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DISCUSSION PAPER SERIES

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ABSTRACT

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

Changes in transport costs can affect mobility in ways that differ across the population, affecting the impacts of transport policies. We randomly assign large price reductions on Uber in Egypt over a 3-month period and collect comprehensive data on participant mobility using Google Timeline. A 50% price reduction quadruples Uber usage and induces a 42% increase in total travel. Effects and welfare gains are larger for women, who are less mobile at baseline and perceive public transit as unsafe. The price elasticity of private vehicle kilometers traveled (-1.28) implies that mobility and external costs increase substantially when ride-hailing prices fall.

JEL Classification: J16, J28, J61, Q55,R41, R48

Keywords: travel demand, travel safety, ride-hailing, mobility on demand

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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 (Bryan et al., 2019, 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, 2018, 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 endogenenity 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. 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 large increases in mobility – participants receiving the 25% price treatment increase their total kilometers traveled (VKT) by 13%, resulting in 196 km of additional travel over the 12-week study period. Those receiving the 50% treatment increase their VKT by 42%, an increase of 644 km over the 12-week period. Comparing the effects on Uber utilization to those on total mobility, we find that individuals use Uber both as a substitute for existing transport on other modes and also to increase their total travel. A 50% (25%) price reduction results in an increase of 61 (24) km/week in Uber travel and an increase of 54 (16) km/week in total travel. We estimate that the price elasticity of demand for mobility is -0.84 for the average participant in the our sample.

These average effects mask important heterogeneity by gender. Point estimates indicate that the price elasticity of demand for mobility is substantially higher among women (-1.10) than men (-0.63). Women are less mobile, but also have a higher Uber utilization at baseline. Female participants respond more strongly to the 50% treatment, 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 the 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 buses – the least safe travel option reported by female participants in our study. This substitution pattern is particularly strong among women who reported at baseline that they perceived the bus as an unsafe mode of transit. During the intervention, we find that women in the treatment groups report feeling much safer on long trips relative to their counterparts in the control group. There is no difference in feelings of travel safety among men.

We then use the experimental estimates to study two sets of policy questions. We begin by considering ride-hailing markets in particular. We use experimentally identified demand elasticities to estimate the welfare impacts of sustained reductions in the price of ride-hailing services, as well as costs resulting from increased emissions and congestion. We find that a 50% price reduction generates 3,104 EGP per year in consumer surplus for the women in our sample and 2,240 EGP per year for men.[1] For each Egyptian pound spent on Uber services, participants receive 0.23 EGP in consumer surplus at the 75% price level and 0.55 EGP in surplus at the 50% price level. Price reductions provide substantial benefits to women in particular, who have lower incomes and receive substantially higher surplus from price reductions. The consumer surplus generated by a 50% reduction in Uber prices exceeds 7.5% of the income of females in our sample (versus 3.4% for men). Our findings on consumer surplus complement recent estimates identified using Uber's surge-pricing system in the US market (Cohen et al., 2016). Whereas Cohen et al. (2016) find that US consumers have relatively inelastic demand in the context of individual rides during surge pricing periods, our estimates from large, randomly assigned price reductions indicate that consumer demand in the Cairo sample is highly elastic.[2]

Highly elastic demand in developing country cities lends credence to concern about growth in the external costs produced by ride-hailing services. Researchers have predicted that costs in ride-hailing markets could fall by 40-80% as connected and autonomous ve-

[1] 1 USD is equivalent to about 16 Egyptian Pounds.

[2] Differences will also arise from the very different parts of the demand curve analyzed in the studies or differences in the populations and context studied.

hicle (CAV) technologies improve (Narayanan et al., 2020). We examine the potential impacts of reductions in the price of ride-hailing services on congestion and emissions externalities, which requires disentangling total mobility effects from the effects of substitution from mass transit (bus/metro) to private modes (car/taxi). When accounting for these differences, we estimate that the price elasticity of demand for *private* vehicle kilometers traveled (VKT) is -1.28 in Cairo. This is driven in large part by substitution from buses. We use this elasticity parameter and other estimates of transportation externalities in Cairo to estimate the external costs associated with the demand response to lower-cost private mobility services. We find that a 50% price reduction could increase the external costs attributable to Cairo's transportation sector by 13-25%, which is 59% higher than the consumer surplus generated by the same price reduction. We consider the impacts of a uniform tax levied on low price ride-hailing services and find disproportionate impacts on female mobility, suggesting that policymakers need to carefully consider the design of taxes in cities where female safety on public transit is a concern.

In a second set of policy exercises, we use survey 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 time (VOT) and the value of safety (VOS) in the Cairo transport market. We then simulate the welfare benefits of increases in the safety and speed of the available transit modes. Our estimates suggest that a policy that leaves no passenger feeling unsafe on public transit would yield 46.5 billion EGP per year in annual benefits for Cairo's population. 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] Our findings indicate that while subsidies to Uber would increase female safety in travel, interventions that increase the safety of Cairo's public bus system to the level currently reported for metro trips could yield nearly 80 billion EGP in annual benefits. This would be equivalent to the benefits generated from a 32% increase in the speed of public buses.

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 impermanence 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

[3]Cairo's metro system operates a limited number of female-only cars. No such option exists on the bus system, which serves a far greater share of the population. Approximately 25% of recent travel by women in our sample is done by bus while approximately 7% is done by metro.

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 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, 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, 2018, 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 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 congestion and emissions impacts 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.[4]

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

[4] A database compiled by the World Resources Institute identifies more than 45 cities in Brazil, China, India, and Mexico that tax ride-hailing services (World Resources Institute, 2020).

[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).

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).

2.1 Experimental Design

We study the demand response to experimental variation in the price of ride-hailing services in Cairo. The experiment applied a price reduction to 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).[7] See Appendix J 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

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

[7]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.

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 all regressions). After randomization, individuals were sent an email to welcome them into the study and to inform them about their treatment status.[8] The first cohorts were enrolled in July 2019, with the final cohorts enrolled in December 2019.[9] 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.[10] Price 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).[11]

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

[8]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 an online job board, 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.

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

[10]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.

[11]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.

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 Uber.

In an effort to better understand baseline travel behavior and perceptions of available options, we collected detailed data on a participants' longest trip 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 Careem), public bus, private bus (Swvl), and metro.[12] 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

[12] 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.

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. Digital and mobile-based technologies provide distinct advantages over earlier methods that depend exclusively upon respondent recall (Kreindler, 2018, 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.[13]

All participants consented to allow Uber to share trip-level Uber utilization data with

[13]These one-time credits have the potential to have differential impacts due to their interaction with reduced prices. On average a KM traveled on Uber cost approximately 6.5 EGP, so those in the 50% treatment could travel an additional 4KM on each credit relative to control. A conservative estimate would put the upper bound on this impact at 20 KM over the study period. By comparison, our impact estimates are equivalent to an increase of over 700KM in distance traveled on Uber in the 50% group relative to control during the study period.

the research team, including the 3-month period preceding the study, the study period, and a post-period following the completion of the study.[14] For each trip, this dataset records the Uber service used (e.g. UberX, Uber Bus, etc), the time of the trip (rounded to the nearest hour), the start and end locations of the trip (rounded to the 4th digit latitude/longitude), the distance and duration of the trip, the fare (both before and after the application of the price treatment, if appropriate), and any credits applied for payment of a trip (including the 25 EGP credits obtained after the completion of each survey).

4 Impacts on Uber Utilization

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

$$Y_i = \beta_1 T_1 + \beta_2 T_2 + \beta_0 Y_{0_{DPL}} + \delta_C + \gamma_F + \lambda_S + \varepsilon_i$$

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.[15] 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 those 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[16]; (3) The IHS transformation dampens the effects of outliers, while retaining realizations in outcomes that have a value of zero.

[14] We analyze the post-treatment impacts of the subsidies in Appendix D.

[15] 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 E. 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.

[16] 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 their procedure 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 if we were to use nominal levels instead of the IHS transformation.

4.1 Effects on Uber Usage

Table 1 reports estimates of the effects of the price reduction on the utilization of Uber services for transportation in the three experimental groups: control, 25% price 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 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.[17] 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 explore the distribution of treatment effects discussed above by plotting estimates from quantile regressions in Figure 2. While we do find evidence of heterogeneity in

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

the behavioral response to price changes on the Uber platform, these results indicate that estimates of average treatment effects are not driven by a small group of "super-users." Panel A presents the impacts 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 quantile treatment effects 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 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 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. Elasticities estimated on behavior with respect to changes in the price of gasoline or taxis could be quite different.

Experiments on the Salience and Length of Treatment

It is possible that certain features of our experimental setting affected the large elasticities that we estimate. In order to better understand the distinction between the effect of the price change and other features of our experimental setting, we implemented two additional 1-week experiments. The first experiment provides people with a pre-announced 1 week subsidy, while the second experiment provides people with an unannounced 1 week subsidy. By comparing the estimates from the two experiments we can determine how important the salience of the discounts are on the impacts of the subsidies. By comparing the pre-announced subsidy to the first week of our full study, we can assess how important the length of the subsidy is to our estimates.

For these experiments we utilize a sample of individuals who signed up for the study but were not enrolled, either because of over-subscription to the study or because these individuals did not not complete the baseline survey. 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.[18] 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 faces 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 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 point estimates on kilometers travel on Uber or 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 the duration of experimental treatment. We compare 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

[18]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.

that a participant travels to (origins or destinations) across the 12-week study period.

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

We dig deeper into effects on Uber travel behavior by testing for increased travel to major universities, hospitals and metro stops throughout Cairo.[19] 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).[20] 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 55.8 km per 3 days for the control group, point estimates suggest that total mobility increases by 0.12 IHS points (approx. 7 km or 13% of the control mean)

[19]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 C.

[20]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.

for participants who receive a 25% price reduction, though this effect is not statistically significant. Total mobility increases by 0.35 IHS points (approx. 23 km or 42% of the control mean) among participants who receive a 50% reduction.

At baseline, the average male participant in our sample travels more than twice as much as the average female participant (75 km vs. 35 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. 6 km or 17% of the control mean) in the low treatment group. In the high treatment group, we estimate an increase of 0.44 IHS points (approx. 19 km or 55% of the control mean). Differences by gender are not significant, but suggest smaller effects for men in both treatment groups. These estimates imply that women in the 50% (25%) group traveled an additional 538 km (169 km) overall over the course of the study relative to the control group, and men in the 50% (25%) group traveled an additional 679 km (198 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 -0.93, and for men it is -0.5. 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 impacts 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.

Is Uber a Substitute or Complement to Other Modes of Travel?

