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

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Current Draft: April 2021
First Draft: November 2020

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 42% in total mobility. These effects are stronger for women, who are less mobile at baseline and perceive public transit as unsafe. Female participants report large increases in experienced safety on recent trips, owing to substitution away from public buses. Structural estimates of the demand for safety indicate that a policy that leaves no passenger feeling unsafe on Cairo's public transit system would yield $4.8 Billion PPP in annual benefits. Technology-induced reductions in the price of ride-hailing services could also generate considerable consumer surplus ($1.74 Billion PPP) but would be accompanied by substantial increases in external costs ($1.1 Billion PPP) resulting from increases in private vehicle travel.

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1 Introduction

Meaningful changes in the cost of transportation can have wide-ranging impacts on the spatial organization of cities through housing markets, labor markets, and migration behavior (Monte et al., 2018, Tsivanidis, 2018, Baum-Snow et al., 2017). Price changes do not affect everyone equally. Variation in the safety, accessibility and reliability of available transit options can affect the price elasticity of demand for travel and subsequent economic outcomes (Kondylis et al., 2020, Kreindler, 2020, Anderson, 2014, Bryan et al., 2014, Desmet and Rossi-Hansberg, 2013). Learning how different groups respond to price changes can provide key insights into their underlying demand for mobility and help guide infrastructure investment and transportation policy. This is especially important in the developing world, where rapid growth in urban transport demand has occurred without commensurate investment in transit infrastructure (Henderson and Turner, 2020, Bryan et al., 2019).

Attempts to study the demand for mobility have been limited by endogeneity concerns and a lack of comprehensive micro-data on transportation behavior. 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 trip-level administrative data from Uber to estimate the demand response to lower-cost transport services on the ride-hailing platform. We then combine this analysis with individual-level data collected from Google Maps' Timeline to estimate the demand for *total mobility (km/day)*. We examine shifts in travel outside the Uber platform and a broader set of related outcomes collected in follow-up phone surveys.

The experiment reveals 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 even larger increases in overall mobility by inducing complementary travel on other transit modes – participants receiving the 50% treatment increase their VKT by 42%, an increase of 1,033 km over the 12-week period. Combining these results with direct evidence on transport mode-switching, we find a countervailing 9 percentage point effect on substitution away from public buses. While riders in the 50% price treatment shift a substantial fraction of their trips on public buses to Uber, total travel increases are sufficiently large that *total* bus travel does not decline. Taken together, this evidence

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

reveals that participants use ride-hailing services *both* as a complement and as a substitute to public transit and that net effects depend on the relative magnitudes of adjustment along multiple margins that have not been studied collectively in prior work.

These average effects mask important heterogeneity by gender. Point estimates indicate that the price elasticity of demand for mobility is substantially higher among women (-1.26) than men (-0.51). Female participants, who are less mobile at baseline but have a 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 Uber, where all participants tend to report feeling safe. Women have similar expectations as men regarding the relative cost and duration of trips taken using the different modes. 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.

In the final section, we use the experimental estimates to examine two sets of policy questions. We first use data on counterfactual expectations of price, duration, and safety of trips taken by available modes in a discrete choice framework to estimate the value of safety (VOS) and the value of time (VOT) in the Cairo transport market. We simulate the welfare benefits of increases in the safety of public transit modes. Our estimates suggest that a policy that leaves no passenger feeling unsafe on public transit would yield \$4.8 Billion PPP per year in annual benefits for Cairo's population.[2] The lion's share of these benefits come from improvements to the safety of Cairo's public buses. While women consistently report buses to be the least safe option in Cairo, they are also the most widely used public transit mode. Cairo has implemented a system of female-only cars on the metro system, but not on the more widely-used bus system.[3]

In a second policy analysis, we explore the implications of market-wide reductions in the price of ride-hailing services on private vehicle travel. 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). To consider the effects of technology-induced price reductions, we develop a model that (1) recovers 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

[2]1 USD is equivalent to about 15.5 Egyptian Pounds, with a PPP rate of 4.32 (Bank, 2020)

[3]Cairo's metro system operates a limited number of female-only cars. Approximately 25% of recent travel by women in our sample is done by bus while approximately 7% is done by metro.

then (2) adjusts 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 -1.28 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 -1.09. Using this market-level elasticity estimate, we find that a 50% price reduction would result in an 11% increase in the external costs attributable to Cairo's transportation sector, or $1.1 Billion PPP per year.[4] External costs amount to just over 60% of the $1.74 Billion PPP in consumer surplus that would be generated by the same 50% price reduction. This increase in benefits would be concentrated in 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 tax instruments to address externalities in the ride-hailing market and to redistribute the surplus (World Resources Institute, 2020). Our findings suggest the need for careful designs, as the burden of a uniform tax on ride-hailing services in cities such as Cairo could disproportionately affect female mobility.

We highlight three important caveats to consider when interpreting our results. First, as with any experimental study implemented on a specific sample, we may be concerned about whether these results would translate to other markets and to non-experimental settings. We run two auxiliary experiments to test the importance of the salience and length of the price reductions in our experimental design and find that they do not drive 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 timescales that fall outside the scope of this particular study.

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,

[4]In the absence of a technology-induced price reduction, a government could consider a direct subsidy program. However, this would cost nearly $6.6 Billion PPP, which would not be cost-effective.

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 made use of high-frequency price variation to estimate price elasticities for gasoline or private transportation services, with demonstrable benefits over models with more aggregate data (Levin et al., 2017, Cohen et al., 2016). It remains difficult to study sustained changes in the price of transport services (Schaal and Fajgelbaum, 2020, Ahlfeldt et al., 2016). Other work 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 contribute to this literature by randomizing the price of mobility services for a 3-month period to estimate the demand for mobility, a key parameter that has implications for several fields including urban, trade, and development economics.

A unique 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 specific mechanisms through which price reductions in transport services affect mobility, including substitution across modes, changes in the geography of travel, and learning. We consider the impacts on individuals over a period of multiple months, providing insight into longer-run responses than have been available in prior work that exploits exogenous shifts in the price of transport. There is growing interest in using digital technologies to measure transportation decisions and map physical movements (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 on a range of questions.

Our paper also builds on a growing set of economic studies of the impacts of ride-hailing markets (Goldszmidt et al., 2020, Alvarez and Argente, 2020, Leard and Xing, 2020, Young and Farber, 2019, Castillo, 2019, Moskatel and Slusky, 2019, Hall et al., 2018, Cohen et al., 2016). Thus far, the ride-hailing literature has relied heavily upon observational or stated-preferences methods. We combine a field experiment with detailed surveys to more fully characterize the demand for ride-hailing services, as well as substitution behavior and effects on private VKT. Sustained price changes allow us to gain traction on mechanisms underlying the benefits and costs of ride-hailing services in developing country cities, though additional work will be needed to understand effects on longer-run decisions such as car purchase behavior and housing/employment location choices. We identify key sources of heterogeneity by gender and safety perceptions, demonstrating an important link 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 (Kondylis et al., 2020, Jayachandran, 2019, Velásquez, 2019, Borker, 2018). 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. Section 6 outlines several policy implications. Section 7 discusses robustness tests and 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 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). 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 ridesharing market also includes a large competitor in "Careem," which provides services that are similar to Uber.[5] The market is 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.[6] Household expenditures on transportation services are not smooth or linear 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 due to car ownership and taxi usage. 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).

[5]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).
[6]This estimate comes from Egypt's Household Income, Consumption and Expenditure Survey of 2015 (Economic Research Forum, 2015).

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[7] 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 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).[8] 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 to link to a registration page that provided more detailed information about the study and the opportunity to enroll. 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

[7]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.

[8]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.

all regressions). After randomization, individuals were sent an email to welcome them into the study and to inform them about their treatment status.[9] The first cohorts were enrolled in July 2019, with the final cohorts enrolled in December 2019.[10] 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 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.[11] 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).[12]

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. The average respondent reports traveling 53 km/week and spending about 10 hours on that travel, according to self-reported Google timeline data. 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 richer than the average Cairene, which is unsurprising given that selection depends on utilization of

[9]The results below will show that individuals respond to the subsidies quickly, 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 were informed about a popular online job board that includes thousands of vacancies, and another were 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.

[10]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.

[11]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.

[12]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.

Uber.

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) 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 modes that participants use for their longest trips on a given day. The 3 primary modes of transit are bus, Uber, 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 then 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.[13] 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 Uber. Not surprisingly, Uber is considered a more expensive option than all but taxi services. Uber is also considered to offer a faster trip from origin to destination than bus, Swvl, and taxi services and not substantially different from metro services or transport by private car. Interestingly, Uber is 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 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. 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 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.

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.

[13] A few companies in Cairo (such as *Swvl*) now provide private bus services that people reserve in advance. This is similar to the Greyhound bus service in the US. 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.

Digital and mobile-based technologies provide distinct advantages over earlier methods that depend exclusively upon respondent recall (Kreindler, 2020, Martin and Thornton, 2017). Google Timeline records all 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 is unable to differentiate between car and bus travel. Study participants read off their summary statistics to our surveyors over the phone. We utilized this method to avoid any participant concerns about potential violations of privacy.

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. 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.[14]

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 a post-period following the completion of the study.[15] 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).

[14]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 6.5 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 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.

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

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_F represents fixed effects for each round of follow-up surveys, and λ_S represents randomization strata fixed effects.[16] 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.[17]

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 treatment, and 50% price 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

[16] 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 also control for two additional information treatments that were cross-randomized on the sample which are outside the scope of this paper.

[17] A recent paper discusses the potential for the scale of the dependent variable to affect the 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.

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.[18] 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 2. We do not interpret these as quantile treatment effects, as that would require a strong 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.

4.2 Price Elasticity of Demand

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

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

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 several potential reasons: (1) Prior studies have typically examined the effects of short-run price changes; (2) Whereas prior studies have typically focused on transport markets with higher-quality substitutes, this study specifically focuses on a transit-constrained city; (3) The large price changes examined in this study may induce significant substitution from lower quality substitutes. As far as we are aware, this price treatment was the largest and longest that Uber has provided to riders; (4) Most prior elasticity estimates in the literature have not focused on markets with ride-hailing services; (5) 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 and the elasticities that we estimate. In order to better disentangle the experimental effect of the price change from the length of the study period and the salience of announced discounts, we implemented two additional 1-week experiments with additional waves of participants. The first experiment provides a sample of participants with a pre-announced 1 week subsidy, while the second experiment provides a separate sample with an unannounced 1 week subsidy. If participants increased their use of Uber services to take advantage of discounts that they knew would be offered for a limited time, then we would expect that the impacts of the pre-announced subsidy would be larger than the unannounced subsidy. We do not find this to be the case. We also compare the results from the auxiliary experiments to the first week of the main experiment and find no differences. This provides us confidence that our estimates are not driven by strategic overuse.

In particular, in the first 1-week 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.[19] 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. In the second experiment, we did not inform the groups about the price reductions, but all of the prices they faced were discounted according to their treatment assignment.

The results of these two experiments are reported alongside estimates of effects from the first week of the main experiment in Table 2. To estimate the impact of the salience of the treatment, we compare impacts on Uber utilization for the 10% treatment group in columns 3 & 4 versus columns 5 & 6. We do not find any evidence of statistical differences in kilometers traveled on Uber or in weekly Uber trips. Estimates of 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. This implies that our results are not driven by the salience of the treatment.

We then 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. We find that the number of trips taken on Uber is larger in the main experiment, though it is also statistically equivalent to the number of trips taken in the 1-week experiment. Hence, it does not appear that intervention length is driving the impacts we find in our main experiment.

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

[19]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.

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.[20] 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 utilization and that subsidies increase Uber travel to an expanded set of locations in Cairo. However, it is not clear whether the price treatments simply induce substitution away from other modes of travel or whether subsidies for Uber services reduce mobility frictions that otherwise limit the participant's ability to travel, thereby increasing their overall mobility and distance traveled.

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).[21] Table 4 reports estimates for each of the treatment groups. Columns 1 and 2 report effects on total distance traveled in the past 3 days, as reported on a participant's Google Timeline on the day of a follow-up survey. Relative to the mean of 88 km per 3 days for the control group, point estimates suggest that total mobility increases by 0.10 IHS points (approx. 9 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 0.35 IHS points (approx. 37 km or 42% of the control mean) among participants who receive a 50% reduction.

The average male participant in our sample travels nearly twice as much as the average female participant (112 km vs. 62 km in a three day period). 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 0.16 IHS points (approx. 10 km

[20]We define a trip to a hospital or university using buffers of 100 meters, 175 meters, or 250 meters around the buildings using OpenStreetMap. These locations and their boundaries are illustrated in Appendix E.

[21]It is possible that Google Timeline is more precise when individuals are using Uber because of the intensity of GPS usage on the mobile phone. This could bias our experimental results because those in treatment use Uber more. We test for this by comparing the coefficient of variation in total distance traveled on days that include Uber trips and those that do not, and we find no significant difference.

or 17% of the control mean) in the low treatment group. In the high treatment group, we estimate an increase of 0.49 IHS points (approx. 39 km or 63% of the control mean). Differences by gender are not 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 1,092 km (280 km) overall over the course of the study relative to the control group, and men in the 50% (25%) group traveled an additional 815 km (94 km) relative to control over the 12 weeks.

In Panel B of Table 4 we report estimates of the price elasticity of demand for mobility (total travel). The average elasticity for women is -1.02, and for men it is -0.32. These estimates are consistent with other estimates of price elasticity of travel demand, although to our knowledge no prior study has fully accounted for substitution by measuring effects on total mobility (Frondel and Vance, 2009, Flores-Guri, 2003). This is likely to be especially important in many transport markets in developing country cities, where travel is not dominated by a single transit mode such as car travel. Figure 2 includes results from quantile regressions of total distance traveled by treatment and gender in Panel C. We find that the results are evenly distributed across all quantiles, providing evidence that our average treatment effects are not driven by a small subset of users who dramatically increase, or reduce, their overall mobility.

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 VKT (Tirachini and Gomez-Lobo, 2020) and others indicating that they increase public transit use (Hall et al., 2018).[22] The literature has thus far been unable to reconcile these results.

