Consumer Surplus of Alternative Payment Methods: Paying Uber with Cash*

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Abstract

We estimate the private benefits for Uber riders from using alternative payment methods. We focus on Mexico where riders have the option to use cash or credit cards to pay for rides. We use three field experiments involving approximately 400,000 riders to estimate the loss of private benefits for riders if a ban on cash payments is implemented. We find that Uber riders, using cash as means of payment either sometimes or exclusively, suffer an average loss of approximately 50% of their expenditures on trips paid in cash before the ban.

JEL Classification Numbers: E4, E5
Keywords: Cash, Credit, Money Demand, Consumer Surplus, Means of Payments

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1 Summary and Introduction

In this paper, we aim to contribute to the money demand literature by estimating the private benefits for consumers of using alternative payment methods. We consider the case of Uber trips in Mexico, where riders can pay with either a credit card or with cash.

We use a simple model in which riders choose the number of Uber trips that they take and view paying Uber with cash or with credit as different goods. We assume weak separable preferences so that we can define the demand for Uber "composite trips", an aggregate of both type of trips, separately from the choice of payment. Furthermore, we model both the extensive margin choice of registering a credit card to have access to both payment methods and the intensive margin choice of how many trips to take with each of the available payment methods. We allow for heterogeneity among riders in their preferences for paying in cash or in credit, in their preferences for composite trips relative to other goods, and in the cost they pay to register a credit card in the application.

We then use three large field experiments to parameterize our model and estimate the loss in consumer surplus from a ban on the use of cash. We complement and validate these results with a large survey instrument conducted on the same population and two other independently run experiments. First, we estimate the elasticity of substitution between paying for trips in cash versus credit by using price variation in discounts for trips paid in cash or discounts for trips paid with credit. Second, we use discounts given regardless of the means of payments to estimate the price elasticity for Uber. And, lastly, we give small rewards (credit for future trips on their Uber account) if riders register a credit card in the application to estimate the fixed cost of registering a card. We combine this information with our structural model to produce theoretically based estimates of the consumer surplus. We find that the riders of this platform who use cash, either sometimes or exclusively, would suffer an average private cost of at least 50% of the expenditures on Uber rides paid in cash before the ban.

The magnitude of our estimates of the loss in consumer surplus from a ban on cash reflects the following. First, we argue that the effects on riders that exclusively use credit before the ban on cash is likely to be small, so we ignore them. Second, about 20% of the expenditure on Uber is accounted by riders that exclusively pay trips in cash (riders without a registered credit card) and about 50% of the expenditure is accounted by riders that use both cash and credit cards. Third, while riders that use both means of payments react to changes in their relative prices, they view both payment methods as very far from perfect substitutes. We estimate an elasticity of substitution between cash and credit of about three. Fourth, while riders without registered credit cards react to incentives, we estimate that a significant fraction of them face large costs of registering a card. Fifth, we find that riders have a relatively low elasticity of demand for composite Uber trips –we estimate elasticities of demand lower than 1.5 and much lower for some groups.

Background, Related Literature on Payments, and General Estimation Strategy

The general area in which our paper makes a contribution is the optimal choice of means of payment, which itself can be thought as a part of the study of money demand. Examples of earlier theoretical papers on the choice of payment are the cash-credit model in Lucas and Stokey (1987), and the model of multiple payment methods in Prescott (1987), as well as many studies that follow them such as Whitesell (1989), Lacker and Schreft (1996), Freeman and Kydland (2000), Lucas and Nicolini (2015), Koulayev et al. (2016), and Stokey (2019). There is also related work which follows the search theoretical literature of money as a payment method, largely started by Kiyotaki and Wright (1989), which incorporates credit payments as in Kocherlakota (1998), Lagos and Wright (2005), or Wang et al. (2019).

Recently, the use of cash has received considerable attention by policymakers, who many times have expressed their negative assessment of its role. Rogoff's (2017) book, for example, is called "The curse of cash". A concrete recent policy carried out along these lines was the demonetization in India –see Chodorow-Reich et al. (2018) for a description and evaluation of its macroeconomic effects. Moreover, the use of cash as a payment method for Uber in Mexico, as well as in other countries such as Panama, has had severe restrictions. In particular, cash was originally not allowed in several cities in Mexico (for example in Mexico City or in the city of Queretaro) and was even banned in the city of Puebla, where payments in cash were previously available. Only recently, the Mexican Supreme Court has ruled the prohibition of cash as a means of payment by local jurisdictions as unconstitutional.[1] Lastly, in Argentina the restriction from the government on Uber rides amounted to a prohibition on using credit cards as payment method. Motivated by these recent policies, we estimate the consumer surplus loss caused by banning cash as a payment method in a city where it was available.

In more than 400 cities worldwide, Uber allows its riders to select cash as a payment method –in the same way that their app allows riders to set more than one credit card as a means of payment. If a rider selects cash, then the rider pays the driver in the same way that the rider would pay for a taxi ride.[2] Section 2 gives more background on the use of cash in Uber. One of the goals of the paper is to estimate the change in the consumer surplus

[1] See the decision of the "Suprema Corte de Justicia de la Nacion" in the case of "Ley de Movilidad Sustentable pare el Estado de Colima" in October of 2018.

[2] There are small differences, such as the ability of Uber to credit either party with differences in the fare if they cannot exactly make change.

for riders after cash is banned in a city. We distinguish between the effect on riders that use *both* payment methods (we refer to them as mixed riders), and the effect on riders that do *not* declare a credit card in the application (we refer to them as pure cash riders).

We build on Alvarez and Argente (2020), who use several quasi-natural experiments to estimate the effect of the entry (and the effect of the ban) of cash on the total number of trips, total fares, the number of trips paid with credit, the average price, the average surge multiplier, the number of active riders, the number of active drives, the rider or driver sign up rates, the price of taxis, as well as other related variables. They show that cash is heavily used by Uber riders and that there are large effects on the total number of trips and fares after an introduction (or ban) on cash. They also find no statistically significant effect from the entry of cash on Uber prices, the average surge multiplier, the riders' waiting times of arrival, or the price of competitors such as that of other ride-hailing companies and taxis. This is relevant since it will allow us to ignore the effect of the entry of cash on pure credit riders.[3] Importantly, they provide evidence of the relevance of mixed users, those riders using both payment methods (card and cash) actively. They show, using a natural experiment of a ban on cash in the city of Puebla, that there is evidence of imperfect substitution across payment methods both at the intensive and extensive margins (users adopting card as a payment method after a ban on cash).

For this reason, we distinguish between the effect on mixed riders and the effect on pure cash riders. We consider the entry of cash to a city as a demand shock for Uber trips. If Uber is a platform merely connecting riders with drivers, we can analyze the entry of cash as the change in an industry equilibrium after a demand shock. This shock can lead to an increase in prices as well as quantities, whose magnitude will depend on the riders' elasticity of demand and as well as the drivers' supply elasticity. If prices were to increase, there would be an increase in the producer surplus for drivers and a loss in consumer surplus for the previous riders, especially those who do not use cash (i.e., those who we refer to as pure credit riders). On the other hand, new riders who either use cash exclusively or who consider the possibility of using cash –even if they also use other payment methods– would benefit. Giving the lack of effect on prices, we conclude that the entry of cash has no effect on the pure credit riders' consumer surplus. This evidence is consistent with an elastic supply of drivers at the relevant time horizon (in terms of number of active drivers as well as hours worked per driver), and hence we disregard the effect on the entry of cash on the drivers' producer surplus. We use evidence from three large field experiments (randomized control trials) in which we randomly give riders different prices for paying with cash, paying with

[3] While our study focuses on riders, the same reasons imply a small effect of the entry or ban on cash on drivers. We do not focus on the effect of cash as a method of payment on drivers because our data and the evidence from Alvarez and Argente (2020) comes mostly from the riders' side.

credit, or paying with either payment method, as well as different rewards to register their credit cards in the application. We combine the evidence from a variety of field experiments and a survey with the evidence documented by Alvarez and Argente (2020) to parameterize our model and estimate the loss in consumer surplus from a ban on the use of cash.

Riders' Model and Consumer Surplus

Given that there are large changes in quantities (such as the total number of trips) with the entry or the ban of cash for payment across Mexican cities, we turn to the estimation of the effect of such policies on the consumer surplus. For that, we need to estimate how Uber riders value the use of cash. To do so, we use the standard theory on consumer demand and consider Uber trips paid in cash as a different good than those paid with credit. As long as the price of all other goods stays constant, the rider's consumer surplus from paying Uber in cash can be obtained by integrating the area under demand, starting with the current price up to the price at which the demand reaches zero. As the price of paying Uber in cash increases, riders who have credit cards can substitute rides paid with cash for rides paid with credit cards and also for other goods. Likewise, as the price of paying Uber in cash increases, riders without credit cards can substitute rides paid with cash for other goods or register a credit card in the application. In other words, we can consider both the intensive and extensive margin decisions to estimate the (entire) demand for paying Uber in cash.

In principle, we can estimate the demand for paying Uber in cash by designing a set of experiments with increasingly higher prices for Uber paid in cash. Unfortunately for our study, we cannot implement such experiments. Instead, we implement three experiments in which we reduce prices (i.e., we offer discounts) to riders: two of the experiments target pure cash riders and one mixed riders. The two experiments for pure cash riders aim at estimating both the intensive and extensive margin responses of riders to the incentive. The one for mixed riders aims at measuring only the intensive margin response to prices. We use these experiments to estimate a parametric model which can compute the consumer surplus lost if cash is banned. Below we outline the experiments and how we use their findings.

We consider a simple model of an Uber rider who is in a city where he or she can pay in cash or with credit. There are three goods in the model: Uber trips paid in cash, Uber trips paid in credit, and an outside good. We assume that the utility function is quasi-linear in the outside good, a simplification which we argue is a good approximation given the low budget share of Uber trips.[4] We assume that a rider can register a credit card in the Uber

[4]In Section 3.5, we test all the restrictions implied by our experimental data on an aggregate quasi-linear utility function and find that all restrictions are satisfied. Quasi-linearity is well-known to make the consumer surplus, the compensating variation, and the equivalent variation identical. Additionally, even though we only have three goods, we can consider a setup with more goods, some of them closer substitutes and some

app only after paying a fixed cost. Otherwise, riders can only pay with cash. With enough randomized price increases, we could in principle identify the model without any parametric assumptions. In practice, we have a limited number of experiments and only price decreases. Thus, we use a parametric version of the model to conduct the necessary extrapolation and estimate the consumer surplus. Whenever we have to make a choice, we take a conservative approach, such as in our choices for parametric forms and other auxiliary assumptions; that is, we choose the versions that give the smaller consumer surplus from using cash. The rider's model and the strategy for identification of the relevant parameters is discussed in Section 3.

Field Experiments

The three randomized control experiments were conducted in the State of Mexico. These experiments are discussed in Section 4. For each rider we know their historical number of trips, the average price paid per trip, the average miles per trip, whether they have registered a credit card in the application, the percentage of trips in cash, and his or her tenure with Uber among other things. The first experiments gave discounts to mixed users that were specific to the means of payments. In particular, the experiment had a total of six treatment groups of about 20,000 riders, each with a registered credit card. These riders received discounts of either 10% or 20%. Some of them received discounts for paying for trips in cash, some received discounts for paying with credit, while others received discounts regardless of payment method. The control group (approximately 90,000 riders) received no discounts. We estimate an elasticity of substitution between paying for trips (or miles) in cash versus credit by using the price variation in the discounts for trips paid in cash or discounts for trips paid with credit. Our estimate of the elasticity of substitution is about three. Additionally, we use the discounts given regardless of the means of payment, that is, a discount just to use Uber, to estimate the price elasticity for Uber rides. We estimate price elasticities for miles as large as 1.1 evaluated at current prices.

Next, we discuss the estimate of consumer surplus lost in a cash ban for mixed riders. To put this in perspective, about 50% of the riders in the State of Mexico are mixed riders. Our estimation uses the estimates of the elasticity of substitution between Uber paid in cash and Uber paid in credit, the price elasticity of Uber trips (or miles), the historical distributions at the rider level of the share of expenditure in cash, and the number of trips per week. As discussed above, this is equivalent to increasing the price in cash from its current value to infinity –or to the price at which there will be no more trips paid in cash. The effect of this increase can be decomposed into two parts. The first is the change in choice of payment for

close complements of Uber. As long as we keep the price of these goods fixed, the consumer surplus measured in the simple three good model is the same as in the one with all these other goods.

Uber for a given number of trips, which depends on the elasticity of substitution between paying for Uber rides with cash and paying with credit, as well as the share of trips paid in cash. The second is given by the changes on the ideal price index for Uber trips caused by the cash ban, which depends on the price elasticity of Uber trips. Integrating across all types of mixed users we find that the loss in consumer surplus is larger than 25% of the total amount spent on Uber by the mixed riders.

We use the second and third field experiments to estimate the consumer surplus of pure cash riders, which are about 25% of the riders in the State of Mexico. A ban in cash increases the price of a trip which for a pure cash rider means that either he or she registers a credit card and becomes a pure credit rider, or he or she ceases to use Uber. Thus, to measure this loss in consumer surplus we use data from two different experiments that target the population of pure cash riders as well as information from the ban on cash in the city of Puebla studied in Alvarez and Argente (2020). In the first experiment, we randomize the size of the discount faced by pure cash riders for a week and measure the effect on their miles and number of trips. We use four treatment groups of 23,000 riders each with discounts of 10%, 15%, 20%, and 25% and a control group of 56,000 riders. From this experiment, we estimate the demand for Uber trips for pure cash riders. For instance, we find price elasticity for miles (or trips) of about 1.3 evaluated at current prices.

The second experiment on the pure cash riders involves giving them a small reward (credit for future trips on their Uber account) if they register a credit card in the application. We have six treatment groups of about 20,000 riders each. We offer reward equivalents of about 3, 6, or 9 times the average weekly expenditure on Uber if they register a credit card. The reward is offered to a group of riders if they register a card in less than a week and the same reward if offered to another group of riders if they do so in less than six weeks. We consider these two time frames to test for the hypothesis that riders may not register their credit card in the application even though they do have one. Our understanding is that it is difficult to obtain a credit card in Mexico within one week, but reasonable within six. Thus, the temporal migration patterns (e.g. pure cash riders becoming mixed riders) are informative about whether the likely margin of response is to register a credit card that the riders already have, or to obtain a new credit card. We obtain two findings from this experiment. The first is that the small incentives raise the rate of registering a credit card about twice as much as the one for the control group.[5] The second is that the rate at which pure cash users register a credit card in six weeks is higher, but relatively close to the rate for the case of one week. Indeed, most of the excess migration to credit cards occurs in the first week. From the second

[5]This corresponds to the rate at which riders register a credit card *conditional* on making a trip. This conditioning is used for the week-long experiment to ensure that riders are aware of the promotion. The difference is smaller if we use the unconditional rates.

finding we conclude that the migration from cash to credit for small rewards is mostly riders registering credit cards they already own.

We use the two experiments for pure cash riders, the elasticity of substitution between paying Uber in cash or paying with credit for mixed users, and the rate at which these riders only use credit after the ban in Puebla studied in Alvarez and Argente (2020) to estimate the parameters that we need to compute the consumer surplus lost from a ban on cash. If no cash riders become credit users, then the loss from banning cash is the same as the consumer surplus from using Uber, which we estimate for this group to be at least as large as 50% of their expenditures on Uber. On the other hand, from the evidence in Puebla we know that there may be about 30% of pure cash riders who switched to credit cards. Using the second experiment for pure cash riders, as well as the elasticity of substitution between cash and credit previously estimated for mixed users, we estimate a consumer surplus loss for those that migrate to credit as just below 40% of their expenditures on Uber. Aggregating both groups we obtain that the average loss in consumer surplus from a ban on cash for pure cash riders is about 47% of their expenditures on Uber.

Throughout, we compare and complement the estimation of the price elasticity of Uber trips (and miles) with two other price experiments, a quasi-natural experiment in Uber Panama, and a survey instrument. We use the data of two independently conducted randomized price experiments implemented by Uber to compare the price elasticities we obtained in our experiments. These experiments were not designed to measure the price elasticities of a cash rider nor to measure the elasticity of substitution between paying for Uber trips in cash or paying with credit. Yet, in both cases, we find that the price elasticities are roughly similar to ours when we take into account the different populations that were subject to discounts. One of the experiments is particularly useful since it allows us to compare the elasticity found in our experiment (obtained with discounts that lasted only for one week) to estimates where the discounts lasted for four weeks, which presumably better approximates a permanent change in prices. The elasticities estimated in our experiments are very similar to those found in that experiment. The quasi-natural experiment in Panama is important because of a sudden and very large change in the cost and licensing requirement for drivers that dramatically decreased the number of drivers allowed to work for Uber. This experience allows us to estimate the price elasticity for Uber trips with large price *increases* and to validate our structural assumptions.

Furthermore, in order to obtain more evidence about the choke prices of the users in our experiments, the price at which the demand becomes zero, we implement a survey instrument. The survey was sent to the users almost a year after the experiments took place and asked the users how would they respond to different price changes, including very large price increases.

We verify that for price changes similar to those in our experiments, the reported elasticities are informative about the revealed preference elasticities. We then compare the reported choke prices to those implied by our model. We find that both are remarkably close, providing additional validation to our structural assumptions.

Contribution and Limitations of the Study

In summary, in the State of Mexico 20% of expenditure is accounted by pure cash riders, and 50% are mixed riders –whose cash share of trips is about 42%. Aggregating the estimates discussed above, we find that the loss in consumer surplus due to a ban in cash is about 50% of the expenditure on Uber paid in cash. Importantly, given that lower income households are more likely to rely on cash as their primary mode of payment (Alvarez and Argente, 2020), the cost from a ban on cash falls disproportionately on these households.

As explained above, given that we use price discounts instead of price increases, our strategy necessarily involves estimating a demand function for prices below the current equilibrium prices and extrapolating prices above them. To do this extrapolation, we use a parametric model for the demand for Uber composite trips as well as its corresponding indirect utility. In our choice of the definition of Uber trips and our parametric model we strive to be conservative by making choices that give a lower bound to the consumer surplus. For instance, our choice of the functional form of the demand with constant semi-elasticity is not only consistent with the local convexity we find in the relationship between composite trips and prices, but it also indicates a finite choke price. For pure cash riders it means a choke price about twice as large as the current equilibrium price. To put this price in perspective, our estimates of the consumer surplus of a cash rider who faces a prohibitively large cost for adopting credit is about half of the expenditure on an Uber trip. Instead, Cohen et al. (2016) use a discontinuity design based on the rounding of prices dictated by the surge algorithm to estimate the consumer surplus of Uber for three large U.S cities and find it to be about 1.6 of the expenditure of Uber riders. This difference is in large part explained by the different elasticity that Cohen et al. (2016) estimates for US riders versus pure and mixed users in the State of Mexico. In our case the price elasticity at the current equilibrium values is 1.3 for pure cash users, 1.1, for mixed users, and 0.7 for pure credit users. In Cohen et al. (2016) the price elasticity is below 0.55.[6]

Lastly, we think that obtaining a well identified estimate of the elasticity of substitution between cash and credit for a given good (Uber rides) is in itself an interesting contribution to the empirical studies of money demand. We estimate this elasticity to be about three, which is surprisingly low. Our strategy does not identify the mechanism for this low elasticity.

[6]See Table 3 of Cohen et al. (2016), first row with surge multiplier 1.2.

One possibility is that the high use of cash in other goods in Mexico, makes the use of cash in Uber complementary even for those that own credit cards.[7] For instance, Alvarez and Lippi (2017) construct a model in which cash and credit are used simultaneously and find some evidence consistent with the proposed mechanism for developed countries. There are very few studies on the behavior of a household when faced with a differential cost in the means of payment. Klee (2008) estimates the time it takes to pay using different methods in grocery stores by using data from time stamped cash registers but has no variations in the prices. Humphrey et al. (2001) use aggregate semiannual time series from Norway during the 1990s and the observed price variations across payment methods to estimate the pattern of substitution between cash, checks, and debit cards. Amromin et al. (2006) use a one time change in the toll booth prices on a Chicago highway, which differ depending on whether the payment is made in cash or with a transponder; the price of the tolls paid in cash doubled and those with a transponder kept constant.

2 Institutional Background

Although Uber went live in 2010, it only started accepting cash as a payment method in May of 2015. The ride-hailing company first rolled out cash into the application's payment options in Hyderabad, India. Following its success, they extended the option to four more cities in India that year. By the end of 2016, the cash payment option became available in over 150 cities and, by 2018, this number grew to over 400 cities and 60 countries. This includes most Latin American countries including Brazil and Mexico, the two largest in terms of population.

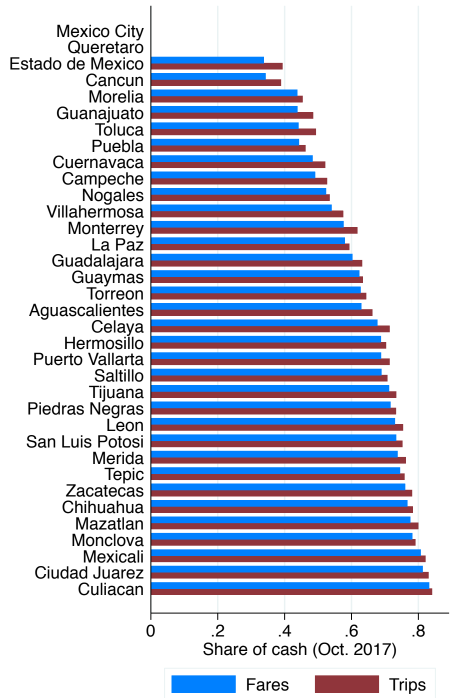
Uber was launched in Mexico in 2013. The first city with the service was the Greater Mexico City, which is composed of Mexico City and its adjacent municipalities in the State of Mexico. As of 2018, Uber was in more than 40 cities in Mexico. The Greater Mexico City is one of the top ten most active cities in the world in terms of rides for the company. Cash as a payment option was introduced in Mexico in 2016 after the experience the year before in India. Figure 1 shows the share of trips and fares paid in cash in the cities where Uber was available in October of 2017. The figure shows that for most cities, more than half of the trips and fares are paid in cash.[8]

A few local governments, nonetheless, prohibited cash as a payment method for Uber rides

[7] Cash is the main method of payment used in Mexico. Around 95% of all transactions below 25 USD and 87% of transactions above 25 USD are conducted in cash. The share of transactions paid in cash is above 90% for most goods in the economy.

[8] On average, the trips paid in cash are shorter. As a result, the share of fares paid in cash is slightly lower than the share of trips paid in cash.

Figure 1: Uber Mexico: Share of Cash by City



Note: The graph shows the share of trips and fares paid in cash in different cities in Mexico. The red bars show the fraction of trips paid in cash. The blue bars show the share of fares paid in cash. The sample of cities are those that were active in October of 2017.

at first. Cash was not allowed in Mexico City (as defined by its political boundaries) at first, even if it was allowed in all surrounding areas. In this case, the local government prohibited drivers from receiving any payments in cash, non-banking pre-paid cards, or payment systems in convenience stores through electronic wallets. The same occurred in the city of Queretaro, which is a mid-size city close to Mexico City. In Puebla, payments were limited to electronic payments, but the government did not enforce this until the murder of a young student allegedly by a Cabify driver, another ride-hailing firm. The ban on cash in the city of Puebla took place in December of 2017. In November of 2018, the Mexican Supreme Court struck down a state ban on cash fares for ride-hailing firms that set a national precedent for Uber and other firms. By a vote of 8-3, the court ruled that a ban on cash fares in the small western state of Colima was unconstitutional. Uber introduced cash as a payment option in Mexico City and Queretaro after the court's decision.

3 Rider's Model and Consumer Surplus

We describe the rider's preferences used to estimate the cost of a ban. We assume that during a ban the price paid for Uber in credit as well as the price paid for other related goods, such as taxis, are kept constant. These assumptions simplify the problem, but they are also consistent with the available evidence in Mexico documented by Alvarez and Argente (2020). Thus, we ignore the potential cost for the drivers or the benefits for pure credit users registered before the ban coming from a potential price decrease. Hence, our model exclusively studies the problem of riders that face potentially different prices for Uber rides paid in cash and in credit, and fixed prices for the rest of the goods.

The essential ingredients are a general utility function for $n+1$ goods, one good being "Uber composite trips", and good $n+1$ representing the rest of the goods, with constant marginal utility, i.e. utility is quasi-linear. We distinguish as different goods Uber rides paid in cash and Uber rides paid in credit. Technically, composite Uber rides are given by an aggregator of Uber rides paid in cash and Uber rides paid in credit. We complement this intensive margin problem with the problem of choosing to register a credit card, which we assume is subject to a fixed cost. In particular, agents have access to Uber trips paid in credit only if they pay a fixed cost.

We consider the welfare cost for riders in the case of a ban on cash as means of payment for Uber rides. In particular, we start with an initial situation where riders face the same price for Uber rides paid in cash and Uber rides paid in credit. Facing equal prices, heterogeneous riders choose whether to register a credit card or not. Starting from this situation, we consider the change in riders welfare, measured in dollars, if there is a ban on Uber rides paid in cash or, equivalently, the welfare effect of increasing the price of Uber rides paid in cash to infinity. We show that this welfare loss equals the area under the demand for Uber rides paid in cash, which takes into account both intensive and extensive margin, as well as the initial conditions. We discuss the challenges to identify this demand, the assumptions, and the data we use to attempt to overcome them.