By comparing increases in overall distance traveled from Table 4 to the increases in "Uber distance traveled" from Table 1, we can directly examine the extent to which price reductions induce participants to substitute away from other travel modes relative to increasing their total mobility. On average, riders who received a 25% price reduction increased their Uber travel by approximately 24 km/week and increased their total mobility by 16 km/week. This implies that about one third of additional kilometers on Uber involved substitution from other modes of transport. Riders who received a 50% reduction increased their Uber travel by 61 km/week and their total mobility by 53 km/week, implying that approximately 13% of their Uber travel involved substitution away from other modes.

We find stark differences in these relationships when considered separately for each gender. Female riders in the 25% group increase their Uber travel by 27 km/week and their total travel by 14 km/week. In the 50% treatment group, female riders increase their Uber travel by 71 km/week and total travel by 44 km/week. These estimates imply that about 40% of increased Uber travel among female riders involves substitution from other modes. On the other hand, male riders in the 25% group increase their Uber travel by 21 km/week and total travel by 7 km/week. In the 50% treatment group, male riders increase their Uber travel by 54 km/week and total travel by 57 km/week. This implies about only 15% of Uber travel by men is used as a substitute away from other travel modes.

5.2 Effects on Transport Mode and Safety

Our results point to differences in substitution behavior by gender. Our baseline survey also 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 three different pieces of information: (1) self-reported transit mode use, (2) self-reported levels of safety on recent trips, and (3) heterogeneity in effects on Uber use and total mobility among safety-conscious riders.

In Table 5, we report estimates of the effects of our treatments on self-reported transport mode used for the longest trip taken the day before our survey. The estimates reveal strong evidence of substitution away from certain modes. For female riders in the 50% treatment group, the fare reduction increases the likelihood of using Uber (for the longest trip) by 12 percentage points and a decrease in bus use of 11 percentage points. The impacts for men are statistically equivalent, but with smaller point estimates. This is consistent with evidence from our baseline survey, which indicates that women are most likely to report feeling highly unsafe on buses. We also observe a smaller shift away from long trips using taxis, which are perceived as less safe and more costly than Uber services.

In Table 6, we delve deeper by examining the 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.[21]

[21] Table B4 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.

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 B5 helps explain this by showing how women who took the bus at baseline substitute away from the bus more, while men don't. Taken together, these results indicate that price reductions on Uber lead to important differences in travel by gender and baseline behavior and perceptions. In particular, women substitute away from using the bus for long trips and subsequently report feeling more safe on their recent trips. This result is stronger for women who perceived the bus as an unsafe mode of transit at baseline.

5.3 Effects on Labor Market Outcomes

Reduction in the cost of ride-hailing services could improve the ability of job seekers to better match with existing vacancies. Previous studies, such as Franklin (2018), 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.

More specifically, we find that among individuals who were searching for a job at baseline, there is a 3 percentage point decrease in the 25% treatment group (standard error = 4 percentage points) and a 2 percentage point increase in the 50% group (standard error = 4 percentage points). Neither of these estimates are statistically different from zero. We find a decrease in application rates in the 25% group but no impacts in the 50% group. We also find no change in the likelihood that they are currently working.

While we intended to collect data on longer-term employment outcomes, those plans were negatively affected by the COVID-19 pandemic. Overall, these results imply that a general decrease in the costs of private transport is unlikely to have transformative effects on labor market outcomes in the short term.

6 Policy Implications

Governments around the world are responding to the growth of the ride-hailing market in a number of ways. Our results can shed light on a range of questions facing policymakers, including developing a more complete understanding of the impacts of reductions in the price of ride-hailing services on welfare and travel behavior. Some researchers have estimated that innovations in these and other technologies could reduce the cost of ride-hailing services by 40-80% (Narayanan et al., 2020). We limit our discussion to the specific impacts on ridership and do not speculate about general equilibrium impacts or other shifts that could occur simultaneously with shifts in price across longer-term horizons, which are beyond the scope of this paper.

Tables 1 and 4 include estimated price elasticities of demand for Uber usage and for total mobility. We use these elasticities to consider the benefits and external costs associated with meaningful reductions in the price of ride-hailing services. We discuss effects on travel mode choice and private vehicle kilometers traveled and distributional implications of a uniform tax on ride-hailing services. We then examine the experimental variation from our price treatments in a discrete choice framework that allows us to consider a broader set of questions regarding the demand for key attributes of transport services available in Cairo. We use this method to estimate the value that participants in our study place on safety and time and then simulate the welfare effects of changes in safety on public transit and changes in travel time on the Cairo transit network.

6.1 Benefits and External Costs of Uber Price Reductions

Impacts on Welfare and Consumer Surplus

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 $P_{0.5}$. We provide details on these calculations in Appendix F and an illustration of the procedure in Appendix Figure F.1. We estimate effects of the two price reductions on consumer surplus, which measures the impacts on rider welfare. A 25% price reduction in Uber services produces 726 EGP in annual consumer surplus for the men and 932 EGP for women. A 50% price reduction produces 2,240 EGP per year for men and 3,104 EGP for women.[22] Extrapolating to the population of Cairo (10.35M

[22]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

women and 10.65M men) and applying a 0.2 estimate for the Uber penetration rate in the Cairo market, our estimates suggests that a 50% price reduction generates 11.2 billion EGP per year in consumer surplus in Cairo.[23] This is equivalent to approximately 0.29% of the annual GDP in Egypt.

For each Egyptian pound spent on Uber services, participants receive 0.23 EGP in surplus at the 75% price level and 0.55 EGP in consumer surplus at the 50% price level. Price reductions disproportionately benefit female riders. At the 50% price level, consumer surplus exceeds 7.5% of the average income for women in our sample (versus 3.4% for men). The average income of female participants in our sample is 38% lower than that of male participants. However, female participants receive 28-40% more surplus than male riders. These estimates indicate that price reductions on ride-hailing services can generate substantial consumer surplus, particularly among women.

Changes in Private Vehicle Kilometers Traveled

Our experiment suggests that large reductions in the price of ride-hailing services result in an increase in single-occupancy trips, which could generate substantial external costs in highly congested cities such as Cairo. In this section, we examine the effects of a 50% price reduction on expected additional private vehicle kilometers traveled (VKT). As discussed in section 5.1 above, increases in utilization of ride-hailing services do not translate directly into additional vehicle kilometers traveled (VKT) due to substitution effects: in the absence of our price treatments, a portion of those kilometers would have occurred on a different mode of travel. To estimate private VKT we first determine the effect of price reductions on additional vehicle kilometers traveled using our Google Timeline data on total mobility. Table 4 provides elasticity estimates for total mobility indicating 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. By combining these estimates of increases in total VKT with information about substitution across travel modes, we estimate the proportion of additional VKT that would be made in private vehicles (i.e. taxis, single-occupancy ride-hailing services, and personal cars).[24] Estimates reported in table 5 indicate that a 50% price reduction in Uber services induces a 12 percentage point shift away from public transport to private transport (calculated on base of 42% public transport utilization). We estimate a 7 percentage point reduction

in US markets finds very large consumer surplus at current market prices (baseline), suggesting that our 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 G assumes that demand is approximately linear across the intervals from P to $P_0.75$ and from $P_0.75$ to $P_0.5$.

[23] This estimate is derived from publicly available data on the number of Uber riders in 2018 divided by the population of Cairo (Reuters, 2018).

[24] As shown in Table B3, virtually all of the additional travel on Uber services is made using UberX single-occupancy services.

in public transport use for men (calculated on a base of 36%). 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.[25]

For women in the control group, we estimate that 52% of the 81 km in total travel done per week occurs in private vehicles. This yields an estimate of 42 km private VKT per week. In the context of a 50% price reduction, female riders increase their private vehicle kilometers traveled to 64% of their total 126 kilometers that they travel per week. This yields an estimate of 81 km in private VKT for the high treatment group.

Taken together, these estimates indicate that a 50% price reduction would induce a 98% increase in private vehicle kilometers traveled among women in our sample, implying a VKT elasticity of -1.96. The equivalent calculation for men suggests a 45% increase in private VKT and an elasticity of -0.90. Using the pooled sample, we estimate a VKT elasticity of -1.28, which is different from the -0.84 travel elasticity that we estimated without accounting for substitution behavior.

External Costs

The potential increase in private VKT described in the prior subsection could have significant impacts on transport externalities, which are already a major problem in Egypt. We construct a basic estimate of the additional external cost ($W_{Externality}$) associated with a 50% reduction in the price of ride-hailing services using the following equation:

$$W_{Externality} = \lambda_{WB} * f_T(E_{PVKT}, \Delta P_{MoD}, PP_{MoD}), \tag{1}$$

where (1) E_{PVKT} represents the average elasticity of private VKT relative to the price of Uber services, (2) ΔP_{MoD} represents the price of ride-hailing services, (3) PP_{MoD} represents the Uber penetration rate in Cairo (proportion of population using ride-hailing services), (4) f_T represents a road technology that reflects the relationship between traffic volume and congestion, and (5) λ_{WB} represents the external costs of transport at baseline prices.

The reduced form elasticities estimated from the 50% reduction (treatment 2) in the experiment provide an estimate of E_{PVKT}. We use a range of 0.2-0.4 as an estimate of the Uber penetration rate (PP_{MoD}) in Cairo. The lower bound is derived from publicly available data on the number of Uber riders in 2018 divided by the population of Cairo (Reuters, 2018). However, we would expect that a large price reduction would also induce new users to download and use ride-hailing applications, thereby increasing the

[25]We view this assumption as conservative because it is more likely that people take long trips using a bus or metro services as a result of the "first/last" mile problem, which reduces the probability of short trips on bus/metro services.

penetration rate. Our upper-bound estimate captures a doubling of the penetration rate (to 0.4). We also allow for different assumptions about the relationship between traffic volume and congestion. We begin by assuming that congestion increases linearly with traffic volume, which is consistent with recent findings reported by Kreindler (2018). We examine the sensitivity of our estimates to this assumption by allowing a quadratic form, which is consistent with Madireddy et al. (2011). Finally, we rely on the findings from a comprehensive World Bank study of the current cost of transport externalities in Cairo, which reports a total cost that is equivalent to 47 billion EGP in 2010 (Nakat et al., 2014, 2013).[26]

These parameter values yield a 2x2 matrix of estimates that reflect: (1) low/high penetration rates and (2) linear/quadratic congestion costs. Using a linear road technology, we estimate that a 50% reduction in the price of Uber services could increase external costs by 0.46% of Egypt's GDP (about 22 billion EGP) with smaller penetration rates or 0.92% of GDP with larger Uber penetration rates.[27] These estimates become considerably larger in the case of a quadratic road technology: 0.97% and 2.1% of GDP for small and large penetration rates, respectively. These estimates suggest that a 50% reduction in the price of ride-hailing services today could increase external costs of transport by at least 12.8% from 3.6% to 4.06% of Egypt's GDP. By comparison, the entire information and communication technology sector in Egypt accounts for 4% of GDP (ENTRA, 2019).