Our research design allows us to directly evaluate how total mobility changes as Uber usage changes at the individual level. We compare changes in total mobility from Table 4 to the increases in Uber distance traveled from Table 1. A 25% price reduction increased Uber travel by approximately 24 km/week and increased total mobility by 21 km/week, which implies that a minimum of one eighth of additional kilometers on Uber involved substitution from other modes of transport. On the other hand, the 50% price reduction increased Uber travel by 61 km/week and total mobility by 86 km/week, implying that a sufficiently large price reduction for ride-hailing services can induce complementary uses of other modes of travel.

We dig deeper using estimates from Table 5, which reports the results from 5 discrete regressions that measure treatment effects on the self-reported transport mode used for the longest trip (based on distance) made the day before our survey. The estimates

[22] 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.

reveal evidence of *substitution* away from the primary transit mode used by the Cairo sample: the public bus. The 50% fare reduction increases the likelihood of using Uber (for the longest trip) by 11 percentage points, while reducing the likelihood of bus use by 9 percentage points. We also observe a smaller (2 percentage point) shift away from long trips using taxis, which are perceived as less safe and more costly than Uber services.

Substitution away from buses in the 50% treatment group may seem to contradict the simultaneous finding of complementarity. However, a comparison of these effects reveals that the substitution response does not have a net effect on overall bus travel due to the magnitude of the impact on total distance traveled. Estimates from Table 4 and Table 5 indicate that the average rider in the control group reports traveling 88 km over a 3-day period and that 33% of this travel is done using the public bus, which yields an estimate of approximately 29 km in bus travel for riders in control.[23] Participants in the 50% treatment group increase their total travel to 125 km over a 3-day period and also reduce bus ridership from 33% to 24% of their overall travel. The combined impact of these two responses results in 30 km of bus travel for the average rider in the 50% price treatment, which is still slightly higher than the 29 km of bus travel made by the average rider in control.

The findings above illustrate the critical importance of understanding the multi-margin responses to shifts in the price of personal transport services. In the absence of evidence on total mobility impacts, it would appear that price changes result in large shifts in bus ridership through substitution effects. Indeed, this partial view has motivated a widespread concern about the impact of ride-hailing technologies on public transit revenues. While this is an important concern that deserves examination in other settings, our micro-level findings indicate that even considerable substitution effects do not necessarily convert into large reductions in public transit use in the presence of a strong intensive margin response. The implication for metro use, where we observe no evidence of mode substitution, is that the 50% price reduction induced an overall increase through complementarity. This is corroborated by our finding of increases in Uber travel to and from metro stations. Indeed, it is not difficult to imagine that riders who have become more mobile (and use Uber to access more places) will also increase their use of other modes in multi-part journeys or for return trips.

[23]For these calculations, we assume that a percent change in the likelihood of taking a long trip using a given mode converts into a percent change in distance using that mode. While information about the longest trip is generally considered to be the most informative single measure of trip-taking behavior and the least subject to recall bias, we note that the substitution behavior reported on longest trips is not necessarily representative of substitution for all trips. In Appendix Table C2, we split the sample into those for whom the longest trip is a large fraction of their total time spent in travel and those for whom it is a small fraction (a day with many trips). We find that bus substitution is nearly identical for these two groups.

5.3 Effects on Safety While Traveling

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, 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 that there is no impact on perceived safety among men.[24]

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.

[24] 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.

5.4 Effects on Labor Market Outcomes

Reductions in the cost of ride-hailing services could improve the ability of job seekers to better match with existing vacancies. Previous studies, such as Abebe et al. (2020), Franklin (2018), Abebe et al. (2017), 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 8 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 *and* we can rule out large labor market effects (in the short-run). This suggests the need for further work to understand the causes of differences in effects within this body of literature. It may be the case that the transfers in the earlier literature lead to larger impacts on labor market outcomes due to some combination of how they are targeted and the sample context. Overall, our results imply that even a sizeable reductions in the price of private transport is unlikely to have transformative effects on short-run labor market outcomes.

6 Policy Implications

Governments around the world are responding to the growth in transport demand and concomitant advances in transport technologies. 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 use our experimental findings to examine the welfare impacts of potential increases in the safety of public transit options and of reductions in the price of ride-hailing services. We first use our price treatments in a discrete choice framework to obtain structural estimates of key transport demand parameters among participants in our study: the value of safety (VOS) and value of time (VOT). We then use these estimates to simulate the potential welfare impacts from increases in the safety of public transit modes on the Cairo transit network.

A second policy analysis makes use of the VOT estimate, along with price elasticity and mode substitution estimates from the experiment, to develop a model of transport demand that considers the effects of market-wide reductions in the price of private transport services on consumer surplus and external costs. The model examines impacts in an equilibrium where price reductions on ride-hailing services affect the quantity of travel demanded while also affecting travel times through induced congestion. Riders respond through extensive margin adjustments (increased mobility) as well as mode substitution. We use the model to examine equilibrium effects on consumer surplus and external costs, as well as the distributional implications of a uniform tax on ride-hailing services.

6.1 Welfare Impacts of Potential Changes in Safety and Time

As outlined in section 3.1, we asked participants to recall the longest trip they took in the day prior to the survey and to provide information about their mode of travel, time to destination, monetary cost and perceived safety on the trip. We then asked them to consider what would have happened if they took that same trip using each of the dominant modes of transportation recorded in the baseline survey. We use these data and the experimental variation from our treatments to model the trade-offs between cost, safety, and speed in the minds of travelers using a discrete choice framework. We then estimate consumer willingness-to-pay for changes in the duration and safety of their trips.

Discrete Choice Model

The model treats riders who are making transit mode choices as decision-makers. Riders maximize the utility of their longest trip made yesterday by choosing among four transit modes: Metro, Bus, Taxi and Uber.[25] Rider utility functions consist of two components. The first includes mode choice related characteristics. In addition to cost and time, we add safety to the utility function to capture potential safety concerns related to public transit. The second component includes rider demographics that influence the choice of transit. As described in Small et al. (2007), the experimental variation in prices allows us to introduce mode-specific fixed-effects to control for unobserved characteristics such as comfort that might co-vary with the cost/duration/safety of different modes.

Formally, the utility of rider i choosing transit mode j for choice occasion m is:

$$U_{ijm} = -\alpha p_{ijm} + \gamma t_{ijm} + \eta s_{ijm} + X_i' B + \theta_j + \epsilon_{ijm}, \tag{2}$$

[25]We omit the private car option from this analysis out of concern that participants may not accurately report the monetary cost of trips made by car, which requires knowledge of fuel, vehicle ownership, and maintenance costs attributable to a specific trip.

where α is the marginal utility of cost, γ is the marginal utility of time, and η is the marginal utility of safety. X_i represents a vector of demographics, including average income, gender, car ownership and an indicator for metro users (at baseline). θ_j are mode-specific fixed effects that control for unobserved characteristics on which the four modes may differ. We include ϵ_{ijm} which represents an unobserved idiosyncratic taste shock that we assumed is i.i.d distributed according to the type 1 extreme value distribution.

We follow Small et al. (2005) in calculating the value of time and value of safety as the ratios of parameters with cost as the denominator, allowing us to estimate the "price" of time and safety:

$$VOT = \frac{\partial U_{ijm}/\partial t_{ijm}}{\partial U_{ijm}/\partial p_{ijm}} = \frac{\gamma}{\alpha}, \qquad VOS = \frac{\partial U_{ijm}/\partial s_{ijm}}{\partial U_{ijm}/\partial p_{ijm}} = \frac{\eta}{\alpha} \tag{3}$$

Following the control function method pioneered by Petrin and Train (2010), we introduce experimental variation in prices using two indicator variables for the treatment status of a rider: (1) treatment group and (2) whether the trip is taken at baseline or in the experimental phase of the study. Estimates of the coefficient on price α are therefore identified from experimental variation in price treatments. Estimates of γ and η are identified from variation in trip times and safety levels, conditional on mode-specific fixed effects that absorb variation in other unobservable dimensions of the different modes.[26] Following Train (2009), we define consumer surplus in our model as the utility a rider receives from a given choice situation calculated in Egyptian pounds, i.e. $CS_{im} = (1/\alpha)max_j(U_{ijm})$. In expectation, this is:

$$E(CS_{im}) = \frac{1}{\alpha} ln(\sum_{j=1}^{J} e^{V_{ijm}}) + C \tag{4}$$

where α is the marginal utility of income, $V_{ijm} = -\alpha p_{ijm} + \gamma t_{ijm} + \eta s_{ijm} + X_i' B + \theta_j$ is the product of the parameters and all observed variables, C is an indicator for the absolute level of utility, which is unknown. The change in consumer surplus that results from a policy change is calculated as the difference between the two log-sum terms:

$$\Delta E(CS_{im}) = \frac{1}{\alpha}[ln(\sum_{j=1}^{J^1} e^{V^1_{ijm}}) - ln(\sum_{j=1}^{J^0} e^{V^0_{ijm}})] \tag{5}$$

[26] In Appendix H, we evaluate the consistency of parameter estimates using a second specification addresses the potential correlation between the preferences of individual riders and their residential location, which could endogenously affect mode choices. We construct a set of Hausman instruments that incorporate our exogenously determined experiment groups. Specifically, we calculate the leave-out average values for cost, duration and safety for riders within the same experimental group that live in the same geographic location at baseline. Identification of our 3 parameters of interest requires the assumption that the experimental groups are not correlated with unobserved endogenous parameters, which is sensible given our randomization procedure. Table H.3 reports the estimates from the conditional logit model. Column 1 reports estimates from a specification with experimental instruments, whereas columns 2-4 report estimates from specifications that utilize the experimental and Hausman instruments. We find no evidence of statistical differences in the point estimates for cost, time, and safety parameters from equation 2 or in estimates of the value of time (VOT) or the value of safety (VOS) from equation 3.

where the superscript 1 and 0 indicates the treatment and counterfactual conditions.

Value of Safety and Value of Time Estimates

Table 9 reports the estimates from our preferred specification of the conditional logit model, which makes use of exogenous variation from instruments derived from our experimental treatments. Column 1 reports estimates from the pooled sample, whereas columns 2 and 3 estimate the split sample by gender. We estimate a value of time of 1.2 EGP per trip-minute, which translates to 72 EGP/hour for the pooled sample. This is nearly double the 33.6 EGP hourly wage for the average participant in our sample, which may reflect the severe disamenities (congestion, risk, stress) associated with a the marginal minute spent in transport in Cairo. This estimate is somewhat higher, though not statistically different, for women (1.3) and men (1.13). Estimates of the value of safety imply that the average rider in our study is willing to pay 27.8 EGP to realize a unit increase in perceived safety (i.e. from *very unsafe* to *unsafe* or from *neutral* to *safe*) in a trip. This value is 20% higher for female riders (30.0 EGP), when compared to male riders (24.8 EGP), though these estimates are also not statistically different.

Welfare Effects from Increasing the Safety and Speed of Public Transit

We use estimates of the value of safety (VOS) reported in Table 9 to simulate the impact of increasing the perceived safety of bus and metro trips on the welfare of participants in our sample. Panel A of figure 3 illustrates the results of three simulations: (1) increasing the perceived safety to a level where no rider feels unsafe on public transit (43.3% of riders who felt *very unsafe* or *unsafe* feel at least neutral about safety of public transit modes), (2) increasing perceived safety to a level where all riders feel at least *safe* on public transit, and (3) increasing perceived safety to a level where all riders feel *very safe* on public transit.[27] Our estimates indicate that increases in perceived safety to a level where no rider feels *unsafe* on public transit would result in a 7.6 EGP increase in welfare per trip for the average female rider in our sample and an 4.6 EGP increase in welfare for the average male rider in our sample. Differences in benefits to female/male riders are driven in small part by differences in our point estimates for the value of safety in the Table 9 and in large part by a compositional effect of feelings of being unsafe. A much larger fraction of women report feeling *unsafe* or *very unsafe* on bus trips, such that a policy that leaves no rider feeling unsafe/very unsafe has a disproportionate impact on women in our sample. These effects can be compared to the average trip cost of 10.7 EGP on bus or 69.1 EGP on Uber.

Our results also suggest that further increases in safety result in substantially larger

[27] This simulation adopts a conservative approach to valuing changes in safety among riders who already felt *neutral*, *safe*, or *very safe* on public transit at baseline. For these riders, increases in safety have no effect.

welfare impacts for women. We find that benefits of 19.8 EGP per trip if all female riders felt that public transit options felt *safe* and 37.5 EGP per trip if they felt *very safe*. The effects grow at a slower rate for men: 13.6 EGP per trip if all male riders felt that public transit options felt *safe* and 28.1 EGP per trip if they felt *very safe*. Extrapolating from our sample to the population of Cairo, our estimates suggest that an increase in public transit safety to a level where no passenger feels unsafe would yield $4.8 Billion PPP in annual benefits.[28] This estimate relies on the assumption that the willingness-to-pay for safety in our experimental sample is representative of the willingness-to-pay for the population, which we cannot test. However, this estimate suggests that the benefits from improved safety on public transit would be very large even if the Cairo population has a lower value of safety than the participants in our experiment.

Panel B of Figure 3 plots the results of the same simulation, while focusing specifically on buses. Comparison of results between the two panels illustrates that the potential benefits from increases in the safety of public transit services would result almost exclusively from safety improvements on buses. This finding is consistent with results from the baseline survey, where participants rate buses to be the least safe option in Cairo. For female participants, this may be partially explained by the existence of female-only cars on the metro system. Gender-specific buses are not currently an option in Cairo. However, our results suggest that female-only bus or other improved safety options could yield enormous benefits. On the right hand side of the figure, we hold individual-level differences in risk preferences constant by examining the welfare gains associated with increases in bus safety to the level of safety for taxi, metro, and Uber trips reported for each individual trip.[29] For the average trip in the sample, we find that an increase in the average participant's perceived safety on buses to the level expected on the metro system would yield between 9.44-11.15 EGP in benefits. Extrapolating to the population of Cairo, these estimates suggest that an increase in bus safety to the level of metro would yield $2.9 Billion PPP in annual benefits. We do not observe differences by gender, except when we simulate the gains associated with increasing bus safety to the level expected on Uber.