3.1 Intensive Margin Rider's Problem

We assume that the rider's utility function is given by

$$u(x_1, x_2, \ldots, x_n; \phi) + x_{n+1}$$

where x_1 are composite Uber rides (to be defined in detailed below), the goods or services $x_2, x_3, \ldots, x_n$ are close substitutes and/or complements to Uber (say, for example, taxis), and the good x_{n+1} represents the rest of the goods and services. Preferences are quasi-linear, with the marginal utility of income normalized to one. We assume that $u(\cdot;\theta)$ is strictly concave and increasing in its n arguments. We let ϕ index the preferences of different riders, and let K be the distribution of ϕ across riders.[9]

One advantage of quasi-linear preferences is its simplicity, since equivalent and compensated variations are the same. We also think that it is a reasonable assumption given the small share of expenditure that goes to Uber rides. We take an agnostic, reduced form approach to the reasons why riders prefer one type of payment to the other by modeling them as two different goods. In particular, Uber composite rides x_1 are themselves given by a constant returns to scale function $x_1 = H(a, c; \phi)$, whose arguments are a, denoting Uber rides paid in cash, and c, denoting Uber rides paid in credit. Composite rides equal total rides only when both means of payment are available. The function H summarizes the preferences between paying in cash or credit. We assume that $H(\cdot;\phi)$ has constant returns to scale and that it is strictly quasi-concave. It is convenient to have a specific notation for the price of Uber rides paid in cash, for which we use p_a, and Uber rides paid with credit, for which we use p_c. Note that, in general, a rider facing finite values of (p_a, p_c) will use both means of payments. We let $p_2, ..., p_n$ the price of the rest of the goods.

Summarizing, the utility function is quasi-linear and weakly separable in rides paid in cash and in credit. The intensive problem for the rider is:

$$v(p_a, p_c, p_2, \ldots, p_n; \phi) = \max_{a,c,x_2,\ldots,x_{n+1}} u\left(H\left(a, c; \phi\right)\right), x_2, \ldots, x_n; \theta) + x_{n+1} \tag{1}$$

$$\text{subject to } p_a a + p_c c + \sum_{i=2}^{n} p_i x_i + x_{n+1} = I$$

where I is the total income of the rider. Furthermore, we assume throughout that I is large enough so that there is always positive consumption of the good $n + 1$. Note that we have normalized $p_{n+1} = 1$, so we can interpret the numeraire as dollars (or pesos!). The indirect utility function v is one of the key objects of our theory, since we will use it to measure consumer surplus. As discussed above, in our analysis we will keep the prices $\{p_2, \ldots, p_n\}$ fixed, so we omit them for most expressions. For instance, we write $v(p_a, p_c; \phi)$ suppressing $\{p_2, \ldots, p_n\}$. We denote the optimal choices for Uber rides paid in cash and in credit solving the intensive margin problem in equation (1) as: $\tilde{a}(p_a, p_c; \phi)$ and $\tilde{c}(p_a, p_c; \phi)$.

Our weakly separable specification allows us to isolate the choice of the means of payment from the total demand for Uber rides. In particular, given the assumption that H is homogeneous of degree one, a rider choice of her share of trips paid in cash depends only

[9]Almost all the time we use ϕ to refer to types defined by variables that we can observe.

the rider's type ϕ and the relative prices of Uber rides paid in cash vs credit p_a/p_c, but it does not depend on the total income I or any feature of the utility function u. On the other hand, taking prices $p_a = p_c = P$ faced for riders that have access to both means of payments, the demand of Uber composite rides depends only on its common price P and on the utility function u and it is independent of the function H. In general, we can define the ideal price of one composite Uber rides using H as:

$$\mathbb{P}(p_a, p_c; \phi) = \min_{a,c} p_a a + p_c c \text{ subject to } H(a, c; \phi) = 1 \tag{2}$$

We normalize the units of $H(\cdot; \phi)$ so that $H(p, p; \phi) = p$ for any $p > 0$. We let $a(p_a, p_c)$ and $c(p_a, p_c)$ be the choices that attain the minimum in equation (2) so that $\mathbb{P}(p_a, p_c) = p_a a(p_a, p_c) + p_c c(p_a, p_c)$. The functions a and c are homogeneous of degree zero in (p_a, p_c) while $\mathbb{P}$ is homogeneous of degree one in (p_a, p_c). The ideal price index is given by $\mathbb{P}(p_a, p_c)$, and increasing in convex function of (p_a, p_c). We assume that H is such that $\mathbb{P}(\infty, 1; \phi)$ and $\mathbb{P}(1, \infty; \phi)$ are both finite. For instance, if H is given by a CES function, we require the elasticity of substitution to be larger than one.

3.2 Extensive Margin Rider's Problem

We assume that a rider can use a credit card to pay for her rides only if she pays a (flow) fixed cost $\psi \geq 0$. We denote by $\theta = (\psi, \phi)$ a vector that completely specify the type of the rider. Thus the full problem for the rider is:

$$\mathcal{V}(p_a, p_c; \theta) \equiv \max \left\{ v\left(p_a, p_c; \phi\right) - \psi \, , \, v\left(p_a, \infty; \phi\right) \right\} \tag{3}$$

The first option is to pay the fixed cost ψ –which is part of rider type θ– and face prices (p_a, p_c) for rides. The second choice is to save the fixed cost ψ, but to have access only to rides pay with cash, which we represent as having an infinite price for rides paid in credit i.e. $p_c = \infty$. We let $1_c\left(p_a, p_c; \theta\right) \in \{0, 1\}$ be an indicator which equals one if the optimal decision in equation (3) is to register a credit card in the application and zero otherwise.

We express the fixed cost in its equivalent flow value, which we denote by ψ. This converts the fixed cost in units comparable with $v\left(p_a, p_c; \phi\right)$, which is a flow. Later on we introduce a discount rate ρ which converts the flows into stocks, so that ψ/ρ will be its stock value or actual value of the fixed cost. The discount rate ρ incorporates pure time discounting and the expected duration for the registration of the credit card and/or the expected duration of the Uber service.

We can now define the rider's demands for Uber paid in cash and credit, denoted by

a^*, c^*, taking into account the intensive and extensive margins:

$$\left(a^*\left(p_a, p_c; \theta\right), c^*\left(p_a, p_c; \theta\right)\right) = \begin{cases} \left(\tilde{a}\left(p_a, p_c; \phi\right), \tilde{c}\left(p_a, p_c; \phi\right)\right) & \text{if } 1_c\left(p_a, p_c; \theta\right) = 1 \\ \left(\tilde{a}\left(p_a, \infty; \phi\right), 0\right) & \text{if } 1_c\left(p_a, p_c; \theta\right) = 0 \end{cases}$$

for any type $\theta = (\psi, \phi)$.

We use the cumulative distribution functions G and K to describe the distribution of fixed cost conditional on ϕ, and the distribution of ϕ respectively. In particular we let $\psi \sim G(\cdot|\phi)$ and $\phi \sim K(\cdot)$ describe the cross sectional distribution of $\theta = (\psi, \phi)$. We assume that the distribution of ψ conditional ϕ has a continuous density and denote this density as $g(\psi|\phi) = G'(\psi|\phi)$ for all (ψ, ϕ). We use F for the implied distribution of types θ.

3.3 Welfare Cost of Ban in Cash and Consumer Surplus

Given the assumption of quasi-linearity we can aggregate the welfare level of riders and measure it in units of numeraire. We normalize the units of a trip so that when both means of payments are available, the price of a trip is 1, i.e. we normalize the length of rides so that prices before the ban are $p_a = p_c = 1$. We denote the consumer surplus lost in the ban of cash by CS_{ban}, which we define as follows. We assume that riders have access to both cash and credit before the ban and that they have already made their optimal choice regarding registering a card by solving the problem in equation (1). The prior decision of registering a card is summarized by $1_c\left(1, 1; \theta\right)$ and the distribution of types F. The consumer surplus lost in the ban is:

$$\begin{aligned} \mathcal{CS}_{ban} = & \int 1_c\left(1, 1; \theta\right)\left[v(1, 1; \phi) - v(\infty, 1; \phi)\right] dF(\theta) \\ & + \int \left[1 - 1_c\left(1, 1; \theta\right)\right]\left[v(1, \infty; \phi) - \mathcal{V}(\infty, 1; \theta)\right] dF(\theta) \end{aligned} \tag{4}$$

The first term counts those riders that before the ban have registered a credit card, as denoted by the indicator 1_c. These riders are either pure credit users or mixed users. Their net utility flow before the ban is $v(1, 1; \phi)$. Note that in the past they have paid the fixed cost to register the card but, at this point, this is a sunk cost and the decision is irreversible. After the ban these riders face a much higher price of cash rides, i.e. their utility flow value is $v(\infty, 1; \phi)$. The second term counts the riders that before the ban were pure cash users. Their utility function flow value before the ban is $v(1, \infty; \phi)$. After the ban these riders have the choice of either paying the fixed cost and becoming pure credit users, which gives a utility flow value $v(1, \infty; \phi) - \psi$, or just dropping from Uber, which corresponds to a net utility flow $v(\infty, \infty; \phi)$. This last choice is taking into account in the term $\mathcal{V}(\infty, 1; \theta)$.

Alternatively, and more generally, we can define for any $p_a \geq 1$ the consumer surplus lost due to an increase in the price of cash from 1 to $p_a \geq 1$ as:

$$\begin{aligned} \mathcal{CS}(p_a, 1) = & \int 1_c(1, 1; \theta) \left[v(1, 1; \phi) - v(p_a, 1; \phi) \right] dF(\theta) \\ & + \int \left[1 - 1_c(1, 1; \theta) \right] \left[v(1, p_a; \phi) - \mathcal{V}(p_a, 1; \phi) \right] dF(\theta) \end{aligned} \tag{5}$$

We can represent the ban as an arbitrarily large price for Uber trips in cash, i.e. as $\lim \mathcal{CS}(p_a) = \mathcal{CS}_{ban}$ as $p_a \to \infty$.

Following standard arguments in demand theory, the consumer surplus lost in the ban of cash can be computed as the area below the aggregate demand for Uber in cash. First, we define the aggregate demand for a city where cash was allowed, and where, unexpectedly the price increases to $p_a \geq 1$:

$$A(p_a, 1) = \int 1_c(1, 1; \theta) \, \tilde{a}(p_a, 1; \phi) dF(\theta) + \int (1 - 1_c(1, 1; \theta)) \, a^*(p_a, 1; \theta) dF(\theta) \tag{6}$$

Note that the definition of the aggregate demand breaks the integral into the same two groups of riders as in equation (5). The first is the group that has already registered the card, according to the decision at the original prices $(p_a, p_c) = (1, 1)$, for which $1_c(1, 1; \theta) = 1$. The second are the remaining riders, which have not registered a card and, hence, they may consider to do it optimally.

Proposition 1. Assume that $G(\cdot|\phi)$ has a continuous density, and that for almost all riders θ, the income I is large enough so they consume the outside good. Then

$$\mathcal{CS}_{ban} = \int_1^\infty A(p_a, 1) dp_a \tag{7}$$

Note that the demand that satisfies equation (7) is the *aggregate* demand. The proof of this proposition is in the appendix. It combines the envelope theorem for the intensive margin, with the assumption of a density g for the fixed cost to take care of the extensive margin.

3.4 Identification

In this section, we explain the challenges to identify the consumer surplus and how we try to overcome them. In principle, based on Proposition 1, if we can observe the changes on aggregate quantity of the trips paid in cash after permanent increases on its price p_a, for increasingly larger values of p_a while keeping everything else fixed, we can trace out the aggregate demand A, and thus estimate the consumer surplus. In practice, we run price experiments for short periods of time, where we can only decrease prices, or where we give rewards for registering credit cards. The reaction of price increases versus price decreases of Uber paid in cash may be different for at least two reasons. First, the demand function may have different curvature for high and low prices. And, second, because of the irreversibility of the decision to registering a card. To overcome these challenges, we conduct three different experiments and also bring to bear information from the reaction of riders to the ban in Puebla documented in Alvarez and Argente (2020). We combine this information with a structural model to produce theoretically based estimates of the consumer surplus. We use a parametric version because our experiments contain a limited amount of price points and rewards variation.

Our first result is to represent the problem for the Uber rider in two stages. This allows us to clarify which features of the indirect utility function are identified by each experiment.

Two stage representation of rider's intensive margin problem. As a preliminary step, we define the utility function $U(\cdot; \phi, p_2, \ldots, p_n) : \mathbb{R}_+ \to \mathbb{R}$ to embed all the information of the utility function u in a simple set up, for fixed prices of the related goods $\{p_2, \ldots, p_n\}$.

$$U(X; \phi, p_2, \ldots, p_n) \equiv \max_{x_2, x_3, \ldots, x_n} u(X, x_2, \ldots, x_n; \phi) + I - \left[\sum_{i=2}^{n} p_i x_i\right] \tag{8}$$

This problem simply creates an utility function with Uber composite rides, denoted by X as its main argument by maximizing out the remaining of related goods 2 to n, at prices $\{p_2, \ldots, p_n\}$. As in other cases, we will omit the dependence of prices $\{p_2, \ldots, p_n\}$. Using U we can define the following indirect utility function $V(\cdot; \phi) : \mathbb{R} \to \mathbb{R}$ in a problem for a rider choosing the number of composite rides X at price P:

$$V(P; \phi) = \max_{x \geq 0} U(x; \phi) + [I' - Px] \tag{9}$$

Note that we are using that preferences are quasi-linear. We let the optimal solution be $X(P; p_2, \ldots, p_n \phi)$, with first order condition $U'(X(P)) = P$ if $X(P) > 0$ and $U'(X(P)) \leq P$

otherwise.

We summarize the use of U and V and its relationship with v in a very simple proposition.

PROPOSITION 2. Fixing prices $\{p_1, \ldots, p_n\}$ and type ϕ, X solves the problem in (equation (9)), for U defined as in equation (8), if and only if $x_1 = X$ solves:

$$\max_{x_1, x_2, \ldots, x_n} u\left(x_1, x_2, \ldots, x_n\right) + \left[I - \sum_{i=1}^{I} p_i x_i\right].$$

Moreover, the indirect utility $v(\cdot)$ can be written as

$$v(p_a, p_c; \phi) = V\left(\mathbb{P}\left(p_a, p_c; \phi\right); \phi\right). \tag{10}$$

Finally, the solution of the intensive margin problem $(\tilde{a}, \tilde{c})$ can be written as:

$$\tilde{a}(p_a, p_c; \phi) = a\left(\frac{p_a}{p_c}, 1; \phi\right) X\left(\mathbb{P}(p_a, p_c); \phi\right) \tag{11}$$

$$\tilde{c}(p_a, p_c; \phi) = c\left(\frac{p_a}{p_c}, 1; \phi\right) X\left(\mathbb{P}(p_a, p_c); \phi\right) \tag{12}$$

where a, c are the solutions of problem (equation (2)), and X is the solution of problem (equation (9)).

We can use these results to discuss the assumption we use to identify the functions required to compute $\mathcal{CS}_{ban}$.

Identification of cash-credit choice utility H. For a given rider type ϕ, we can identify H if we observe the ratio of the choices $\tilde{a}(p_a, p_c; \phi)/\tilde{c}(p_a, p_c; \phi)$ as we exogenously vary p_a/p_c. Or equivalently, we can identify H by tracing the share of trips paid in cash $p_a\tilde{a}/(p_a\tilde{a} + p_c\tilde{c})$ as function of p_a/p_c. In this result we are using heavily the assumption that the function H is homogeneous of degree one. There are two important caveats/limitations. First, to identify it non-parametrically we need large variation of the ratio p_a/p_c. Instead, in our experiment we will face riders in the control and treatment groups with values of (p_a, p_c), which give us nine different values of p_a/p_c. We describe the experiment and how we use them in detail below. Second, we cannot identify H for riders that do not have registered credit cards. Faced with these challenges we use a parametric form of H. In particular, we assume that H is CES and we add the assumption that the same estimated H also holds for the pure-cash group, except for the parameter that controls the share of cash. Furthermore, we have access to the historic data of the share of trips paid for each user with a registered credit card at equal prices, i.e. when $p_a = p_c = 1$.

Identification of Uber rides utility U. It is clear from the definition of U in equation (8) and from problem (equation (9)) that U is identified by observing how $\tilde{c}(p, p; \phi)$ and $\tilde{a}(p, p; \phi)$ change as the price of both Uber rides $p = p_a = p_c$ changes, since $p = \mathbb{P}(p, p; \phi)$. Moreover, for pure cash riders (riders that have no access to credit), we can also identify U by changing the price of trips paid in cash p_a, which gives $\mathbb{P}(p_a, \infty; \phi) = p_a \, \mathbb{P}(1, \infty; \phi)$.[10] Importantly, we use the functional form of U, and its associated demand X, to extrapolate the shape for the indirect utility V estimated from variation on X in experiments where prices are lower than the current price, i.e. when $p < 1$, to the values of V when then price are higher than the current one, i.e to $p > 1$. The functional form is clearly important in this step.

Identification of the distribution of fixed cost g. Assume that the indirect utility function $v(p, \infty; \phi)$ and $v(p, p; \phi)$ are known. Additionally, assume that pure cash riders, whom are indexed by ϕ, are faced with different levels of flow rewards d to be obtained only if they registered a card. Then we can identify the distribution $\psi \sim g(\cdot|\phi)$ using the fraction that have registered a card for different values of d. This follows from the inequalities implied in equation (3). In principle, if we were to have a large number of experiments, each indexed by the size of the reward d offered to riders, and observe the fraction that register a card, we can identify the entire conditional density of fixed cost $g(\cdot|\phi)$.

While we design an experiment where pure cash riders are faced with rewards, the assumption that v is known for these riders needs to be discussed. In particular, while we design an experiment to identify U for pure cash users, we do not know the function H for these riders. The reason we do not know this function is that, by their vary nature, pure cash riders have not been faced (nor they can be easily faced) with interior choices for credit prices. To solve this problem we assume that some aspects of H are the same as those for mixed riders, i.e. riders for which we have identified H. In particular, we assume that η, the elasticity of substitution of H, is the same as the one estimated by mixed users, but we allow for a rider specific share parameter α–see below for more detail. In fact, we will only obtain an interval of feasible values for the share α based upon the experimental evidence and the observed behavior of riders after the ban in Puebla.

We list here the constraints on the distribution of fixed cost of migrating to credit ψ and on the distribution of ϕ implied from being a cash user, from the estimates of excess migration from Puebla, and from the experiments on payments to migration to credit. They all apply

[10] In particular, if we decrease p_a we can also disregard the incentives of pure cash riders to registered a card. Also, if the constant $\mathbb{P}(1, \infty; \phi)$ is not known, then we can identify U up to a constant, see case 4 of Appendix **??**.

exclusively to pure cash riders. We fix a value of ϕ for a group of pure cash riders. For now we assume we know the function $v(p_a, p_c; \phi)$ for these riders. We describe a set of conditions so the behavior of these riders is consistent with their observed behavior. In particular it must be consistent with: (1) the choice of pure cash users of not registering a card while cash was allowed, (2) the observed excess migration of pure cash users to pure credit users after the ban in Puebla, 3) the change in trips for the pure cash users that migrated to pure credit users after the ban in Puebla, and 4) the experimental evidence on the excess migration for different reward levels.

1) *Pure cash users prefer not to switch to become mixed/credit when cash is allowed.* The condition that ensures that pure cash users prefer not to become credit/mixed users is:

$$\psi \geq v(1, 1; \phi) - v(1, \infty; \phi) \tag{13}$$

for all cash users and for all value of ψ in the support of $G(\cdot|\phi)$. The right hand side of this equation defines the lower bound of the support $G(\cdot|\phi)$ which we refer to as $\underline{\psi}(\phi)$.

2) *Excess migration from cash to credit after the ban in Puebla.* For the second condition we use that fraction m_{ban} of pure-cash users in Puebla migrated to credit after the ban on cash, in excess to those that migrated before ban. We thus have:

$$\psi \leq v(\infty, 1; \phi) - v(\infty, \infty; \phi) \text{ for fraction } m_{ban} \text{ and} \tag{14}$$

$$\psi \geq v(\infty, 1; \phi) - v(\infty, \infty; \phi) \text{ for fraction } 1 - m_{ban} \tag{15}$$

The right hand side of these inequalities defines a value of ψ such that for higher values pure cash riders prefer to stop using Uber. We refer to this value as $\psi_{ban}(\phi)$.

3) *Change on trips for pure cash users that migrated to credit in Puebla.* In Puebla we keep tract of the number of trips for pure cash users that become pure credit users after the ban. We found out that they decrease the number of trips. Thus for those values of ϕ we must have

$$0 < \tilde{a}(\infty, 1; \phi) \leq \tilde{a}(1, \infty; \phi) \tag{16}$$

4) *Experimental evidence on the excess migration due to incentives.* In our experiment, pure cash riders are offered a one time payment d_j, from which we measure the induced (excess)

migration of fraction m_j of pure cash riders to become credit/mixed riders by registering a card. We index each level incentives as well as each fraction of the treatment group that migrate by j.

$$\psi \leq v(1,1;\phi) - v(1,\infty;\phi) + \rho d_j \text{ for fraction } m_j \text{ and} \tag{17}$$

$$\psi \geq v(1,1;\phi) - v(1,\infty;\phi) + \rho d_j \text{ for fraction } 1 - m_j \tag{18}$$

for each reward level j.

In Appendix F we implement all these inequalities to describe the (small) interval of α's consistent with our estimates. For each value of α we find the remaining parameters of U and G and compute the consumer surplus lost in a ban in cash by pure cash users.

3.5 Random Quasi-linear Utility and Test at the Aggregate Level

Before stating the functional forms we use to extrapolate the behavior of demand for low prices to high prices, we clarify two aspects of our model. The first is that we assume a quasi-linear utility function subject to idiosyncratic unobservable shocks at the rider level. This specification aggregates to a quasi-linear utility for a group of ex-ante identical riders with the same observables. The second is that we can test all restrictions implied by our experimental data (our two RCT's) on that aggregate utility function. The null hypothesis for the test is that the data set given by the experiments was generated by some quasi-linear utility function at the aggregate level. This test consists on checking several inequalities as explained below.

We assume that the rider's i utility function of cash and credit rides (a_i, c_i) is given by the composition of version H and $\tilde{U}$. We fix the type ϕ and allow for unobservable idiosyncratic shocks ω to $\tilde{U}$, so the utility function of the rider (ϕ, ω) is:

$$\tilde{U}\left(H\left(a_i, c_i; \phi\right); \phi, \omega\right) \tag{19}$$

where $\tilde{U}(\cdot;\phi,\omega)$ has been described above in equation (8). The function $H(\cdot;\phi)$ is the cash-credit sub-utility function described above, which can depend on the observable type ϕ, but cannot depend on the idiosyncratic shock ω.

It is well know that quasi-linearity is preserved under aggregation. We assume that the rider's random shocks ω are distributed across riders according to $\mu(\cdot|\phi)$ for a given observable type ϕ. We define the utility for the representative rider of observable type ϕ as:

$$U(a,c;\phi) \equiv \max_{a_i,c_i} \int \tilde{U}\left(H\left(a_i(\omega), c_i(\omega);\phi\right);\phi,\omega\right)\,\mu(d\omega|\phi) \tag{20}$$
$$\text{subject to: } a = \int a_i(\omega)\,\mu(d\omega|\phi) \text{ and } c = \int c_i(\omega)\,\mu(d\omega|\phi)\,.$$

Note that, since we assume that H is the same for all ω's, the utility of the representative rider is also homothetic with the same H. In words, the shocks ω only change the demand for Uber composite trips, but they don't change the choice of means of payments.

To test whether the data can be approximated using a quasi-linear utility, we use the test proposed by Allen and Rehbeck (2018). The null hypothesis of this test is that a data set of Uber rides paid in cash and credit $\{a^t, c^t\}_{t=1}^T$ and their corresponding prices $\{p_a^t, p_c^t\}_{t=1}^T$ were generated by maximizing some quasi-linear utility function, where t indexes the choices corresponding to the different prices. These choices are generated by a quasi-linear utility function if there is a function $U(a,c;\phi)$ for which (a^t, c^t) maximizes $U(a,c;\phi) - p_a^t a - p_c^t c$ for all t. In particular, Allen and Rehbeck's (2018) test of quasi-linearity of $\tilde{U}$ consists of finding utility levels $\{\bar{U}^t\}_{t=1}^T$ for which the following $(T-1)T$ inequalities hold:

$$\bar{U}^r - p_a^r a^r - p_c^r c^r \geq \bar{U}^s - p_a^r a^s - p_c^r c^s \text{ for all } r,s = 1,\ldots T, \text{ and } r \neq s$$

This, in turn, is equivalent to a test of $J \equiv \sum_{\ell=2}^{K} K!/((K-\ell)!\ell)$ inequalities on partial sums of $p_a^r a^s + p_c^r c^s$ for different values of s and r. To be concrete, in one of our experiments we have one control and six treatment effects, so that the test consists on checking up to $J = 2,365$ inequalities. Note that this notation includes the case where there are only changes on the price of cash, as it is the case in the experiments to pure cash users. In this case, with one control and four treatments, the test is equivalent to test up to $J = 84$ inequalities. We implement this test using the linear programming problem suggested by Allen and Rehbeck (2018). The summary statistics of the necessary data to conduct this test is reported in Table B1 and Table B2 in Appendix B.6. We found that all restrictions are satisfied for the two price experiments described below.