Implications of a Uniform Tax on Ride-hailing Services

Given the potential for large external costs, a natural policy response might be to tax ride-hailing services along with other private transport services. Our experimental findings suggest the need for careful attention to the design of such policies and consideration of distributional impacts. In particular, the results from the present experiment suggest that a uniform tax on ride-hailing services in Cairo would disproportionately restrict the mobility of women. This appears to result from the fact that women are more likely to feel unsafe on public transit and use ride-hailing services to substitute away from public buses.

We consider the effects of a tax on Uber services at the reduced price (50% of baseline prices) by considering an equal and opposite (symmetric) demand response to a price increase. In this scenario, a 100% tax would increase prices to the baseline levels observed in this study. This 100% tax would reduce overall female mobility by 35% while

[26]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. The authors estimate the total external costs of transport to be 3.6% of Egypt's GDP. These estimates do not account for the effects of ride-hailing services on external costs related to driving while picking up riders or searching for parking.

[27]This assumes a total population of 21 million inhabitants in Cairo and a current GDP of 3.9 trillion EGP

reducing overall male mobility by 24%. This would occur though a 47% reduction in private vehicle travel by women and a 31% reduction for men.

Furthermore we can use our estimates to examine the implications of a new tax on ride-hailing services in the current pricing environment. If we assume that our elasticities from subsidies are symmetric, then we would expect that a 25% increase in the cost of Uber services would reduce the overall mobility of riders by 13%. This tax would also have an unequal impact by gender, resulting in a 20% reduction in total travel among women and a 9% reduction among men. Based on our experimental estimates, we would project a 7 percentage point shift away from Uber services, with about half of those trips now occurring in private cars and taxis and the other half occurring on public transit. Using the procedure outlined in section 6.1, we estimate that a 25% tax would induce a 29% reduction in private VKT for women and 12% for men.

6.2 Welfare Impacts of Potential Changes in Safety and Time

In this section, we decompose demand responses induced by the experiment to examine demand for key attributes of transport services. As outlined in section 3.1, we asked participants to recall the longest trip they took in the day prior to the survey and then asked them 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.[28] 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. Formally, the utility of rider i choosing transit mode j and for choice occasion m is:

$$U_{ijm} = -\alpha_i p_{ijm} + \gamma_i t_{ijm} + \eta_i s_{ijm} + X'_{ijm}\beta_i + \epsilon_{ijm} \tag{2}$$

[28]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.

α_i is the marginal utility of cost, γ_i is the marginal utility of time, and η_i is the marginal utility of safety. X_{ijt} represents a vector of demographics, including average income, gender, car ownership and an indicator for metro users (at baseline). We include ϵ_{ijm} which represents an unobserved idiosyncratic taste shock, which is i.i.d distributed according to the type 1 extreme value distribution. Following the work of Small et al. (2005) and others, we calculate 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:

$$VOT_i = \frac{\partial U_{ijm}/\partial t_{ijm}}{\partial U_{ijm}/\partial p_{ijm}} = \frac{\gamma_i}{\alpha_i}, \qquad VOS_i = \frac{\partial U_{ijm}/\partial s_{ijm}}{\partial U_{ijm}/\partial p_{ijm}} = \frac{\eta_i}{\alpha_i} \tag{3}$$

To address potential bias from endogenous relationships between travel choices and the cost/duration/safety of different modes, we employ the control function approach using instruments generated from the experiment (Petrin and Train, 2010). This approach is implemented in two steps that follow standard linear applications of the control function method. In the first stage, the endogenous variables are regressed on the instruments and other exogenous variables. In the second stage, the residuals from the regressions enter the maximum likelihood estimation as the control function.

We estimate the model with two kinds of instruments. First, we rely solely on the experimental variation using two indicator variables that capture 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. In a second specification, we construct a set of Hausman-type 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 in the same geographic location. The validity of these instruments is based on the assumption that the experimental groups are not correlated with unobserved endogenous parameters, which is reasonable given our randomization procedure.

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. $CS_{im} = (1/\alpha_i)max_j(U_{ijm})$. In expectation, this is:

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

where α_i is the marginal utility of income, $V_{ijm} = -\alpha_i p_{ijm} + \gamma_i t_{ijm} + \eta_i s_{ijm} + X'_{ijm}\beta_i$ 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:

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

where the superscript 0 and 1 indicates before or after the policy change.

Parameter 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.

We examine the robustness of the model parameters across different sets of specifications in Appendix G.[29] 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.

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.[30] Our estimates indicate that increases in perceived safety to a level

[29]Table G.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.

[30]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

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 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 46.5 billion EGP in annual benefits, or 1.2% of the annual GDP of Egypt. 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 substantially 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.[31] 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

effect.

[31] 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.

of Cairo, these estimates suggest that an increase in bus safety to the level of metro would yield 78.8 billion EGP in annual benefits, or 2% of the annual GDP of Egypt. We do not observe differences by gender, except when we simulate the gains associated with increasing bus safety to the level expected on Uber.

The effects of safety improvements can be compared to estimates of the benefits from faster trips on the different transit modes using estimates of the value of time (VOT) reported in Table 9.[32] Panel C of figure 3 illustrates the results of a simulation that reduces the expected duration of trips on all available modes by 10%. These estimates indicate that increases in the expected speed of available transit options would generate meaningful benefits. This is particularly true for buses, which participants reported to be the slowest available transport option. Our simulations indicate that participants would value a 10% reduction in the expected travel time on bus at about 3 EGP per trip. Extrapolating to the population, this 10% reduction in expected travel times on public buses would generate 22.8 billion EGP per year. A comparison of welfare impacts from from safety improvements indicates that in order to achieve the level of benefit produced by an increase in the safety of a bus trip to the level of safety experienced on the metro, bus trips would need to become 32% faster.

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 B9 reports the results of these regressions.

[32]Trip times include wait times and the duration of trips, such that reduced trip times could be achieved through reductions in congestion or improved service.

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 B6 - B8 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 B7 & B8 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.

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 E 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.

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. While our 12-week treatments were effectively complete before the onset of the COVID-19 crisis (see Appendix I), 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.

Our experimental design does not permit a direct or complete examination of the general equilibrium effects from price reductions on ride-hailing services for the full population of Cairo (in perpetuity). We are therefore limited in our ability to provide comprehensive estimates of the welfare effects associated with large price changes. We view a broader examination of effects that includes adjacent sectors like housing, education, and the labor market as a fruitful 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 induces an increase of 13% in total travel. A 50% discount induces 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 are they not close to satiating their demand for travel. This has important implications for academics and policymakers, as it implies that improvements in transportation services could substantially increase mobility and also congestion/emissions externalities in cities like Cairo. As the technology and availability of connected and autonomous vehicles (CAVs) improves, the cost of ride-hailing services could drop by more than the highest (50%) fare reduction in our study (Narayanan et al., 2020). A price change of this magnitude would generate consumer surplus that is equivalent to 5% of the income of the average participant in our study.

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) and mobility 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 ride-hailing services, as well impact mobility. Using our experiment to conduct counterfactual policy simulations, we find that increases to the safety of public transit could yield more than 46.5 billion EGP in public benefits, mainly driven by benefits to women on buses.

Policymakers will have to consider these benefits alongside the potential for substantial increases in the external cost of transportation related to increased utilization. Our results indicate that price reductions could result in substantial increases in private vehicle kilometers traveled, which may be characteristic of developing country cities where price reductions induce high rates of substitution from public buses. In the Cairo sample, we estimate that a 50% price reduction could induce a 64% increase in private vehicle kilometers traveled and increase the external costs from the transport sector by 13-25%. This would be equivalent to 0.46-0.92% of the GDP of Egypt and 59% larger than the consumer surplus generated by the same price reduction. 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. Unlike many conventional transport services, ride-hailing platforms provide a unique opportunity for researchers and policymakers to collaborate in the design, implementation, and evaluation of optimal policy instruments to address all components of increased demand for personalized travel.

References

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

Ahlfeldt, G. M., S. J. Redding, D. M. Sturm, and N. Wolf (2015): "The Economics of Density: Evidence from the Berlin Wall," *Econometrica*, 83, 2127–2189.

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

Allen, T. and C. Arkolakis (2019): "The Welfare Effects of Transportation Infrastructure Improvements," Working Paper.

Alvarez, F. and D. Argente (2020): "On the Effects of the Availability of Means of Payments: The Case of Uber," Working Paper.

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

Asher, S. and P. Novosad (2018): "Rural Roads and Local Economic Development," *The American Economic Review*.

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

Baum-Snow, N., L. Brandt, J. V. Henderson, M. A. Turner, and Q. Zhang (2017): "Roads, Railroads, and Decentralization of Chinese Cities," *Review of Economics and Statistics*, 99, 435–448.

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

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

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

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

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

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

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

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

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

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

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

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

ENTRA (2019): "ICT Sector in Egypt," https://tra.gov.eg/en/telecom-market.

Flores-Guri, D. (2003): "An Economic Analysis of Regulated Taxicab Markets," *Review of Industrial Organization*, 23, 255–266.

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

Frondel, M. and C. Vance (2009): "Do High Oil Prices Matter? Evidence on the Mobility Behavior of German Households," *Environmental and Resource Economics*, 43, 81–94.

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

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

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

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

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

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

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

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

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

Henderson, J. V. and M. A. Turner (2020): "Urbanization in the Developing World: Too Early or Too Slow?" *Journal of Economic Perspectives*, 34.

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

Karlan, D. and C. Udry (2020): "A Call for Structured Ethics Appendices in Social Science Papers," .

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

Kreindler, G. E. (2018): "The Welfare Effect of Road Congestion Pricing: Experimental Evidence and Equilibrium Implications," Working Paper.

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

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

Madireddy, M., B. De Coensel, A. Can, B. Degraeuwe, B. Beusen, I. De Vlieger, and D. Botteldooren (2011): "Assessment of the Impact of Speed Limit Reduction and Traffic Signal Coordination on Vehicle Emissions Using an Integrated Approach," *Transportation Research Part D: Transport and Environment*, 16, 504–508.

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

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

Monte, F., S. J. Redding, and E. Rossi-Hansberg (2018): "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, 108, 3855–90.

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

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

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

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

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

Petrin, A. and K. Train (2010): "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research*, 47, 3–13.

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

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

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

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

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

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

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

Small, K. A., C. Winston, and J. Yan (2005): "Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability," *Econometrica*, 73, 1367–1382.

Train, K. E. (2009): *Discrete Choice Methods with Simulation*, Cambridge Uni Press.