We also use estimates from the discrete choice model to simulate the consumer surplus from reductions in the price of speed and safety amenities associated with ride-hailing services. We find that a 25% price reduction on the average trip yields 5.93 EGP for men and 8.26 EGP for women. A 50% price reduction on the average trip yields 12.80 EGP for men and 17.67 EGP for women. While the benefits from price reductions on ride-hailing services are of a similar magnitude to those from increases in bus safety

[28]We will use an estimated population of 15.56 million people in Cairo (Pricewaterhouse Coopers, 2009), which we will assume is evenly split by gender.

[29]If a participant perceives buses to be *very unsafe* for a particular trip and metro to be *neutral*, then our simulation measures the welfare gain associated with an increase in the bus option from *very unsafe* to *neutral* for that trip.

on a per trip basis, they accrue to a considerably smaller base of Uber users. Given publicly available estimates that 20% of the Cairo population uses ride-hailing services, these estimates imply annual benefits of \$871 Million PPP for the 50% reduction and \$406 Million PPP per year for the 25% reduction.[30] These consumer surplus estimates do not capture benefits from extensive margin effects (increased travel) or account for the potential costs associated with congestion from a market-level price reduction, which we examine in the following section.

6.2 Implications of Market-Level Price Reductions

This section explores the impacts of a *market-level* reduction in the price of ride-hailing services on private kilometers traveled (PVKT). Understanding the effects of market-level price reductions on PVKT requires considering: (1) the combined effects of extensive margin adjustments and substitution and (2) endogenous effects of congestion. An increase in market-level congestion would be accompanied by an increase in travel time, which would increase the effective price of travel and exert downward pressure on demand. We use the behavioral demand elasticities from the experiment and our estimates of rider VOT to inform a simple model of transport supply and demand in Cairo. Using this model, we estimate equilibrium demand elasticities and then study the implications of market-level price reductions on external costs and consumer surplus.

A Simple Continuous Supply and Demand Framework for Mobility

Equilibrium travel in Cairo is given by the following demand and supply equations:

$$\Delta X_{PT} = f(\Delta P_U) = \varepsilon_{Eq} * \Delta P_U \tag{6}$$

$$\Delta P_E = \Delta P_U + g(\Delta X_{PT}, PR_U) * (C_{VOT}) \tag{7}$$

The demand equation defines the change in private vehicle kilometers traveled (X_{PT}) 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 function of the change in kilometers traveled and the proportion of the population that

[30] The utilization rate of Uber is derived from publicly available data on the number of riders in 2018 divided by the population of Greater Cairo (Reuters, 2018).

uses ride-hailing services (PR_U). We assume this function is linear as shown by Kreindler (2020). Solving the model generates the following expressions:

$$\varepsilon_{Eq} = \varepsilon_{PVKT} * \gamma \tag{8}$$

$$\gamma = 1/(1 - \varepsilon_{PVKT} * PR_U * C_{VOT}) \tag{9}$$

Equation 8 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 9 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 5.1, 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:

$$\varepsilon_{PVKT} = f(\varepsilon_{ext}, \varepsilon_{sub}) \tag{10}$$

That is, the elasticity of private vehicle kilometers traveled (ε_{PVKT}) is a function of how riders respond in their demand on the intensive 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 42% increase in total VKT. This translates to an average elasticity of -0.84, which is higher for women than men (-1.1 vs -0.63) in Cairo.[31] We measure ε_{sub} using estimates of substitution from Table 5, which indicate that a 50% price reduction in Uber services induces a 9 percentage point shift away from public transport to private transport (calculated on base of 39% public transport utilization, and hence 61% private vehicle travel). Using the conservative assumption that the average proportion of long trips taken on public transport in each 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.[32]

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

[32] We view this assumption as conservative because 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. In Appendix Table C2, we split the sample into those for whom the longest trip is a large fraction of their total time spent in travel and those for whom it is a small fraction (a day with many trips). We find that the bus substitution effect is nearly identical for these two groups.

The average person in the control group travels 88 km over the period of our survey. 61% (54 km) of this is done in private vehicles. Treatment leads to a 42% increase in overall kilometers traveled (an additional 37 km, for a total of 125 km traveled) and a 9 percentage point shift in travel by private modes (to 70%). Treated individuals travel 87.5 km in private vehicles, leading to a 62% overall increase in private vehicle kilometers traveled. This implies that the price elasticity of demand for private travel $\varepsilon_{PVKT} =$ -1.24, in contrast the -0.84 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 -1.94 for women, and -0.79 for men. In both cases, failing to account for substitution yields underestimates of the private vehicle elasticities by about one third.

Equilibrium Elasticity of Private Travel Demand

We now use the behavioral parameter (ε_{PVKT}) and equations 8 & 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.[33] To get the normalized value of time we take the VOT estimate from Table 9 which shows that the cost of an additional minute at 1.2 EGP/minute, we multiply this by average minutes per kilometer in our data (2.7 minutes) and then divide by the average cost per kilometer (5.3 EGP). Together this provides a value of γ of 0.87 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 87% as large as the behavioral elasticity alone would suggest. This yields an equilibrium PVKT elasticity of -1.1. Our findings indicate that women in Cairo have a higher demand elasticity and a higher value of time than their male counterparts. An analysis done separately by gender produces an adjustment parameter of 0.80 for women and 0.91 for men, which results in an equilibrium elasticity of -1.55 for women and -0.72 for men.

Consumer Surplus and External Costs

We use the experimentally identified elasticities to compute the total benefits and consumer surplus resulting from reductions in the price of Uber services to each of the two levels: $P_{0.75}$ and $P_{0.5}$.[34] A 50% price reduction produces 2,032 EGP per year for men and 2,820 EGP for women.[35] Extrapolating to the population of Cairo (15.56M, which we

[33]The penetration rate is derived from publicly available data on the number of Uber riders in 2018 divided by the population of Cairo (Reuters, 2018). Our study does not provide insight into the effects of price changes on increases in the adoption rate of ride-hailing technologies. Equation 7 explains how our estimates would change as more people begin using Uber, but for our current policy exercises we assume that this remains constant.

[34]See Appendix J for details on these calculations and Appendix Figure J.1 for an illustration of the procedure.

[35]This calculation provides an estimate of the *increase* in consumer surplus from each of the two price reductions relative to the existing market price. The results of recent empirical work from Uber riders in US markets finds very large consumer surplus at current market prices (baseline), suggesting that our

will split evenly by gender) and again applying the 0.2 estimate of the share of the Cairo population that uses ride-hailing services and would be directly affected by the price change, our estimates suggest that a 50% price reduction generates 7.55 Billion EGP per year in consumer surplus.[36] This is equivalent to 0.53% of Cairo's GDP, or $1.74 Billion PPP per year.

We can 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:

$$\alpha_{eq} = \alpha_0 * h(\Delta P_U, PR_U) \tag{11}$$

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 8, $f(\Delta P_U) = \Delta X_{PT}$). A comprehensive World Bank study of transport externalities in Cairo estimates a total current cost that is equivalent to 47 billion EGP, which is 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 0.2 estimate of the share of the Cairo population using ride-hailing services, and a 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 55% increase in private kilometers traveled for Uber users and an 11% increase in external costs in the transport sector. This is equivalent to 0.33% of Cairo GDP, or $1.1 Billion PPP per year.[37]

A comparison of the consumer surplus estimate (0.63% of GDP) and the external costs estimate (0.4% of GDP) suggests the potential for significant increases in welfare from a technology-induced price changes change. 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 $6.6 billion PPP, or 2% of Cairo's GDP.[38] 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 population who use Uber. Appendix Table B2 shows that Uber riders are likely to

estimates provide a lower bound on the *total* consumer surplus at any price equal to or lower than $P_{baseline}$ (Cohen et al., 2016). The procedure defined in Appendix H assumes that demand is approximately linear across the intervals from P to $P_{0.75}$ and from $P_{0.75}$ to $P_{0.5}$.

[36] The World Bank reports a PPP conversion rate of 4.32 (Bank, 2020).

[37] Pricewaterhouse Coopers estimates Cairo's GDP to be $330 Billion PPP with a population of 15.56 million people (Pricewaterhouse Coopers, 2009).

[38] This calculation is made in the following way: the average elasticity of Uber KM traveled is -8.96, the equilibrium adjustment parameter is 0.87, the average KM traveled in a week for baseline is 13.6, the average cost of a kilometer is 5.3 EGP, the penetration rate is 0.2, the population of Cairo is 15.56 million, and the PPP conversion rate is 4.32.

have higher incomes than the average Cairo resident. The external costs, however, would be more evenly distributed across the population given general effects on road users (incl. bus riders) and residents affected by pollution exposures. Hence, a technology-induced price reduction may be distributionally regressive.

Governments around the world are considering the use of taxes to address external costs and redistribute gains from ride-hailing services more equally across society. However, differences in price responses by gender imply that a uniform tax on ride-hailing services could affect female mobility much more than male mobility. Hence, policymakers in markets with less safe public transit options need to carefully consider how tax burdens may differ by population subgroups.

7 Robustness Tests and Study Limitations

As with any study, we must be cautious in interpreting our results and their implications for policy. In this section, we discuss the robustness of our results as well as key limitations.

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.

First, an 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 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 B3 - B5 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 B4 & B5 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 B6 & B7 (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.

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. While our point estimates suggest that effects are small, confidence intervals regarding search behavior include what would be considered both large positive and negative effects. As a result, we limit our discussion of the labor market impacts of price reductions for ride-hailing services. 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.[39] 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

Using an experiment with Uber in Cairo, we randomly assigned reductions in the price of ride-hailing services to study demand responses on: (1) Uber utilization and (2) total travel per week. We find strong responses on both outcomes to the fare reductions. For the average participant in our study, a 25% discount induced an increase of 11% in total travel. A 50% discount induced an increase of nearly 42% in total travel. These results provide 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.

As connected and autonomous vehicles (CAV) technologies improve, the cost of ride-hailing services could drop by more than the highest (50%) fare reduction in our study (Narayanan et al., 2020). Our estimates suggest that technology-induced price changes could yield large welfare effects. In the Cairo sample, we estimate that a 50% reduction in the price of ride-hailing services would produce consumer surplus that is equivalent to 0.63% of GDP and would generate external costs equivalent to 0.4% of GDP. Substantial external costs from increases in private vehicle kilometers traveled may be characteristic of developing country cities where price reductions increase overall travel while inducing substitution from public buses. If implemented through a government subsidy, the price

[39] 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.

reduction would no longer be welfare enhancing. The total cost of the subsidy would be equivalent to \$6.6 billion PPP, or 2% of Cairo's GDP. Policymakers will need to consider nuanced distributional implications of price changes for ride-hailing services in cities like Cairo. Benefits generated by price reductions 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. Hence, even if welfare positive overall, it could be regressive. An obvious response will be the implementation of taxes to redistribute the gain more equally across society. one potential complication is that due to the differential responses to price changes by gender, a uniform tax would decrease female mobility much more than it would decrease male mobility. Hence, policymakers need to carefully consider how tax burdens may differ by population subgroups.

Our results 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. We find that effects on Uber utilization (and associated consumer surplus) are stronger among female participants. In baseline and follow-up surveys, we find that women perceive outside options as less safe, which is consistent with growing evidence from other cities. We find strong evidence that women in Cairo substitute away from buses when Uber prices fall. Women report concomitant increases in personal safety in recent travel. Taken together, these results suggest that safety amenities can strongly affect the demand for mobility. Using our experiment to conduct counterfactual policy simulations, we find that increases to the safety of public transit could yield \$4.8 Billion PPP in annual benefits. These benefits would disproportionately accrue to female bus-riders and would potentially reduce the returns from substitution to private modes.

Ride-hailing services will likely continue to transform the option set in cities around the world, with direct effects on mobility and also raising concern about shifts from public to private vehicle travel. when paired with careful data collection methods, ride-hailing platforms provide a unique opportunity for researchers and policymakers to more rigorously examine complex behavioral responses to shifts in the transportation sector and provide a basis for the design of evidence-based policy instruments.

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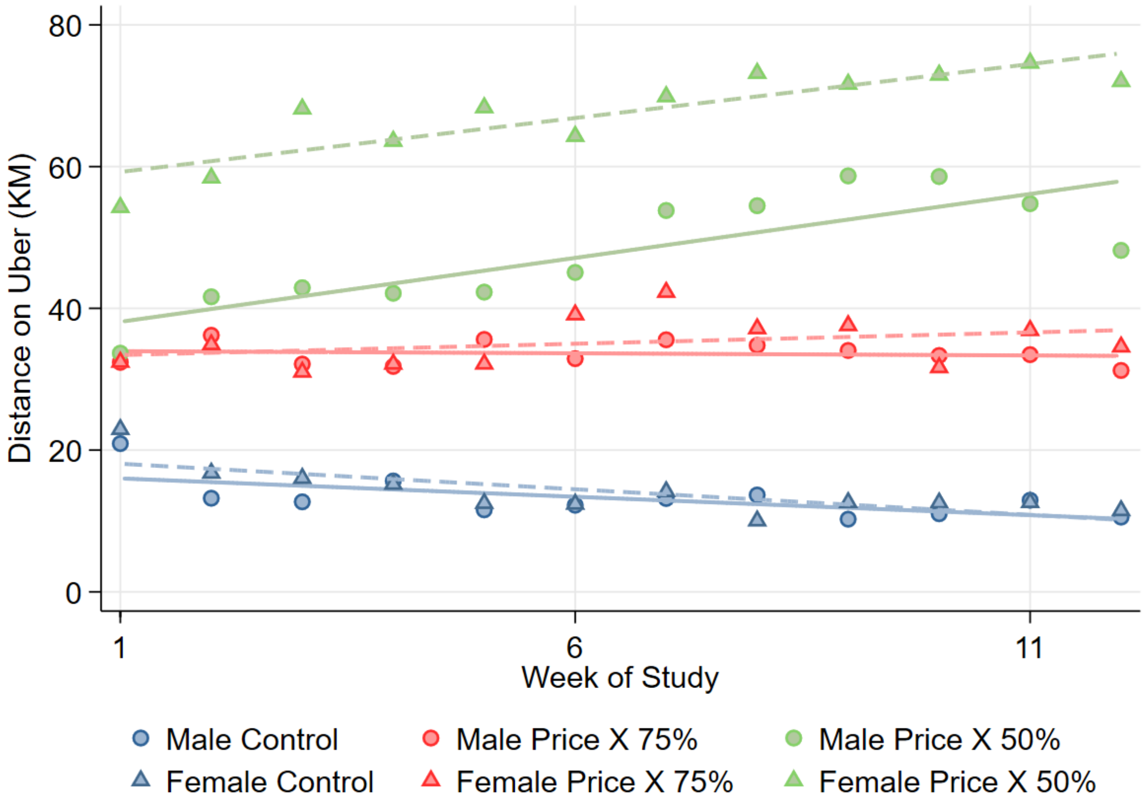
Figures

Figure 1. Uber Usage Over Time

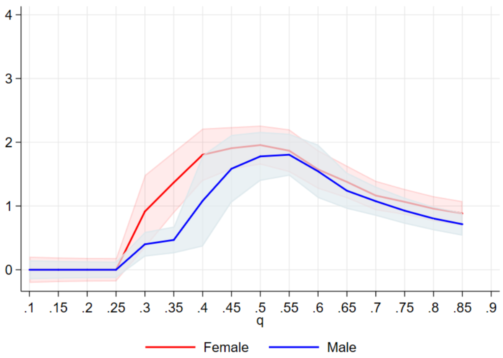


Notes: This figure plots average weekly kilometers traveled on Uber by experiment group, split by gender. The y-axis is reported using nominal kilometers, and the x-axis is the week of the study, including the initial week with the subsidy at "0."