3.6 Functional Forms

In this section, we discuss our parameterization of U, H, and G. The utility function U defines the demand for Uber composite rides. In our choice of U we aim to be conservative in the implied magnitude of the consumer surplus, as we describe below. In particular, we let

$$U(x;\phi) = -k \exp\left(-\left(x+\bar{x}\right)/k\right)$$

so U has two parameters, $k >$ and $\bar{x} > 0$. The demand that solves the problem (equation (9)) is:

$$X(P;\phi) = -k\log P + k\log \bar{P}$$

so k and $\bar{P}$ are indexed by ϕ. This demand has a constant semi-elasticity $k \geq 0$. The parameter $\bar{P}$ is the price at which the demand is zero, i.e. $X(\bar{P};\phi) = 0$, and it is given by $\bar{P} = e^{-\bar{x}/k}$. The price $\bar{P}$ is also refer to as the "choke" price. Note that the price elasticity of this demand function is:

$$\epsilon(P) \equiv -\frac{P}{X(P)}\frac{\partial X(P)}{\partial P} = -\frac{1}{\log\left(\bar{P}/P\right)}, \text{ or } \bar{P}/P = \exp\left(\frac{1}{\epsilon(P)}\right).$$

The consumer surplus of a rider with this utility function

$$C(P_0;\phi) = \int_{P_0}^{\bar{P}} X(p;\phi)dp \text{ and}$$
$$\frac{C(P_0;\phi)}{P_0X(P_0;\phi)} = \epsilon(P_0)\left[\exp\left(\frac{1}{\epsilon(P_0)}\right) - 1\right] - 1$$

Note that the demand X is convex on P, a feature that is consistent with our experimental data. The convexity implies that the consumer surplus relative to revenue is larger than the one for a linear demand with the same revenue and elasticity at P_0, which will be $\frac{1}{2}\frac{1}{\epsilon(P_0)}$. Yet, as Figure 5 shows, the difference is not very large; for instance at $\epsilon(P) = 1.3$ the consumer surplus relative to revenue is slightly above 1/2. To put it in perspective, if we were to use a demand with constant elasticity and evaluate the consumer surplus relative to revenue we would obtain: $\frac{1}{\epsilon-1}$. For the elasticities we consider, which are close to one, a demand function with constant elasticity would give a consumer surplus that can be an order of magnitude larger than the one obtained with our semi-log demand. Additionally, Figure 5 shows the ratio of the choke price to the current price at which the elasticity is evaluated for the demand function with constant semi-elasticity, i.e. it displays $\bar{P}/P = \exp(1/\epsilon(P))$. For instance, at $\epsilon = 1.3$ the choke price is about 2.1 times larger than the price at which the elasticity is evaluated. So at this elasticity, riders will not longer use Uber if the price will be 2.2 higher than the current price. In Appendix B, we derive these expressions as well as the indirect utility V.

For $H(\cdot;\phi)$ we use a constant elasticity of substitution (CES) function described by two parameters: an elasticity of substitution η and a share parameter for credit α. To be precise, if $p_a = p_c = p$ for any p, the optimal demands gives $p_c c/(p_c c+p_a a) = \alpha$ and $p_a a/(p_c c+p_a a) = 1-\alpha$. The parameters (α, η) are part of the type ϕ. Moreover, the price of a composite Uber ride satisfy the standard expression $\mathbb{P}(p_a, p_c; \phi) = [\alpha p_c^{1-\eta} + (1-\alpha) p_a^{1-\eta}]^{1/(1-\eta)}$.

In Appendix B, we derive the expressions for the different cash and credit demands: $a(p_a, p_c; \phi), \tilde{a}(p_a, p_c; \phi), c(p_a, p_c; \phi), \tilde{c}(p_a, p_c; \phi)$, the indirect utility function $v(p_a, p_c; \phi)$, and other comparisons between indirect utility functions used in the computation of the consumer surplus.

3.7 Assumptions

We are now ready to describe exactly the assumption used to identify and compute the consumer surplus lost in a ban.

1. Riders that have registered a credit card can pay with cash or credit at the same prices prior to the ban. They are assigned a rider specific value of α.

2. All riders have a function H with the same elasticity of substitution η. We can relax this assumption to make η specific to a group of riders with the same observable characteristics.

3. All mixed riders have the same value of the semi-elasticity of demand for Uber k, but can have a rider specific $\bar{P}$. We can relax this assumption to make k specific to a group of riders with the same observable characteristic.

4. All pure-cash riders have the same value of the parameter α.

5. All pure-cash riders have the same value of the semi-elasticity of demand for Uber k, but are allowed to have different choke price $\bar{P}$.

6. The density g of the distribution of fixed cost of registering a card ψ is the same for all pure-cash users.

Two comments are in order. First, the value of the choke point $\bar{P}$ shifts the demand so that at the same baseline riders have more trips. Second, in the case of pure cash users, to recover the parameters $(k, \bar{P})$ of U and V using price variation we need the constant $\mathbb{P}(1, \infty; \phi)$. With our assumption on a common α for all pure cash users, as well as our functional form for H, we have that $\mathbb{P}(1, \infty; \phi) = (1-\alpha)^{1/(1-\eta)}$.[11] Hence, for each α for pure cash users we can identify all the parameters. The restrictions given by equation (13) and equation (14), as well as the fact that in Puebla cash users that converted to credit after the cash ban decrease their number of trips, gives a small *range* of value of α for pure cash users.

[11]See the expression for $a^*(p_a, \infty; \phi)$ in Appendix **??**. This expression depends on $k, \bar{P}$ and $(1-\alpha)^{1/(1-\eta)}$.

4 Experiments

In this section, we describe three large field experiments that took place in the State of Mexico between August and September of 2018. In Experiment 1, we vary the prices of cash and/or credit (i.e. p_a and/or p_c) for mixed users to estimate the elasticity of substitution between cash and credit η as well as the price elasticity of demand $\epsilon(P)$. In Experiment 2, we vary the price p_a for pure cash users to estimate the price elasticity of demand $\epsilon(P)$. Lastly, in Experiment 3 we face pure cash users with different incentives to register a credit card in the application to estimate the distribution of fixed cost g. We describe each of the experiments in more detail below.

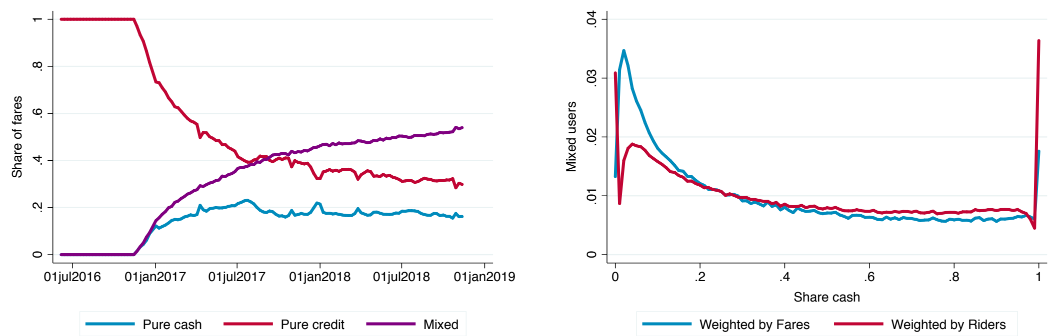
4.1 Experiment 1: Mixed Users

The experiment took place in the State of Mexico from August 21st to August 27th 2018. Our sample of users includes those who signed up in the State of Mexico and whose most frequent city for Uber trips is the State of Mexico. They also must have a card on file not banned by Uber, a verified mobile, and not subject to other experiments at the same time. In addition, the users in our sample took at least 2 trips in 2018 and took at least one trip since April 1st 2018. Appendix C1 shows descriptive statistics of the users in our sample. Importantly, in this experiment we focus on mixed users, those users who have at least one trip paid in cash and at least one paid with card before the beginning of our experiment. Panel (a) of Figure 2 shows the share of fares paid by mixed users over time in the State of Mexico. The figure shows that mixed users account for approximately half of the fares paid in the State of Mexico. Panel (b) shows the distribution of mixed users over their share of fares paid in cash.

We have six treatment groups, each composed of approximately 11 thousand riders and a control group of 90 thousand riders. The treatment and control groups were balanced in the following observables: average of weekly historical trips, average of weekly historical fares, log tenure (in weeks), and average of weekly historical fares paid in cash. Riders in the treatment groups received the following promotions: i) 10% off if the trip is paid with cash, ii) 10% off if the trip is paid with card, iii) 10% off regardless of the payment method, iv) 20% off if the trip is paid in cash, v) 20% off if the trip is paid with card, and vi) 20% off regardless of the payment method. The discounts were applied to all the trips the riders in each treatment group took during the entire week. At the beginning of the week the riders in the treatment groups received an introductory email describing the promotion. At the same time, the promotion showed up in the main screen of their phone once they opened the application (helix card). Two reminder emails were sent (in the middle of the week and two

Figure 2: State of Mexico: Share of Fares by Type of User

(a) Share of Fares by User Type (b) Distribution Mixed Users



Note: Panel (a) shows the share of total fares paid by different types of users in the State of Mexico. The red line shows the share of fares paid by pure credit users, those that have never pay an Uber ride in cash. The blue line shows the share of fares for pure cash users, those that have not registered a card in the application. The purple line shows the share of fares of mixed users, those that have at least one trip paid in cash and at least one paid in credit. Panel (b) shows the distribution of mixed users a function of the share of fares paid in cash. The sample of users are those with at least 4 weeks of tenure that had used both methods of payments and that took at least 5 trips after they become mixed users. The blue line shows the distribution of mixed users weighted by fares and the red line shows the distribution weighted by riders.

days before the promotions expired).[12]

Table 1 shows our estimates of η, the elasticity of substitution between Uber rides paid in cash and Uber rides paid in credit under several closely related specifications. While the point estimates vary across different specifications displayed in Table 1, we summarize our result as by saying that $\eta \approx 3$ or smaller. We compare the behavior of the share of trips paid in credit, i.e. $s_c \equiv p_c c/(p_c c + p_a a)$, among mixed riders with positive trips during the week of the experiment in treatments facing different relative prices p_a/p_c. Our preferred specifications are in columns (5) and (7), where we linearize the optimal choice of the share of credit s_c for a CES function H, as a function of the relative prices p_a/p_c, the share parameter α, and the elasticity of substitution η –see Appendix C.2 for the derivation of the approximation. The first and second order approximations around $p_c/p_a = 1$ are:

$$s_c = \alpha - (\eta - 1)\alpha(1-\alpha)\ln\left(\frac{p_c}{p_a}\right), \text{ and} \tag{21}$$

$$s_c = \alpha - (\eta - 1)\alpha(1-\alpha)\ln\left(\frac{p_c}{p_a}\right) + \frac{1}{2}(1-\eta)^2(1-\alpha)\alpha\left[1-2\alpha\right]\left(\ln\left(\frac{p_c}{p_a}\right)\right)^2 \tag{22}$$

In column (5) we use each mixed rider's historical trips in Uber to estimate α as the share

[12] Examples of the emails sent communicating the promotions can be found in Appendix C.5.

of trips paid in credit s_c outside our experiment, i.e. when $p_a = p_c$, so that our estimating equation becomes linear. In column (7) we instrument α, to reduce the potential bias due to measurement error. The source of measurement error on α is that we estimate it from historical data of the riders, which depends on the number of trips they have taken. In column (6) we use the second order approximation of the optimal decision for s_c. In columns (1) to (4) we divide each side of equation (21) by our estimate of $\alpha(1-\alpha)$ and run the regression:

$$\tilde{s}_c = 1/(1-\alpha) - (\eta - 1)\log(p_c/p_a) \tag{23}$$

This regression has the advantage of "moving" the measurement error on α to the left hand side variable and hence possibly reducing the attenuation biased that such measurement error may cause. We refer to this specification as the transformed share case. For robustness we try specifications with and without controls (historical fares and tenure in Uber), specifications that split price increases and price decreases, and specifications that use different thresholds to define the set of mixed users (those with more than 5% and less than 95% of their fares paid in cash, etc).[13] Importantly, we find that the estimates for η are similar for price increases and price decreases (Table C28) and constant in the riders' cash share (Figure C2), which we believe provides additional portability to our estimates for this parameter.

An alternative estimate of the elasticity of substitution can be obtained by aggregating across riders the decision for the share of trips on credit. For this purpose, we write the second order approximation to the decision of the share of credit s_c as a function of the prices faced by a single rider and as a function of her share parameter α and of the common elasticity of substitution η. In Appendix C.2, we show that for the range of parameter of interest the first oder approximation is very accurate and the second order approximation is almost exact. We interpret equation (22) as the expected value of the share of credit trips. We let μ be the distribution of α across the experiment's population. Riders enter into this population if they satisfy the conditions to be in the experiment –such as being active mixed riders– and they do so with weights proportional to the probability of having a trip within a week. Control and treatment groups differ only in the randomly allocated prices p_c/p_a, so the the expected value of $\bar{s}_c(p_c/p_a)$ is given by:

$$\bar{s}_c\left(\frac{p_c}{p_a}\right) = m_1 - (\eta-1)m_2 \ln\left(\frac{p_c}{p_a}\right) + m_3\,(1-\eta)^2\left(\ln\left(\frac{p_c}{p_a}\right)\right)^2 \tag{24}$$

$$m_1 = \int \alpha\mu(d\alpha),\; m_2 = \int \alpha(1-\alpha)\mu(d\alpha),\;\text{ and } m_3 = \frac{1}{2}\int (1-\alpha)\alpha\,[1-2\alpha]\,\mu(d\alpha)$$

We estimate μ by using the distribution of the share of credit prior to the experiment for the

[13]These robustness checks can be found in Appendix C.3.4.

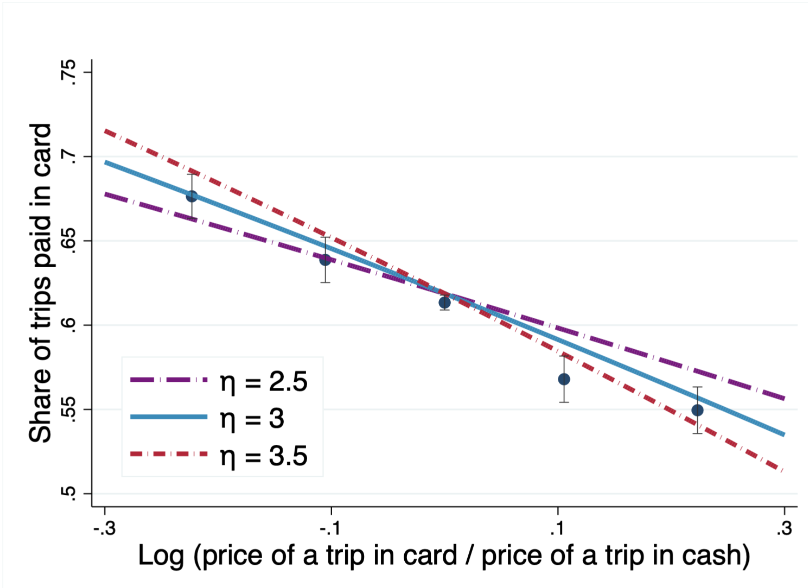
Table 1: Elasticity of Substitution: Mixed Users (Miles)

Note: The table reports estimates of the elasticity of substitution between cash and credit for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. Column (1) reports the results after using the transformed share specification denoted in equation (23) and including mixed users with more than 1% of their fares paid in cash and less than 99% of their fares paid in cash. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95% of their fares paid in cash. Column (4) includes the constant specified in equation (23) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (21). Column (6) estimates the elasticity using the CES second order approximation in equation (22). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predicted share of fares paid in credit (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (21) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elasticity	3.169***	2.893***	2.620***	2.992***	2.569***	2.569***	2.241***
	(0.373)	(0.349)	(0.181)	(0.217)	(0.103)	(0.103)	(0.080)
Obs.	52,562	52,562	44,927	52,562	52,562	52,562	67,984
Controls	No	Yes	Yes	Yes	Yes	Yes	No
Type	1 pct	1 pct	5 pct	1 pct	1 pct	1 pct	1 pct
Spec.	Transf.	Transf.	Transf.	Transf.-Cons	CES - First	CES - Second	CES - First IV

54,470 riders with positive trips during the experiment. The estimated values for the three moments are $m_1 = 0.6187, m_2 = 0.1349$ and $m_3 = -0.0081$, with very small standard errors. In Figure 3, we plot the actual average share across riders for each of the four treatment groups (10% and 20% cash discount and 10% and 20% credit discounts) and for the control group, including its 95% confidence interval. We also plot three versions of the theoretical prediction equation (24), using the estimated moments (m_1, m_2, m_3). Each line corresponds to a different value of the elasticity of substitution, namely $\eta = 2.5, \eta = 3$ and $\eta = 3.5$, a range of values suggested by the regressions on Table 1. We note that given the small value of m_3 the relationship between $\bar{s}$ and $\log(p_c/p_a)$ is almost linear, i.e. the first order approximation for the expected share is very accurate. Second, the dots, which correspond to the average credit share for control and treatment groups for each price, are arranged in an almost linear segment. Third, a value of $\eta = 3$ gives a very good fit.

Figure 3: Experiment I and Elasticity of Substitution η



Note: The dots are the average credit share for control and treatment groups with the corresponding relative price. The vertical lines are 95% standard error bands. The solid and dotted lines are the theoretical prediction for the expected credit share displayed in equation (24) using the estimated values of m_1, m_2 and m_3. The lines differ in the value of the parameter η.

Similarly, we estimate the composite Uber price elasticity ϵ for mixed users imposing our functional (constant semi-elasticity), and using the treatments where Uber prices $P = p_a = p_c$ are the same for rides paid in cash and paid with credit cards. These are essentially regressions of the miles during the week of the experiment on the log of the price and a constant, as shown in Table 2. We find that the elasticity ϵ, evaluated at current prices, is approximately 1.1 or smaller, which corresponds to the first two columns of Table 2 labeled AA. We also include the results of two other independently conducted experiments by Uber, labeled as Mandin and Ubernomics. Interestingly, the Mandin experiment had price variation that lasted four weeks and the elasticities are similar to ours–see Section 4.2.1 for more details. Appendix C.3.2 contains several robustness exercises including estimates of the semi-elasticity of demand, the elasticity of demand of number trips, the elasticity of demand for users that have taken at least 5 trips, and the Poisson regression specification.

Figure 4, using our functional form for U and h, displays the consumer surplus as share of expenditure on Uber for each share of cash fares in the horizontal axis. Each line in the figure corresponds to different parameter values for ϵ and η, chosen around our preferred estimates. Using our preferred estimate values for η and ϵ, the observed distribution of cash shares, and the observed distribution of total fares, we estimate a consumer surplus lost in a ban of cash of about 25% of the total fares paid by mixed users.[14] Since the average cash share of mixed users is 0.37, the consumer surplus lost by mixed users is about 67% of their expenditure on trips paid in cash.[15] To put this into perspective, mixed users account for about 50% of the total expenditure on Uber rides in the State of Mexico, see Table 2. Lastly, Alvarez and Argente (2020), studying evidence from a ban on cash in Puebla, provide evidence that the long-run elasticity of substitution is larger than the short-run elasticity. For $\eta = 5$, the consumer surplus lost for mixed users is 42.6% of their expenditure on trips paid in cash.[16]

Table 2: Elasticity of Demand: Mixed Users (Miles)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, share of fares paid in cash, cash trips, and cash trips squared. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Elasticity	1.082***	1.030***	1.096***	1.278***	1.452***
	(0.103)	(0.086)	(0.093)	(0.075)	(0.296)
Observations	109,365	109,365	98,773	11,660	4,306
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

4.2 Experiment 2: Pure Cash Users

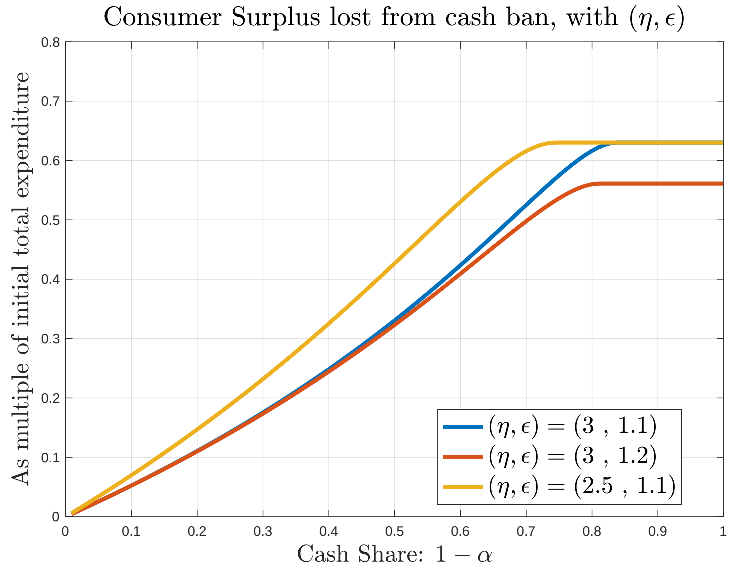
The second experiment took place in the State of Mexico during the same week as the previous experiment (August 21st to August 27th, 2018). Our sample of users includes those

[14]The average of the ratio of consumer surplus to the total expenditure in Uber, using $\eta = 3$, $\epsilon = 1.1$, and the distribution of the α, weighted by fares, is 0.2463. This figure is for mixed riders with more than 5 trips and more than four weeks of tenure.

[15]To be precise, using the cash share for mixed users of 0.3685, we get $0.6682 = 0.2463/0.3685$.

[16]An alternative research design proposed by Ivan Werning and Marios Angeletos would have been to only use the changes in prices paid with cash to estimate the consumer surplus loss for mixed users (e.g. using the same four discounts as we use in Experiment 2). On one hand, this alternative design has the advantage of yielding a more direct measure of the curvature of mixed users' demand for cash trips. On the other hand, our methodology has the advantages of being able to at least *increase relative prices* and also of estimating the parameter η. We find η of interest by itself and use it for several counterfactuals. Figure B1 in Section B.7 shows how our implied functional form captures the shape of the mixed users' demand for cash trips.

Figure 4: Consumer Surplus: Mixed Users



Note: The figure shows the model estimates of the consumer surplus (as a multiple of initial total fares) as a function of the cash share of users. The graph plots the estimates for different combinations of the elasticity of demand ϵ and the elasticity of substitution between cash and credit η. The consumer surplus estimates are for mixed users, those that have paid at least one trip in credit and at least one trip in cash.

who signed up in the State of Mexico and whose most frequent city of travel is the State of Mexico. Since this experiment is targeted to pure cash users, we focus on users that have not registered a card with Uber. In addition, the users in our sample own a verified mobile and were not subject to other experiments at the time of the experiment. The users in our sample took at least 2 trips in 2018 and took at least one trip since April 1st of 2018.

We have four treatment groups each composed of approximately 20 thousand riders and a control group of 56 thousand riders. The treatment and control groups were balanced in the following observables: average of weekly historical trips, average of weekly historical fares, and log tenure (in weeks). We have 4 treatment groups each getting 10%, 15%, 20%, and 25% off of all the trips taken during the week of the experiment. At the beginning of the week the riders received an introductory email describing the promotion. At the same time, the promotion showed up in the main screen of their phone once they opened the application (helix card). Two reminder emails were sent (in the middle of the week and two days before the promotions expired).[17]

Using the miles traveled during the week of the experiment as dependent variable, we estimate a price elasticity of demand ϵ of almost 1.4, when evaluated at current prices. Our

[17] Examples can be found in Appendix C.5.

baseline case is the semi-log demand corresponding to our functional form specification. Table 3 displays the estimates under columns AA, as well as estimates using the same specification for two independently run experiments discussed in Section 4.2.1. Other specifications and further robustness exercises can be found in Appendix C.3.1. This estimate is robust to using controls such as the average of weekly historical trips, average of weekly historical trips squared, average of weekly historical fares, and log tenure (in weeks).