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

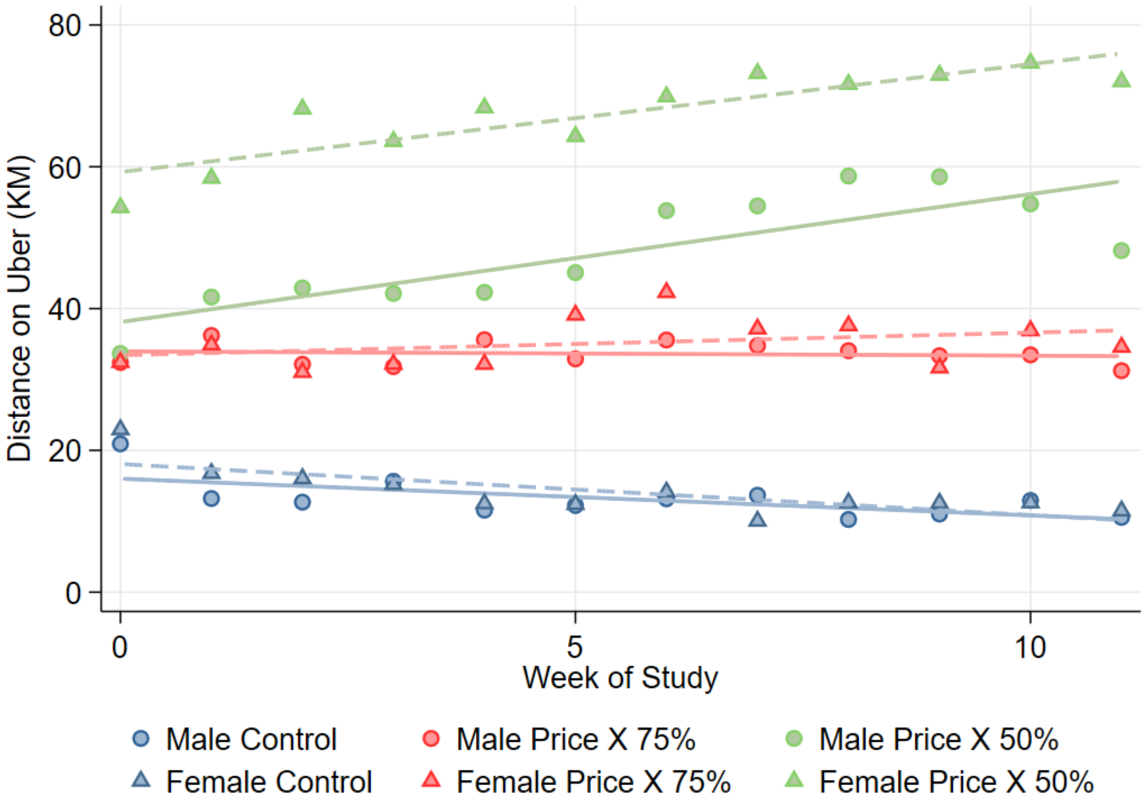
Velásquez, A. (2019): "The Economic Burden of Crime: Evidence from Mexico," *Journal of Human Resources*, 0716–8072r2.

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

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

Figures

Figure 1. Uber Usage Over Time

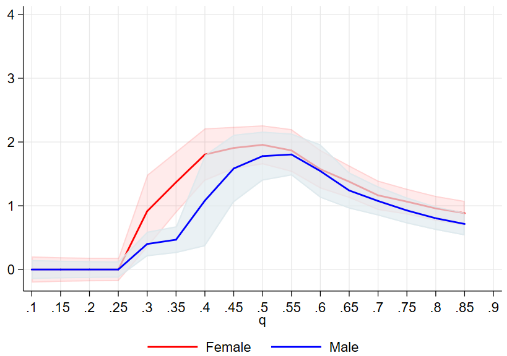


Notes: This figure plots average weekly kilometers traveled on Uber by experiment group, split by gender. The y-axis is reported using nominal kilometers, and the x-axis is the week of the study, including the initial week with the subsidy at "0."

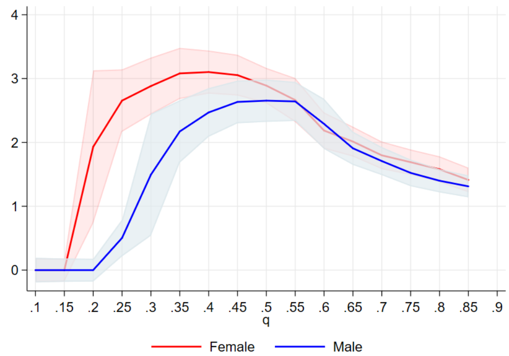
Figure 2. Quantile Regressions

Panel A: Total Weekly Uber Distance (IHS)

25% Price Reduction

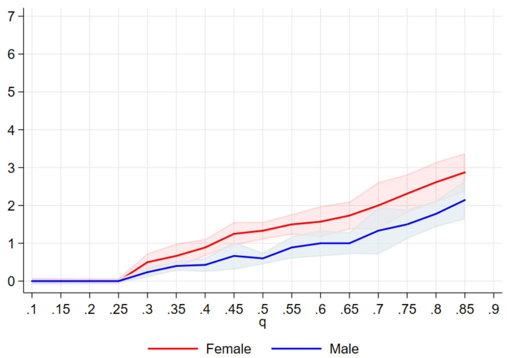


50% Price Reduction

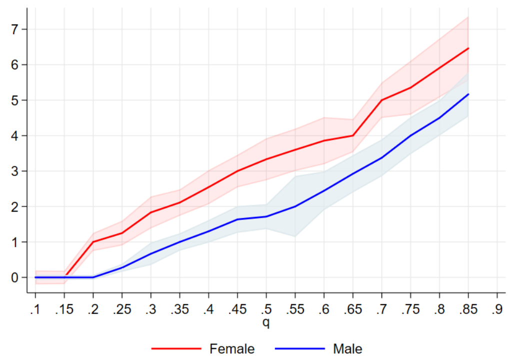


Panel B: Number of Weekly Uber Trips

25% Price Reduction

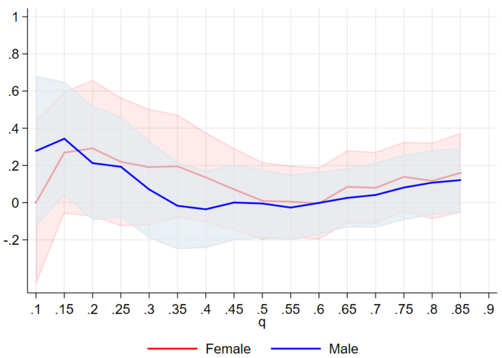


50% Price Reduction

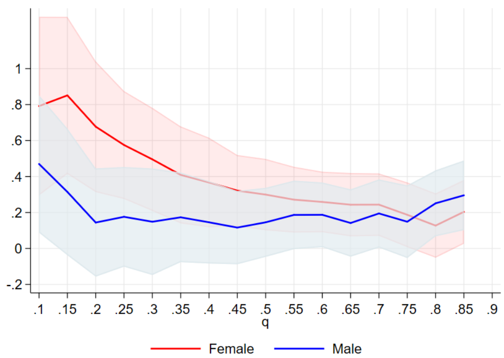


Panel C: Total Distance (IHS)

25% Price Reduction

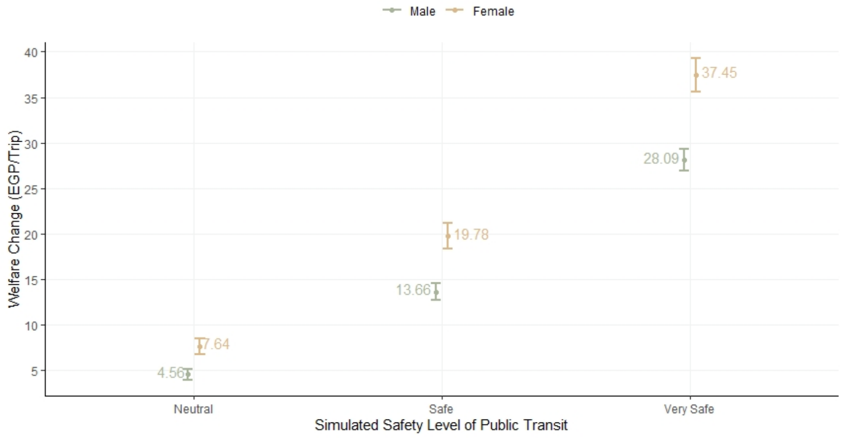


50% Price Reduction

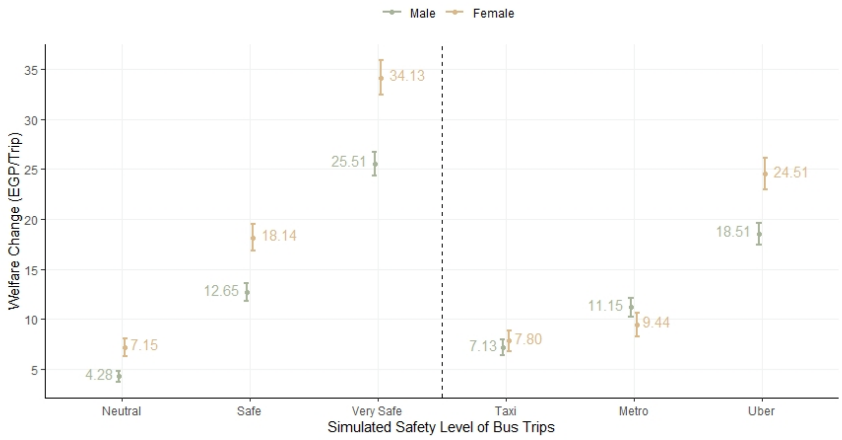


Notes: This figure plots the results of quantile regressions of the impacts of the treatment split by gender. Panel A reports impacts on weekly distance kilometers traveled on Uber, Panel B reports impacts on the average number of weekly Uber trips, and Panel C reports impacts on the total distance using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

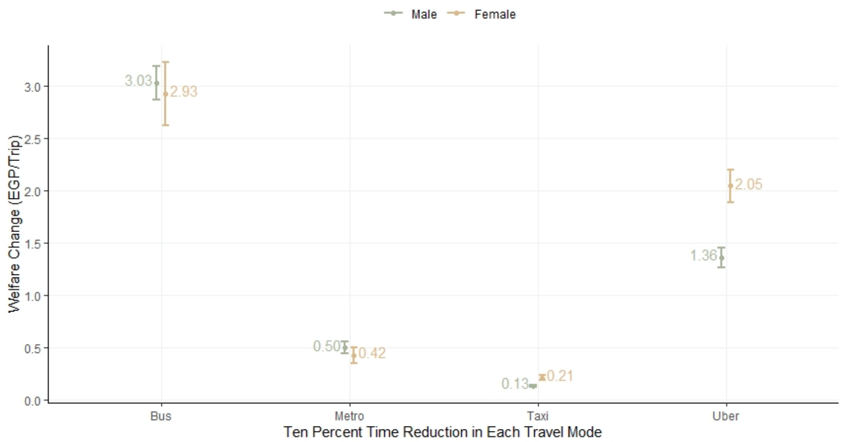
Figure 3. Welfare Impacts: Increases in Safety on Public Transit