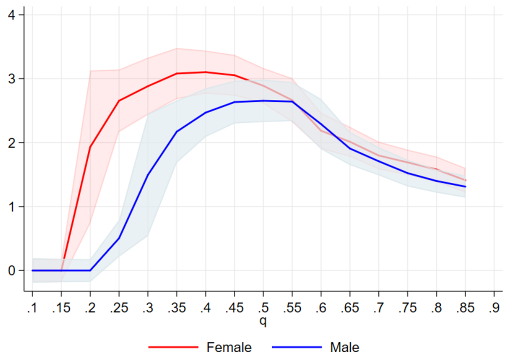
Figure 2. Quantile Regressions

Panel A: Total Weekly Uber Distance (IHS)

25% Price Reduction

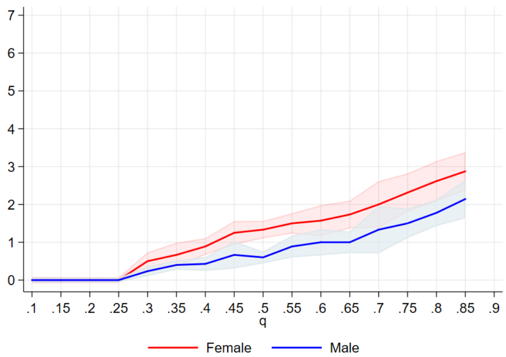


50% Price Reduction

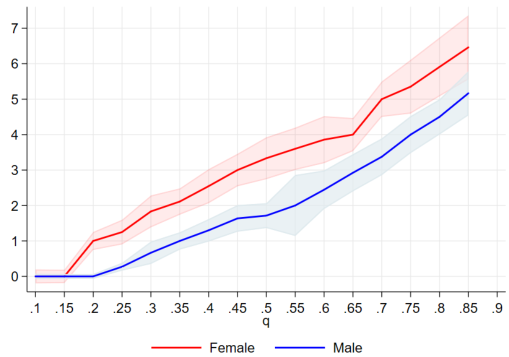


Panel B: Number of Weekly Uber Trips

25% Price Reduction

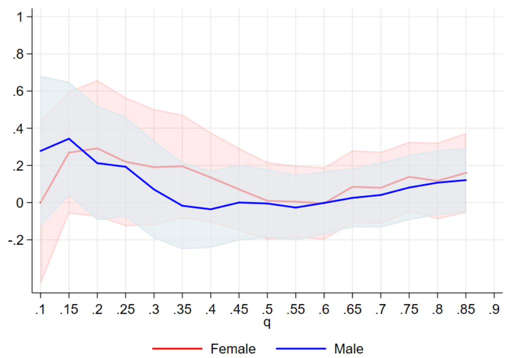


50% Price Reduction

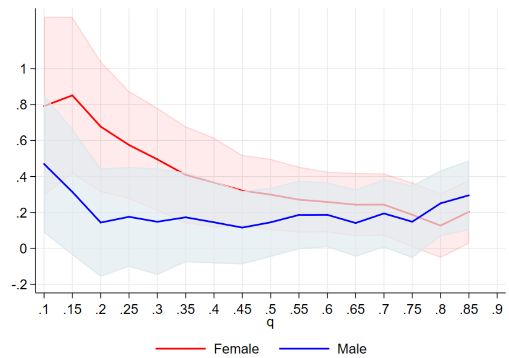


Panel C: Total Distance (IHS)

25% Price Reduction



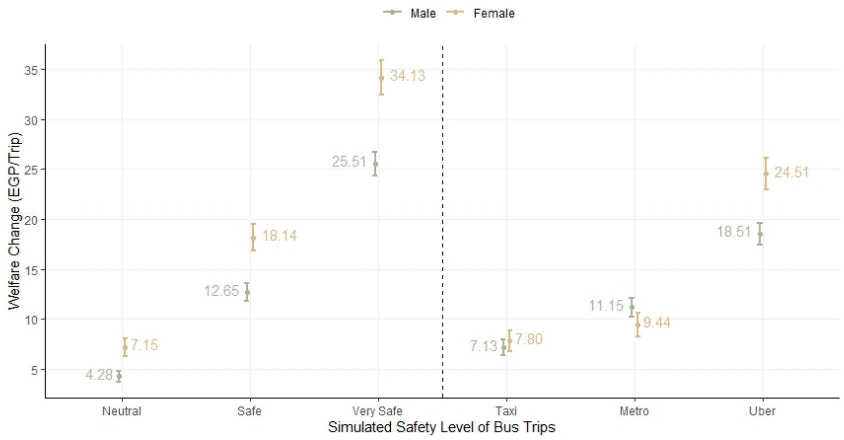
50% Price Reduction



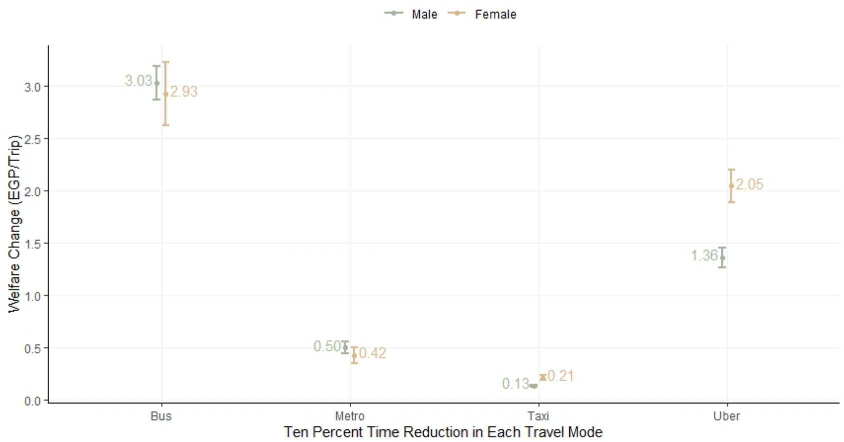
Notes: This figure plots the results of quantile regressions of the impacts of the treatment split by gender. Panel A reports impacts on weekly distance kilometers traveled on Uber, Panel B reports impacts on the average number of weekly Uber trips, and Panel C reports impacts on the total distance using 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.

Figure 3. Welfare Impacts: Increases in Safety on Public Transit

Panel A: Increases in Safety on Public Transit (Metro and Bus)



Panel B: Increases in Safety on Bus Transit



Panel C: Reductions in Travel Time by Mode

Notes: Panels A and B report results from simulations of changes in consumer surplus for women (red) and men (blue) resulting from increases in safety as defined in Equation 5 based on the parameter estimates from the discrete choice model specified in Equation 2. Participants rate the safety of each trips if taken by each mode using the following levels: *Very Unsafe*, *Unsafe*, *Neutral*, *Safe*, *Very Safe*. Estimates reported in Panel A simulate changes in consumer surplus that result from increases in the safety level of public transit (bus or metro) options for each trip described in the survey. Specifically, for each trip that where bus or metro options are rated as *Unsafe* or *Very Unsafe*, Panel A reports the consumer surplus increase from an increase to a level of Neutral (left), Safe (middle), Very Safe (right). Panel B reports estimates from a simulation of changes in the safety level of the bus option alone (left side) and increases in the reported safety of a trip if taken using the Bus mode to the level reported by the same user for the same trip when considering the Taxi (left), Metro (middle), or Uber (right). Panel C reports estimates from a simulation of the increase in consumer surplus obtained from a 10% reduction in travel time on each of the different modes for the average trip.

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. 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 in Total Mobility

Panel A: Experimental Impacts	Total KM Past 3 Days (IHS)	
	(1)	(2)
Price X 75%	0.10	0.16
	(0.09)	(0.14)
Price X 75% * Male		-0.13
		(0.19)
Price X 50%	0.35***	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

Panel B: Elasticity Estimation	Total KM Past 3 Days (IHS)		
	(1) Overall	(2) Female	(3) Male
Price X 75%	-0.40	-0.77	-0.13
	[-1.20 , 0.39]	[-2.10 , 0.54]	[-1.09 , 0.83]
Price X 50%	-0.84	-1.26	-0.51
	[-1.30 , -0.38]	[-2.04 , -0.47]	[-1.06 , -0.04]

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 Mode Used (Longest Trip)

	Metro		Bus		Taxi		Uber		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price X 75%	0.00	-0.02	-0.03	-0.05	-0.02**	-0.03**	0.07***	0.09***	-0.02	0.01
	(0.01)	(0.02)	(0.02)	(0.04)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
Price X 75% * Male		0.03		0.02		0.02		-0.04		-0.04
		(0.03)		(0.05)		(0.01)		(0.04)		(0.05)
Price X 50%	0.00	-0.01	-0.09***	-0.11***	-0.02**	-0.03**	0.11***	0.12***	0.00	0.03
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
Price X 50% * Male		0.02		0.03		0.02		-0.02		-0.06
		(0.03)		(0.05)		(0.01)		(0.04)		(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

Notes: This table 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. 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	
	(1)	(2)
Price X 75%	0.06	0.17*
	(0.06)	(0.09)
Price X 75% * Male		-0.22*
		(0.12)
Price X 50%	0.09*	0.20**
	(0.06)	(0.08)
Price X 50% * Male		-0.19*
		(0.11)
Observations	3182	3182
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 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 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%	0.08	0.19	-0.05	-0.01	-0.01	0.08
	(0.11)	(0.17)	(0.15)	(0.17)	(0.23)	(0.23)
Price X 75% * Bus User	0.08	0.05	0.07	0.72*	0.32	0.61
	(0.20)	(0.31)	(0.25)	(0.32)	(0.65)	(0.40)
Price X 50%	0.33**	0.53***	0.14	0.25	0.42*	-0.15
	(0.10)	(0.14)	(0.14)	(0.14)	(0.18)	(0.25)
Price X 50% * Bus User	0.01	-0.19	0.13	0.53	0.25	0.48
	(0.18)	(0.28)	(0.22)	(0.31)	(0.62)	(0.39)
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 controls chosen using a double-post-lasso procedure. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

Table 8. 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.

Table 9. Conditional Logit with Treatment as IV

Panel A: Parameter Estimation	Overall	Female	Male
Cost	-0.012^{***}	-0.014^{***}	-0.012^{***}
	(0.002)	(0.003)	(0.003)
Time	-0.015^{***}	-0.018^{***}	-0.014^{***}
	(0.002)	(0.004)	(0.003)
Safety	-0.343^{***}	-0.403^{***}	-0.300^{***}
	(0.043)	(0.070)	(0.056)
First Stage F-Stat			
Cost.Uber	11.834	3.878	12.215
Cost.Bus	1.011	1.146	2.354
Cost.Metro	0.63	0.793	1.257
Cost.Taxi	0.787	1.8	1.585
Observations	1289	514	775
Demographic Controls	Yes	Yes	Yes
Transport Mode Intercepts	Yes	Yes	Yes
Panel B: Amenity Value Estimation	**Overall**	**Female**	**Male**
Value of Time	1.197^{***}	1.332^{***}	1.133^{***}
	(0.256)	(0.418)	(0.324)
Value of Safety	27.774^{***}	29.864^{***}	24.849^{***}
	(5.556)	(8.216)	(7.147)
Observations	1289	514	775