Table 3: Elasticity of Demand: Pure Cash Users (Miles)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

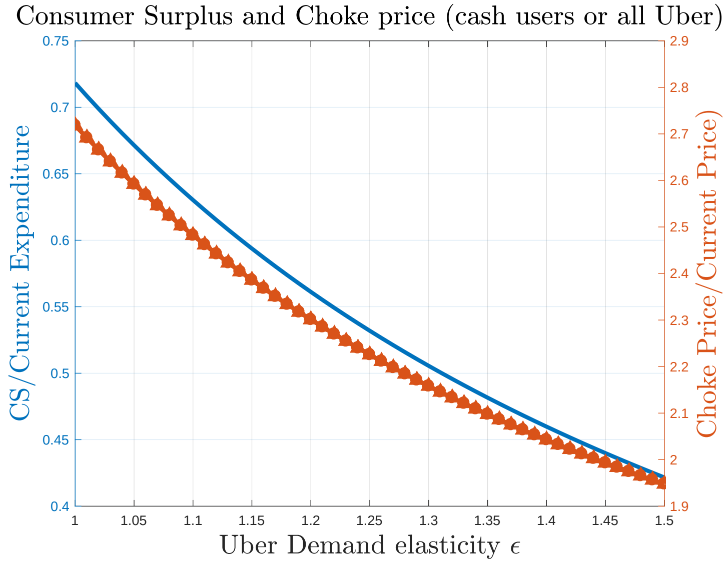
	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Elasticity	1.375***	1.383***	1.113***	0.813**
	(0.101)	(0.078)	(0.165)	(0.414)
Observations	138,725	138,725	4,279	3,569
Controls	No	Yes	Yes	Yes

Figure 5 displays the estimated consumer surplus for pure cash users for different elasticity estimates. Using 1.38 as our elasticity measure, we estimate a consumer surplus of approximately 46.7% of the total fares per year. This figure displays the corresponding choke price implied by our functional form, as a multiple of the current price corresponding to different elasticities. The choke prices corresponding to our preferrer price elasticity are about 2 times the current prices. The consumer surplus lost displayed in Figure 5 is, however, an upper bound estimate given that, after a large price increase, some users might decide to migrate to credit rather than leaving Uber completely. In fact, in Puebla, only 65% of the users left after a ban on cash. To adjust the consumer surplus of these riders we use both the experience in Puebla, as well as a third experiment to estimate the fixed cost of adopting credit. Section 4.3 provides more details.

4.2.1 Other experiments: Ubernomics, Mandin, and Panama

In this section, we describe other field experiments conducted by Uber that we use to provide external validity to our estimates of the elasticity of demand for cash and mixed users. Unlike

Figure 5: Consumer Surplus and Choke Price: Cash Users



Note: The figure shows the model estimates of the consumer surplus (as a multiple of initial total fares) as a function of the elasticity of demand ϵ. The graphs also shows the model estimates of the choke point, the price at which the demand for Uber trips is zero as a function of ϵ. The estimates are for pure cash users, those that never registered a card in the application.

our experiments which were explicitly designed to estimate the elasticity and curvature of the demand function, these experiments were not. Nonetheless, we can still use these experiments to estimate the elasticity and curvature. We are able to select riders and construct control variables to make the samples comparable using their historical data. In these exercises we obtain elasticities similar those found in our experiments.

In addition, we use a natural experiment that occurred in the country of Panama, where the government suddenly restricted the supply of drivers. Given that the price of Uber rides increased substantially after the government regulation went into effect, we use this case study to validate our functional form assumptions and to compute yet another estimate of the elasticity of demand. We find that, even in weeks when the price of Uber rides almost doubles, our functional form assumption of exponential utility fits well the patterns observed in Panama. Lastly, we use a survey instrument to validate our model. We first confirm that the reported elasticities are informative of the revealed preference elasticities. We then compare the choke prices implied by our model to those reported in the survey. We find the responses align well with the choke prices predicted by our structural framework.

Ubernomics

The experiment took place in the Greater Mexico City from May 15th to May 22nd of 2017, only a few months after the introduction of cash in the State of Mexico. The treatment groups received 10% and 20% off in all rides taken the week of the experiment. The day before the experiment started, all riders in the treatment groups were emailed and received an in-app notification informing them of the relevant price change. The promotion went live on Monday at 4 am local time and lasted through the following Monday at 4 am. Riders received a reminder of the promotion on Wednesday and Friday. To guarantee that the sample in this experiment is comparable to the one used in our experiments, we only consider riders whose most frequent city is the Greater Mexico City. Table C2 shows descriptive statistics of the users in this experiment. The sample includes 4,869 pure cash users and 4,306 mixed users. To guarantee that the estimates of the elasticity of demand are comparable across experiments, we estimate them controlling for the same observables we use to balance the treatment groups in our experiment: average of weekly historical trips, average of weekly historical fares, and log tenure (in weeks). Appendix C.3 shows the estimates of the elasticity of demand for pure cash users (Table 3) and mixed users (Table 2). The tables show that the estimates are close to those found using our experimental data; the null hypothesis that these elasticities are the same cannot be rejected.

Mandin Experiment

The Mandin (Demand Incentive) experiment took place in all areas of the Greater Mexico City (except for the South) in June 2018 and lasted four weeks. Riders were segmented depending on the number of trips they took during the last month and area of the city where they take most of their trips. Distinct levels of discounts were given to each Rider segment. The geographic areas they considered and the distribution of riders in each area are: North (30% of CDMX trips), West (8%), Center (32%), South (14%), and East (15%). Furthermore, they segmented riders according to the number of trips they took during the last year in the following categories: Remain (Trips ≤ 10), Regular ($10 <$ Trips ≤ 20), Mid ($20 <$ Trips ≤ 30), Power ($30 <$ Trips < 50), and Rockstar (Trips ≥ 50).

In this experiment, the control group was composed by users in the segments Remain, Regular, Mid, Power and Rockstar. The treatment groups were the following: 10% off: Remain and Regular; 20% off: Remain, Regular, Mid, Power and Rockstar; 30% off: Mid, Power and Rockstar. Discounts were offered to targeted riders through an automatic promo apply, and periodic communications were sent to them with the intention to incentivize usage.

To guarantee that the sample in this experiment is comparable to the one we use we consider riders whose most frequent city is the Greater Mexico City as in our experiment. Table C3 describes the characteristics of the users that took part of the experiment. In addition, we control for the same observables we use to balance the treatment groups in our experiment: average of weekly historical trips, average of weekly historical fares, and log tenure (in weeks). Using the data of this experiment we find an elasticity of 1.1 for pure cash users and 1.2 for mixed users, which are within the range of those estimated in our experiment. Importantly, given that this experiment lasted four weeks, we consider these findings as evidence that the short-run elasticity and the medium-run elasticity of Uber rides are very similar.

Panama

Uber launched in Panama in February of 2014. At the beginning only the UberBlack service was available. UberX was launched in May of 2015 and today it accounts for more than 95% of all trips. Until recently, Uber was only active in 3 provinces: Panama City, Panama West and Colon.[18] The most active province in terms of rides is Panama City. In August of 2016, the option of paying in cash was introduced in the country in part due to the low credit card penetration in the country. Cash was introduced in all provinces at the same time and within a year more than half of the trips were paid with this method of payment.[19]

In October of 2017 a decree imposing restrictions on Uber was put in place. The decree includes a prohibition on cash as a payment method for trips taken in Uber. In addition, the decree requires a special license for drivers (i.e. an "E1" type), which only nationals over 21 can obtain. The license has a cost of around $200 USD and can only be obtained after a 36 hour seminar. The decree also imposes a fleet cap of 2 cars and a geographic limitation to Uber so that it can only operate in 4 out of 10 provinces. The restrictions involving drivers went into effect January 2, 2018.[20] A total of 83% of all Uber drivers did not have the E1 license and were disconnected from the application. In addition, due to the unexpected reduction in the supply of drivers, the fraction of surged trips rose from an average of 16% in 2017 to an average of 45% in 2018. Figure 6 shows that the share of trips in cash also decreased drastically from more than 50% in 2017 to less than 35% in 2018. The number of trips paid in cash decreased more than those paid with credit cards, consistent with our findings that the demand for Uber trips paid in cash is more elastic than that for trips paid

[18] A recent Supreme Court decision has allowed Uber to provide services in more provinces.

[19] Cabify is also present in Panama since June of 2016, however, as in Mexico, their market share is still very low.

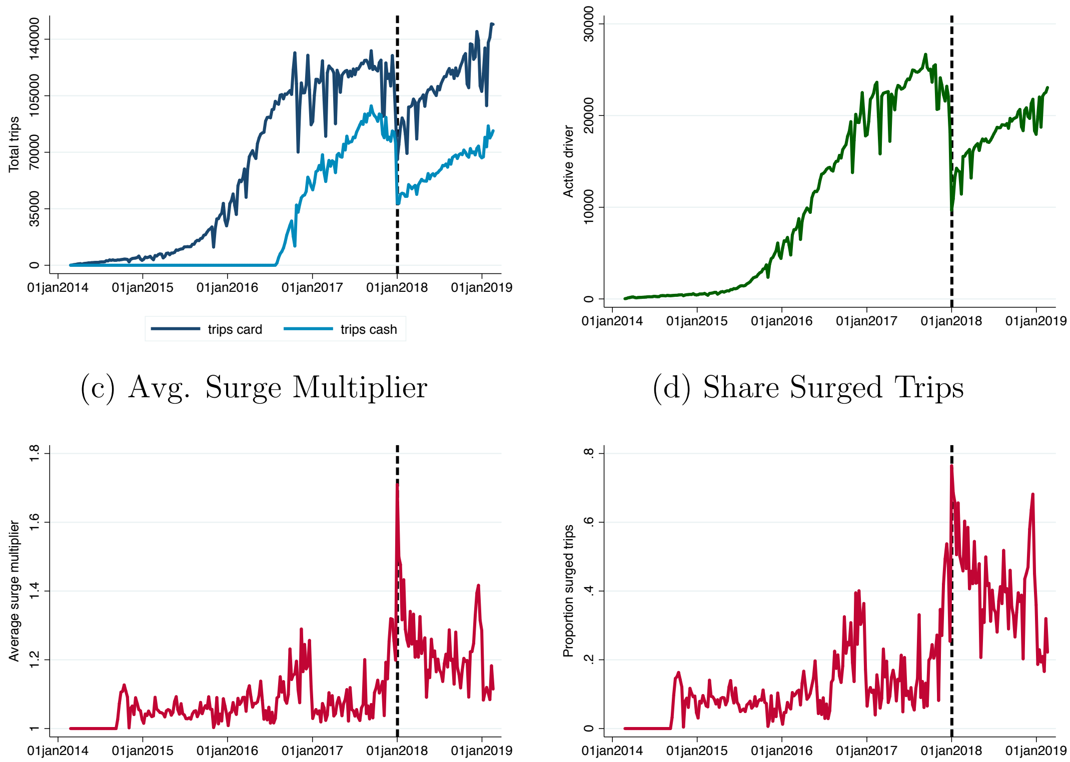
[20] Uber negotiated an extension of the deadline for the ban on cash. The extension expired on May 2019, and it was renewed until October 2019, when cash payments were banned temporarily. Cash was reintroduced in February 2020. Alvarez and Argente (2020) provide a more detailed description of these events.

with credit card.

Figure 6: Panama: Trips, Fares, and Drivers

(a) Trips (b) Active Drivers

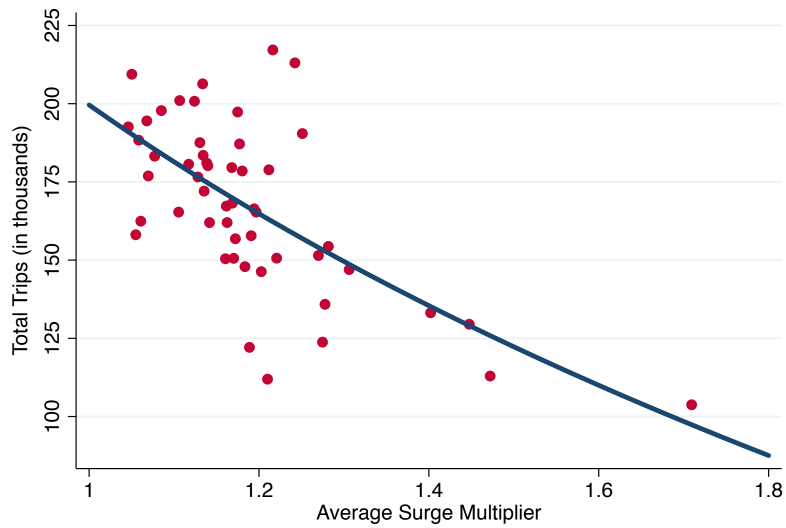
(c) Avg. Surge Multiplier (d) Share Surged Trips



Note: The figure shows the evolution of trips, active drivers, the average surge multiplier and the share of surged trips in Panama. The frequency of the data is weekly. The black dotted line denotes the date the decree by the government restricting the supply of drivers went into effect.

Interpreting this natural experiment as an exogenous decrease in the supply of drivers, we use the information of the total trips and the average surge multiplier (prices) to trace the Uber demand function for Panama. Figure 7 shows the trips as a function of prices for each of the 52 weeks in 2018 that followed the restriction to the supply of drivers. The blue line shows the fit of a semi-log demand function, the one implied by our functional form choices. The graph shows that, even for very high prices, those that we are unable to explore in our experiments, the curve fits the patterns of total trips and prices remarkably well. Under this specification, we estimate an elasticity of demand of approximately 1 for all trips in the city of Panama. If we restrict attention to rides paid in cash we estimate a lower elasticity of about 0.95, both elasticities evaluated at base-line prices. The share of cash before the restriction on drivers was about 0.4, but decreased after, consistently with the higher elasticity. All these features are consistent with the ones we found in our experiments in the State of Mexico.[21]

Figure 7: Panama: Total Trips and Prices (2018)



Note: The figure plots the total weekly trips and the average weekly surge multiplier for Panama. Each dot is a week in 2018, the weeks after the decree went into effect reducing the supply of drivers in the country. The surge multiplier is seasonally adjusted. The line is a semi-log function.

4.2.2 Survey Instrument: Choke Prices

In order to obtain more evidence about the choke prices of the users in our experiments, we use a survey instrument to ask them how would they respond to different price changes. The survey was sent to the users 11 months after the experiments took place. We design 6 different surveys that were randomly given to users, each with 3 questions. We received more than 6 thousand responses, an average of 1056 responses per survey.[22] This format allowed us to minimize the response time and, at the same time, allowed us to obtain several responses to a given question. For example, all surveys included the following question: "If your receive a 20% discount for one week, how would you change your trips...". Some users were given the options to respond a) no change, b) increase less than 10%, c) increase more than 10%. A second set of users were given the options to respond a) no change, b)

[21]We provide details on these estimates in Section D.

[22]The surveys were sent through email to all users that participated in experiment 1 and experiment 2 on July 9th, 2019 and they were open until July 16th, 2019. A total of 433,356 users received a survey, 287,233 participated in experiment 1 (mixed and pure credit users) and 146,123 participated in experiment 2 (pure cash users). The response rate was 1.46%.

increase less than 20%, c) increase more than 20%. And a third set of users were given the options to respond a) no change, b) increase less than 30%, c) increase more than 30%. Each survey also included two other symmetric questions, one related to a permanent and large price decrease (e.g. "If the price of trips is permanently reduced by half, how would you change your trips...") and another related to a permanent and large price increase (e.g. "If the price of trips is permanently doubled, how would you change your trips..."). Half of the surveys sent asked users to respond to permanently doubling prices or permanently reducing prices by half, whereas the other half asked the response from users if prices were permanently tripled or reduced by a third. In response to the question about a permanent price increase, the users had the following options to respond about the change in their trips: i) no change, ii) decrease substantially, iii) stop traveling. We use the answers to the first questions to compare the elasticities from the survey to those obtained from our experimental design in order to validate the survey instrument. We use the last question of the survey on the permanent doubling or tripling of prices to obtain information about the distribution of choke prices and to compare it to that implied by our structural framework.

To analyze the users' responses we proceed in three steps. First, we adjust the covariate distribution of the survey respondents by reweighting such that it becomes more similar to the covariate distribution of the entire population that participated in our experiments based on their historical trips per week and their tenure. We implement entropy balancing, a multivariate reweighting method described in Hainmueller (2012). Second, we use the responses of the first question to validate the survey instrument by confirming that the reported elasticities are informative about the revealed preference elasticities obtained in our experiments; the bounds implied by the survey responses align with those in the data.[23] And, lastly, we use the responses of the third question to compare the reported choke prices to those implied by our model. In this section, we focus on this last step but we provide more details of the previous two steps in Appendix H.

In our structural framework, for mixed users in the control group (facing prices equal to 1 in our model), the implied choke price is defined as:

$$\bar{P} = \exp\left(\frac{X(P)}{-k}\right) \tag{25}$$

where $X(P)$ is the number of miles a rider travels in a week and k is the semi-elasticity we have estimated using our experiments. Since the responses of the survey only provide

[23]There is a recent literature examining the external validity of survey instruments as low-cost alternatives to experimental evidence that concludes that that survey-based data are informative for prediction but do not necessarily provide precise quantitative responses. Examples of this work are Karlan, Osman and Zinman (2016), Parker and Souleles (2019), and Hainmueller, Hangartner and Yamamoto (2015).

us with a distribution of choke prices, we implement equation (25) in the data to obtain the distribution of choke prices implied by our structural assumptions. This requires taking stance on the riders' heterogeneity. In this case, we use each user's average of weekly historical fares to approximate $X(P)$ and the semi-elasticity estimated in our experiments.[24] Table 4 presents the distribution of choke prices for mixed users.

Table 4: Distribution of Choke Prices

Note: The table shows moments of the distribution of choke prices implied by framework described in Section 3 for both mixed users and pure cash users. To approximate $X(P)$ we use each user's average of weekly historical fares. To minimize the measurement error, we trim the top and bottom one percent. The semi-elasticity k is that estimated for each group of users presented in Table C4 and Table C10.

Choke Price	(1) Mean	(2) Std. Dev.	(3) 10th	(4) 25th	(5) Median	(6) 75th	(7) 90th
Mixed users	6.0	20.7	1.18	1.35	1.82	3.28	8.19
Pure cash users	4.8	12.0	1.62	1.78	2.18	3.36	6.7

The median choke price for mixed users implied by our model is 1.82. There is considerable heterogeneity in the choke prices, the ratio of the 75^{th} percentile and the 25^{th} percentile is 2.42. Given our structural assumptions, if we double prices, 56% of the users would stop traveling and, if we triple prices, approximately 73% of the users would stop using Uber. This is remarkably close to what the users responded in the survey. Approximately, 55.49% of the users responded that they would stop traveling if prices doubled and 66.58 % responded that they would stop traveling if prices were tripled. The choke prices implied in our model are slightly lower than those reported in the survey suggesting that the structure assumed in our model implies a lower bound for the consumer surplus estimates.

Next, we implement a similar approach for the pure cash users. In this case, their choke price is defined as:

$$\bar{P} = \exp\left(\frac{\tilde{a}(p_a, \infty)}{k(1-\alpha)^{\frac{1}{1-\eta}}} + \frac{\log\left(k(1-\alpha)^{\frac{1}{1-\eta}}\right)}{k(1-\alpha)^{\frac{1}{1-\eta}}}\right) \tag{26}$$

where $k(1-\alpha)^{\frac{1}{1-\eta}}$ is our estimated β_1. The median choke price in this case is 2.18 and the ratio of the 75^{th} percentile and the 25^{th} percentile is 1.88. Our model implies that if we double prices, 41% of the users would stop traveling whereas in the survey 54.43% of the

[24] To minimize the measurement error in the average of weekly historical fares, we trim the top and bottom one percent.

users responded that they would stop traveling. If prices triple, our framework implies that 71% would stop traveling, which is remarkably close to the 69.44 % of users that responded that they would strop traveling if prices were to triple. We argue that, given that self-reports are informative about the revealed-preference elasticities, these findings on the choke prices provide additional validation to the structural assumptions we implement.

4.3 Experiment 3: Extensive Margin

The third experiment took place in the State of Mexico from September 17th to October 23rd, 2018. It was targeted to pure cash users in order to understand their credit adoption patterns. Our sample of users includes those who signed up in the State of Mexico and whose most frequent city is the State of Mexico. We focus on users that have not registered a card with Uber. In addition, the users in our sample own a verified mobile and were not subject to other experiments at the time of the experiment. The users in our sample took at least 2 trips in 2018 and took at least one trip since April 1st of 2018.

We offered rewards if the users registered their cards into the application, without imposing restrictions on whether they should pay their subsequent trips using cash or credit. The treatment groups received rewards of 100, 200, or 300 pesos (5.2, 10.5 and 15.7 USD) that are approximately an average of 3, 6, and 9 times their average weekly fares (or approximately 1, 2 and 3 average trips). Given that pure cash users might or might not have a credit card already, the experiment had two treatments for each reward with two different horizons. The first lasted only one week and targeted users that might already have a credit card but have not registered it in the application. The second lasted 6 weeks in order to allow enough time for users to obtain a credit card in case they did not have one already. These users received email reminders of the promotion every week. Overall, our experiment has 6 treatment groups (e.g. 3 incentive levels lasting one and six weeks) each made of approximately 20 thousand riders and a control group of 40 thousand riders.

Table 5 shows the percent of pure cash users that adopted credit (registered a credit or debit card in the application) in each of the treatment groups conditional on having taken a trip during the weeks of the experiment. Column (1) and (2) show that the adoption during the first week, for the experiment that lasted one week and for the experiment that lasted 6 weeks. The columns show that the adoption of credit during the first week is similar for short and long run horizons. In both cases, the users in the treatment groups responded significantly to the incentives provided relative to the control group. We observe larger migration to credit for larger incentives. For instance, for a reward of slightly above 15.2 USD we obtain an extra migration rate of 4.6%, which is statistically significantly larger than the one corresponding to 5.2 USD, which is 3.3% –see column (3) of the Table.

Table 5: Extensive Margin: Adoption of Credit

Note: The table reports the percent of users that adopted credit for each of the treatment groups in experiment three relative to the control group. Migration is an indicator function that equals one if the user registered a card conditional on taking trip the weeks of the experiment. The variables ”Treatment” report the migration rates relative to the control group of the three treatment groups in the experiment: 3, 6, and 9 times their average weekly fares if the users register a card in the application. Column (3) reports the rates of credit adoption during the first three weeks of the experiment. Column (4) reports the rates of adoption in the last three weeks of the experiment.

	(1) 1 week	(2) 1 week	(3) 1-6 week	(4) 1-3 week	(5) 4-6 week
Treatment 1 - 1 week	0.0241***				
	(0.004)				
Treatment 2 - 1 week	0.0269***				
	(0.004)				
Treatment 3 - 1 week	0.0366***				
	(0.004)				
Treatment 1 - 6 week		0.0166***	0.0333***	0.0283***	0.0112***
		(0.004)	(0.004)	(0.004)	(0.003)
Treatment 2 - 6 week		0.0217***	0.0394***	0.0382***	0.0088***
		(0.004)	(0.004)	(0.004)	(0.003)
Treatment 3 - 6 week		0.0390***	0.0468***	0.0485***	0.0088***
		(0.004)	(0.004)	(0.004)	(0.003)
Observations	20,609	20,677	46,996	36,184	46,996
R-squared	0.005	0.005	0.005	0.006	0.001

Column (3) shows the overall migration that took place over the span of 6 weeks and Column (4) and (5) examine the migration of weeks 1-3 and weeks 4-6 respectively. The columns show that the share of users migrating during the first three weeks of the experiment is substantially larger than the share of users migrating in the last three weeks of the experiment. This indicates that, although our incentives were enough to encourage migration of the marginal users, they were not enough to substantially incentivize users that did not own a credit card. In fact, Table C29 shows that users under our treatment groups were more likely to use credit as a payment method more than 6 months after our experiment ended. The table shows that, conditional on traveling between April and June of 2019 and having taken a trip during the weeks of our experiments, the probabiliy of paying with credit is larger for users in our treatment groups. Lastly, Table C30 in Appendix C.4 shows unconditional migration rates – users registering a card in the application regardless of whether they took trips during the weeks of the experiment. The table shows that the overall the unconditional migration over the 6 weeks that the experiment lasted are similar to those presented in Table 5.

4.4 Net Consumer Surplus Lost in the Ban for Pure Cash Users

In this section, we use a variety of observations to estimate the consumer surplus lost in a ban, taking into account the effect of those pure cash riders that choose to pay the fixed cost and become pure credit users after the ban. To do so, we combine different aspects of the theory with evidence gathered from several experiments. On the theoretical side we use the specifications of preferences described in Section 3.6, with their implications for demand derived in Appendix **??**, the corresponding indirect utility functions derived in Appendix B.4, and the conditions that fixed cost and indirect utility have to satisfy for the optimal registration/adoption of credit cards, as described in equation (14) and equation (17). We also use the parameters estimated in Experiment 2 for the demand of trips for pure cash users, the elasticity of substitution between cash and credit estimated in Experiment 1 for mixed users (which we assume applies to cash users), the migration rates under each of the incentive levels described in Section 4.3 from Experiment 3, and the total migration and change in the number of trips observed in the city of Puebla after the ban on cash. With this information we jointly estimate the counterfactual share parameter α for pure cash users, the parameters for the utility function U for composite rides for pure cash users (k and $\bar{P}$), and the distribution of the fixed cost G. Using these parameters we compute the net consumer surplus loss. Appendix F goes over details of these calculations.

According to the evidence from Puebla, about 70% of the pure cash riders stop using Uber after the ban of cash. From Table 3 our estimated elasticities at pre-ban prices are just below 1.4 for this group, so their consumer surplus loss is almost 0.49 of their yearly expenditure in Uber. For the remaining 30% of riders the losses are smaller.[25] Using the information from Experiment III we obtain a lower bound for net consumer surplus lost for pure cash users of about 0.47 of the yearly expenditure in Uber. Appendix F presents the detailed calculations for this lower bound. It also shows the net consumer surplus lost computed cell-by-cell, where the cells are percentiles of the distribution of the historical number of trips. The resulting values are much higher due to the convexity of the consumer surplus and the large skewness of this distribution.