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*** (0.08)	1.11*** (0.11)	1.76*** (0.15)	1.96*** (0.21)
Price X 75% * Male		-0.18 (0.15)		-0.35 (0.30)
Price X 50%	1.70*** (0.08)	1.85*** (0.12)	3.66*** (0.20)	4.12*** (0.31)
Price X 50% * Male		-0.27* (0.16)		-0.84** (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 [-8.67 , -5.38]	-8.17 [-10.89 , -5.45]	-6.04 [-8.05 , -4.02]	-4.65 [-5.43 , -3.86]	-4.93 [-5.98 , -3.87]	-4.26 [-5.41 , -3.12]
Price X 50%	-8.96 [-10.67 , -7.23]	-10.74 [-13.65 , -7.83]	-7.63 [-9.67 , -5.58]	-4.85 [-5.37 , -4.33]	-5.20 [-5.94 , -4.46]	-4.49 [-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* (0.19)	0.38 (0.24)	0.44* (0.18)	0.51 (0.32)
Price X 90% * Male			-0.24 (0.25)	-0.21 (0.33)	-0.46 (0.26)	-0.35 (0.45)
Price X 75%	0.29* (0.17)	0.86*** (0.30)				
Price X 75% * Male	0.01 (0.24)	-0.12 (0.42)				
Price X 50%	0.65*** (0.17)	2.11*** (0.37)			0.77*** (0.19)	1.45*** (0.36)
Price X 50% * Male	-0.07 (0.24)	-0.80* (0.47)			0.04 (0.27)	0.79 (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%	0.12	0.16
	(0.09)	(0.13)
Price X 75% * Male		-0.07
		(0.18)
Price X 50%	0.35***	0.44***
	(0.08)	(0.11)
Price X 50% * Male		-0.16
		(0.16)
Observations	3476	3476
Control Group Mean Levels	55.8	34.8
Control Group Mean Levels (Male)		75.1

Panel B: Elasticity Estimation			
	Total KM Past 3 Days (IHS)		
	(1) Overall	(2) Female	(3) Male
Price X 75%	-0.53	-0.75	-0.38
	[-1.31 , 0.24]	[-1.96 , 0.46]	[-1.38 , 0.62]
Price X 50%	-0.84	-1.10	-0.63
	[-1.28 , -0.40]	[-1.77 , -0.42]	[-1.20 , -0.05]

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 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 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%	0.11	0.21	0.00	0.01	-0.06	0.21
	(0.11)	(0.16)	(0.14)	(0.16)	(0.21)	(0.23)
Price X 75% * Bus User	0.06	-0.03	0.09	0.61	0.11	0.59
	(0.19)	(0.28)	(0.25)	(0.33)	(0.59)	(0.39)
Price X 50%	0.29**	0.46***	0.13	0.25	0.35**	0.00
	(0.10)	(0.13)	(0.14)	(0.14)	(0.17)	(0.24)
Price X 50% * Bus User	0.13	-0.11	0.27	0.49	0.12	0.42
	(0.17)	(0.26)	(0.22)	(0.30)	(0.57)	(0.39)
Observations	3476	1666	1810	1313	780	533
Control Group Mean Levels	60.2	34.5	88.8	57.5	40.6	86.1
Control Group Mean Levels (Bus User)	46.4	35.8	52.9	41.6	32.5	46.4

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

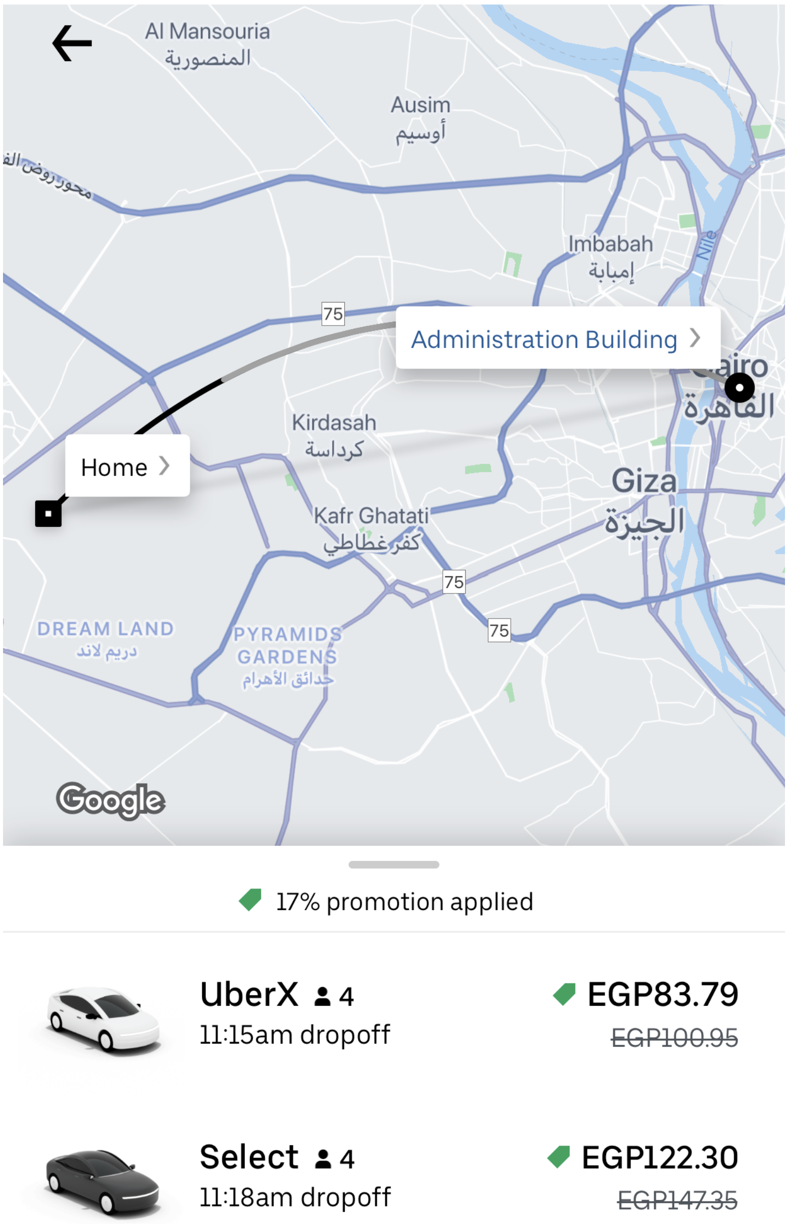
Notes: Panel A reports estimates from a conditional logit estimation using the two treatment arms, before and after the start of the experimental price change, as our instrumental variables. The conditional logit uses data on individual expectations of amenities across different modes of travel. Estimations 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