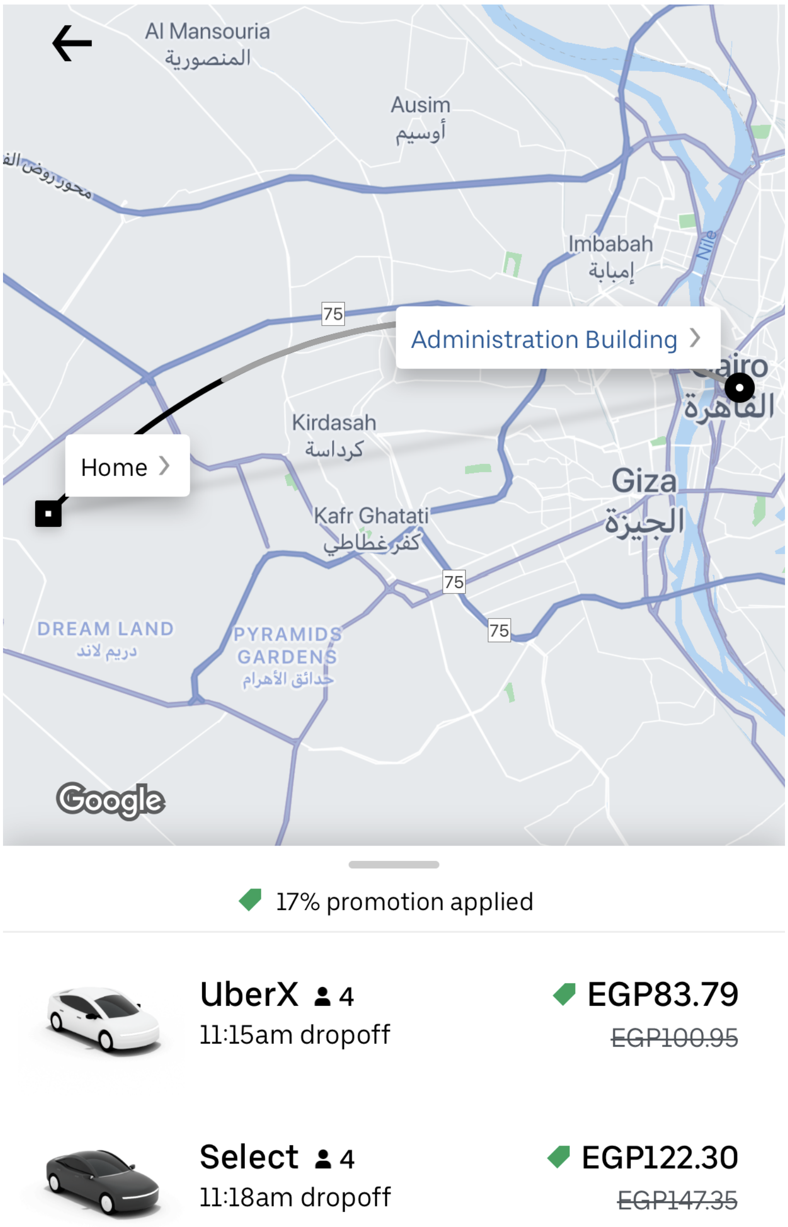
Notes: Panel A reports estimates from a conditional logit estimation using the two treatment arms, before and after the start of the experimental price change, as our instrumental variables. The conditional logit uses data on individual expectations of amenities across different modes of travel. Estimations include controls for baseline demographics and separate intercepts for each travel mode. Columns (2) & (3) estimate the parameters separately by gender. Panel B utilizes the parameters to produce estimates for the value of time and the value of safety in local currency. Significance: *.10; **.05; ***.01.

Appendices

A Experimental Design

A1. Price Information for Treated Riders

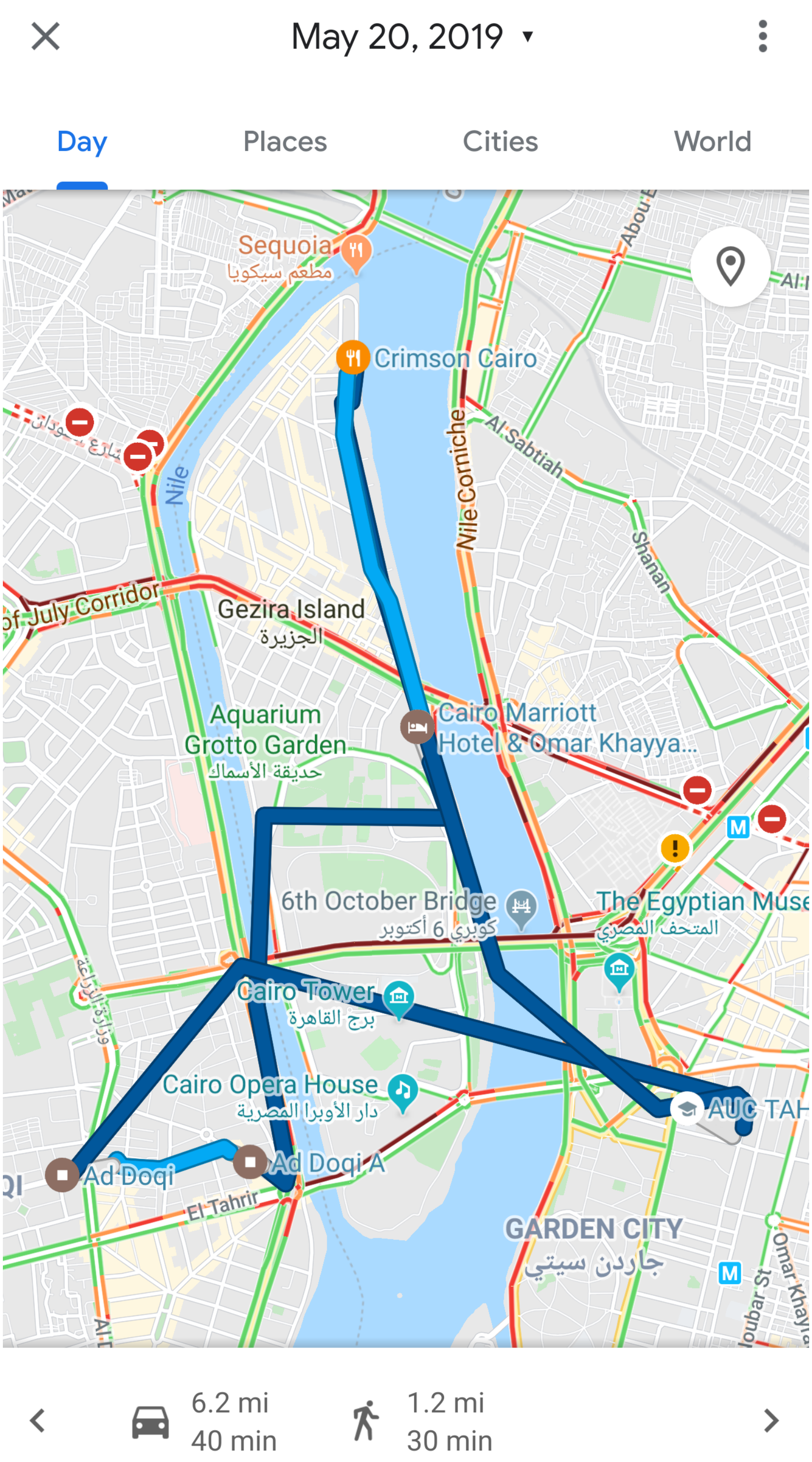
Figure A.1. Uber Price Information



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

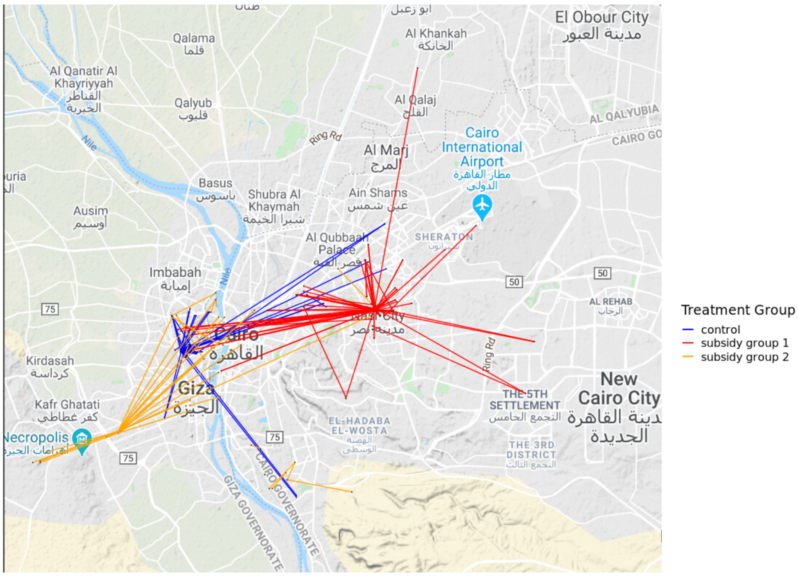
Figure A.2. Google Timeline Platform

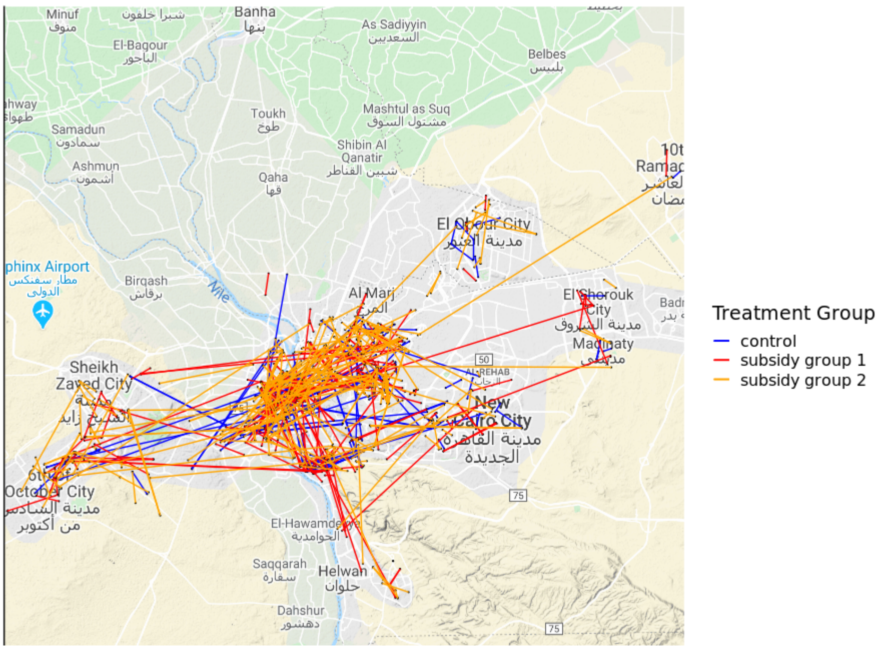


Notes: The figure illustrates the location and travel information displayed to participants on the Google Timeline application. The application provides total travel data for each date after the application is enabled.

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.

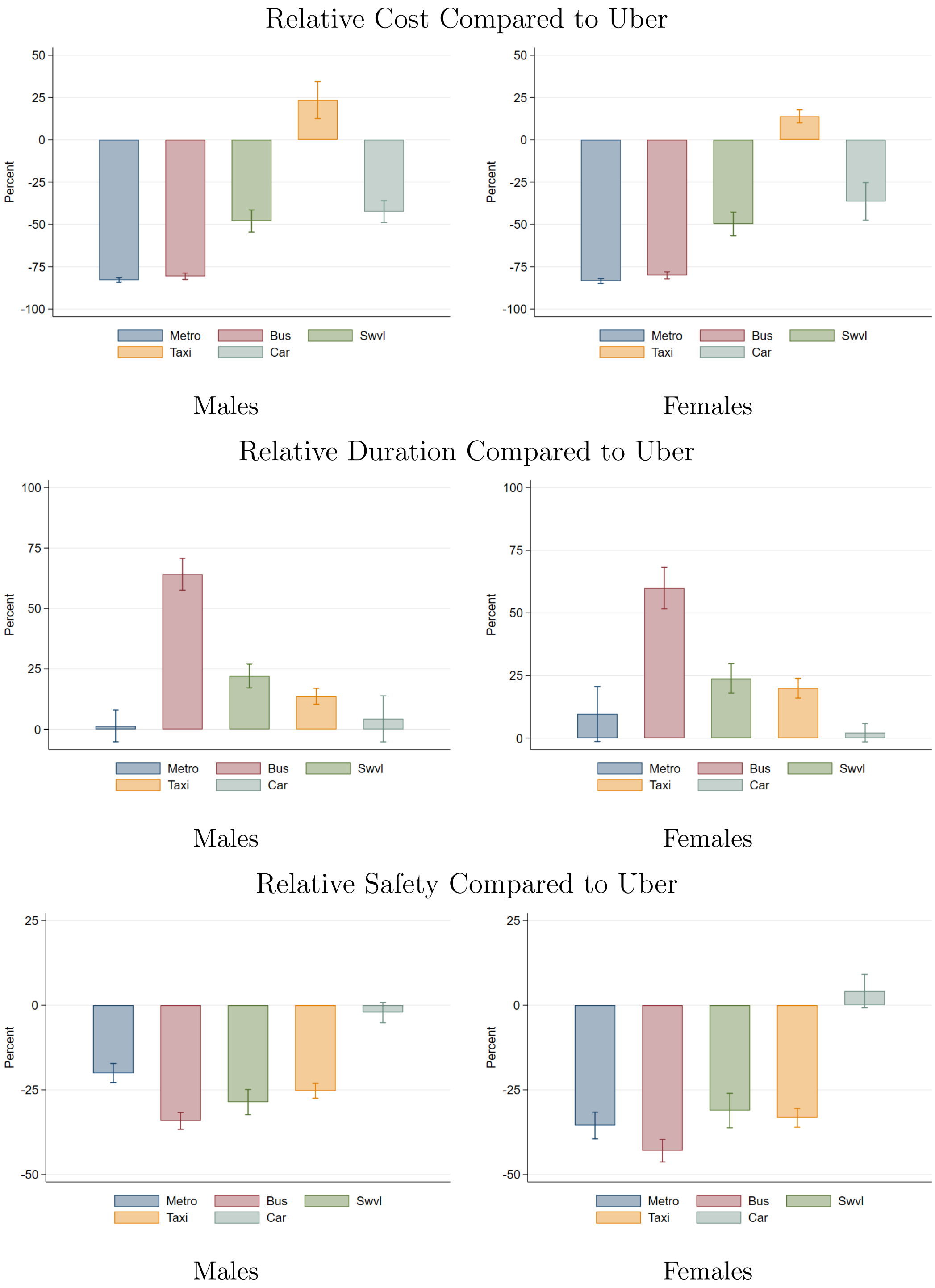
B Sample Characteristics and Attrition

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. Tables B3-B4 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



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.