[25] Indeed, in Appendix E we correct this estimate to take into account observable differences between Puebla and the State of Mexico, which may lower this estimate up to 29% given that the State of Mexico is slightly poorer and has less banking penetration. In the spirit of obtaining a lower bound on the consumer surplus lost, we keep the 30% figure.

5 Conclusion: Ban on Cash and Beyond

We combine a theoretical model with three large field experiments in Mexico to estimate the consumer surplus of using cash as a payment method in Uber. The total consumer surplus lost by a ban on the use of cash as a fraction of the total expenditure of Uber paid in cash is a least 50%. We estimate a loss in consumer surplus of least 47% of the expenditure of pure cash users, which account for 20% of total expenditure on Uber. For mixed users we estimate a loss in consumer surplus of at about 25% of their expenditure in Uber, which account for about 50% of total expenditure in Uber by all users. Adding up the loss of consumer surplus from pure cash users and mixed users the consumer surplus lost is about 30% of the total expenditure on Uber rides of these two groups. Taking into account that mixed users paid in cash about 37% of their total expenditure in Uber, we obtain our 50% headline figure for the lower bound of the consumer surplus lost in a ban on cash.[26]

We have several other findings which we believe are of independent interest. For instance, in our field experiments we found that mixed users, those that use both payment methods, have an elasticity of substitution between Uber rides paid in cash and Uber rides paid in credit of about 3. We also found a statistically significant but small elasticity of the adoption/registration of credit cards when riders are given incentives. A reward of 15 USD increases the adoption rate by less than 5%, which is largely explained by the registering of existing credit cards. We believe that these elasticities are of independent interest for the literature on payment methods, and more generally, for the literature on money demand.

We think our result can be used to approximate the effect of similar policies applied in other cities in Mexico and elsewhere, i.e. to estimate the cost of a cash ban as 1/2 of the fares of Uber paid in cash. For instance, a ban on cash was in effect in the state of San Luis Potosí, Mexico from mid July of 2019 to the end of September of the same year. Our results are also relevant for Panama. While cash is accepted as means of payment everywhere, it had a precarious legal status for almost three years. Cash had been originally banned, but the implementation of the ban has been temporarily suspended by three consecutive decrees from the government. It was then banned on September of 2019 until the Supreme Court ruled the prohibition of cash as unconstitutional at the end of December of the same year. We have estimated price elasticities for riders of different types in Panama that are similar to those in the State of Mexico –see Section 4.2.1 and Appendix D. Thus, assuming the rest of the parameters are as in the State of Mexico, the ban in cash in Panama will caused a temporary consumer surplus lost of approximately 50% of the trips paid in cash in Panama

[26]The calculation for the consumer surplus lost in cash is the average of the consumer surplus of pure cash users and mixed users weighted by their share on the total cash expenditures: $0.47 \times \frac{0.20}{0.2+0.5\times0.37} + 0.67 \times \frac{0.5\times0.37}{0.2+0.5\times0.37} = 0.56 > 0.5$.

at the time. Finally, our estimates are relevant for policies applied in the southern cone. For instance, cash is banned in all cities of Uruguay, except Punta del Este. In Argentina, the municipal government of the city of Buenos Aires, as a way to curtail the use of Uber, issued a prohibition on the processing of credit cards payments, which had the implication that credit cards were not accepted in the entire country, and hence for a while riders could only pay in cash in Argentina. Motivated by this, we have estimated the consumer surplus losses from a ban on credit, assuming that all the parameters are as in the state of Mexico –see Appendix G for details. We found that the consumer surplus loss of a ban in credit is about 0.80 the expenditure on Uber paid in credit before the ban. This loss is higher than the one for a ban on cash because for pure credit users it is fully equivalent to a ban on Uber, they have larger expenditure and they are more inelastic. Moreover, for mixed users their share of credit is 63%, so they are more affected by a ban of credit, than by a ban on cash. Lastly, our findings of the low substitutability across payment methods imply that the optimal response of shifting away from cash payments during the COVID-19 pandemic is not without cost to users.

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APPENDIX

A Proofs

Proof. (of Proposition 1) The first step uses a standard results form demand theory. From the definition of the indirect utility function $v(p_a, p_c; \theta)$. Given the quasi-linearity replacing the budget constraint, and using the assumption that I is large enough:

$$v(p_a, p_c, p_2, \ldots, p_n; \phi) = \max_{a,c,x_2,\ldots,x_n} u\left(H\left(a, c; \phi\right)\right), x_2, \ldots, x_n; \theta) - \left[p_a a + p_c c + \sum_{i=2}^{n} p_i x_i\right] + I$$

Thus, using the envelope theorem:

$$\frac{\partial}{\partial p_a} v(p_a, p_c, p_2, \ldots, p_n; \phi) = -\tilde{a}\left(p_a, p_c, p_2, \ldots, p_n; \phi\right)$$

Hence, using the fundamental theorem of calculus:

$$v(\bar{p}_a, p_c, p_2, \ldots, p_n; \phi) - v(\underline{p_a}, p_c, p_2, \ldots, p_n; \phi) = -\int_{\underline{p_a}}^{\bar{p}_a} \tilde{a}\left(p_a, p_c, p_2, \ldots, p_n; \phi\right) dp_a$$

The second step, uses a characterization of the extensive margin choice. We can write the two parts of the expression for $\mathcal{C}_{ban}$. First we take the case of those that prior to the ban have registered a card, i.e. those types for which $1_c\left(1, 1; \theta\right) = 1$. The third step describes the adoption decision as a threshold rule on ψ. To do so, we rewrite the vector of type as $(\psi, \phi) = \theta$, so that ϕ contains all the information of the types except the fixed cost, i.e. u and H are indexed on ϕ. Using this notation we can fix a type ϕ and describe her decision to register a credit card as:

$$1_c\left(p_a, p_c; (\psi, \phi)\right) = 1 \iff \psi \leq \bar{\psi}(p_a, p_c; \phi) \equiv v(p_a, p_c; \phi) - v(p_a, \infty; \phi)$$

The fourth step is to differentiate the firm term of $\mathcal{CS}(p_a, 1)$:

$$\begin{aligned}
&\frac{\partial}{\partial p_a} \int 1_c\left(1, 1; \theta\right)\left[v(1, 1; \phi) - v(p_a, 1; \phi)\right] dF(\theta) \\
&= -\int 1_c\left(1, 1; \theta\right) \frac{\partial}{\partial p_a} v(p_a, 1; \phi) dF(\theta) \\
&= \int 1_c\left(1, 1; \theta\right) \tilde{a}(p_a, 1; \phi) dF(\theta)
\end{aligned}$$

where the last term uses the expression derived for the derivative of the indirect utility function.

The fifth step is to rewrite the second term of $\mathcal{CS}(p_a, 1)$:

$$
\begin{aligned}
&\int \left[1 - 1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi) - \mathcal{V}(p_a,1;\theta)\right] dF(\theta) \\
&= \int \left(\int_{\underline{\psi}}^{\bar{\psi}(p_a,1;\phi)} \left[1 - 1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi) - \mathcal{V}(p_a,1;\theta)\right] g(\psi|\phi) d\psi \right) dK(\phi) \\
&+ \int \left(\int_{\bar{\psi}(p_a,1;\phi)}^{\infty} \left[1 - 1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi) - \mathcal{V}(p_a,1;\theta)\right] g(\psi|\phi) d\psi \right) dK(\phi) \\
&= \int \left(\int_{\underline{\psi}}^{\bar{\psi}(p_a,1;\phi)} \left[1 - 1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi) - v(p_a,1;\phi) + \psi\right] g(\psi|\phi) d\psi \right) dK(\phi) \\
&+ \int \left(\int_{\bar{\psi}(p_a,1;\phi)}^{\infty} \left[1 - 1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi) - v(p_a,\infty;\phi)\right] g(\psi|\phi) d\psi \right) dK(\phi)
\end{aligned}
$$

where we first use that $\theta = (\psi, \phi)$, and then we use the characterization of the optimality of registering a credit card in $\mathcal{V}$ in terms of $\bar{\psi}$. Now we compute the derivative of this second term with respect to p_a:

$$
\begin{aligned}
&\frac{\partial}{\partial p_a} \int \left[1 - 1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi) - \mathcal{V}(p_a,1;\theta)\right] dF(\theta) \\
&= -\int \left(\int_{\underline{\psi}}^{\bar{\psi}(p_a,1;\phi)} \left[1 - 1_c\left(1,1;\theta\right)\right] \frac{\partial}{\partial p_a} v(p_a,1;\phi) g(\psi|\phi) d\psi \right) dK(\phi) \\
&- \int \left(\int_{\bar{\psi}(p_a,1;\phi)}^{\infty} \left[1 - 1_c\left(1,1;\theta\right)\right] \frac{\partial}{\partial p_a} v(p_a,\infty;\phi) g(\psi|\phi) d\psi \right) dK(\phi) \\
&+ \int \left(\left[v(1,\infty;\phi) - v(p_a,1;\phi) + \bar{\psi}(p_a,1;\phi) - v(1,\infty;\phi) + v(p_a,\infty;\phi)\right] g(\psi|\phi) \right) dK(\phi)
\end{aligned}
$$

where we pass the derivative inside the integral sign, and use Leibniz rule. Rearranging terms and using the definition of $\bar{\psi}$ we have eliminate the last term:

$$
\begin{aligned}
&\frac{\partial}{\partial p_a} \int \left[1 - 1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi) - \mathcal{V}(p_a,1;\theta)\right] dF(\theta) \\
&= -\int \left(\int_{\underline{\psi}}^{\bar{\psi}(p_a,1;\phi)} \left[1 - 1_c\left(1,1;\theta\right)\right] \frac{\partial}{\partial p_a} v(p_a,1;\phi) g(\psi|\phi) d\psi \right) dK(\phi) \\
&- \int \left(\int_{\bar{\psi}(p_a,1;\phi)}^{\infty} \left[1 - 1_c\left(1,1;\theta\right)\right] \frac{\partial}{\partial p_a} v(p_a,\infty;\phi) g(\psi|\phi) d\psi \right) dK(\phi)
\end{aligned}
$$

and using the derivative of the indirect utility function:

$$\frac{\partial}{\partial p_a}\int\left[1-1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi)-\mathcal{V}(p_a,1;\theta)\right]dF(\theta)$$
$$=\int\left(\int_{\underline{\psi}}^{\bar{\psi}(p_a,1;\phi)}\left[1-1_c\left(1,1;\theta\right)\right]\tilde{a}(p_a,1;\phi)g(\psi|\phi)d\psi\right)dK(\phi)$$
$$+\int\left(\int_{\bar{\psi}(p_a,1;\phi)}^{\infty}\left[1-1_c\left(1,1;\theta\right)\right]\tilde{a}(p_a,\infty;\phi)g(\psi|\phi)d\psi\right)dK(\phi)$$

which can also be written, using the characterization of optimality the extensive margin decision as:

$$\frac{\partial}{\partial p_a}\int\left[1-1_c\left(1,1;\theta\right)\right]\left[v(1,\infty;\phi)-\mathcal{V}(p_a,1;\theta)\right]dF(\theta)$$
$$=\int\left[1-1_c\left(1,1;\theta\right)\right]a^*(p_a,1;\theta)dF(\theta)$$

Putting the two parts together we have:

$$\frac{\partial}{\partial p_a}\mathcal{CS}(p_a,1)=A(p_a,1)\,.$$

Using the definition we can verify that $\mathcal{CS}(1,1)=0$. Thus

$$\mathcal{CS}(p_a,1)=\int_1^{p_a}A(p,1)dp\,.$$

□

B Details on the Rider's Model

This section presents some details on the rider's model.

B.1 CES Sub-utility for Means of Payments Choice

Let $H(a,c) = \left[\alpha^{\frac{1}{\eta}} c^{\frac{\eta-1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} a^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$ so α and $1-\alpha$ are the share of rides in credit and cash when both prices are the same, i.e. if $p_a = p_c = 1$. The parameter η is the elasticity of substitution.

The optimal credit and cash trips, which minimize expenditure subject to obtaining one util of composite trips are:

$$c(p_a, p_c) = c\left(\frac{p_a}{p_c}, 1\right) = \alpha\left[\alpha + (1-\alpha)\left(\frac{p_a}{p_c}\right)^{1-\eta}\right]^{\frac{\eta}{1-\eta}}$$

$$a(p_a, p_c) = a\left(\frac{p_a}{p_c}, 1\right) = (1-\alpha)\left[\alpha\left(\frac{p_c}{p_a}\right)^{1-\eta} + (1-\alpha)\right]^{\frac{\eta}{1-\eta}}$$

Note that $c(p,p) = \alpha$ and $a(p,p) = 1-\alpha$, i.e. α and $1-\alpha$ are the shares at equal prices. Note also that, as standard:

$$\frac{a(p_a, p_c)}{c(p_a, p_c)} = \frac{1-\alpha}{\alpha}\left(\frac{p_a}{p_c}\right)^{-\eta}$$

The ideal price index is:

$$\mathbb{P}(p_a, p_c) = \left[\alpha p_c^{1-\eta} + (1-\alpha) p_a^{1-\eta}\right]^{\frac{1}{1-\eta}}$$

B.2 Exponential Utility for Composite Rides

Let denote the aggregate composite trips by x. Assume that:

$$U(x) = -k\exp\left(-\left(x+\bar{x}\right)/k\right)$$

We are interested in:

$$U'(x) = P$$

or

$$\exp\left(-\left(x+\bar{x}\right)/k\right) = P \text{ or } -\left(x+\bar{x}\right)/k = \log P \text{ or } x = -k\log P - \bar{x}$$

In general:

$$X(P) = -k \log P - \bar{x}$$

The choke point is:

$$X(\bar{P}) = 0 = -k \log \bar{P} - \bar{x} \text{ or } \log \bar{P} = -\bar{x}/k$$

Demand, Choke price and elasticity. Note we can write:

$$X(P) = -k \log P + k \log \bar{P} \tag{27}$$

so that the intercept divided by the slope is the choke point. Also note:

$$\begin{aligned} -P\frac{\partial X(P)}{\partial P} &= k \text{ thus} \\ -\frac{P}{X(P)}\frac{\partial X(P)}{\partial p} &= \frac{k}{k\log(\bar{P}/P)} = \frac{1}{\log(\bar{P}/P)} \text{ or} \\ \bar{P}/P &= \exp\left(\frac{1}{-\frac{P}{X(P)}\frac{\partial X(P)}{\partial P}}\right) \end{aligned}$$

We can define the elasticity as:

$$\epsilon(P) \equiv -\frac{P}{X(P)}\frac{\partial X(P)}{\partial P}$$

$$\bar{P}/P = \exp\left(\frac{1}{\epsilon(P)}\right)$$

Consumer Surplus for composite trips. We define the consumer surplus as:

$$C(P_0) = \int_{P_0}^{\bar{P}} X(p)dp$$

so using the form of the demand as well as the first order conditions, we have:

$$\begin{aligned} C(P_0) = \int_{P_0}^{\bar{P}} X(p)dp &= -k\int_{P_0}^{\bar{P}} \log p dp + [-\bar{x}]\,(\bar{P} - P_0) \\ &= k(\bar{P} - P_0) - P_0 X(P_0) \end{aligned}$$

which are, in principle, observables, since we can estimate k and $\bar{p}$. To see that the consumer surplus is positive note that:

$$C(P_0) = k\left[\left(\bar{P} - P_0\right) - P_0\left(\log \bar{P} - \log P_0\right)\right] > 0$$

where the inequality follows from the concavity of log. Note that :

$$C(P_0) = kP_0\left(\frac{\bar{P} - P_0}{P_0}\right)^2 + o\left(\left(\bar{P} - P_0\right)^2\right)$$

We can normalize the consumer surplus by the current revenue:

$$\frac{C(P_0)}{P_0 X(P_0)} = \frac{k}{X(P_0)}\frac{(\bar{P} - P_0)}{P_0} - 1 = \epsilon(P_0)\left[\exp\left(\frac{1}{\epsilon(P_0)}\right) - 1\right] - 1$$

where $\epsilon(P_0)$ is the elasticity evaluated at p_0. Note that expanding the exponential up to second order only we get:

$$\frac{C(P_0)}{P_0 X(P_0)} > \epsilon(P_0)\left[1 + \frac{1}{\epsilon(P_0)} + \frac{1}{2}\left(\frac{1}{\epsilon(P_0)}\right)^2 - 1\right] - 1 = \frac{1}{2}\frac{1}{\epsilon(P_0)}$$

which is the expression for a linear demand. The inequality follows because the remaining terms in the MacLaurin expansion are all positive. As $\epsilon(P_0) \to \infty$, the two expression converge.

B.3 Demand Functions for Different Users Types

In this section we use the demand for composite rides coming from an exponential utility function $U(\cdot)$ described by parameters k, λ and $\bar{P}$, as well as CES sub-utility H, which share parameter α for credit and with elasticity of substitution η. Note that composite rids equal total rides only when both means of payment are available. In what follows, we consider several other cases:

1. Mixed users cash demand when facing $p = p_a = p_c$:

$$\tilde{a}(p, p) = \begin{cases} (1-\alpha)k \log \bar{P} - (1-\alpha)k \log p & \text{if } p < \bar{P} \\ 0 \text{ otherwise} & \end{cases}$$

2. Mixed users cash demand for arbitrary prices (p_a, p_c):

$$\tilde{a}(p_a, p_c) = \begin{cases} (1-\alpha)k \left(\frac{p_a}{\mathbb{P}(p_a,p_c)}\right)^{-\eta} \left[\log\left(\frac{\bar{P}}{\mathbb{P}(p_a,p_c)}\right)\right] & \text{if } \mathbb{P}(p_a, p_c) \leq \bar{P} \\ 0 & \text{if } \mathbb{P}(p_a, p_c) > \bar{P} \end{cases}$$

3. Mixed users cash demand for arbitrary cash price p_a but fixed credit price $p_c = 1$:

$$\tilde{a}(p_a, 1) = \begin{cases} k(1-\alpha) \left(\frac{p_a}{\mathbb{P}(p_a,1)}\right)^{-\eta} \log\left(\frac{\bar{P}}{\mathbb{P}(p_a,1)}\right) & \text{if } \mathbb{P}(p_a, 1) < \bar{P} \\ 0 & \text{otherwise} \end{cases}$$

4. Pure cash users, i.e. users facing arbitrary p_a but infinite credit price $p_c = \infty$.

$$\tilde{a}(p_a, \infty) = \begin{cases} k(1-\alpha)^{\frac{1}{1-\eta}} \left[\log\left(\frac{\bar{P}}{(1-\alpha)^{\frac{1}{1-\eta}}}\right)\right] - k(1-\alpha)^{\frac{1}{1-\eta}} \log p_a & \text{if } (1-\alpha)^{\frac{1}{1-\eta}} p_a < \bar{P} \\ 0 & \text{otherwise} \end{cases}$$

5. Pure credit users, i.e. credit demand when facing arbitrary p_c but infinite cash price $p_a = \infty$.

$$\tilde{c}(\infty, p_c) = \begin{cases} k\alpha^{\frac{1}{1-\eta}} \left[\log\left(\frac{\bar{P}}{\alpha^{\frac{1}{1-\eta}}}\right)\right] - k\alpha^{\frac{1}{1-\eta}} \log p_c & \text{if } \alpha^{\frac{1}{1-\eta}} p_c < \bar{P} \\ 0 & \text{otherwise} \end{cases}$$

Note that if $p_c = p_a = 1$, when both means of payments are available, total trips $T = X(1) = k \ln \bar{P}$. This is because the total demand for trips paid in credit is $\tilde{c}(1,1) = \alpha X(1)$ and the total demand for trips paid in cash is $\tilde{a}(1,1) = (1-\alpha)X(1)$ so that $T = \tilde{c}(1,1) + \tilde{a}(1,1) = X(1)$.

B.4 Indirect Utility

Let U be exponential $U(x) = -\exp\left(-(x+\bar{x})/k\right)/k$ and $H(a,c) = \left[\alpha c^{1-\frac{1}{\eta}} + (1-\alpha)a^{1-\frac{1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$ CES as above.

The indirect utility $v(p_a, p_c)$ is thus

$$v(p_a, p_c) = U(X(P)) + (I - PX(P)) = -ke^{-X(P)/k}e^{-\bar{x}/k} + (I - PX(P))$$

Using that the demand is $X(P) = -k\log(P/\bar{P})$ and $e^{-\bar{x}/k} = \bar{P}$ we have:

$$v(p_a, p_c) = -ke^{\log P/\bar{P}}\bar{P} + (I + Pk\log(P/\bar{P})) = -k\frac{P}{\bar{P}}\bar{P} + (I + Pk\log(P/\bar{P}))$$

Thus the indirect utility, in terms of the numeraire:

$$v(p_a, p_c) = \begin{cases} k\mathbb{P}(p_a, p_c)\left[\log(\mathbb{P}(p_a, p_c)/\bar{P}) - 1\right] + kI & \text{if } \mathbb{P}(p_a, p_c) \leq \bar{P} \\ -k\bar{P} + kI & \text{if } \mathbb{P}(p_a, p_c) > \bar{P} \end{cases}$$

Indirect Utilities for selected cases

1. Mixed user

$$v(1, 1) = -k + kI - k\log\bar{P}$$

2. Pure cash user

$$v(1, \infty) = \begin{cases} k(1-\alpha)^{\frac{1}{1-\eta}}\left[\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] + kI & (1-\alpha)^{\frac{1}{1-\eta}} \leq \bar{P} \\ -k\bar{P} + kI & \text{if } (1-\alpha)^{\frac{1}{1-\eta}} > \bar{P} \end{cases}$$

3. Pure credit user

$$v(\infty, 1) = \begin{cases} k\alpha^{\frac{1}{1-\eta}}\left[\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] + kI & \alpha^{\frac{1}{1-\eta}} \leq \bar{P} \\ -k\bar{P} + kI & \text{if } \alpha^{\frac{1}{1-\eta}} > \bar{P} \end{cases}$$

4. Non-Uber user

$$v(\infty, \infty) = -k\bar{P} + kI$$

Indirect Utility Comparisons:

1. Indirect utility of Mixed users vs. Pure credit users, relative to total trips (or fares) of mixed users:

$$\frac{v(1,1) - v(\infty,1)}{(c^*(1,1) + a^*(1,1)))} = \begin{cases} \frac{1}{\log\bar{P}}\left[-\log(\bar{P}) - 1 + \bar{P}\right] & \text{if } \alpha^{\frac{1}{1-\eta}} \geq \bar{P} \\ \frac{1}{\log\bar{P}}\left[-\log(\bar{P}) - 1 - \alpha^{\frac{1}{1-\eta}}\left(\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right)\right] & \text{otherwise} \end{cases} \quad (28)$$

2. Indirect utility of Pure cash users vs. non Uber-users

$$\frac{v(1,\infty)-v(\infty,\infty)}{a^*(1,\infty)} = \begin{cases} \frac{\frac{\bar{P}}{(1-\alpha)^{\frac{1}{1-\eta}}}-1}{\log\left(\frac{\bar{P}}{(1-\alpha)^{\frac{1}{1-\eta}}}\right)} - 1 & \text{if } \bar{P} > (1-\alpha)^{\frac{1}{1-\eta}} \\ 0 & \text{otherwise} \end{cases}$$

and

$$v(1,\infty)-v(\infty,\infty) = \begin{cases} k(1-\alpha)^{\frac{1}{1-\eta}}\left[\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\bar{P}}\right)-1\right]+k\bar{P} & \text{if } \bar{P} > (1-\alpha)^{\frac{1}{1-\eta}} \\ 0 & \text{otherwise} \end{cases}$$

3. Indirect utility of Pure credit users vs. non Uber-users

$$\frac{v(\infty,1)-v(\infty,\infty)}{a^*(1,\infty)} = \begin{cases} \frac{\frac{\bar{P}}{\alpha^{\frac{1}{1-\eta}}}-1}{\log\left(\frac{\bar{P}}{\alpha^{\frac{1}{1-\eta}}}\right)} - 1 & \text{if } \bar{P} > \alpha^{\frac{1}{1-\eta}} \\ 0 & \text{otherwise} \end{cases}$$

and

$$v(\infty,1)-v(\infty,\infty) = \begin{cases} k\alpha^{\frac{1}{1-\eta}}\left[\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right)-1\right]+k\bar{P} & \text{if } \bar{P} > \alpha^{\frac{1}{1-\eta}} \\ 0 & \text{otherwise} \end{cases}$$

4. Indirect utility of Mixed Users vs Pure cash Users

$$\frac{v(1,1)-v(1,\infty)}{a^*(1,\infty)} = \begin{cases} \frac{1}{0}\left[-\log(\bar{P})-1+\bar{P}\right] & \text{if } (1-\alpha)^{\frac{1}{1-\eta}} \geq \bar{P} \text{ and otherwise} \\ \frac{1}{(1-\alpha)^{\frac{1}{1-\eta}}\log\bar{P}}\left[-\log(\bar{P})-1-(1-\alpha)^{\frac{1}{1-\eta}}\left(\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\bar{P}}\right)-1\right)\right] & \end{cases}$$

and

$$v(1,1)-v(1,\infty) = \begin{cases} k\left[-\log(\bar{P})-1+\bar{P}\right] & \text{if } (1-\alpha)^{\frac{1}{1-\eta}} \geq \bar{P} \text{ and otherwise} \\ k\left[-\log(\bar{P})-1-(1-\alpha)^{\frac{1}{1-\eta}}\left(\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\bar{P}}\right)-1\right)\right] & \end{cases}$$

B.5 Heterogeneity of Mixed Users

Index riders by i and assume that $\bar{P}_i$ is rider specific. Assume that the demands of total trips by mixed riders facing $P = p_a = p_c$ can be written as:

$$x_i = k \log \bar{P}_i - k \log P = \beta_{0i} + \beta_1 \log P$$

Thus we assume that k, and hence the slope of the regression, be common across riders. We can then write:

$$\log \bar{P}_i = \frac{\beta_{0i}}{\beta_1}$$

The rider specific elasticity is thus

$$\log \bar{P}_i / \log P = 1/\epsilon_i(P) \text{ or } \log P / \log \bar{P}_i = \epsilon_i(P)$$

and evaluating it at $P = 1$:

$$\log \bar{P}_i = 1/\epsilon_i(1)$$

Thus

$$1/\epsilon_i(1) = \log \bar{P}_i = \frac{\beta_{0i}}{\beta_1} \text{ or } \epsilon_i(1) = \frac{\beta_1}{\beta_{0i}}$$

Note that if we normalize the price to $P = p_a = p_c = 1$, then we are measuring x in fares. Thus, we first estimate the elasticity with a regression in our experimental data of:

$$X_i = \beta_0 + \beta_1 \log P$$

so that β_0 has the interpretation of the fares of the control group. Given the randomization the control group has the same average fares, pre-experiment, as the treatment groups. We let:

$$\epsilon(1) = \beta_1/\beta_0$$

Then we can correct the elasticities to other groups with different fares as follows:

$$\epsilon_i(1) = \frac{\beta_1}{\beta_0}\frac{\beta_0}{\beta_{0,i}} \approx \epsilon(1)\,\frac{Avg\,Fare}{Fare_i}$$

B.6 Random Quasi-linear Utility Test

Table B1: Random Quasi-linear Utility Test: Experiment 1 (Mixed Users)

Note: The table shows descriptive statistics of the mixed users that were part of the experiment described in the main text. The table reports statistics for the control group and the six treatment groups. The variables reported are those use to test that the users in the experiment were maximizing some quasi-linear utility function. The variables reported are the average trips per user, trips paid in cash per user, fares per user, fare paid in cash per user, total users, and the prices faced by users in the control group and the six treatment groups.