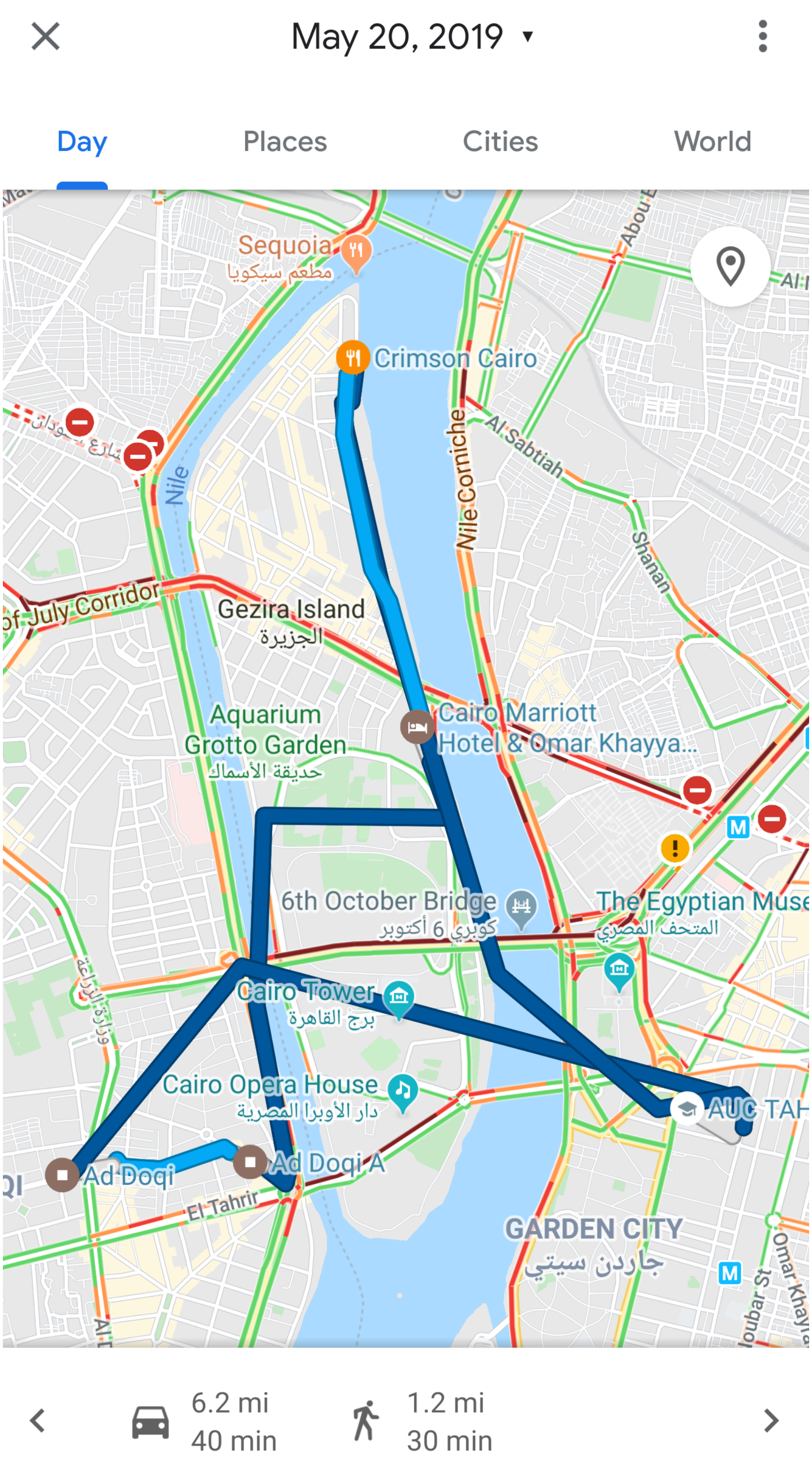
Figure A.1. Uber Price Information



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

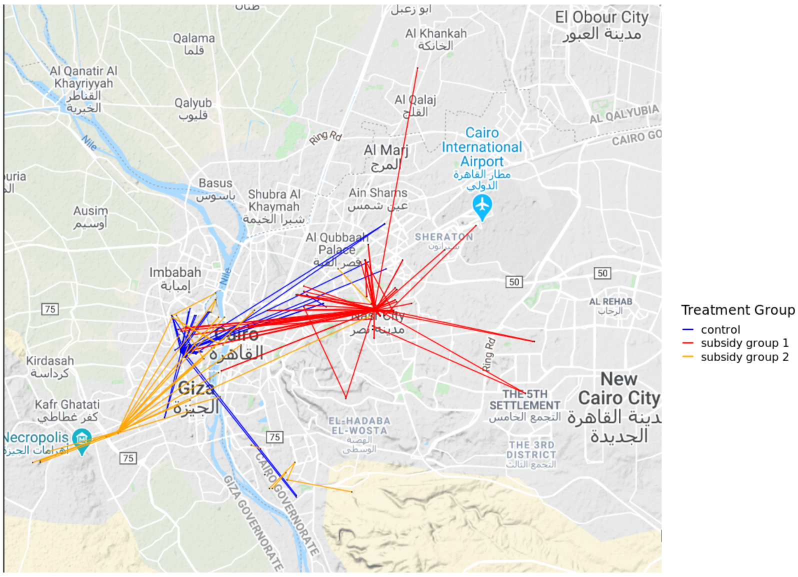
Figure A.2. Google Timeline Platform

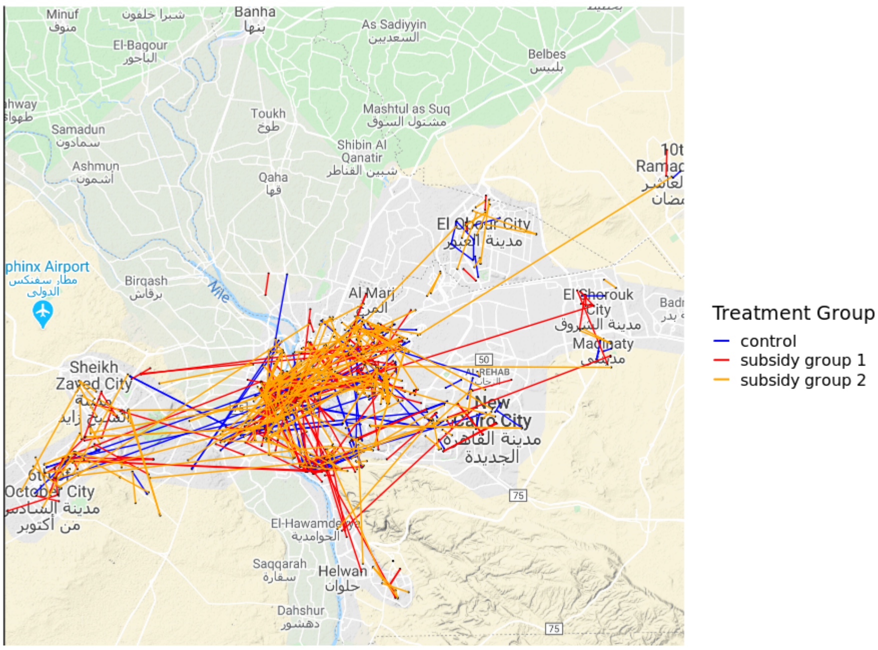


Notes: The figure illustrates the location and travel information displayed to participants on the Google Timeline application. The application provides total travel data for each date after the application is enabled.

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 Additional Figures and Tables

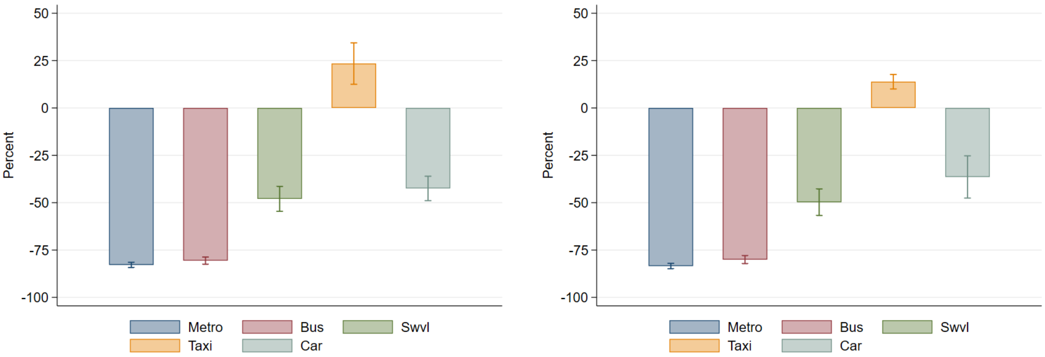
This appendix includes figures and tables that provide additional detail and insights from the experiment. The two figures describe baseline travel behavior and beliefs, split by gender. The tables showcase balance on baseline covariates, how the impacts are spread across the different types of Uber services, how the impacts on transport mode choice differ by baseline bus usage, and how response rates don't change deferentially by baseline characteristics across treatment groups.

Figure B1. Baseline Transport Behavior

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

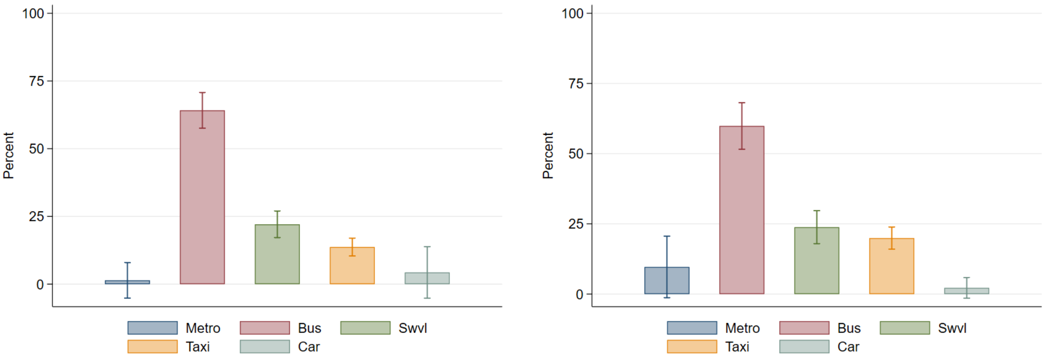
Figure B2. Perceived Cost, Duration, and Safety of Outside Options

Relative Cost Compared to Uber



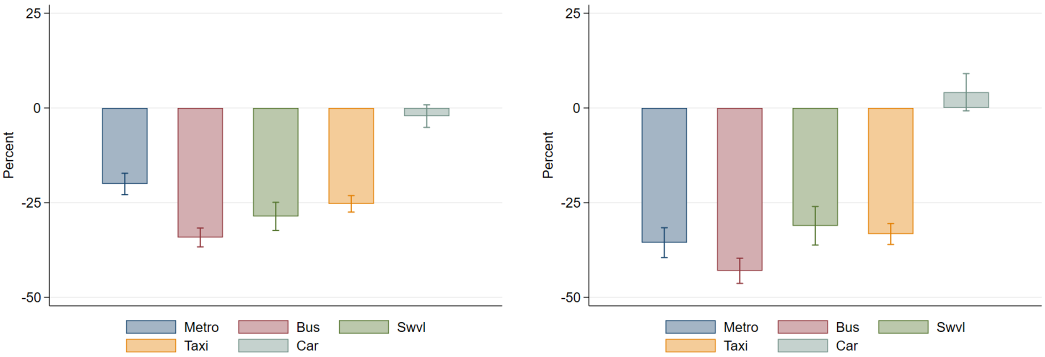
Males Females

Relative Duration Compared to Uber



Males Females

Relative Safety Compared to Uber



Males Females

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

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)	53.03	-2.59	6.26	8.85
	(113.17)	(6.87)	(8.00)	(7.22)
Total Time in Transit (min/week)	604.72	-59.98	-28.86	31.12
	(2,698.80)	(144.62)	(146.43)	(87.86)
Observations	455	954	958	960
Joint F-test (p-value)		0.62	0.89	0.59

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. 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 B4. 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 B5. 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 B6. 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 B7. Impacts of Observable Characteristics on Response Rates (At least 1 Follow Up)

	Dependent variable: Response to Follow-Up	
	(1) Price X 75%	(2) Price X 50%
Treatment	-0.07 (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)
Treatment * Car	0.04 (0.03)	0.04 (0.03)
Treatment * Education	0.02 (0.02)	0.03* (0.02)
Treatment * Married	0.00 (0.03)	-0.01 (0.03)
Treatment * Female	-0.02 (0.03)	0.01 (0.03)
Treatment * Look For Work	0.00 (0.00)	0.00 (0.00)
Constant	1.00*** (0.07)	1.00*** (0.06)
Observations	908	911
F-Test (P Value)	1.28 (0.27)	1.11 (0.36)

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

Table B8. 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	-0.12	-0.12
	(0.11)	(0.11)
Car	-0.06**	-0.06**
	(0.03)	(0.03)
Education	-0.02	-0.02
	(0.02)	(0.02)
Married	-0.02	-0.02
	(0.02)	(0.02)
Female	0.09***	0.09***
	(0.02)	(0.02)
Looking for work	0.00	0.00
	(0.00)	(0.00)
Treatment * Car	0.03	0.08**
	(0.04)	(0.04)
Treatment * Education	0.03	0.03
	(0.02)	(0.02)
Treatment * Married	-0.01	-0.01
	(0.03)	(0.03)
Treatment * Female	-0.04	0.03
	(0.03)	(0.03)
Treatment * Looking for work	0.00	0.00
	(0.00)	(0.00)
Constant	0.66***	0.66***
	(0.08)	(0.08)
Observations	3632	3644
F-Test	0.75	1.56
(P Value)	(0.58)	(0.17)

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 B9. Treatment Heterogeneity by Income

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

Notes: Column(1) report impacts on the inverse hyperbolic sine of weekly kilometers traveled on Uber in a specification that interacts the treatment with a dummy variable that takes the value of 1 if the individual is at baseline in the low income quarter and 0 otherwise. Column (2) report the result for a specification that interacts the treatment with a dummy variable that takes the value of 1 if the individual is at baseline in the High income quarter 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.