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)
Uber Last Week Transportation	0.16	-0.05*	-0.06*	0.00
	(0.37)	(0.03)	(0.03)	(0.03)
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)		0.58	0.84	0.58

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	0.48	0.53	0	0	1	1
	(0.5)	(0.50)	(0.0)	(0.0)	(0.0)	(0.0)
Age	39.26	30.92	40.50	29.95	37.91	31.77
	(13.81)	(9.54)	(13.93)	(9.89)	(13.55)	(9.15)
Married	0.57	0.49	0.60	0.45	0.54	0.52
	(0.49)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)
Hours Worked (hours/week)	49.42	44.47	42.16	39.05	51.90	48.15
	(16.92)	(16.17)	(14.15)	(14.14)	(17.08)	(16.44)
Currently Working	0.48	0.79	0.24	0.68	0.75	0.88
	(0.50)	(0.41)	(0.43)	(0.47)	(0.43)	(0.32)
Monthly Income	3121	4403	2599	3434	3298	5060
	(4491)	(5274)	(2665)	(3813)	(4947)	(5987)
College Education	0.32	0.88	0.31	0.90	0.34	0.86
	(0.47)	(0.32)	(0.46)	(0.30)	(0.47)	(0.34)
High School	0.33	0.09	0.32	0.08	0.34	0.10
	(0.47)	(0.28)	(0.47)	(0.27)	(0.45)	(0.30)
Less than High School	0.31	0.01	0.33	0.01	0.28	0.01
	(0.46)	(0.08)	(0.47)	(0.08)	(0.45)	(0.08)
Car Owner	0.20	0.25	0.21	0.20	0.19	0.29
	(0.40)	(0.43)	(0.41)	(0.40)	(0.39)	(0.46)
Looking for Work	0.05	0.49	0.04	0.33	0.05	0.63
	(0.21)	(0.50)	(0.21)	(0.47)	(0.22)	(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. 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 B4. 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 B5. 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 (0.10)	-0.13 (0.09)
Car	-0.04* (0.02)	-0.04** (0.02)
Education	-0.01 (0.01)	-0.01 (0.01)
Married	-0.01 (0.02)	-0.01 (0.02)
Female	0.00 (0.02)	0.00 (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 (0.03)	0.04 (0.03)
Treatment * Education	0.01 (0.02)	0.03* (0.02)
Treatment * Married	0.00 (0.03)	-0.02 (0.03)
Treatment * Female	-0.03 (0.03)	0.01 (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*** (0.07)	1.01*** (0.06)
Observations	908	911
F-Test (P Value)	1.17 (0.32)	0.91 (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 B6. 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 (0.00)	0.5*** (0.08)	0.1 (0.09)	0.11 (0.14)	0.65*** (0.12)	0.18 (0.14)	-0.11 (0.12)	0.38*** (0.10)	0.03 (0.12)
Price X 50%	0.11 (0.08)	0.74*** (0.07)	0.35*** (0.08)	0.24* (0.12)	0.90*** (0.11)	0.49*** (0.12)	0.02 (0.11)	0.58*** (0.10)	0.23** (0.11)

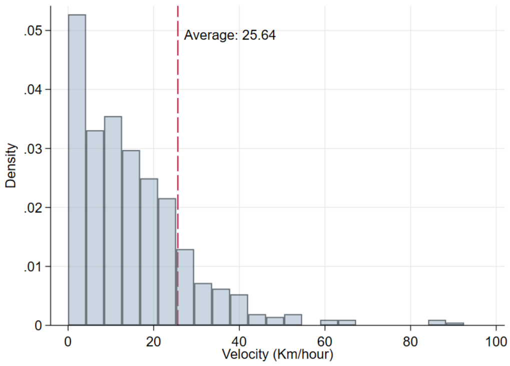
Table B7. Lee Bounds for Safety

	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)

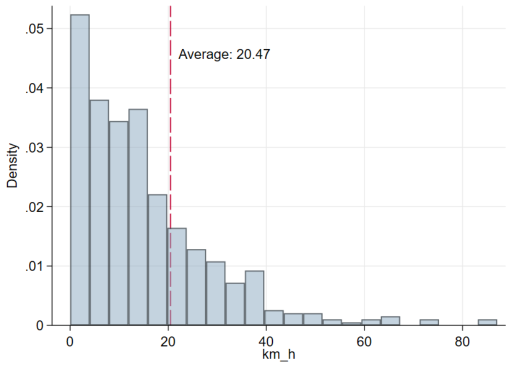
C Measuring Total Mobility

This appendix provides additional detail on the measurement of mobility using Google Timeline. Figure C1 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. Participants in treatment may tend to have their phones turned on more often for Uber services and thereby collect more mobility data.

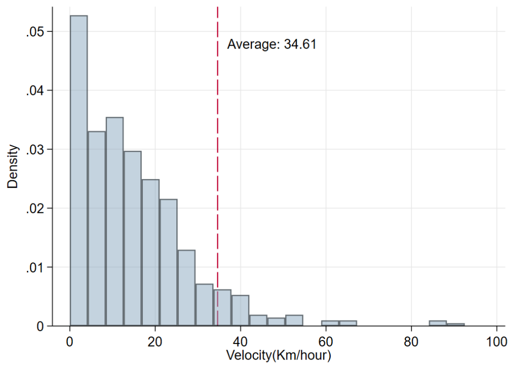
Figure C1. Velocity Histograms by Group



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.

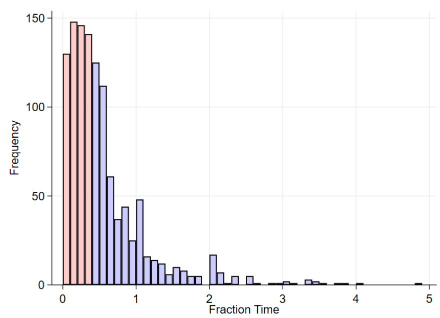
Table C1 examines the coefficient of variation in the total daily travel recorded on days when a participant takes an Uber trip relative to days when a participant does not take an Uber trip (for all three groups). This evidence suggests that there are no significant differences in the variance of recorded travel on such days or across the groups.

Table C1. Coefficient of Variation

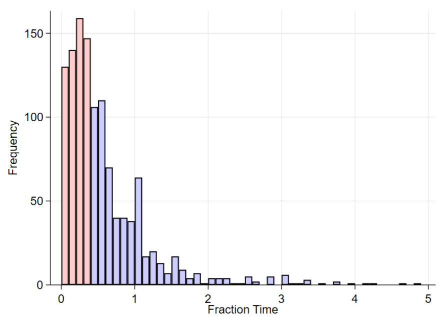
	Overall (1)	Control (2)	Subsidy 25% (3)	Subsidy 50% (4)
Day With Uber	1.41 [1.19, 1.47]	1.32 [1.12, 1.36]	1.47 [1.27, 1.68]	1.44 [1.24, 1.68]
Day Without Uber	1.52 [1.23,1.59]	1.42 [1.33,1.80]	1.55 [1.36, 1.70]	1.59 [1.53, 1.95]

Figure C2 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.

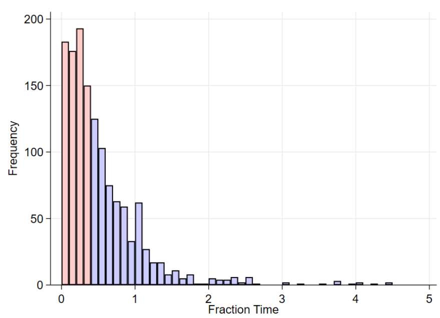
Figure C2. Longest Trip as Fraction of Time Spent Daily Travel Histograms



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 C2 examines evidence of substitution behavior for these two different samples. The estimates are largely consistent with our main findings, indicating that the information on substitution behavior is not sensitive to whether a longest trip represents a larger or smaller fraction of total travel.

Table C2. Longest Trip as Fraction of Time Spent Daily Travel

Panel A: Below the Median	Metro		Bus		Taxi		Uber		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price X 75%	-0.02	-0.02	-0.04	-0.08	-0.03**	-0.04*	0.09***	0.07	0.01	0.08
	(0.02)	(0.02)	(0.03)	(0.05)	(0.01)	(0.02)	(0.03)	(0.05)	(0.03)	(0.05)
Price X 75% * Male		0.01		0.06		0.03		0.04		-0.11*
		(0.03)		(0.07)		(0.03)		(0.06)		(0.07)
Price X 50%	0.009	0.016	-0.1***	-0.14***	-0.03***	-0.05**	0.11***	0.067	-0.01	0.07
	(0.02)	(0.02)	(0.03)	(0.04)	(0.01)	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)
Price X 50% * Male		-0.01		0.07		0.03		0.07		-0.13**
		(0.03)		(0.06)		(0.02)		(0.05)		(0.06)
Observations	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598

Panel B: Above the Median	Metro		Bus		Taxi		Uber		Car	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price X 75%	0.01	-0.02	-0.03	-0.02	0.00	-0.01	0.05	0.10**	-0.04	-0.04
	(0.02)	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)	(0.03)	(0.05)	(0.03)	(0.04)
Price X 75% * Male		0.06		-0.01		0.02		-0.11*		0.01
		(0.04)		(0.06)		(0.02)		(0.06)		(0.06)
Price X 50%	-0.01	-0.03	-0.1***	-0.09**	0.00	-0.01	0.12***	0.17***	0.00	-0.02
	(0.02)	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)	(0.03)	(0.05)	(0.03)	(0.05)
Price X 50% * Male		0.04		-0.01		0.01		-0.10*		0.03
		(0.03)		(0.06)		(0.02)		(0.06)		(0.06)
Observations	1588	1588	1588	1588	1588	1588	1588	1588	1588	1588

Notes: This table 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. 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 A constrains the sample to the low part of the distribution of the variable $Frac_t ime = \frac{Previousdaylongesttriptime}{previousdaytotaltime}$. Panel B constrains the sample to the low part of the distribution of the variable $Frac_t ime$

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***	0.86***
	(0.08)	(0.11)
Price X 75% * Interaction	-0.39*	0.30*
	(0.21)	(0.15)
Price X 50%	1.81***	1.60***
	(0.09)	(0.11)
Price X 50% * Interaction	-0.82***	0.20
	(0.24)	(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