	(1) Trips	(2) Trips Cash	(3) Fares	(4) Fares Cash	(5) Users	(6) Price Cash	(7) Price Credit
Control	0.79	0.31	4.20	1.44	87001	1	1
Treatment 1	0.86	0.38	4.49	1.80	11078	0.9	1
Treatment 2	0.87	0.30	4.63	1.44	11209	1	0.9
Treatment 3	0.88	0.35	4.59	1.67	11175	0.9	0.9
Treatment 4	0.84	0.40	4.40	1.90	11204	0.8	1
Treatment 5	0.88	0.28	4.69	1.29	11261	1	0.8
Treatment 6	0.98	0.39	5.25	1.86	11189	0.8	0.8

Table B2: Random Quasi-linear Utility Test: Experiment 2 (Pure Cash Users)

Note: The table shows descriptive statistics of the pure cash users that were part of the experiment described in the main text. The table reports statistics for the control group and the four treatment groups. The variables reported are those use to test that the users in the experiment were maximizing some quasi-linear utility function. The variables reported are the average trips per user, fares per user, total users, and the prices faced by users in the control group and the four treatment groups.

	(1) Trips	(2) Fares	(3) Users	(4) Price
Control	0.37	1.66	54779	1
Treatment 1	0.41	1.81	22841	0.9
Treatment 2	0.45	2.02	22827	0.85
Treatment 3	0.48	2.17	22836	0.8
Treatment 4	0.51	2.31	22840	0.75

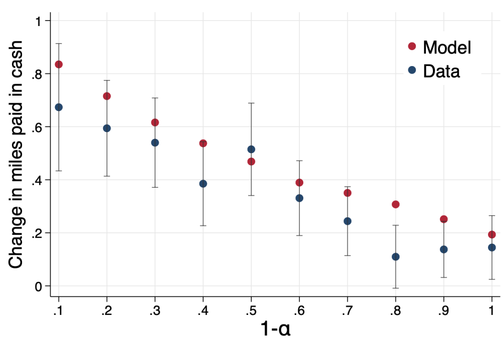
B.7 Implied Elasticities of Mixed Users' Demand for Cash Trips

In this Appendix, we compute the price elasticities of mixed users' demand for cash trips using our structural model – evaluated at the estimated parameters – and compare them with the observed elasticities from the experimental data. In particular, we compare the two elasticities obtained after giving riders discounts on cash trips in Experiment 1; recall that, while there are six treatment groups, only two of them, treatment (i) and treatment (iv), involved discounts conditional on paying only with cash.

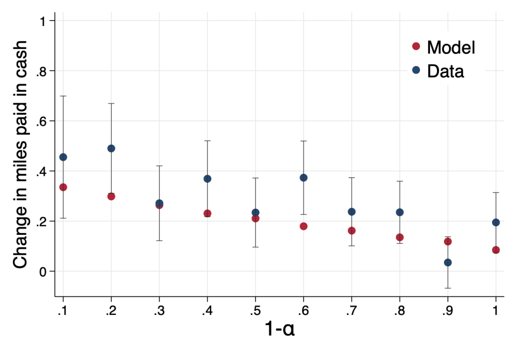
Figure B1 compares the observed percent change in miles paid in cash with those predicted by our model for each decile of the riders' historical cash share. In the data, the riders' elasticities are estimated as the difference between the average number of miles of riders in the treatment and control groups for each of the two discounts. In the model, we use our preferred parameter estimates (i.e. $\eta = 3$ and $\epsilon = 1.1$) to compute the elasticities implied by mixed users' cash demand described in Section B.3 together with a choice of $\bar{P}$ to match the historical cash fares of each rider. Note that η and ϵ are estimated using different price changes; they are estimated using either all six treatment groups in Experiment 1 or using only the treatment groups where Uber prices are the same for rides paid in cash and paid with cards. Figure B1 shows that the model predictions are roughly in line with the observed elasticities for both 20% and 10% discounts on trips paid with cash.

Figure B1: Elasticity of Demand: Trips Paid in Cash (Model vs Data)

(a) 20% off trips paid with cash



(b) 10% off trips paid with cash



Note: Panel (a) shows the percent change in miles paid in cash for mixed users that received 20% off for trips paid in cash (relative to the control group) for different deciles of riders' cash share. Panel (b) shows the percent change in miles paid in cash for mixed users that received 10% off for trips paid in cash (relative to the control group) for different deciles of riders' cash share. The estimates are computed using experimental data collected in the State of Mexico. The vertical lines are 95% standard error bands. The estimates include mixed users with more than 1% of their fares paid in cash and less than 99%. In both panels, the red dots indicate the changes in miles paid in cash for mixed users predicted by the model using $\eta = 3$ and $\epsilon = 1.1$.

C Experiments

C.1 Descriptive Statistics: Experiments

Table C1: Summary Statistics: Experiments

Note: The table reports summary statistics of the users included in the experimental data. Pure cash users are those that have not registered a card in the application. Mixed users are those that have a registered card and have used both payment methods. Column (2) includes users with more than 1% of their fares paid in cash and less than 99%. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Pure credit users are those that have never used cash as a payment method. The table reports the mean of historical variables such as fares, trips, fares in cash, trips paid in cash, share of fares paid in cash, and tenure. All the variables, except for tenure, are computed for the weeks of the calendar year when the experiment took place. The table also reports the average of the fares, trips, fares in cash, and trips paid in cash during the week of the experiment.

	(1) Pure Cash	(2) Mixed 1%	(3) Mixed 5%	(4) Pure Credit
Fares per week (historical)	1.54	4.26	3.84	3.58
Trips per week (historical)	0.36	0.83	0.76	0.52
Fares per week cash (historical)	1.54	1.57	1.57	0.00
Trips per week cash (historical)	0.36	0.34	0.34	0.00
Share of fares cash (historical)	1.00	0.43	0.45	0.00
Tenure in weeks (historical)	42.99	74.52	72.92	90.61
Fares week (experiment)	1.73	4.35	3.94	3.88
Trips week (experiment)	0.40	0.82	0.76	0.55
Fares cash week (experiment)	1.73	1.51	1.51	0.00
Trips cash week (experiment)	0.40	0.32	0.32	0.00
Users	138725	109365	98773	88844

Table C2: Summary Statistics: Ubernomics

Note: The table reports summary statistics of the users included in the Ubernomics experiment. Pure cash users are those that have not registered a card in the application. Mixed users are those that have a registered card and have used both payment methods. Column (2) includes users with more than 1% of their fares paid in cash and less than 99%. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Pure credit users are those that have never used cash as a payment method. The table reports the mean of historical variables such as fares, trips, fares in cash, trips paid in cash, share of fares paid in cash, and tenure. All the variables, except for tenure, are computed for the weeks of the calendar year when the experiment took place. The table also reports the average of the fares, trips, fares in cash, and trips paid in cash during the week of the experiment.

	(1) Pure Cash	(2) Mixed 1%	(3) Mixed 5%	(4) Pure Credit
Fares per week (historical)	1.43	5.29	4.56	5.16
Trips per week (historical)	0.36	1.11	0.98	1.02
Fares per week cash (historical)	1.43	1.33	1.44	0.00
Trips per week cash (historical)	0.36	0.31	0.33	0.00
Share of fares cash (historical)	1.00	0.33	0.37	0.00
Tenure in weeks (historical)	47.36	88.80	85.53	114.83
Fares week (experiment)	3.00	7.00	6.34	6.55
Trips week (experiment)	0.73	1.40	1.27	1.19
Fares cash week (experiment)	2.91	2.22	2.39	0.00
Trips cash week (experiment)	0.71	0.49	0.53	0.00
Users	4869	4306	3719	26162

Table C3: Summary Statistics: Mandin

Note: The table reports summary statistics of the users included in the Mandin experiment. Pure cash users are those that have not registered a card in the application. Mixed users are those that have a registered card and have used both payment methods. Column (2) includes users with more than 1% of their fares paid in cash and less than 99%. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Pure credit users are those that have never used cash as a payment method. The table reports the mean of historical variables such as fares, trips, fares in cash, trips paid in cash, share of fares paid in cash, and tenure. All the variables, except for tenure, are computed for the weeks of the calendar year when the experiment took place. The table also reports the weekly average of the fares, trips, fares in cash, and trips paid in cash during the weeks of the experiment.

	(1) Pure Cash	(2) Mixed 1%	(3) Mixed 5%	(4) Pure Credit
Fares per week (historical)	4.30	12.32	10.61	11.53
Trips per week (historical)	1.08	2.37	2.10	2.12
Fares per week cash (historical)	4.30	3.27	3.65	0.00
Trips per week cash (historical)	1.08	0.71	0.79	0.00
Share of fares cash (historical)	1.00	0.34	0.39	0.00
Tenure in weeks (historical)	50.91	86.15	82.23	115.73
Fares week (experiment)	6.74	14.68	13.21	13.10
Trips week (experiment)	1.66	2.87	2.65	2.47
Fares cash week (experiment)	6.43	4.03	4.48	0.00
Trips cash week (experiment)	1.60	0.89	0.98	0.00
Users	5668	11660	9254	47849

C.2 CES

If H is a CES we obtain the following expression for the ratio of expenditure:

$$\frac{p_a a}{p_c c} = \left(\frac{1-\alpha}{\alpha}\right)\left(\frac{p_a}{p_c}\right)^{1-\eta} \tag{29}$$

using the identity

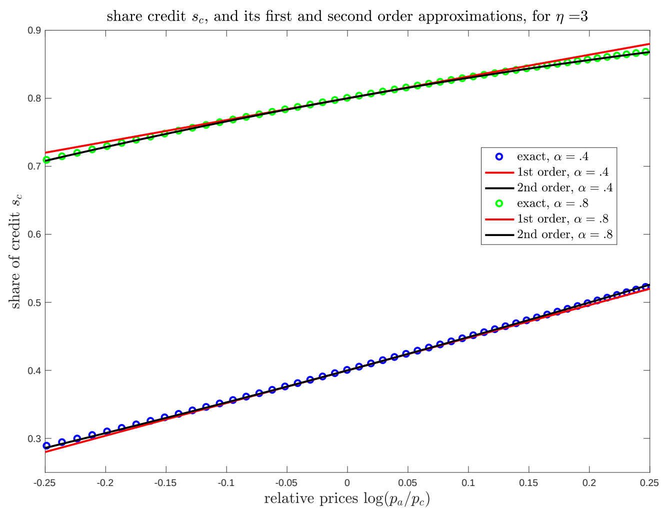
$$s_c = \frac{p_c c}{p_a a + p_c c} = \frac{1}{1 + (p_a a)/(p_c c)} \tag{30}$$

thus

$$s_c = \frac{1}{1 + \left(\frac{1-\alpha}{\alpha}\right)\left(\frac{p_a}{p_c}\right)^{1-\eta}} \tag{31}$$

A first order approximation of s_c around $\log(p_a/p_c) = 0$ gives equation (21). A second order approximation of s_c around $\log(p_a/p_c) = 0$ gives equation (22). Note that the second order approximation can be convex or concave depending on whether $\alpha \geq 1/2$ or not. Figure C1 plots the exact expression given by equation (31) and its first and second order approximation given by equation (21) and equation (22) respectively. The range of the x-axis coincides with the range on variability on the relative prices the experiment for mixed users. The value $\eta = 3$ used for the elasticity of substitution in the figure is our preferred estimate. We plot the exact expression for s_c and its two approximations for two values of α, one above 1/2 and one below. From Figure C1 we conclude that for this range of parameters the first order approximation is very accurate and the second order approximation is almost exact.

Figure C1: Quality of the approximations



Note: The figure plots the share of credit s_c for $\eta = 3$ for two values of α. For each α we plot the exact expression, the first order approximation, and the second order approximation.

C.3 Estimation of Elasticities

C.3.1 Elasticity of Demand: Pure Cash Users

Table C4: Semi-Elasticity of Demand: Pure Cash Users (Miles)

Note: The table reports the semi-elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-2.035***	-2.044***	-6.611***	-2.331**
	(0.127)	(0.116)	(0.982)	(1.189)
Observations	138,725	138,725	4,279	3,569
R-squared	0.002	0.174	0.448	0.181
$\hat{y}$	1.479	1.478	5.937	2.869
Controls	No	Yes	Yes	Yes

Table C5: Elasticity of Demand: Pure Cash Users (Miles - at Least 5 Trips)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Elasticity	1.351***	1.345***	1.138***	0.825*
	(0.105)	(0.082)	(0.176)	(0.464)
Observations	88,326	88,326	3,394	1,869
Controls	No	Yes	Yes	Yes

Table C6: Semi-Elasticity of Demand: Pure Cash Users (Miles - at Least 5 Trips)

Note: The table reports the semi-elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-2.842***	-2.831***	-7.678***	-3.696*
	(0.189)	(0.174)	(1.185)	(2.080)
Observations	88,326	88,326	3,394	1,869
R-squared	0.003	0.159	0.435	0.139
$\hat{y}$	2.104	2.105	6.748	4.482
Controls	No	Yes	Yes	Yes

Table C7: Elasticity of Demand: Pure Cash Users (Trips)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (27) using trips as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Elasticity	1.271***	1.270***	1.080***	1.218***
	(0.093)	(0.071)	(0.157)	(0.384)
Observations	138,725	138,725	4,279	3,569
Controls	No	Yes	Yes	Yes

Table C8: Semi-Elasticity of Demand: Pure Cash Users (Trips)

Note: The table reports the semi-elasticity of demand of pure cash users estimated using equation (27) using trips as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-0.440***	-0.440***	-1.586***	-0.820***
	(0.028)	(0.024)	(0.230)	(0.259)
Observations	138,725	138,725	4,279	3,569
R-squared	0.002	0.214	0.485	0.216
$\hat{y}$	0.346	0.346	1.468	0.674
Controls	No	Yes	Yes	Yes

Table C9: Elasticity of Demand: Pure Cash Users (Trips - Poisson)

Note: The table reports the elasticity of demand of pure cash users estimated using a poisson a regression using trips as dependent variable and the log of prices as independent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-1.094***	-1.110***	-0.795***	-1.091***
	(0.039)	(0.039)	(0.107)	(0.217)
Observations	138,725	138,725	4,279	3,569
Controls	No	Yes	Yes	Yes

C.3.2 Elasticity of Demand: Mixed Users

Table C10: Semi-Elasticity of Demand: Mixed Users (Miles)

Note: The table reports the semi-elasticity of demand of mixed users estimated using equation (27) using miles as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, share of fares paid in cash, cash trips, and cash trips squared. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Log Price	-4.543***	-4.334***	-4.165***	-16.292***	-9.409***
	(0.416)	(0.360)	(0.355)	(0.962)	(1.921)
Observations	109,365	109,365	98,773	11,660	4,306
R-squared	0.001	0.253	0.232	0.550	0.243
$\hat{y}$	4.199	4.206	3.800	12.744	6.478
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

Table C11: Elasticity of Demand: Mixed Users (Miles - at Least 5 Trips)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, share of fares paid in cash, cash trips, and cash trips squared. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Elasticity	1.096***	1.041***	1.109***	1.263***	1.428***
	(0.103)	(0.086)	(0.095)	(0.075)	(0.300)
Observations	97,586	97,586	87,014	11,282	3,930
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

Table C12: Semi-Elasticity of Demand: Mixed Users (Miles - at Least 5 Trips)

Note: The table reports the semi-elasticity of demand of mixed users estimated using equation (27) using miles as dependent variable. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, share of fares paid in cash, cash trips, and cash trips squared. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Log Price	-5.069***	-4.820***	-4.684***	-16.502***	-9.942***
	(0.460)	(0.400)	(0.399)	(0.986)	(2.089)
Observations	97,586	97,586	87,014	11,282	3,930
R-squared	0.001	0.244	0.223	0.545	0.232
$\hat{y}$	4.624	4.632	4.223	13.067	6.963
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

Table C13: Elasticity of Demand: Mixed Users (Trips)

Note: The table reports the elasticity of demand of mixed users estimated using equation (27) using trips as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, share of fares paid in cash, cash trips, and cash trips squared. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Elasticity	1.106***	1.050***	1.084***	1.175***	1.235***
	(0.094)	(0.076)	(0.082)	(0.068)	(0.262)
Observations	109,365	109,365	98,773	11,660	4,306
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

Table C14: Semi-Elasticity of Demand: Mixed Users (Trips)

Note: The table reports the semi-elasticity of demand of mixed users estimated using equation (27) using trips as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, share of fares paid in cash, cash trips, and cash trips squared. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	AA	AA	AA	Mandin	Ubernomics
Log Price	-0.878***	-0.835***	-0.791***	-2.964***	-1.617***
	(0.071)	(0.060)	(0.060)	(0.171)	(0.343)
Observations	109,365	109,365	98,773	11,660	4,306
R-squared	0.001	0.292	0.274	0.557	0.299
$\hat{y}$	0.794	0.795	0.730	2.522	1.309
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

Table C15: Elasticity of Demand: Mixed Users (Trips - Poisson)

Note: The table reports the elasticity of demand of mixed users estimated using a poisson a regression using trips as dependent variable and the log of prices as independent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, share of fares paid in cash, cash trips, and cash trips squared. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	AA	AA	AA	Mandin	Ubernomics
Log Price	-0.996***	-0.998***	-0.998***	-0.829***	-1.133***
	(0.044)	(0.044)	(0.048)	(0.043)	(0.145)
Observations	109,365	109,365	98,773	11,660	4,306
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

C.3.3 Elasticity of Demand: Pure Credit Users

Table C16: Elasticity of Demand: Pure Credit Users (Miles)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Elasticity	0.622***	0.604***	0.776***	0.375***
	(0.114)	(0.092)	(0.037)	(0.121)
Observations	88,844	88,844	47,849	26,162
Controls	No	Yes	Yes	Yes

Table C17: Semi-Elasticity of Demand: Pure Credit Users (Miles)

Note: The table reports the semi-elasticity of demand of pure credit users estimated using equation (27) using miles as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-2.331***	-2.265***	-9.328***	-2.411***
	(0.411)	(0.347)	(0.439)	(0.779)
Observations	88,844	88,844	47,849	26,162
R-squared	0.000	0.290	0.595	0.345
$\hat{y}$	3.745	3.749	12.014	6.423
Controls	No	Yes	Yes	Yes

Table C18: Elasticity of Demand: Pure Credit Users (Miles - at Least 5 Trips)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (27) using miles as dependent variable. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Elasticity	0.608***	0.579***	0.771***	0.376***
	(0.116)	(0.095)	(0.037)	(0.125)
Observations	64,648	64,648	45,036	21,141
Controls	No	Yes	Yes	Yes

Table C19: Semi-Elasticity of Demand: Pure Credit Users (Miles - at Least 5 Trips)

Note: The table reports the semi-elasticity of demand of pure credit users estimated using equation (27) using miles as dependent variable. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-2.957***	-2.824***	-9.671***	-2.850***
	(0.546)	(0.464)	(0.461)	(0.948)
Observations	64,648	64,648	45,036	21,141
R-squared	0.000	0.276	0.588	0.331
$\hat{y}$	4.868	4.875	12.546	7.585
Controls	No	Yes	Yes	Yes

Table C20: Elasticity of Demand: Pure Credit Users (Trips)

Note: The table reports the elasticity of demand of pure credit users estimated using equation (27) using trips as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Elasticity	0.732***	0.707***	0.693***	0.408***
	(0.103)	(0.080)	(0.033)	(0.110)
Observations	88,844	88,844	47,849	26,162
Controls	No	Yes	Yes	Yes

Table C21: Semi-Elasticity of Demand: Pure Credit Users (Trips)

Note: The table reports the semi-elasticity of demand of pure credit users estimated using equation (27) using trips as dependent variable. Column (1) reports the estimates without using controls. Column (2) estimates the semi-elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-0.387***	-0.375***	-1.585***	-0.477***
	(0.052)	(0.043)	(0.075)	(0.128)
Observations	88,844	88,844	47,849	26,162
R-squared	0.001	0.332	0.639	0.396
$\hat{y}$	0.529	0.530	2.287	1.169
Controls	No	Yes	Yes	Yes

Table C22: Elasticity of Demand: Pure Credit Users (Trips - Poisson)

Note: The table reports the elasticity of demand of pure credit users estimated using a poisson a regression using trips as dependent variable and the log of prices as independent variable. Column (1) reports the estimates without using controls. Column (2) estimates the elasticity using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3) reports the results using the users included in the Mandin experiment. Column (4) reports the results using the users included in the Ubernomics experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	AA	AA	Mandin	Ubernomics
Log Price	-0.681***	-0.680***	-0.507***	-0.361***
	(0.052)	(0.051)	(0.024)	(0.066)
Observations	88,844	88,844	47,849	26,162
Controls	No	Yes	Yes	Yes

C.3.4 Elasticity of Substitution: Cash-Credit

Table C23: Semi-Elasticity of Substitution: Mixed Users (Miles)

Note: The table reports estimates of the semi-elasticity of substitution between cash and credit for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. Column (1) reports the results of estimating γ using the transformed share specification denoted in equation (23) and including mixed users with more than 1% of their fares paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Column (4) includes the constant specified in equation (23) as a regressor. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Log Price	0.284***	0.262***	0.285***	0.255***
	(0.021)	(0.018)	(0.020)	(0.017)
Observations	53,966	53,966	46,328	53,966
R-squared	0.003	0.222	0.174	0.304
Controls	No	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct
Specification	Transf.	Transf.	Transf.	Translog-Constant

Table C24: Elasticity of Substitution: Mixed Users (Miles - at Least 5 Trips)

Note: The table reports estimates of the elasticity of substitution between cash and credit for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the results after using the transformed share specification denoted in equation (23) and including mixed users with more than 1% of their fares paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Column (4) includes the constant specified in equation (23) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (21). Column (6) estimates the elasticity using the CES second order approximation in equation (22). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predicted share of fares paid in credit (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (21) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elasticity	3.169***	2.893***	2.620***	2.992***	2.569***	2.569***	2.241***
	(0.373)	(0.349)	(0.181)	(0.217)	(0.103)	(0.103)	(0.080)
Obs.	52,562	52,562	44,927	52,562	52,562	52,562	67,984
Controls	No	Yes	Yes	Yes	Yes	Yes	No
Type	1 pct	1 pct	5 pct	1 pct	1 pct	1 pct	1 pct
Spec.	Transf.	Transf.	Transf.	Transf.-Cons	CES - First	CES - Second	CES - First IV

Table C25: Semi-Elasticity of Substitution: Mixed Users (Miles - at Least 5 Trips)

Note: The table reports estimates of the semi-elasticity of substitution between cash and credit for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the results of estimating γ using the transformed share specification denoted in equation (23) and including mixed users with more than 1% of their fares paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Column (4) includes the constant specified in equation (23) as a regressor. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Log Price	0.275***	0.253***	0.276***	0.247***
	(0.021)	(0.018)	(0.021)	(0.017)
Observations	52,562	52,562	44,927	52,562
R-squared	0.003	0.227	0.179	0.312
Controls	No	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct
Specification	Transf.	Transf.	Transf.	Translog-Constant

Table C26: Elasticity of Substitution: Mixed Users (Trips)