C 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 C.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 E.3, C.2, C.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 C.1. Uber Travel to Unique Locations: Cairo Grid

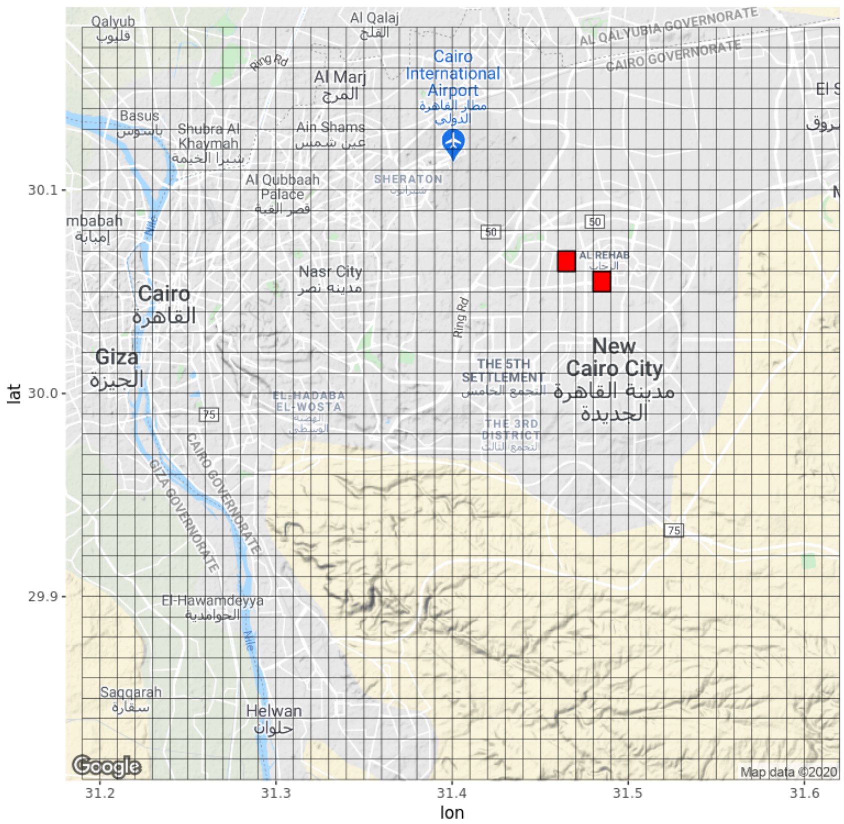


Figure C.2. Trips to Hospitals

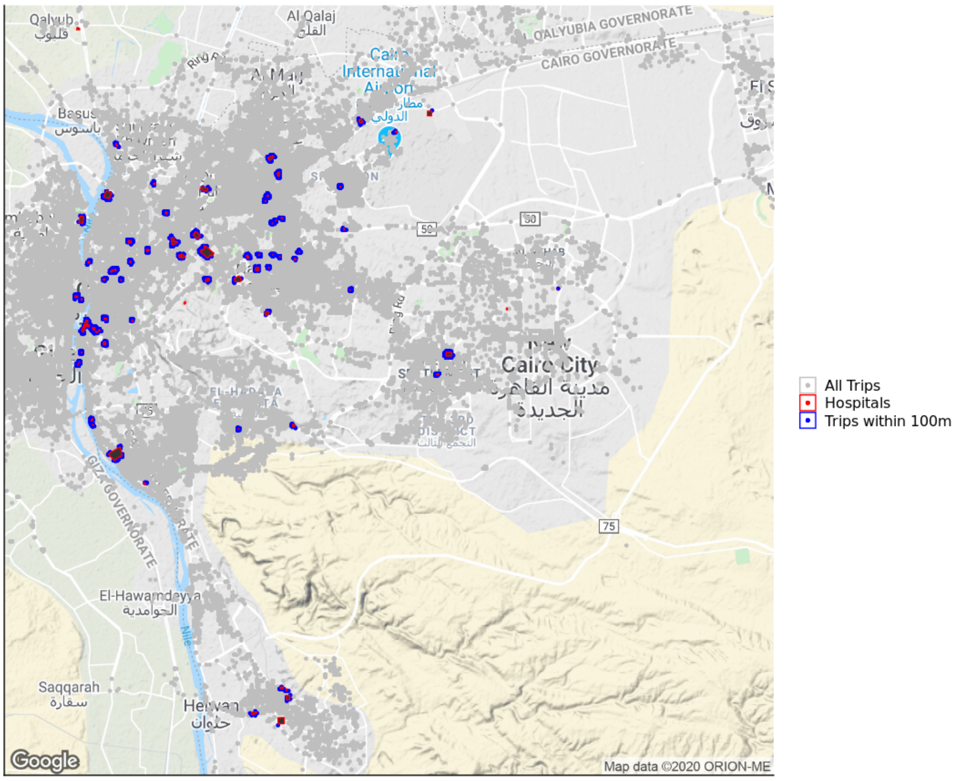


Table C.1. Trips to Hospitals

	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 C.3. Trips to Universities

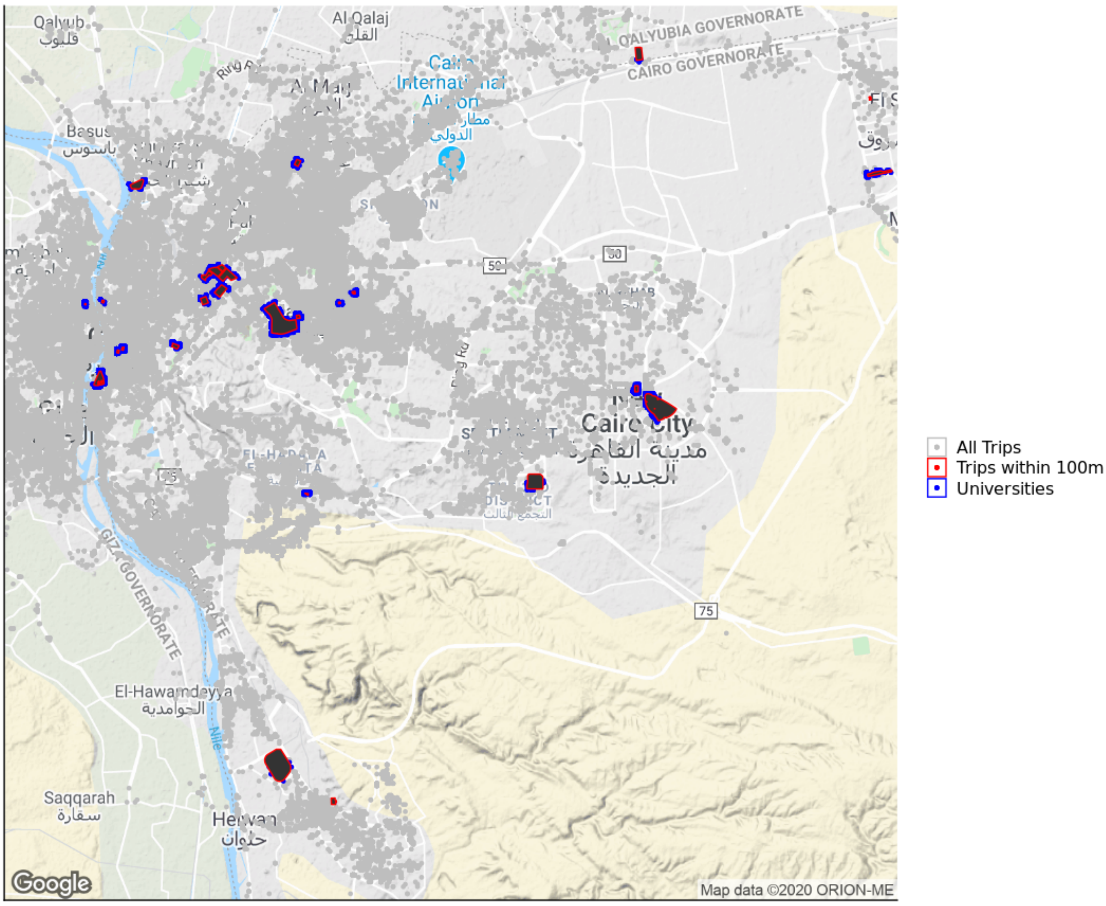


Table C.2. Trips to Universities

	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 C.4. Trips to Metro Stations

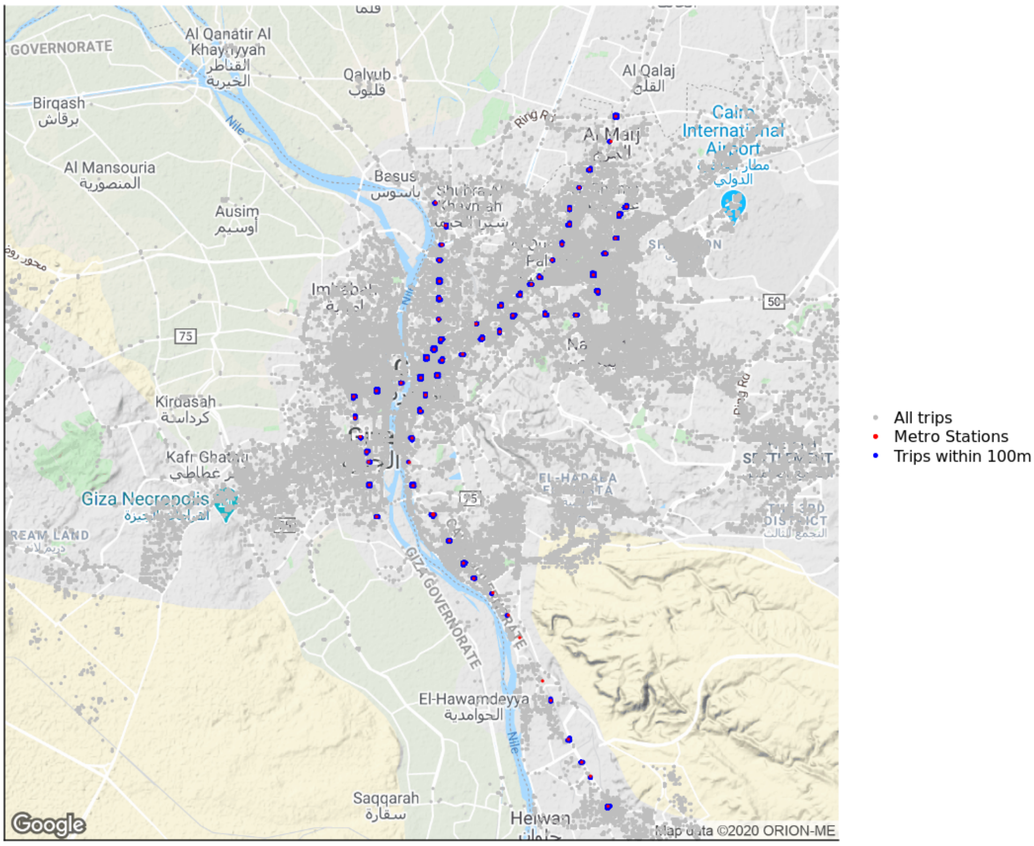


Table C.3. Trips to Metro Stations

	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*** (4.03)	4.80*** (1.49)	16.23** (7.15)	18.19*** (4.63)	10.77*** (3.01)	24.00*** (7.94)	30.71*** (6.27)	25.27*** (6.55)	34.82*** (9.94)
Price X 50%	11.86*** (1.81)	13.74*** (3.05)	10.36*** (2.18)	22.70*** (3.11)	21.68*** (3.81)	22.83*** (4.64)	37.12*** (4.80)	37.97*** (5.49)	35.73*** (7.42)
Constant	4.72*** (0.65)	4.77*** (0.87)	4.69*** (0.98)	8.81*** (0.99)	8.44*** (1.23)	9.14*** (1.55)	15.73*** (2.20)	12.22*** (1.76)	18.64*** (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.