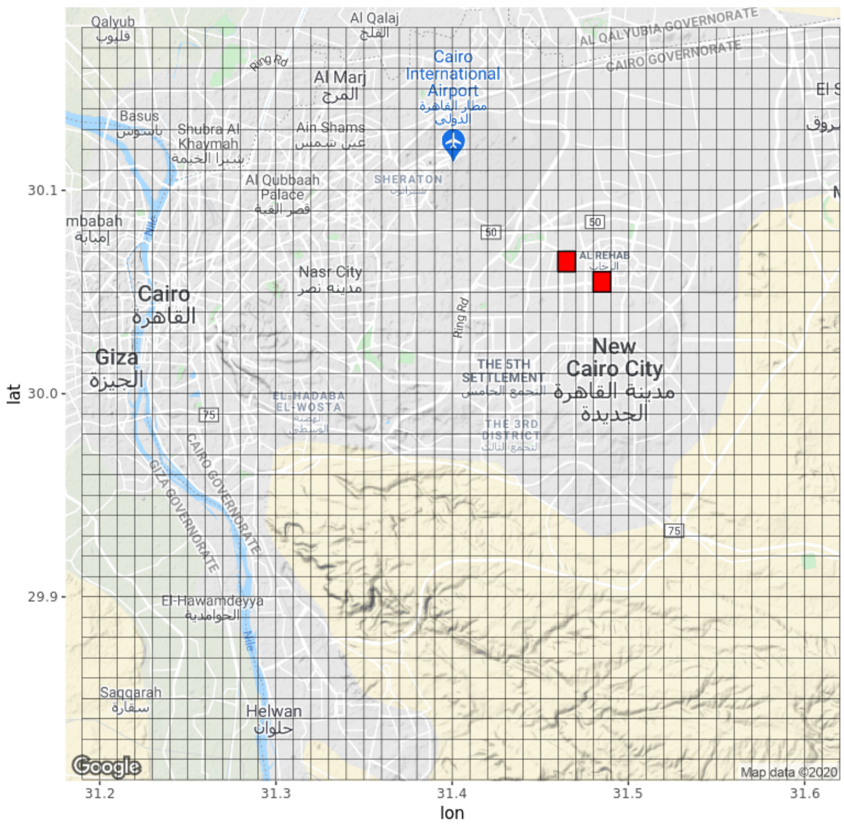


Figure E.2. Trips to Hospitals

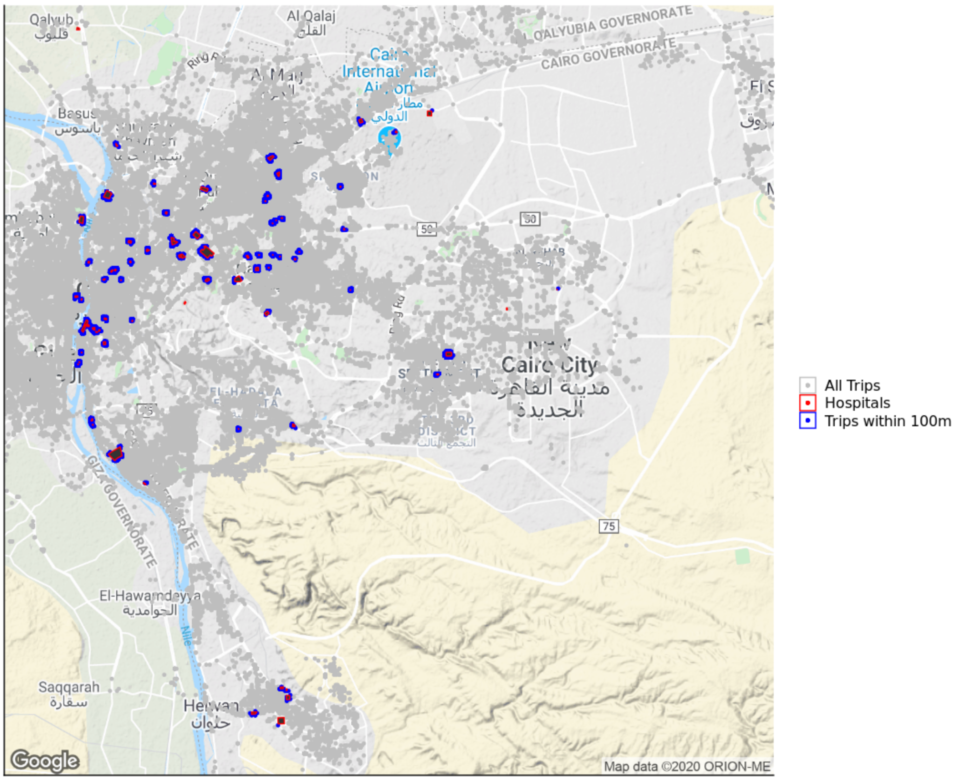


Table E.1. Trips to Hospitals

	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

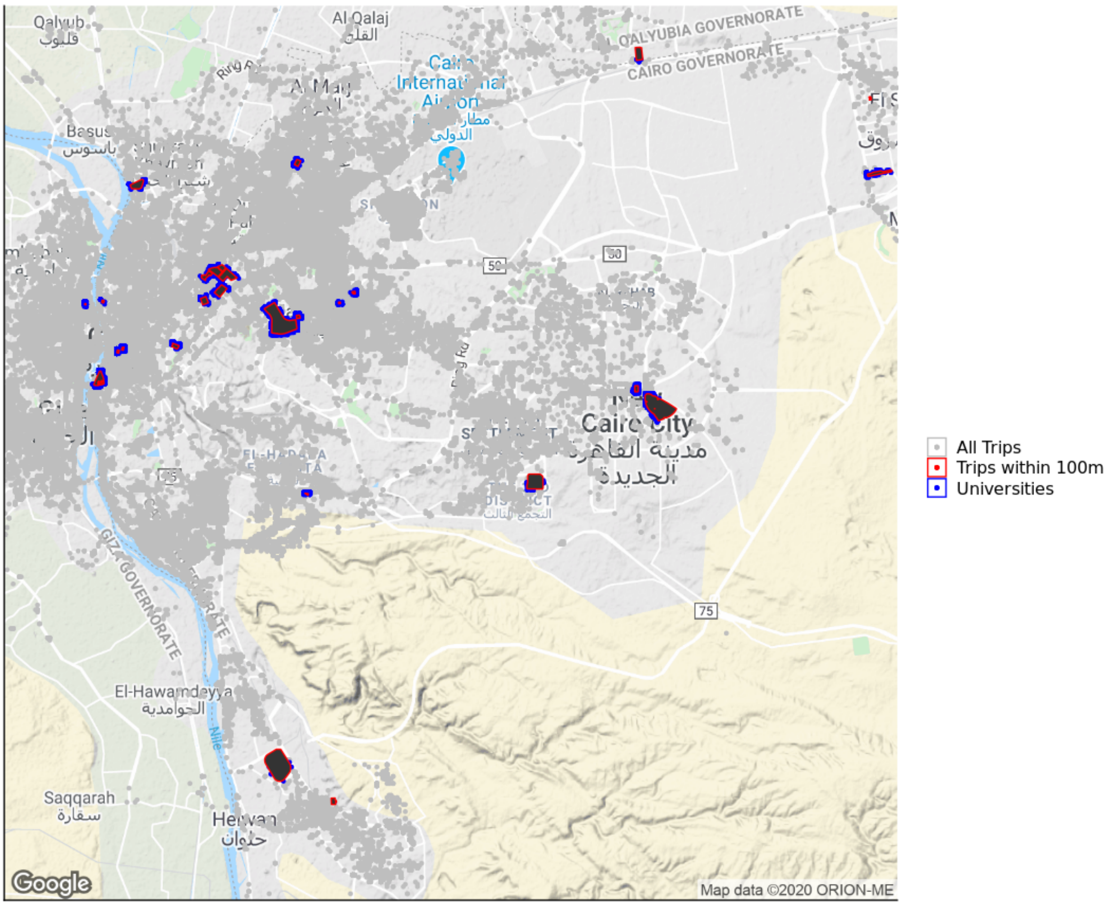


Table E.2. Trips to Universities

	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

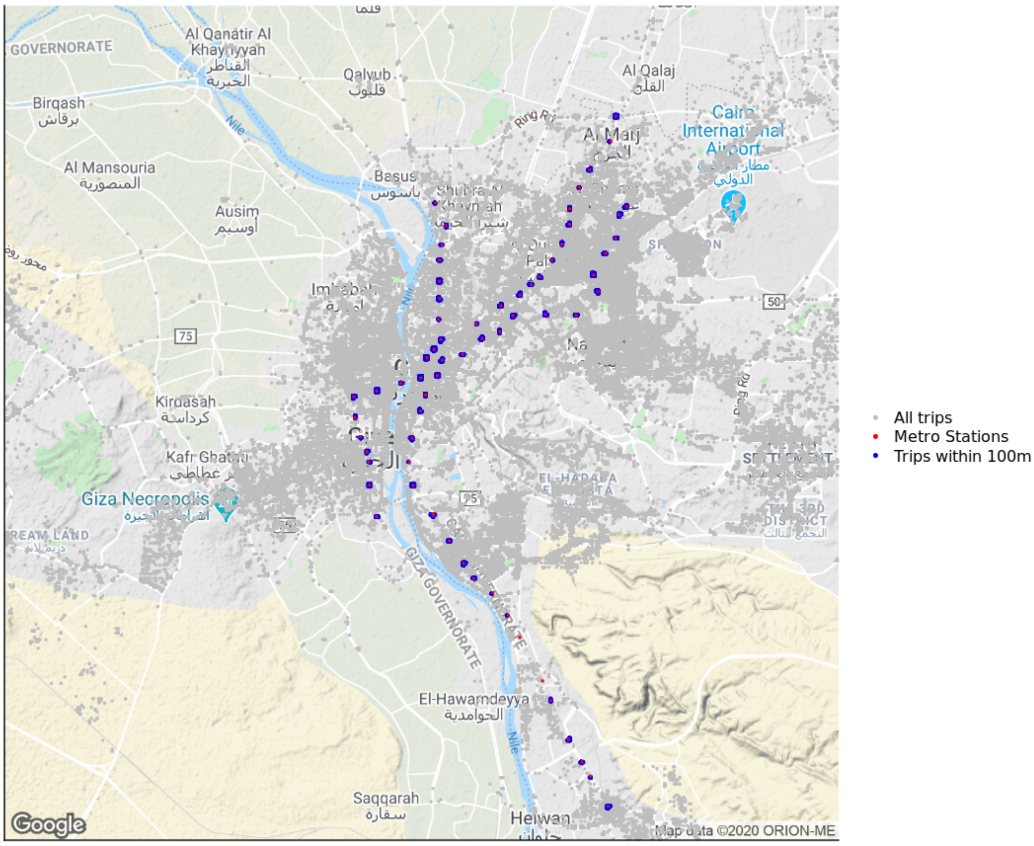


Table E.3. Trips to Metro Stations

	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.

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 (0.09)	0.17 (0.14)
Price X 75% * Male		-0.12 (0.19)
Price X 50%	0.36*** (0.08)	0.49*** (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 (0.01)	-0.02 (0.02)	-0.06** (0.03)	-0.04 (0.04)	-0.02** (0.01)	-0.03** (0.01)	0.10*** (0.02)	0.10*** (0.04)	-0.01 (0.03)	-0.01 (0.04)
Price X 75% * Male		0.03 (0.03)		-0.03 (0.05)		0.02 (0.01)		0.00 (0.05)		-0.01 (0.05)
Price X 50%	0.00 (0.01)	-0.01 (0.02)	-0.1*** (0.03)	-0.1*** (0.04)	-0.02** (0.01)	-0.03** (0.01)	0.13*** (0.02)	0.15*** (0.04)	-0.02 (0.03)	0.00 (0.04)
Price X 50% * Male		0.02 (0.03)		0.02 (0.05)		0.02 (0.01)		-0.03 (0.05)		-0.03 (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.

Table G.8. 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*	-0.03	-0.04	-0.00
	(0.04)	(0.08)	(0.05)	(0.23)	(0.34)	(0.30)	(0.05)	(0.11)	(0.05)
Price X 75% * No Searching	0.08	0.02	0.10	0.60**	0.39	0.67**	-0.03	-0.01	0.00
	(0.05)	(0.08)	(0.06)	(0.25)	(0.36)	(0.32)	(0.09)	(0.13)	(.)
Price X 50%	0.02	-0.04	0.05	-0.01	0.60	-0.20	-0.05	-0.12	0.00
	(0.04)	(0.07)	(0.05)	(0.30)	(0.68)	(0.32)	(0.05)	(0.11)	(0.05)
Price X 50% * No Searching	-0.01	0.02	-0.01	0.07	-0.63	0.34	0.04	0.10	0.00
	(0.04)	(0.08)	(0.06)	(0.30)	(0.70)	(0.33)	(0.09)	(0.13)	(.)
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 (Search)	0.07	0.08	0.07	0.08	0.09	0.05	0.66	0.66	.

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 baseline value of the outcome variable as control. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

H Discrete Choice Model

This section provides details for data used in the discrete choice model described in Section 6.1 and reports results on robustness of our parameter estimates. Table H.1 reports the sample size, mean, and standard deviation of data on the cost, time, and safety of actual and alternate modes that participants report for longest trips taken the day prior to a follow-up survey. The general patterns illustrated in these data are consistent with those found in the baseline survey. In choosing between using Uber and public transit modes, consumers perceive considerable trade-offs in cost for speed and safety. This is most stark in the case of bus travel.

Table H.1. Descriptive Statistics for Amenities

	Cost			Time			Safety		
Variable	Obs	Mean	Sd.	Obs	Mean	Sd.	Obs	Mean	Sd.
Metro	2819	8.15	11.82	2,872	35.91	34.82	2,730	2.54	1.21
Bus	2,916	10.71	27.50	3,067	55.04	43.91	2,942	3.08	1.24
Taxi	3,008	75.61	113.17	3,078	42.00	35.10	2,838	2.87	1.08
Uber	3,126	69.08	124.15	3,177	37.99	34.54	3,028	1.52	0.69

Notes: The table reports summary statistics about 'longest trip yesterday' from the survey. Each section includes actual and expectations of amenities across different modes of travel. Safety is measured from very unsafe (1) to very safe (5).

Table H.2 and figure H.1 illustrate the effects of price reductions on the travel choices made by participants, which are concentrated on three modes. Price reductions in ride-hailing services increase the likelihood of taking a trip using Uber for both genders, though effects are stronger for women, especially in the 50% price treatment. The price reductions in ride-hailing services reduce the likelihood of taking trips by bus, which occurs for both genders but is stronger for women, especially in the 50% price treatment. The price reductions in ride-hailing services reduce the likelihood of taking trips by taxi, though these changes are relative to a low baseline likelihood of taxi use.

Table H.2. Multinomial Logit Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Metro	Bus	Taxi	Metro	Bus	Taxi
Price × 75%	-0.210	-0.398***	-0.667***	-0.0770	-0.584***	-0.497
	(0.159)	(0.0963)	(0.236)	(0.222)	(0.139)	(0.342)
Price × 50%	-0.214	-0.542***	-0.642***	-0.0375	-0.518***	-0.651*
	(0.153)	(0.0943)	(0.224)	(0.219)	(0.137)	(0.352)
female				-0.338	-0.781***	-0.0293
				(0.232)	(0.142)	(0.310)
Price × 75% × female				-0.360	0.366*	-0.345
				(0.323)	(0.195)	(0.476)
Price × 50% × female				-0.363	-0.0451	0.0217
				(0.309)	(0.192)	(0.456)
Constant	-1.329***	0.311***	-1.992***	-1.141***	0.704***	-1.974***
	(0.115)	(0.0695)	(0.152)	(0.169)	(0.102)	(0.239)
Observations	3,188	3,188	3,188	3,186	3,186	3,186

Notes: The table reports multinomial logit estimates using only price treatments and gender as explanatory variables. The numbers in the table report the relative log odds of taking different transit modes to Uber when switching from the control group to different treatment groups. The estimates correspond to the equation: $ln(\frac{P(Mode)}{P(Uber)}) = constant + \beta * Dummy(treatment\_groups)$. Significance: *.10; **.05; ***.01.

Figure H.1. Substitution Patterns from Multinomial Logit

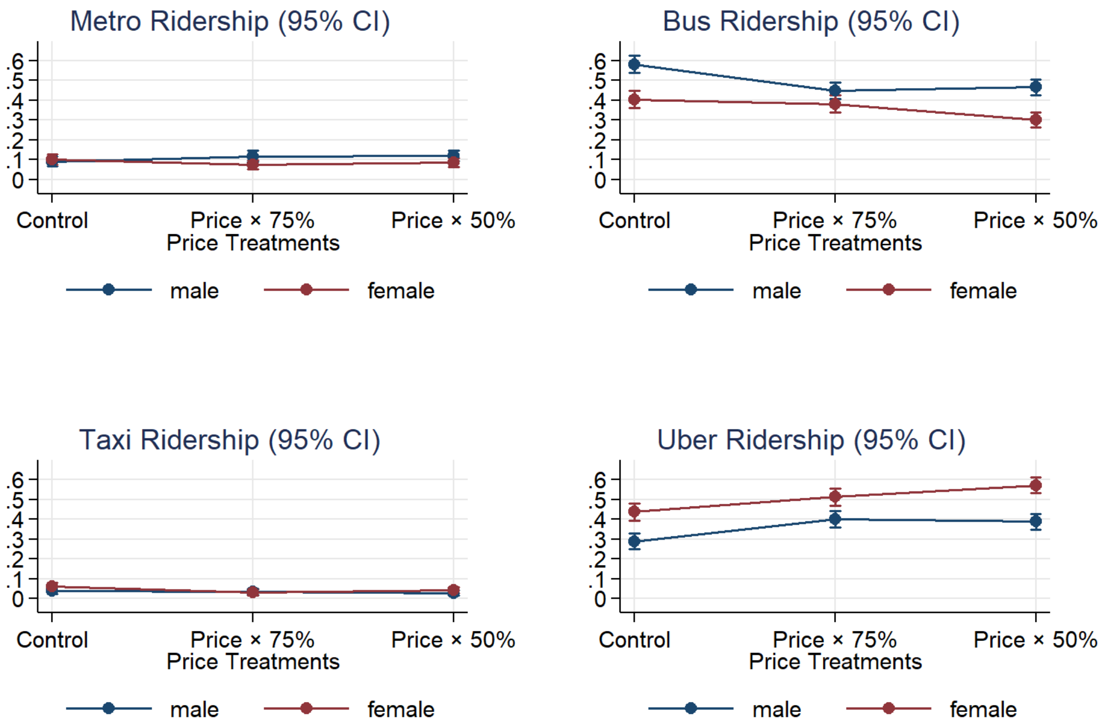


Table H.3 reports the estimates from multiple specifications of the conditional logit model that rely on different instruments. Column 1 reports estimates from a specification without any instruments, whereas columns 2-4 report estimates from specifications that utilize the experimental and Hausman instruments. We find no evidence of statistical differences in the point estimates for cost, time, and safety parameters from equation 2 or in estimates of the value of time (VOT) or the value of safety (VOS) from equation 3. This suggests that the estimates reported in Section 6.1 are robust to different assumptions and sources of exogenous variation. The estimates of value of time range from 1.03-1.2 EGP per trip-minute, which translates to 61.8-72 EGP/hour. This can be compared to the 33.6 EGP hourly wage for the average participant in our sample. The estimates of the value of safety imply that the average rider in our study is willing to pay 26.3-29.8 EGP to realize a unit increase in perceived safety (i.e. from very unsafe to unsafe or from neutral to safe) in a trip.

