.383	0.295

Female	Metro	Bus	Taxi	Uber	Car
Control	0.058	0.292	0.045	0.295	0.310
Price x 75%	0.044	0.257	0.028	0.372	0.299
Price x 50%	0.059	0.183	0.026	0.454	0.279

Male	Metro	Bus	Taxi	Uber	Car
Control	0.062	0.392	0.030	0.190	0.327
Price x 75%	0.061	0.313	0.027	0.288	0.311
Price x 50%	0.066	0.294	0.015	0.315	0.311

Using the equation above, we compute the following values for the price of a kilometer of travel at $P_{1.0}, P_{0.75}, P_{0.5}$ (by gender):

	Control	Price x 75%	Price x 50%
All	3.62	3.45	2.97
Female	3.96	3.64	3.13
Male	3.38	3.34	2.87

The price ratios for total trips are equivalent to the ratios for kilometers traveled because these ratios are constructed from our survey questions that ask about relative prices for the same trip taken on different modes. Our composite prices are subject to the accuracy of mental accounting of the relative prices of trips taken on different modes. Table J.1 reports the results of an analysis of the sensitivity of our total travel consumer surplus CS_{Uber}^{Travel} estimates to: (1) 10% increases/reductions in the relative prices of transport services (relative to Uber) and (2) the use of gas prices for the relative price of car travel, which may be difficult for participants to estimate. Gas prices provide a lower bound on the price of car travel, as they do not account for the full cost of car ownership (purchase costs, vehicle maintenance, insurance) or parking, tolls, or other fees associated with car trips.

Table J.1. Consumer Surplus For Total Mobility - Sensitivity to Relative Prices

	Consumer Surplus with Two Points in the Demand Curve			Consumer Surplus with One Point in the Demand curve		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
$CS_{Experiment}(TotalKm)$	156 [131 , 194]	160 [131 , 199]	153 [132 , 189]	158 [135 , 182]	165 [137 , 193]	152 [132 , 172]
$CS_{Experiment}10\%Reduction(TotalKm)$	148 [124 , 184]	153 [125 , 190]	144 [124 , 179]	150 [127 , 172]	157 [130 , 184]	142 [124 , 161]
$CS_{Experiment}10\%Increase(TotalKm)$	164 [138 , 204]	168 [137 , 209]	161 [140 , 199]	167 [142 , 192]	173 [144 , 202]	161 [140 , 182]
$CS_{Experiment}GasPrices(TotalKm)$	137 [114 , 171]	137 [112 , 170]	137 [117 , 171]	138 [117 , 159]	141 [118 , 165]	134 [117 , 152]

Notes: Columns (1), (2) & (3) report the consumer surplus estimates calculated with two points from the approximation of the elasticity of a reduction of 25% in Uber price and the reduction of 50%. Columns (4), (5) & (6) report the consumer surplus with one point from the approximation of the elasticity of a reduction of 50% of the price of Uber.

Table J.2 reports estimates of consumer surplus using the experimental demand elasticities described in Section 6.1 and the equilibrium elasticities described in Section 6.3. Our estimates of equilibrium response dampens *additional* quantity demanded by 10%. Given the assumptions defined in Section 6 (in line with Alvarez and Argente (2020b)), the estimates below indicate that the individual-level consumer surplus is similar for quantities demanded in the experimental and equilibrium settings. A decomposition of the CS estimates indicates that approximately 27% comes from changes in the quantity demanded. If the equilibrium response dampens the additional quantity by 10%, then we would expect approximately a 3% reduction in CS in equilibrium, which is consistent with the magnitudes below.