D 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 D1 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 D1. 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.

E 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 E.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 E.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 E.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 E.4. Impacts in Total Mobility

	Total KM Past 3 Days (IHS)	
	(1)	(2)
Price X 75%	0.13	0.16
	(0.09)	(0.13)
Price X 75% * Male		-0.06
		(0.18)
Price X 50%	0.35***	0.44***
	(0.08)	(0.11)
Price X 50% * Male		-0.16
		(0.16)
Observations	3476	3476
Control Group Mean Levels	55.8	34.8
Control Group Mean Levels (Male)		75.1

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 E.5. Impacts on Mode Used for Longest Trip

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

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

Table E.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 E.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%	0.11	0.18	0.01	0.05	-0.06	0.16
	(0.11)	(0.16)	(0.14)	(0.15)	(0.21)	(0.22)
Price X 75% * Bus User	0.08	-0.03	0.21	0.56	0.48	0.74
	(0.19)	(0.29)	(0.25)	(0.33)	(0.57)	(0.40)
Price X 50%	0.30**	0.45***	0.15	0.24	0.32	-0.07
	(0.10)	(0.13)	(0.14)	(0.14)	(0.17)	(0.24)
Price X 50% * Bus User	0.15	-0.04	0.32	0.55	0.56	0.78
	(0.17)	(0.26)	(0.23)	(0.31)	(0.52)	(0.40)
Observations	3476	1666	1810	1313	780	533
Control Group Mean Levels	60.2	34.5	88.8	57.5	40.6	86.1
Control Group Mean Levels (Bus User)	46.4	35.8	52.9	41.6	32.5	46.4

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 E.8. Labor Market Impacts

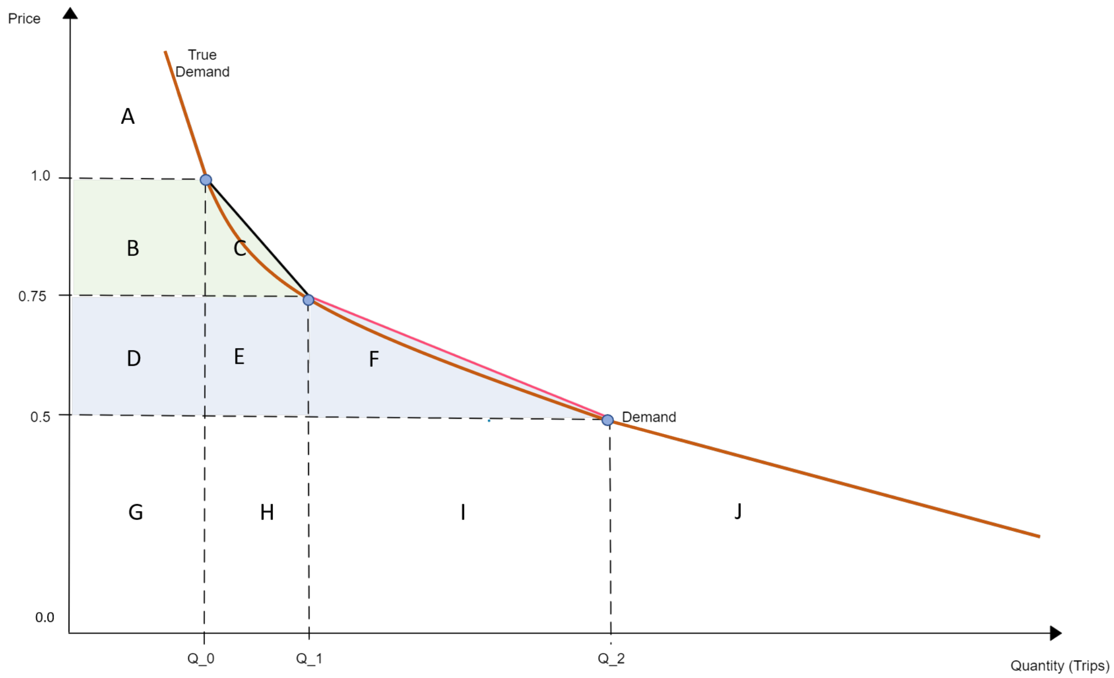
	Searching			Apply			Currently Working		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male	(7) Overall	(8) Female	(9) Male
Price X 75%	-0.03	0.02	-0.04	-0.47**	-0.32	-0.50*	-0.03	-0.04	-0.00
	(0.04)	(0.08)	(0.05)	(0.23)	(0.34)	(0.30)	(0.05)	(0.11)	(0.05)
Price X 75% * No Searching	0.08	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.

F 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 F.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 $P_{1.0}$ (ie. 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.

$$C_{S1} = 0.25 * P_{1.0} * Q_0 + (Q_1 - Q_0) * 0.25 * \frac{P_{1.0}}{2} \tag{1}$$

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.

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

We measure Q_0 and P_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_0 as defined above.

Table F.1. Consumer Surplus

Panel A: Consumer Surplus at 25%	Trips			Weekly KM		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Total Benefit	55.08	62.64	51.17	84.91	98.92	73.85
Expenditure	44.29	50.46	41.02	69.19	80.98	59.89
Consumer Surplus	10.79	12.18	10.15	15.71	17.93	13.96
Consumer Surplus to Expenditure Ratio	0.24	0.24	0.25	0.23	0.22	0.23

Panel B: Consumer Surplus at 50%	Trips			Weekly KM		
	(1) Overall	(2) Female	(3) Male	(4) Overall	(5) Female	(6) Male
Total Benefit	76.63	88.40	70.70	141.83	172.73	119.68
Expenditure	46.76	54.25	42.97	91.67	113.04	76.59
Consumer Surplus	29.87	34.15	27.73	50.16	59.69	43.09
Consumer Surplus to Expenditure Ratio	0.64	0.63	0.64	0.55	0.53	0.56

G Discrete Choice Model

This section provides details for data used in the discrete choice model described in Section 6.2 and reports results on robustness of our parameter estimates. Table G.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 G.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 G.2 and figure G.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 G.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 G.1. Substitution Patterns from Multinomial Logit

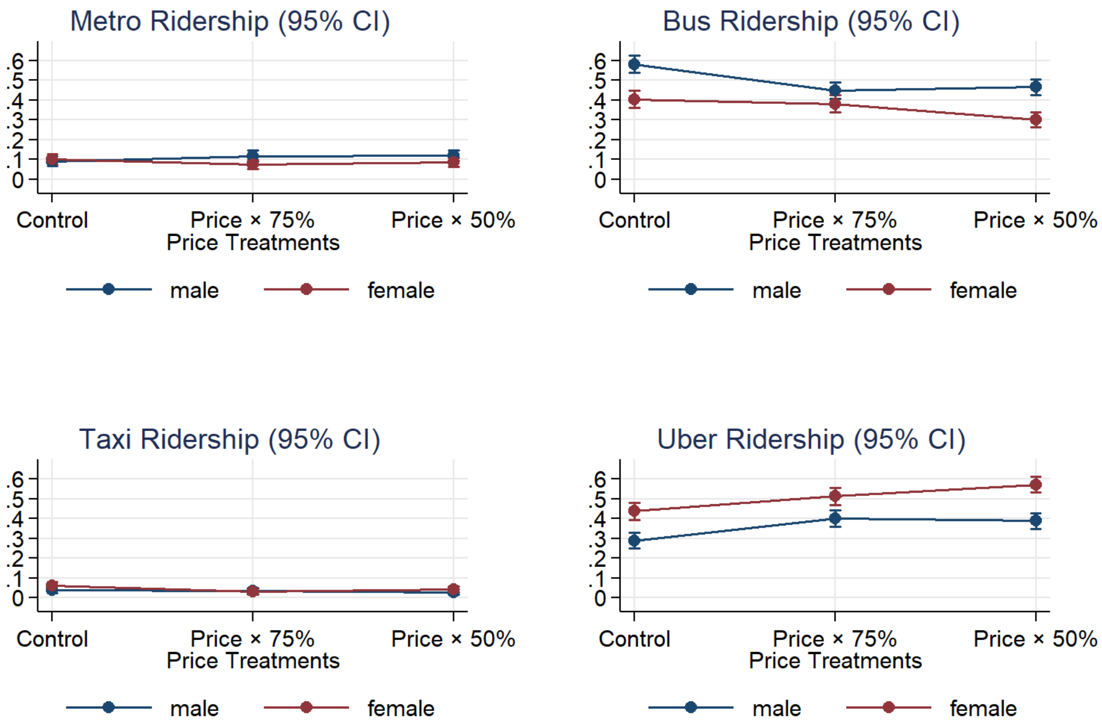


Table G.3 reports the estimates from multiple specifications of the conditional logit model that rely on different instruments. Column 1 reports estimates from a specification without any instruments, whereas columns 2-4 report estimates from specifications that utilize the experimental and Hausman instruments. 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 6.2 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 G.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 G.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 G.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.

H External Validation

Table H.1. External Validation 2

	External Sample		Alternative Sample			
	Weekly Km	Weekly Trips	Weekly Km		Weekly Trips	
	(1)	(2)	(3)	(4)	(5)	(6)
Price X 90%	0.23**	0.49***	-0.13	0.07	0.37	0.66*
	(0.13)	(0.19)	(0.13)	(0.18)	(0.20)	(0.30)
Price X 90% * Male				-0.38		-0.56
				(0.26)		(0.41)
Price X 50%	0.37***	0.80***	0.50***	0.52**	1.75***	1.74***
	(0.13)	(0.22)	(0.14)	(0.20)	(0.26)	(0.37)
Price X 50% * Male				-0.05		0.03
				(0.27)		(0.53)
Observations	1500	1500	1500	1500	1500	1500

Notes: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 for trip level. Columns (3) (4) report the impacts of the two treatment arms on the inverse hyperbolic sine of weekly kilometers traveled on Uber. Columns (5) (6) report the impacts of the two treatment arms on the weekly trips traveled on Uber. Standard errors clustered at the individual level in parentheses. Significance: *.10; **.05; ***.01.

I 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 H.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.

J 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 endogenenity 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.