Table H.3. Conditional Logit Estimates: Comparison Across IV Specifications (all parameters)

	Logit Model	IV experimental	IV Hausman (cost)	IV Hausman (all)
cost	−0.013***	−0.012***	−0.012***	−0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
time	−0.014***	−0.015***	−0.015***	−0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
safe	−0.340***	−0.343***	−0.341***	−0.358***
	(0.043)	(0.043)	(0.043)	(0.047)
Bus:(intercept)	1.265***	1.300***	1.295***	1.308***
	(0.177)	(0.177)	(0.177)	(0.179)
Metro:(intercept)	−2.060***	−2.019***	−2.024***	−1.993***
	(0.298)	(0.296)	(0.296)	(0.297)
Taxi:(intercept)	−1.650***	−1.611***	−1.623***	−1.606***
	(0.338)	(0.338)	(0.339)	(0.338)
Bus:b_avg_income	−0.113***	−0.112***	−0.113***	−0.113***
	(0.021)	(0.021)	(0.021)	(0.021)
Metro:b_avg_income	−0.099***	−0.098***	−0.098***	−0.099***
	(0.036)	(0.036)	(0.036)	(0.036)
Taxi:b_avg_income	−0.010	−0.011	−0.011	−0.011
	(0.038)	(0.038)	(0.038)	(0.037)
Bus:female	−0.677***	−0.666***	−0.673***	−0.665***
	(0.141)	(0.141)	(0.141)	(0.141)
Metro:female	−0.673***	−0.650***	−0.657***	−0.659***
	(0.227)	(0.226)	(0.226)	(0.227)
Taxi:female	0.043	0.028	0.033	0.043
	(0.312)	(0.312)	(0.312)	(0.313)
Bus:car_owner	−0.742***	−0.743***	−0.744***	−0.754***
	(0.188)	(0.189)	(0.189)	(0.189)
Metro:car_owner	−0.346	−0.343	−0.346	−0.334
	(0.296)	(0.295)	(0.296)	(0.297)
Taxi:car_owner	−0.381	−0.407	−0.397	−0.374
	(0.419)	(0.420)	(0.419)	(0.417)
Bus:metro_user	0.347**	0.348**	0.348**	0.347**
	(0.138)	(0.139)	(0.138)	(0.139)
Metro:metro_user	2.183***	2.165***	2.168***	2.173***
	(0.245)	(0.244)	(0.244)	(0.245)
Taxi:metro_user	0.186	0.189	0.188	0.182
	(0.314)	(0.314)	(0.314)	(0.314)
Experimental IV		0.003**		
		(0.002)		
Hausman Cost IV			0.002	0.005***
			(0.001)	(0.002)
Hausman Time IV				0.007***
				(0.003)
Hausman Safe IV				−0.021
				(0.045)
Value of Time	1.098***	1.197***	1.179***	1.028***
	(0.229)	(0.256)	(0.252)	(0.253)
Value of Safety	26.254***	27.774***	27.475***	29.813***
	(5.114)	(5.556)	(5.492)	(6.182)
Num. obs.	1289	1289	1289	1289

Notes: Table reports the estimates from multiple specifications of the conditional logit model using different instruments. Estimations include controls for baseline demographics and separate intercepts for each travel mode. All instruments are used in control function method to control for endogeneity. Column (2) reports estimates from a conditional logit estimation using the two treatment arms, before and after the start of the experimental price change, as our instrumental variables. Column (3) & (4) report estimates using Hausman type IV, the leave-out average value constructed using city locations. Significance: *.10; **.05; ***.01.

In Table H.4, we examine the sensitivity of parameter estimates to different ways of handling self-reports of cost, time, and safety on different modes. To address the concern that some riders would not take into account the subsidies when answering the survey questions, we use imputation to correct the top 10% trips which are most likely misreporting the Uber cost. The imputation uses the average value of cost per minute calculated from the actual Uber trips in the baseline control group, then predicts trip costs for the treated trips using the cost per minute as a factor. We replace the top 10% trips in our data set that have the largest percentage difference between the actual and predicted cost with their predicted Uber cost values.

Table H.4. Conditional Logit Estimates: Sensitivity to Imputed Values

	Logit Model		IV-experimental		IV-Hausman (cost)		IV-Hausman (all)	
	No Impute	Impute (10%)	No Impute	Impute (10%)	No Impute	Impute (10%)	No Impute	Impute (10%)
cost	-0.015^{***}	-0.013^{***}	-0.014^{***}	-0.012^{***}	-0.015^{***}	-0.012^{***}	-0.014^{***}	-0.012^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
time	-0.016^{***}	-0.014^{***}	-0.017^{***}	-0.015^{***}	-0.016^{***}	-0.015^{***}	-0.015^{***}	-0.012^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
safe	-0.332^{***}	-0.340^{***}	-0.331^{***}	-0.343^{***}	-0.331^{***}	-0.341^{***}	-0.339^{***}	-0.358^{***}
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.047)	(0.047)
Value of Time	1.094^{***}	1.098^{***}	1.144^{***}	1.197^{***}	1.125^{***}	1.179^{***}	1.014^{***}	1.028^{***}
	(0.194)	(0.229)	(0.207)	(0.256)	(0.203)	(0.252)	(0.204)	(0.253)
Value of Safety	22.491^{***}	26.254^{***}	22.952^{***}	27.774^{***}	22.753^{***}	27.475^{***}	23.681^{***}	29.813^{***}
	(4.001)	(5.114)	(4.146)	(5.556)	(4.09)	(5.492)	(4.426)	(6.182)
First stage F score								
Cost.Uber			1.611	11.834	36.981	79.746	36.981	79.746
Cost.Bus			1.011	1.011	0.027	0.027	0.027	0.027
Cost.Metro			0.63	0.63	0.175	0.175	0.175	0.175
Cost.Taxi			0.787	0.787	27.968	27.968	27.968	27.968
Time.Uber							13.393	24.191
Time.Bus							0.046	0.046
Time.Metro							2.511	2.511
Time.Taxi							5.993	5.993
Safe.Uber							0.016	0.217
Safe.Bus							1.982	1.982
Safe.Metro							2.324	2.324
Safe.Taxi							1.065	1.065
Num. obs.	1289	1289	1289	1289	1289	1289	1289	1289
Demographic Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mode Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports the estimates from multiple specifications of the conditional logit model using different instruments adjusting for self-report errors. Estimations include controls for baseline demographics and separate intercepts for each travel mode. All instruments are used in control function method to control for endogeneity. Column (2) & (3) reports estimates from a conditional logit estimation using the two treatment arms, before and after the start of the experimental price change, as our instrumental variables. Column (4) - (8) report estimates using Hausman type IV, the leave-out average value constructed using city locations. Column (2), (4), (6), (8) reports estimates after correcting the top 10% trips which are most likely miss reporting the Uber cost. 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:

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

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

The demand equation defines the change in private vehicle kilometers traveled (X_{PT}) 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. 9 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_{PT} 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:

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

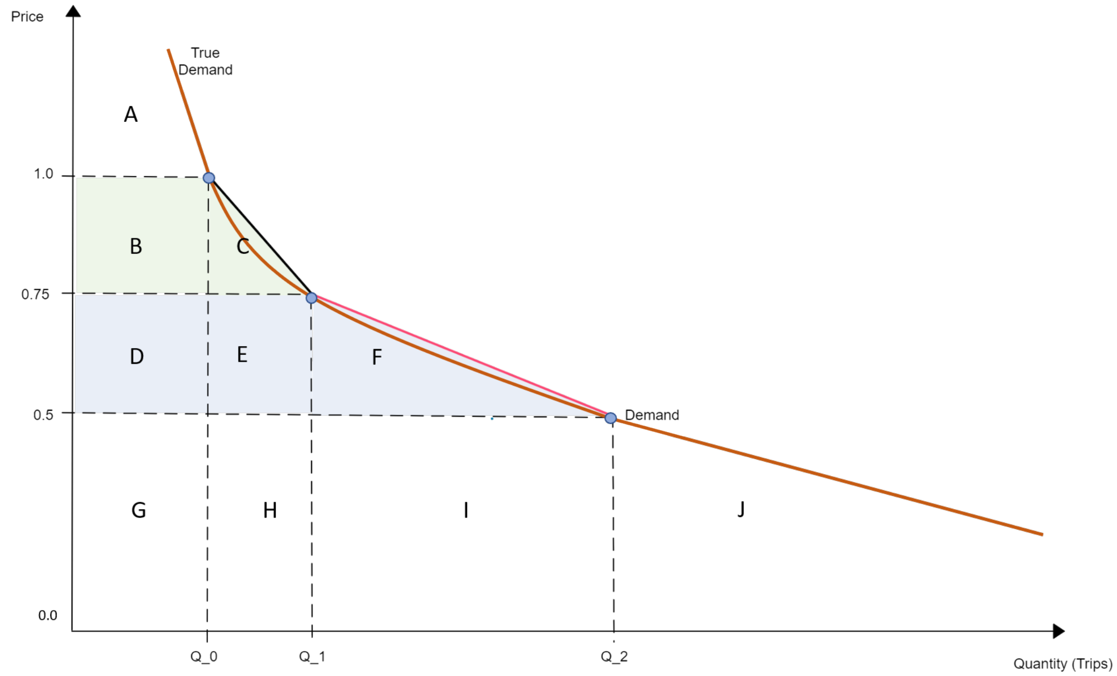
Re-arranging terms, we recover the following expression for gamma:

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

J Consumer Surplus

In this section, we provide a graphical illustration of the procedure that we use to use our experimental estimates of average treatment effects to compute the consumer surplus for Uber for participants in our study.

Figure J.1. Consumer Surplus Weekly Trips On Uber



As illustrated in figure 1, the demand curve for Uber services can be divided into intervals that correspond to each of the two treatment in the study: (1) from $P_{1.0}$ (baseline) to $P_{0.75}$ and (2) from $P_{0.75}$ to $P_{0.50}$. Given the assumption that demand is approximately linear, the surplus for participants that consume Q_1 in Uber services at price $P_{0.75}$ can be approximated by the areas B + C above.

$$C_{S1} = 0.25 * P_{1.0} * Q_0 + (Q_1 - Q_0) * 0.25 * \frac{P_{1.0}}{2} \tag{8}$$

The surplus for participants that consume Q_2 in Uber services at price $P_{0.5}$ can be approximated by the areas D + E + F above.

$$C_{S2} = (0.75 - 0.25) * P_{1.0} * Q_1 + (Q_2 - Q_1) * (0.75 - 0.25) * \frac{P_{1.0}}{2} \tag{9}$$

We measure Q_0 and $P_{1.0}$ using the control mean of trips taken during the experimental period and the control group mean fare: 18.20 EGP. We use estimated demand elasticities (for trips) at Q_1 and Q_2 to derive the weekly consumer surplus of an average user given a price reduction of 25% or 50%. This yields the following estimates:

$$CS_{25\%} = C_{S1} = 10.79$$

$$CS_{50\%} = C_{S1} + C_{S2} = 29.86$$

To calculate the ratio of consumer surplus to total expenditures, we adjust the control mean expenditure to incorporate the reduction in prices facing each treatment group. Expenditures are given by $Q_1 {*} P_{0.75}$ for the 75% treatment group and $Q_2 {*} P_{0.5}$ for the 50% treatment group.

Total benefit for a consumer can be defined as the area under the demand curve. To calculate the total benefit, we used the sum of consumer surplus and total expenditure based on Q_0 and $P_{1.0}$ as defined above.

Table J.1. Consumer Surplus

Panel A: Equilibrium 25% & 50%						
	Estimates at 25% Subsidy			Estimates at 50% Subsidy		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Total Benefit	78.10	91.16	67.52	127.45	153.25	107.41
Expenditure	63.36	74.12	54.61	81.72	99.39	68.32
Consumer Surplus	14.74	17.04	12.91	45.73	54.24	39.09
Consumer Surplus to Expenditure Ratio	0.23	0.23	0.24	0.56	0.55	0.57

Panel B: Partial Equilibrium 25% & 50%						
	Estimates at 25% Subsidy			Estimates at 50% Subsidy		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Total Benefit	84.91	104.54	70.72	141.83	182.54	114.61
Expenditure	69.19	85.58	57.35	91.67	119.46	73.35
Consumer Surplus	15.71	18.95	13.37	50.16	63.08	41.26
Consumer Surplus to Expenditure Ratio	0.23	0.22	0.23	0.55	0.53	0.56

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 Karlan and Udry (2020), 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.