Table J.2. Consumer Surplus For Total Mobility

	Consumer Surplus with Two Points in the Demand Curve			Consumer Surplus with One Point in the Demand curve		
	(1) Average	(2) Female	(3) Male	(4) Average	(5) Female	(6) Male
$\text{CS}_{Experiment}(TotalKm)$	156	160	153	158	165	152
	[131 , 194]	[131 , 199]	[132 , 189]	[135 , 182]	[137 , 193]	[132 , 172]
$\text{CS}_{Equilibrium}(Pop. = 30\%)$	154	157	151	155	160	150
	[131 , 190]	[130 , 195]	[132 , 185]	[134 , 178]	[135 , 187]	[132 , 168]
$\text{CS}_{Equilibrium}(Pop. = 40\%)$	153	156	151	154	159	150
	[131 , 189]	[129 , 193]	[132 , 184]	[133 , 176]	[135 , 185]	[132 , 167]
$\text{CS}_{Equilibrium}(Pop. = 50\%)$	153	155	151	154	158	150
	[130 , 187]	[129 , 192]	[132 , 183]	[133 , 175]	[134 , 183]	[132 , 166]

Notes: Columns (1), (2) & (3) report the consumer surplus estimates calculated with two points from the approximation of the elasticity of a reduction of 25% in Uber price and the reduction of 50%. Columns (4), (5) & (6) report the consumer surplus with one point from the approximation of the elasticity of a reduction of 50% of the price of Uber.

K Adjustments for COVID-19

Our budget allowed us to enroll 1,500 participants, but our last cohort was impacted by the lock-down associated with COVID-19. Since mobility behavior was greatly affected by this unusual worldwide event, we drop this cohort from our main analysis. The sample used in our main analysis consists of 1,373 participants, though we do have administrative data and some follow-up data on the final cohort. Including the final cohort in our analysis does not substantially affect our results, though estimates are slightly attenuated as a result of reductions in mobility levels for all participants in that cohort. COVID-19 also negatively impacted our intended 6-month follow-up survey, which was designed to collect additional data on overall mobility and labor market outcomes three months after the completion of the experiment. We had collected those data for one third of the sample by the time the lock-down began. Given selection and attrition concerns, we do not report these longer-term results.

Table K.1. Main Results including Cohort Affected by COVID-19

	Weekly KM on Uber (IHS)		Weekly Trips on Uber		Total KM Past 3 Days	
	(1)	(2)	(3)	(4)	(5)	(6)
Price X 75%	0.94***	1.03***	1.65***	1.79***	0.14	0.19
	(0.07)	(0.11)	(0.14)	(0.20)	(0.09)	(0.13)
Price X 75% * Male		-0.17		-0.25		-0.15
		(0.14)		(0.29)		(0.17)
Price X 50%	1.60***	1.68***	3.44***	3.73***	0.39***	0.50***
	(0.08)	(0.11)	(0.19)	(0.28)	(0.08)	(0.11)
Price X 50% * Male		-0.15		-0.55		-0.25
		(0.15)		(0.37)		(0.15)
Observations	17964	17964	17964	17964	3670	3670
Control Group Mean Levels	12.1	13.9	1.3	1.6	55.8	34.8
Control Group Mean Levels (Male)		11.4		1.3		75.1

Notes: Column (1) reports the impacts of the two treatment arms on the inverse hyperbolic sine of weekly kilometers traveled on Uber. Column (2) reports the results from a specification that interacts a dummy variable for men, showcasing the differential impact the treatments have for that subgroup. Columns (3) (4) report the estimates from a regression on the weekly number of trips taken on Uber (in levels). Columns (5) & (6) report the impacts on the inverse hyperbolic sine of total kilometers traveled in the three days prior to our follow-up survey as reported by Google Mapsâ âTimelineâ feature. The bottom rows report the control means in levels and split by gender in Columns (2), (4), & (6). Regressions include strata, cohort and follow-up round fixed effects as well as controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

L Ethics of RCT and Uber Collaboration

We have developed this appendix in an effort to describe the ethical considerations of this experiment, and clarify the nature of the collaboration between the researchers and Uber. We follow the framework put forth in Asiedu et al. (2021), for the sake of comparability within economics. When relevant, we quote from the main text or directly from our IRB documentation, which we did not deviate from.

1. **Equipoise**

   Excerpt from Introduction: *Attempts to study the demand for mobility have been limited not only by the complexity of transportation markets, but also by endogeneity concerns and a lack of available micro-data on transportation behavior.*

   ...This paper contributes to a growing empirical literature on the impact of transportation services on commuting patterns and economic activity in cities (Campante and Yanagizawa-Drott, 2017, Asher and Novosad, 2018, Hanna et al., 2017). A primary challenge in this literature is that the provision and prices of transportation services are (almost) never randomly assigned. As a result, empirical efforts have focused on settings characterized by exogenous shocks in service provision (Gupta et al., 2020, Gorback, 2020, Tsivanidis, 2018, Gonzalez-Navarro and Turner, 2018, Ahlfeldt et al., 2015, Anderson, 2014), available instruments (Severen, 2018, Baum-Snow et al., 2017, Duranton and Turner, 2011, Baum-Snow, 2007), and structural approaches (Heblich et al., 2020, Allen and Arkolakis, 2019, Redding and Rossi-Hansberg, 2017).