Note: The table reports estimates of the elasticity of substitution between cash and credit for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative trips between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. Column (1) reports the results after using the transformed share specification denoted in equation (23) and including mixed users with more than 1% of their trips paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their trips paid in cash and less than 95%. Column (4) includes the constant specified in equation (23) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (21). Column (6) estimates the elasticity using the CES second order approximation in equation (22). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predict share of trips paid in credit (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (21) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elasticity	1.449***	1.475***	1.902***	1.593***	1.555***	1.559***	1.331***
	(0.500)	(0.498)	(0.304)	(0.483)	(0.185)	(0.185)	(0.288)
Obs.	3,336	3,336	3,176	3,336	3,336	3,336	1,814
Controls	No	Yes	Yes	Yes	Yes	Yes	No
Type	1 pct	1 pct	5 pct	1 pct	1 pct	1 pct	1 pct
Spec.	Transf.	Transf.	Transf.	Transf.-Cons	CES - First	CES - Second	CES - First IV

Table C27: Elasticity of Substitution: Mixed Users (Trips - at Least 5 Trips)

Note: The table reports estimates of the elasticity of substitution between cash and credit for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative trips between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the results after using the transformed share specification denoted in equation (23) and including mixed users with more than 1% of their trips paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their trips paid in cash and less than 95%. Column (4) includes the constant specified in equation (23) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (21). Column (6) estimates the elasticity using the CES second order approximation in equation (22). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predict share of trips paid in credit (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (21) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

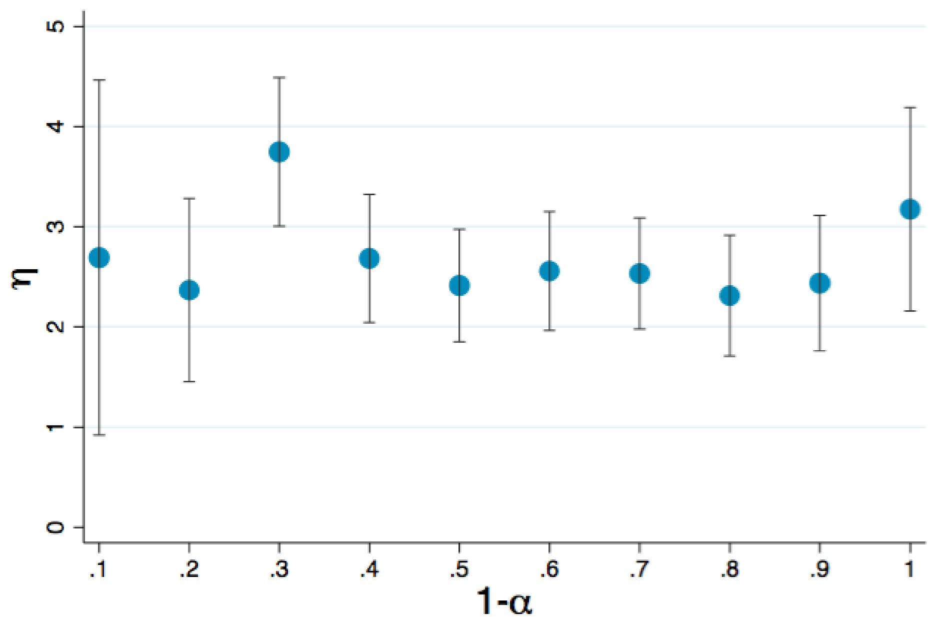
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elasticity	1.449***	1.475***	1.902***	1.593***	1.555***	1.559***	1.352***
	(0.500)	(0.498)	(0.304)	(0.483)	(0.185)	(0.185)	(0.282)
Obs.	3,336	3,336	3,176	3,336	3,336	3,336	1,749
Controls	No	Yes	Yes	Yes	Yes	Yes	No
Type	1 pct	1 pct	5 pct	1 pct	1 pct	1 pct	1 pct
Spec.	Transf.	Transf.	Transf.	Transf.-Cons	CES - First	CES - Second	CES - First IV

Table C28: Elasticity of Substitution: Mixed Users (Miles - Price Increases and Price Decreases)

Note: Note: The table reports estimates of the elasticity of substitution between cash and credit for mixed users after splitting price increases and price decreases. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. Column (1)-(2) estimate the elasticity for positive price changes and negative price changes using the CES first order approximation in equation (21). Column (3)-(4) estimate the elasticity for positive price changes and negative price changes using the CES second order approximation in equation (22). The elasticity in each column is estimated including controls and mixed users with more than 1% of their fares paid in cash and less than 99%. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Elasticity	2.571***	2.644***	2.702***	2.556***
	(0.154)	(0.155)	(0.156)	(0.157)
Observations	46,003	45,856	46,003	45,856
Controls	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	1 pct	1 pct
Specification	CES - First	CES - First	CES - Second	CES - Second
Direction	Only Positive	Only Negative	Only Positive	Only Negative

Figure C2: Elasticity of Substitution: Mixed Users (by Cash Share)



Note: The figure reports estimates of the elasticity of substitution between cash and credit for mixed users for different deciles of the riders' cash share. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between credit and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and credit. Each dot in the figure was estimated using the CES second order approximation in equation (22) including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. The estimates include mixed users with more than 1% of their fares paid in cash and less than 99%. The confidence intervals represent statistical significance at the 5% level.

C.4 Experiment Extensive Margin: Robustness

Table C29: Extensive Margin: Adoption of Credit (Long-Run Effects)

Note: The table reports the percent of users that adopted credit in the long run for each of the treatment groups in experiment three relative to the control group. Migration is an indicator function that equals one if the user took a trip paid in credit from April to June of 2019 conditional on taking trip the weeks of the experiment. The variables "Treatment" report the migration rates relative to the control group of the three treatment groups in the experiment: 3, 6, and 9 times their average weekly fares if the users register a card in the application. Column (1) reports the rates of credit adoption of those users in the experiment that lasted one week. Column (2) reports the rates of credit adoption of those users in the experiment that lasted six weeks.

	(1) 1 week	(2) 1-6 week
Treatment 1 - 1 week	0.0252***	
	(0.009)	
Treatment 2 - 1 week	0.0161*	
	(0.009)	
Treatment 3 - 1 week	0.0171*	
	(0.009)	
Treatment 1 - 6 week		0.0064
		(0.006)
Treatment 2 - 6 week		0.0165***
		(0.006)
Treatment 3 - 6 week		0.0257***
		(0.006)
Constant	0.1477***	0.1390***
	(0.005)	(0.003)
Observations	13,088	28,870
R-squared	0.001	0.001

Table C30: Extensive Margin: Adoption of Credit - Unconditional

Note: The table reports the percent of users that adopted credit for each of the treatment groups in experiment three relative to the control group. Migration is an indicator function that equals one if the user registered a card in the application the weeks of the experiment. The variables ”Treatment” report the migration rates relative to the control group of the three treatment groups in the experiment: 3, 6, and 9 times their average weekly fares if the users register a card in the application. Column (3) reports the rates of credit adoption during the first three weeks of the experiment. Column (4) reports the rates of adoption in the last three weeks of the experiment.

	(1)	(2)	(3)	(4)	(5)
	1 week	1 week	1-6 weeks	1-3 weeks	4-6 weeks
Treatment 1 - 1 week	0.0069***				
	(0.001)				
Treatment 2 - 1 week	0.0073***				
	(0.001)				
Treatment 3 - 1 week	0.0094***				
	(0.001)				
Treatment 1 - 6 week		0.0054***	0.0333***	0.0283***	0.0112***
		(0.001)	(0.004)	(0.004)	(0.003)
Treatment 2 - 6 week		0.0062***	0.0394***	0.0382***	0.0088***
		(0.001)	(0.004)	(0.004)	(0.003)
Treatment 3 - 6 week		0.0106***	0.0468***	0.0485***	0.0088***
		(0.001)	(0.004)	(0.004)	(0.003)
Constant	0.0069***	0.0069***	0.0711***	0.0445***	0.0372***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Observations	96,965	97,035	46,996	36,184	46,996
R-squared	0.001	0.001	0.005	0.006	0.001

C.5 Communication

Email Experiments 1

Subject: Ya tienes un descuento de 10% en tus viajes de esta semana (con EFECTIVO) Pre Header: No tienes que hacer nada, sólo viajar.

Header: Viaja más, pagando menos.

[Name], hemos ingresado a tu cuenta un código promocional para que recibas un 10% de descuento en los viajes que pagues con EFECTIVO durante la semana*.

*Promoción válida por un número máximo de 50 viajes realizados desde las 12 del mediodía del Lunes 20 hasta las 12 del mediodía del Lunes 27 de agosto de 2018.

Email Experiments 2

Subject: Ya tienes un descuento de 10% en tus viajes de esta semana.

Pre Header: Promoción especial sólo por esta semana.

Header: Viaja más, pagando menos.

[Name], hemos ingresado a tu cuenta un el código promocional para que recibas un 10% de descuento en todos tus viajes de esta semana*.

*Promoción válida por un número máximo de 50 viajes realizados desde las 12 del mediodía del Lunes 20 hasta las 12 del mediodía del Lunes 27 de agosto de 2018.

Email Ubernomics

Subject: Tienes 10% de descuento en todos tus viajes esta semana.

¡Esta semana te damos un descuento de hasta 10% aplicado automáticamente en todos tus viajes! Llega a tu trabajo, al gym o a una cena con amigos — todo con un costo por viaje menor.

Email Mandin

Subject line: [Nombre], te regalamos 10% de descuento en tus viajes Pre-Header: No te lo puedes perder.

Title: 10% de descuento en tus siguientes viajes*.

Queremos acompañarte en todos tus viajes. Por eso, entre el 19 de junio y 16 de julio de 2018, podrás disfrutar de 10% de descuento en tus viajes de menos de $200 MXN*.

Tu descuento se aplicará automaáticamente, sólo solicita tu viaje que está a un click de distancia. ¡No dejes pasar esta oportunidad!

Email Experiments 3

[Nombre],

Tenemos una promoción especial para ti con la que podrás obtener 2 viajes con descuento por hasta $50 MXN cada uno. Lo único que tienes que hacer es ingresar una tarjeta de crédito o débito a tus métodos de pago en tu cuenta.

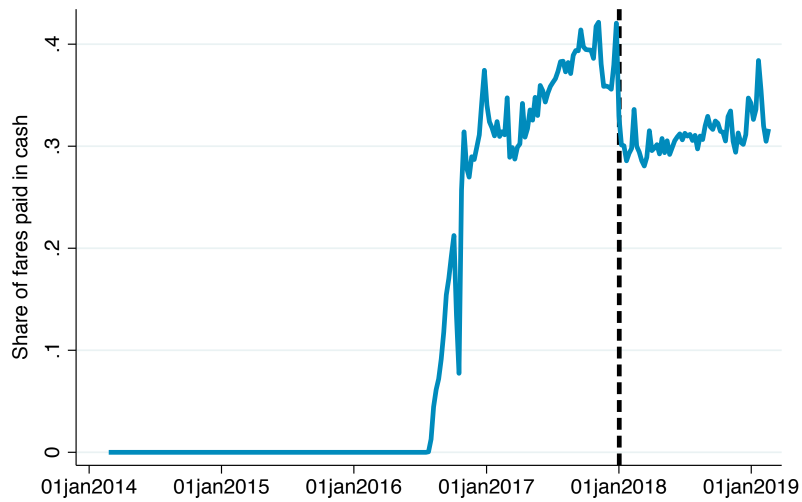
Después de ingresar la tarjeta, espera un periodo de 8 horas para poder utilizar el descuento. Recuerda que podrás disfrutar de esta promoción sin importar el método de pago que elijas para los siguientes viajes.

*Promoción válida desde el lunes 17 de septiembre hasta el domingo 23 de septiembre de 2018. Si el Usuario no consume el valor total del Código, no podrá acumular el remanente en un viaje posterior.

D Panama

Here we collect additional information on the case of Panama. In particular the behaviour of the share of cash and the two regressions estimating semi-log demand functions.

Figure D1: Panama: Share of Fares Paid in Cash



Note: The figure shows the evolution of the share of fares paid in cash in Panama. The frequency of the data is weekly. The black dotted line denotes the date the decree by the government restricting the supply of drivers went into effect.

Table D1: Elasticity of Demand: Panama (Trips)

Note: The table reports the elasticity of demand estimated using equation (27) using trips as dependent variable for Panama. Each observation is a week in 2018; the year after the decree by the government restricting the supply of drivers went into effect. Column (1) reports the estimates using aggregated information of all trips. Column (2) estimates the elasticity using only trips paid in cash. The prices used are the average surge multipler seasonally adjusted using data before the decree went into effect. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) All Trips	(2) Only Cash Trips
Elasticity	0.955***	1.008***
	(0.135)	(0.142)
Observations	52	52
Specification	Semi-log	Semi-log

E Adapting Puebla's Evidence to the State of Mexico

In this section, we adapt the evidence in Alvarez and Argente (2020) on the rate of migration of pure cash riders in Puebla after the ban, to the rate of migration of pure cash users in an hypothetical ban in the State of Mexico. In their counterfactual analysis of the ban in Puebla using synthetic control method, they found that the State of Mexico is one of the cities with higher weights on the synthetic Puebla. Since the excess rate at which pure cash users migrated to become pure credit users after the ban is an important statistic in the identification of the model, we adapt the estimates Alvarez and Argente (2020) obtained using the actual ban in Puebla to the evaluation of an hypothetical ban in the State of Mexico. They found an excess migration rate of about 30% of the pure cash users. We follow a two steps procedure to adapt this estimate to the State of Mexico. The first step is to document the difference in observable indicators for residents of Puebla and State of Mexico, where we define both locations as the municipalities covered by Uber service. The second step is to include some of these observables in their analysis of the rate of migration in Puebla, so we can take into account the difference in observables between the two cities. Overall, these difference change the estimate to the State of Mexico in less than 1%.

Table E1 displays statistics at the census block level for Puebla and the State of Mexico. Table E2 displays statistics at the municipality level for Puebla and for the State of Mexico. From these tables we conclude that, while Puebla and the State of Mexico are relatively similar in the context of the cities served by Uber across Mexico, Puebla's residents have in average about one more year of education, and have higher financial inclusion. In Table E3 we include the census block level variables we have access to in a linear probability model predicting whether a pure cash rider will take trips paid with a credit card in Puebla after the ban. The sample used in this regression are all the trips in three months on the year before and three months after the ban, which are geolocalized and matched with the census at the block level. [27] The presence of a bank in the geographical statistical area (AGEB) and the average years of education have the expected signs, although the values of the coefficients are small and only marginally statistically significant. Using these coefficients and the average difference between the observables in Puebla and in the State of Mexico, we obtain that the indeed the migration rate will be lower in the State of Mexico than in Puebla, but that correction is smaller than 1%, i.e. it is given by $(0.74-0.59)\times 0.0095+(9.95-8.88)\times 0.0056 = 0.0074$.

[27] This sample is smaller than the universe used in Alvarez and Argente (2020). The smaller size of the sample is due to the fact that we need to geolocalize all these trips.

Table E1: Puebla vs State of Mexico: Summary Statistics at the Block Level

Note: The table reports the average across census blocks of different variables for Puebla, Mexico City, and the State of Mexico. The variables reported are the share of banks in the census block, the share of banks in the basic geostatistical area, the share of homes with car, the share of homes with phone, the share of homes with internet and the average years of educations. The average across census blocks is computed weighting each block by the total trips that took place in August of 2017. The source of the demographic variables is the Mexican Census.

	(1) State of Mexico	(2) Mexico City	(3) Puebla
Share of banks in the block	0.12	0.31	0.16
Share of banks in basic geo. area	0.59	0.83	0.74
Share of homes with car	0.46	0.50	0.44
Share of homes with phone	0.65	0.67	0.60
Share of homes with internet	0.36	0.49	0.36
Average years of education	8.88	10.63	9.95
Blocks	60056	53606	19899

Table E2: Puebla vs State of Mexico: Financial Inclusion Statistics

Note: The table reports the per capita averages of several variables related to financial inclusion for Puebla, Mexico City, and the State of Mexico. The variables reported include debit cards per capita, credit cards per capita, ATMs per capita, ATM transactions per capita, bank branches per capita, as well as the income per capita and the total population of each State. The statistics are computed using information of the municipalities where Uber was active in 2017. The source of the data is the 2017 Financial Inclusion Database (BDIF).

	(1) State of Mexico	(2) Mexico City	(3) Puebla
Debit cards per capita	0.64	2.93	0.93
Credit cards per capita	0.21	0.67	0.25
ATMs per capita	2.63	8.49	4.30
ATM transactions per capita	1.13	3.01	1.75
Bank branches per capita	0.99	2.21	1.51
Income per capita (USD)	445.52	707.32	454.15
Population (millions)	11.67	8.81	2.76

Table E3: Puebla: Returning After the Ban of Cash

Note: The table reports the probability of returning from 2017-2018 for users in the city of Puebla. The dependent variable is an indicator variable that equals one if the user was active in 2017 and she is also active in the application in 2018. The independent variables include an indicator variable that equals one if a bank is present in the user's geostatistical area and the average years of education of the census block where the user resides. The sample of users are those that only used cash as a payment method in 2017. The regression is weighted by the total trips they took in 2017.

	(1)	(2)	(3)
User Returning			
Bank in basic geo. area	0.0149***		0.0095***
	(0.002)		(0.001)
Years of Education		0.0061**	0.0056*
		(0.003)	(0.003)
Constant	0.2922***	0.2305***	0.2291***
	(0.007)	(0.024)	(0.025)
Observations	91,111	91,111	91,111
R-squared	0.000	0.001	0.001
Users	Pure Cash	Pure Cash	Pure Cash
Weight	Trips in 2017	Trips in 2017	Trips in 2017

F Net Consumer Surplus Lost in the Ban for Pure Cash Users, Details

In this section we compute the adjustment to the consumer surplus of pure cash users in the case of a ban due to the option of becoming pure credit users. We assume that all the pure cash users have a common value of ϕ but they are heterogeneous with respect to the cost of registering/obtaining a credit card. In particular we obtain an interval for the counterfactual value of α for these riders, and for each value of α we describe the corresponding values of k and $\bar{P}$. We assume that the elasticity of substitution η is the same as the one we estimate from mixed users.

For each feasible value of α and the corresponding values of $(k, \bar{P})$ and distribution $g(\cdot)$ for ψ we compute the consumer surplus lost in the ban as:

$$\begin{aligned} CS_{ban,a}(\phi) &\equiv v(1,\infty;\phi) - \int \max\{v(\infty,1;\phi) - \psi, v(\infty,\infty;\phi)\} g(\psi|\phi) d\psi \\ &= v(1,\infty;\phi) - v(\infty,\infty;\phi) \\ &\quad - [v(\infty,1;\phi) - v(\infty,\infty;\phi)] \int_{\underline{\psi}}^{\max\{\underline{\psi},\psi_{ban}\}} g(\psi|\phi) d\psi + \int_{\underline{\psi}}^{\max\{\underline{\psi},\psi_{ban}\}} \psi g(\psi|\phi) d\psi \end{aligned} \tag{32}$$

where g is the distribution of fixed cost among the pure cash users before the ban conditional on ϕ, $\underline{\psi}$ is the lower bound of the support of g, and ψ_{ban} is the highest fixed cost for which a rider will migrate from being pure cash to pure credit in the case of a ban. Note that a lower bound of equation (32) is

$$\begin{aligned} CS_{ban,a}(\phi) \geq \underline{CS}_{ban,a}(\phi) &\equiv v(1,\infty;\phi) - v(\infty,\infty;\phi) \\ &\quad - \left[v(\infty,1;\phi) - \underline{\psi} - v(\infty,\infty;\phi)\right] \int_{\underline{\psi}}^{\max\{\underline{\psi},\psi_{ban}\}} g(\psi|\phi) d\psi \end{aligned} \tag{33}$$

We proceed in two steps. The first step jointly identify the set of values for ϕ and range of values $\underline{\psi}$ and ψ_{ban}. The second step obtains the distribution g within $[\underline{\psi}, \psi_{ban}]$.

1. We obtain a set of values of $\phi = (\eta, \alpha, k, \bar{P})$, which can be represented as an interval for α and the corresponding unique values for each value of α in this interval. These parameter have to satisfy the following conditions/assumptions, which are discussed at the end of Section 3.4.

   (a) The (common) elasticity of substitution η on the function H is the same as the one for mixed riders. Here we use the CES functional form for H.

(b) The value of η and the two parameter values (β_0, β_1) characterizing the demand of pure cash rides $\tilde{a}(p, \infty; \phi) = \beta_0 + \beta_1 \log p$ give two equations for the parameters $(\alpha, k, \bar{P})$. The derivation uses that H is CES and U being exponential. The equations are:

$$\beta_0 = k(1-\alpha)^{\frac{1}{1-\eta}} \left[\log \left(\frac{\bar{P}}{(1-\alpha)^{\frac{1}{1-\eta}}} \right) \right] \tag{34}$$

$$\beta_1 = -k(1-\alpha)^{\frac{1}{1-\eta}} \tag{35}$$

(c) Pure cash users that become pure credit users take fewer rides after the ban. In term of the model it means that $\tilde{a}(1, \infty; \phi) > \tilde{c}(\infty, 1; \phi) > 0$. This was shown in the analysis of Puebla by Alvarez and Argente (2020). Using the expression in Appendix **??** we have:

$$\alpha \leq 1/2 \tag{36}$$

(d) The demand of a pure cash rider that becomes a pure credit rider after the ban must be strictly positive, or $\tilde{a}(\infty, 1; \phi)$. The estimated parameters β_0, β_1 and equation (34) and equation (35) enforce that the demand of pure cash users is positive. Using the expressions in Appendix **??** we have:

$$\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}} \leq 1 \tag{37}$$

Proposition 3. Assume that $\eta > 1$, $\beta_0 > 0$, and $\beta_1 < 0$. The set of values for which α satisfies all the conditions described in step 1 above is contained in an interval $[\underline{\alpha}, 1/2]$ where $\underline{\alpha} = 1/\left[1 + \exp\left((1-\eta)\beta_0/\beta_1\right)\right]$. The values of $\bar{P}$ and k for each α are given by

$$\bar{P} = (1-\alpha)^{\frac{1}{1-\eta}} e^{-\beta_0/\beta_1} \text{ and } k = \frac{-\beta_1}{(1-\alpha)^{\frac{1}{1-\eta}}}. \tag{38}$$

2. The last step is to estimate the distribution g corresponding to each set of values (α, k, $\bar{P}$, $\underline{\psi}$, ψ_{ban}).

(a) Prior to the ban, pure cash riders must prefer to use cash, i.e. they must be indifferent when ψ is at the lower bound of the support for g:

$$\underline{\psi} \equiv v(1,1;\phi) - v(1,\infty;\phi) = -k(1+\log \bar{P}) - k(1-\alpha)^{\frac{1}{1-\eta}}\left[\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] \tag{39}$$

where $\underline{\psi}$ is the lower bound of the support of ψ.

(b) ψ_{ban} triggers that no pure cash users want to registered a card:

$$\psi_{ban} = v(\infty,1;\phi) - v(\infty,\infty;\phi) \equiv k\alpha^{\frac{1}{1-\eta}}\left[\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] + k\bar{P} \tag{40}$$

(c) The value of $\int_{\underline{\psi}}^{\max\{\underline{\psi},\psi_{ban}\}} g(\psi|\phi)d\psi$ is the excess migration of pure cash riders to pure credit riders.

(d) The shape of g in the interval $[\underline{\psi},\, \psi_{ban}]$ is obtained by using the information of the Experiment 3, given the parameters $(\alpha,\, k,\, \bar{P},\, \eta)$. For a given discount rate ρ, these experiments give three values of the CDF for g inside the interval $[\underline{\psi},\, \psi_{ban}]$. See equation (17) for the relevant expressions. We interpolate these values so that they are consistent with the experiments and, among them, we choose the one with the highest cost (in a first order stochastic dominance sense). Furthermore, we use $\rho = 0.25$ so the expected duration of the fixed cost is four years.