2. **Role of Researchers with Respect to Implementation:**

   Christensen and Osman are active researchers in the project. They designed the treatment arms and managed the data collection activities and all of the data analysis.

3. **Potential Harms to Research Participants from the Interventions:**

   Excerpt From IRB 19102: *There are no known risks other than the normal privacy risks from participation in any research study. All participants will provide consent. Initial consent will be obtained through an online form. We will send an email to individuals in the follow-up experiments to give them the opportunity to opt-out of the follow up experiment.*

4. **Potential Harms to Research Participants from Data Collection or Research Protocols**

   Excerpt From IRB 19102: *Individuals will enroll in the study by providing the researchers their identifying information, including the email address that is associated with their Uber account. We will generate two unique IDs for each of these email addresses, and we will provide one of the ID/email address combinations to Uber. Uber will send us back rider data using the unique ID. Uber staff will not have access to any additional information about the participants in our study or obtain any new information at all about sample participants.*

   Individuals will be given unique IDs. Personal identifying information will be kept separate. Only de-identified data will ever be shared. The identity key will be kept *separate from participant data, maintained in an encrypted folder on PI hard-drives, on a password protected computer.*

5. **Potential Harms to Non-Participants:** Non-participants did not receive incentives, but were not subject to any known risk due to non-participation.

6. **Potential Harms to Research Staff:** Research staff running phone surveys, analyzing data, and implementing price changes on the Uber platform are not subject to any known risk.

7. **Scarcity:** The price treatments in this study reduced the price of Uber services for individuals assigned to treatment groups and did not negatively affect the aggregate value programs/services currently offered by Uber.

8. **Counterfactual Policy:** All participants in the study received incentives for participation in surveys, directly from price reductions, or both. No participants were adversely affected relative to counterfactual conditions had they opted out of the study.

9. **Researcher Independence:** This study was conducted through a collaboration between PIs Christensen and Osman and Uber Research. The study was conceived and designed by Christensen and Osman, who maintained full intellectual freedom throughout all stages of the project through the following:

   (a) All experimental protocols were defined and agreed upon prior to initiating the partnership. Access to Uber administrative data and protocols for maintaining the privacy of participants were established in a legal agreement between the University of Illinois and Uber Technologies, which was executed on 10/15/2018. Uber staff never had access to any data collected outside their platform, including the data collected via participant surveys or Google Timeline.

   (b) Research was conducted with the understanding that research design, empirical tests, and interpretation of results would be based on established methods/practices/literature in economics, irrespective of any other considerations.

   (c) Research results were reported to Uber after the completion of analysis and shared outside the research team after completion of the working paper. Uber reserved the right to review the contents of the working paper before public release to ensure that no confidential information was shared, but did not shape or in any way influence the analysis or interpretation of results.

10. **Financial Conflicts of Interest:** Christensen and Osman did not receive any form of financial compensation from Uber as part of this study (nor did any assistants or staff associated with the UIUC research team). No Uber employee was named as a PI or participant in any research grant that provided funding for this project.

11. **Reputational Conflicts of Interest:** The research questions pursued in this study and the results described in this study are novel and different form of prior work conducted by the authors. We perceive no reputational conflicts of interest.

12. **Feedback to Participants or Communities:** We intend to share our results with participants via email after our work is subject to peer-review.

13. **Foreseeable Misuse of Research Results:** The authors recognize that the results described in this paper involve research questions that are relevant for public policy and regulatory activities in ride-hailing markets. Any misinterpretation or deliberate mis-characterization of the results of this study could have implications for individuals, communities and firms affected by these markets. We dedicate Section 7 to a discussion of the limitations of the study and method and will provide de-identified data for full transparency/replicability.