Next, we note that the consumer surplus lost, for those that do not switch to credit after the ban, is independent of α. This is the quantity plotted in Figure 5 (as a fraction of expenditure) and it is only a function of β_0, β_1. To see this recall that the consumer surplus lost for this group is defined as:

$$CS_{ban,a}(\phi) \equiv v(1,\infty;\phi) - v(\infty,\infty;\phi) = k(1-\alpha)^{\frac{1}{1-\eta}}\left[\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\log \bar{P}}\right) - 1\right] + k\bar{P}$$

Using the definitions of β_0 and β_1 and Proposition 3 we can write

$$\widehat{CS}_{ban,a}(\beta_0,\beta_1) = -\beta_0 + \beta_1 - \beta_1 \exp\left(-\beta_0/\beta_1\right) \tag{41}$$

On the other hand, the consumer surplus of pure cash users who switch to credit can be written as a function of α given β_0, β_1, and η. Using Proposition 3 and the definitions of β_0 and β_1 and substituting into equations equation (39) and equation (40) we find

$$\underline{\widehat{\psi}}(\alpha;\beta_0,\beta_1,\eta) = \frac{\beta_1}{(1-\alpha)^{\frac{1}{1-\eta}}}\left(1+\frac{1}{1-\eta}\log(1-\alpha)-\frac{\beta_0}{\beta_1}\right)-\beta_1+\beta_0 \tag{42}$$

and

$$\widehat{\psi}_{ban}(\alpha;\beta_0,\beta_1,\eta) = -\beta_1\left(\frac{\alpha}{1-\alpha}\right)^{\frac{1}{1-\eta}}\left[\frac{1}{1-\eta}\log\left(\frac{\alpha}{1-\alpha}\right)+\frac{\beta_0}{\beta_1}-1\right]-\beta_1 e^{-\beta_0/\beta_1} \tag{43}$$

The consumer surplus lost for switchers can be written as

$$\widehat{CS}_{ban,a}(\alpha;\beta_0,\beta_1,\eta) = \left[-\beta_0+\beta_1-\beta_1\exp\left(-\beta_0/\beta_1\right)\right] - \int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}},\widehat{\psi}_{ban}\}}\left[\psi-\underline{\widehat{\psi}}\right]\widehat{g}(\psi)d\psi$$

with lower bound

$$\underline{\widehat{CS}}_{ban,a}(\alpha;\beta_0,\beta_1,\eta) \equiv \left[-\beta_0+\beta_1-\beta_1\exp\left(-\beta_0/\beta_1\right)\right] - \tilde{\psi}\int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}},\widehat{\psi}_{ban}\}}\widehat{g}(\psi)d\psi \tag{44}$$

where $\tilde{\psi} \equiv \widehat{\psi}_{ban} - \underline{\widehat{\psi}}$ and $\widehat{g}$, $\underline{\widehat{\psi}}$, $\widehat{\psi}_{ban}$, and $\tilde{\psi}$ are evaluated at $(\alpha;\beta_0,\beta_1,\eta)$.[28] Given that $\tilde{\psi}$ only affects the consumer surplus of the users that switch to credit after the ban, given β_0, β_1, and η, we can obtain the lower bound of the net consumer surplus by evaluating $\tilde{\psi}$ for all values of $\alpha \in [\underline{\alpha}, \alpha = 1/2]$. In practice $\tilde{\psi}$ is a single-peaked function with maximum either at $\alpha = \underline{\alpha}$ or at $\alpha = 1/2$.

F.1 Case with No Heterogeneity

We begin with the case without heterogeneity, all users have the same ϕ. From Table C4 we obtain obtain the following point estimates $\beta_1 = -2.044$ and $\beta_0 = 1.54$ for the miles specification. We use the mile specification because the price of a trip has been normalized to one, as in the theory. This corresponds to an elasticity of 1.38. Aiming to be conservative, this is the largest elasticity, which gives the lowest consumer surplus. Using the values β_0 and β_1 we obtain a consumer surplus lost by the pure cash users that do *not* migrate after the ban, estimated using equation (41), of approximately 39.4 USD per year, or about 0.49 of the yearly expenditure on rides paid in cash.

Moreover, with this values of β_0, β_1 and our benchmark estimates of η, $\alpha \in [0.37, 0.5]$. The difference $\tilde{\psi}$ is increasing in α within this interval, ranging between $\tilde{\psi} = 0$ at $\alpha = 0.37$ and and $\tilde{\psi} = 10.8$ USD per year at $\alpha = 0.5$. Thus we can use the lower bound on the consumer

[28] In what follows, to simplify the notation, we use this convention.

surplus lost is given by selecting $\alpha = 0.5$ and using the formula for the lower bound we obtain $\widehat{\underline{CS}}_{ban,a} \geq 36.1$ USD per year or about 0.45 of the yearly expenditure of cash rides in Uber. For this lower bound we have used $\int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}},\widehat{\psi}_{ban}\}} \hat{g}(\psi)d\psi = 0.3$, based on Puebla.

We can use the results of Experiment 3 to obtain a better estimate of $\int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}},\widehat{\psi}_{ban}\}} \psi\hat{g}(\psi)d\psi$. We use that for one time rewards of 5.3, 10.5 and 15.7 USD the excess migration rate in six weeks have been 3.3%, 3.9% and 4.7% respectively –see Table 5, column (3). Since these are one time rewards, we need to convert them into flows, by using a rate of discount, which should take into account the duration of the credit cards. To be conservative we use $\rho = 0.2$, so the average duration is 5 years, i.e. the rewards are about 1, 2.1, and 3.6 USD dollars per year. We can use these figures to obtain a tighter upper bound as follows:

$$\begin{aligned}
&\int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}},\widehat{\psi}_{ban}\}} \left[\psi - \underline{\psi}\right] \hat{g}(\psi)d\psi \\
&\leq 1 \times 0.033 + 2.1 \times (0.039 - 0.033) + 3.6 \times (0.047 - 0.039) + (10.8 - 3.6) \times (0.3 - 0.047) \\
&= 1.9 \leq 0.3 \times 10.8 = 3.24
\end{aligned}$$

In this case we obtain $\widehat{CS}_{ban,a} \approx 39.4 - 1.9 = 37.5$ USD per year or about 0.47 of the yearly expenditure on Uber paid in cash by pure cash riders. This calculation is our headline number for pure cash users. The results are similar if, instead of using $\eta = 3$, we use a higher value (i.e. η=5). In this case, the net consumer surplus lost is 33.8 USD per year or about 0.42 of the yearly expenditure on Uber paid in cash by pure cash riders.

F.2 Case with Heterogeneity

Next, we allow consumer to have different β_0. This is, for each percentile of the distribution of β_0 reported in Columns (1)-(2) of Table F1, we compute the consumer surplus lost of both pure cash users that do not switch to credit and those that do. Columns (3) reports the percentiles that migrate to credit after a ban on cash consistent to our model (i.e. $\tilde{\psi} > 0$).

We again aim to provide a lower bound for the consumer surplus lost. First, in order to be consistent with the evidence from Puebla, we allow 30% of the users to migrate. We choose the percentiles, whose migration is consistent with our model and with lower consumer surplus lost. These percentiles are reported in Column (4). Second, we evaluate $\widehat{\underline{CS}}_{ban,a}$ at $\alpha = 1/2$ since, for all percentiles that switched to credit, it provides a maximum value for $\tilde{\psi}$ and hence a lower bound for the net consumer surplus. The last column reports the lower bound of the net consumer surplus lost for each percentile. Notice that the net consumer surplus lost is convex in β_0 as shown in equation (41). The consumer surplus lost is drastically higher for pure cash users that travel more using the application because of the convexity of the net consumer surplus lost and due to the large skewness of the distribution of historical trips. The median net consumer surplus lost is 10.3 USD and the mean is 187 USD. If we use a higher value for η (i.e. η=5), the results are similar, the median is 10.6 USD and the mean is 183 USD.

Table F1: Net Consumer Surplus Lost in the Ban for Pure Cash Users

Note: The table reports the net consumer surplus lost of pure cash users after a ban on cash for several percentiles of miles per week, β_0. The net consumer surplus lost is the adjustment to the consumer surplus of pure cash users in the case of a ban due to the option of becoming pure credit users. Column (3) shows the percentiles of the distribution of β_0 that switch to credit (i.e. $\tilde{\psi} > 0$) according to our model. Column (4) shows the percentiles that percentiles of the distribution of β_0 that we elect to migrate to credit in order to be consistent with the data of Puebla (30% of the population) and also to provide a lower bound of the consumer surplus lost. Column (5) reports the lower bound of the net consumer surplus lost by the pure cash users, those that migrate are adjusted by the costs paid to migrate. All calculations use β_1 = -2.044, η=3, and α=1/2 since for that α the consumer surplus lower bound is attained. The average β_0 in our sample is 1.54.

(1) Percentile	(2) β_0	(3) Consistent	(4) Migrate	(5) Net Consumer Surplus Lost (USD)
5	0.16	0	0	0.3471
10	0.23	0	0	0.7359
15	0.30	0	0	1.2043
20	0.36	0	0	1.7879
25	0.42	0	0	2.5156
30	0.49	0	0	3.4231
35	0.57	0	0	4.5722
40	0.65	0	0	6.0297
45	0.74	0	0	7.9076
50	0.84	0	0	10.356
55	0.95	0	0	13.582
60	1.08	0	0	18.011
65	1.23	1	1	24.092
70	1.42	1	1	31.169
75	1.65	1	1	41.562
80	1.96	1	1	57.984
85	2.38	1	1	86.454
90	3.01	1	1	144.71
95	4.11	1	0	309.54
100	8.24	1	0	2974.3

G Ban on the Use of Credit: Argentina

Motivated by the recent legal framework in Argentina, where local credit cards could not be used as a means of payment for Uber rides, we consider a ban on the use of credit in the State of Mexico. The situation in Argentina was that Uber riders could not be paid using credit cards, whose payments are processed by one of the two local firms processing credit card payments. This was due to an initial injunction issued by a public attorney of the City of Buenos Aires, even though it has now been reversed in an appeal. The reason the ban was nationwide, even though the initial injunction was for the city of Buenos Aires, was that the credit card processors cannot distinguish the location where the charges of riders were originated. Uber riders using credit card whose payments were processed abroad, such as most international tourists, were able to pay for Uber rides using their credit cards.

In our calculations we assume that the initial conditions are exactly as the situation in the State of Mexico during 2018 (so that cash and credit are available as means of payment, and we can use our estimates for several quantities) and a permanent unexpected ban on credit is enacted. We distinguish the effect on three type of riders (classified when both cash and credit were available): pure cash riders, mixed riders, and pure credit riders. We will continue to assume that prices will not change, and that drivers will not be affected.

The ban in credit has no effect on the 25% pure cash riders (which account for about 20% of the fares). Pure cash riders continue to be pure cash riders after the ban, and will pay the same price. The ban in credit has a similar effect in mixed riders that the ban in cash. The magnitudes for the ban on credit will be different than the magnitude of the ban in cash because the distribution of the share for credit trips for mixed riders is not symmetric around 0.5. Using the distribution of riders cash share weighted by their total fares –as in Figure 2, a elasticity of substitution $\eta = 3$, and a price elasticity $\epsilon = 1.1$, we obtain that the consumer surplus lost by a ban on credit is 0.43 of the total expenditure of mixed users.

The ban on credit has a large effect on the pure credit riders. Given our assumption of no fixed cost to use cash, we rationalize that rider does not use cash (i.e. that she is a pure credit rider) as having a value of $\alpha \approx 1$. This means that pure credit riders will stop using Uber altogether after a ban in credit and, hence, their loss will be the entire consumer surplus of using Uber. This will be a large multiple of their revenue, since these users tend to be the more inelastic ones. Our estimates for the price elasticity of Uber rides for pure credit users is $\epsilon \approx 0.7$, see Appendix C.3.3. With this elasticity, the consumer surplus lost by the pure credit rides is about 1.22 of their total expenditure in Uber. This number is comparable to the consumer surplus of using Uber estimated by Cohen et al. (2016) using U.S. data and a different identification scheme, which is 1.66. Recall that in that in the U.S. only credit is available as a means of payment. Lastly, we can aggregate the consumer surplus lost by a ban on credit computed above among mixed and pure credit users by weighting them by their share of total expenditure in Uber paid with credit. The consumer surplus lost by a ban on credit is $0.82 = 1.22 \times \frac{0.30}{0.30+0.50\times0.63} + 0.43 \times \frac{0.50\times0.63}{0.30+0.50\times0.63}$ of the total expenditure paid on credit before the ban.

H Survey

The survey was sent to all the users that participated in experiments 1 and 2 approximately 11 months after the experiments took place. The surveys were sent through email on July 9th, 2019 and they were open until July 16th, 2019. We design 6 different surveys, each with 3 questions. This format allowed us to minimize the response time and, at the same time, allowed us to obtain several responses to a given question. A total of 433,356 users received a survey, 287,233 participated in experiment 1 (mixed and pure credit users) and 146,123 participated in experiment 2 (pure cash users). We randomize the 6 surveys within each of the treatment and control groups in experiment 1 and 2. For example, experiment 1 has 6 treatment groups and 1 control group. Within each of those groups a random sample of users got each of the surveys. Since experiment 2 has 4 treatment groups and 1 control group, approximately 72,220 people received each of the surveys. We received 6,341 responses. After dropping illegible responses (in a few cases users provided other information rather than that asked in the questions) and duplicates, our total sample contains an average of 933.5 responses per survey. If a given user responded the survey more than once we kept the response with less missing answers or, in case of a tie, we kept their last response.

All surveys included the following question: "If your receive a 20% discount for one week, how would you change your trips...". Some users were given the options to respond a) no change, b) increase less than 10%, c) increase more than 10%. A second set of users were given the options to respond a) no change, b) increase less than 20%, c) increase more than 20%. And a third set of users were given the options to respond a) no change, b) increase less than 30%, c) increase more than 30%. Each survey also included two additional questions. We split the sample of users in two groups. To the first group we asked the following two questions: 1) "If the price of trips is permanently reduced by half, how would you change your trips..." and 2)"If the price of trips is permanently doubled, how would you change your trips...". To the second group we asked: 1) "If the price of trips is permanently reduced to a third, how would you change your trips..." and 2) "If the price of trips is permanently tripled, how would you change your trips...".

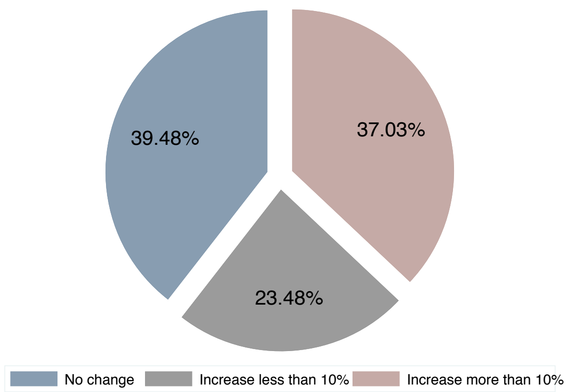
To analyze the responses, we adjust the covariate distribution of the survey respondents by reweighting such that it becomes more similar to the covariate distribution of the entire population that participated in our experiments. We implement entropy balancing, a multivariate reweighting method described in Hainmueller (2012). Entropy balancing is based on a maximum entropy reweighting scheme that fit weights that satisfy a set of balance constraints that involve exact balance on the first, second, and possibly higher moments of the covariate distributions in the treatment and control groups. We reweight the sample of survey respondents based on the historical trips per week and their tenure based on the first and second moments of the distribution. Using higher moments do not affect our findings. The distribution of responses for each question is provided in Section H.1 for mixed users and Section H.2 for pure cash users.

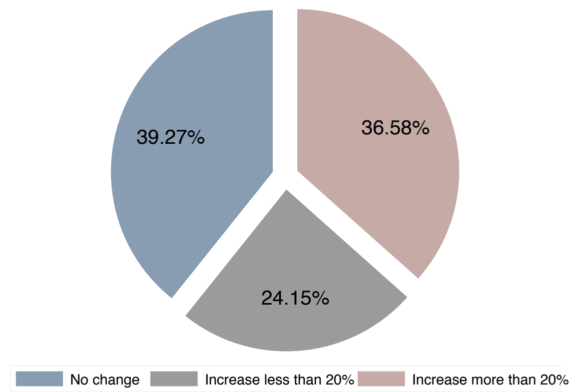
In order to provide external validity to our survey-based evidence, we compare the bounds in the elasticity of demand implied by the survey to those implied by the field experiments. We use the first question of the survey, where users are asked to describe their behavior if they were to receive a 20% discount for one week. Recall that equation (27) shows the relationship between the demand, the choke price, and the elasticity of demand implied by our model. The equation can be used to recover the response of users to a change in prices P that is consistent with both our experimental evidence and our structural framework. We implement equation (27) using the semi-elasticity k estimated in our field experiments and the choke prices $\bar{P}$ of users recovered (when they face prices equal to 1) from the average of their weekly historical fares.[29] In this case, when we decrease prices by 20%, given that in our model users always change their trips if prices change, we find that 11% of users would increase their trips less than 10 %, 32% of users would increase their trips less than 20%, and 49% of users would increase their trips less than 30%. The responses of the survey are remarkably similar. They show that,, conditional on users changing their trips, 14.75% of the users would increase their trips less than 10%, 39.7% would increase their trips less than 20%, and 46% of users would increase their trips less than 30%. Overall, we find that the estimated bounds of the elasticity of demand in the survey are informative of the revealed bounds obtained using our experimental data.

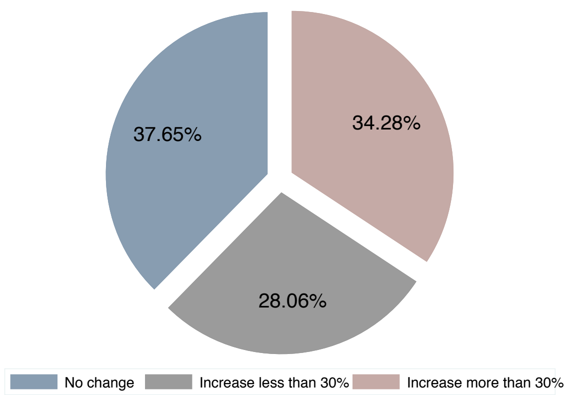
[29] To minimize the measurement error in the average of weekly historical fares, we trim the top and bottom one percent.

H.1 Mixed Users

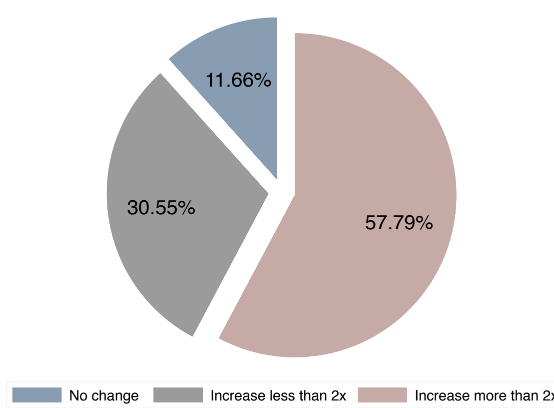
Question 1: If your receive a 20% discount for one week, how would you change your trips...



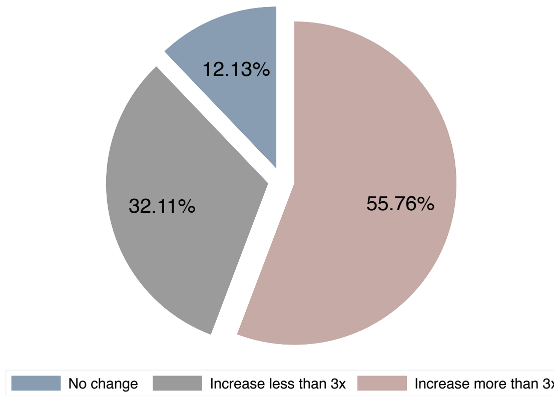




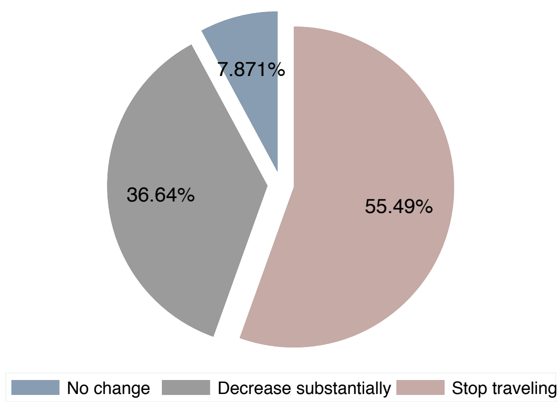
Question 2a: If the price of trips is permanently reduced by half, how would you change your trips...



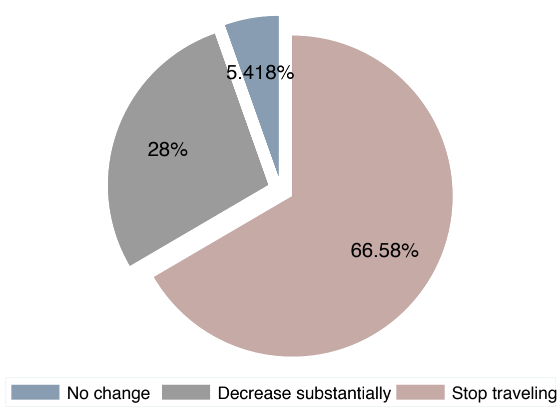
Question 2a: If the price of trips is permanently reduced to a third, how would you change your trips...



Question 3a: If the price of trips is permanently doubled, how would you change your trips...

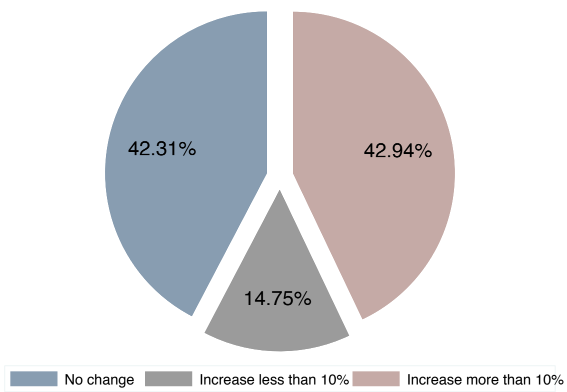


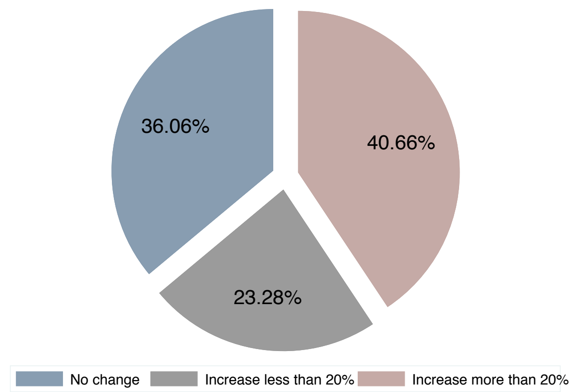
Question 3a: If the price of trips is permanently tripled, how would you change your trips...

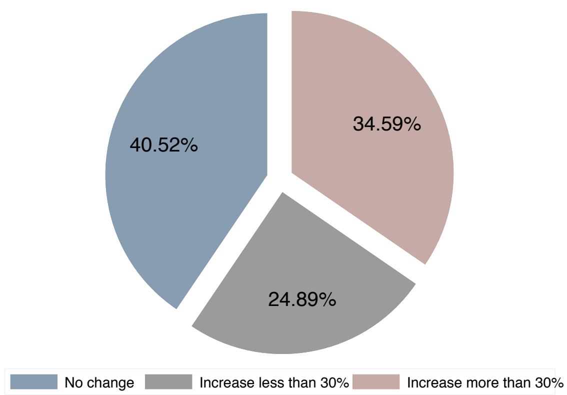


H.2 Pure Cash Users

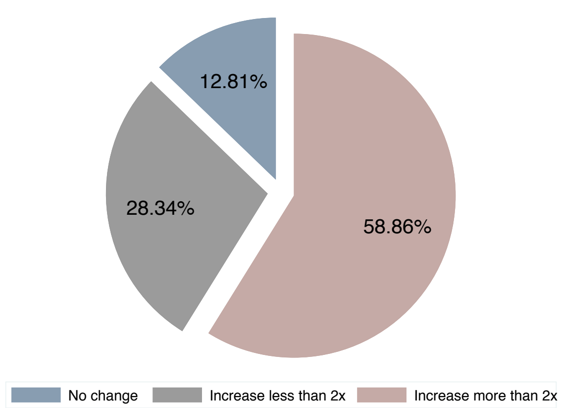
Question 1: If your receive a 20% discount for one week, how would you change your trips...



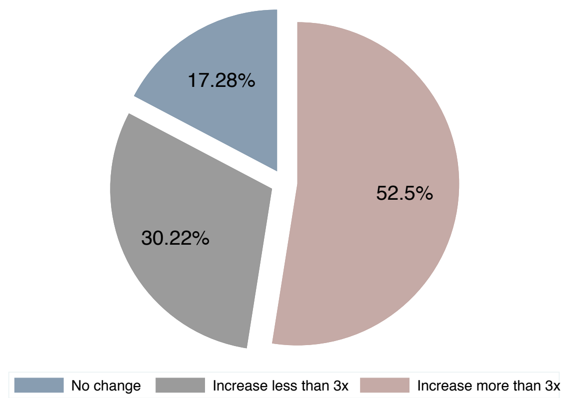




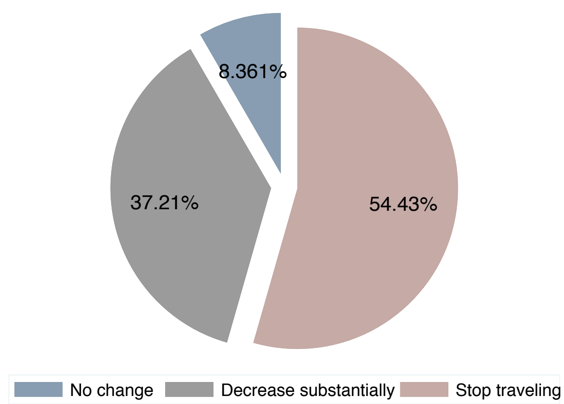
Question 2a: If the price of trips is permanently reduced by half, how would you change your trips...



Question 2a: If the price of trips is permanently reduced to a third, how would you change your trips...



Question 3a: If the price of trips is permanently doubled, how would you change your trips...



Question 3a: If the price of trips is permanently tripled, how would you change your trips...