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

Fernando Alvarez†
University of Chicago

David Argente‡
Pennsylvania State University

October 2019

[Link to the latest version]

Abstract

We estimate the private benefits for Uber riders from using alternative payment methods. We focus on Mexico, where contrary to the US, riders have the option to use cash or credit cards to pay Uber drives. We use three large field experiments as well as several quasi-natural experiments to estimate the loss in private benefits for riders if a ban of cash as a payment method on Uber is implemented. We find that the Uber riders who use cash as means of payment, either sometimes or exclusively, suffer an average loss of approximately 50% of the expenditure of trips paid in cash before the ban. Further, the cost from the ban on cash falls disproportionately on lower income households.

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

---

*We want to thank Andy Abel, Manual Amador, George Alessandria, Andy Atkeson, Gadi Barlevy, Mark Bills, Anmol Bhandari, Stephane Bonhomme, Sara Castellanos, Doireann Fitzgerald, Greg Kaplan, Narayana Kocherlakota, John List, Ellen Mc Grattan, Juanpa Nicolini, Francesco Lippi, Enrique Seira, Rob Shimer, Harald Uhlig, and Venky Venkateswaran for their comments and suggestions. We also want to thank the participants in the seminars at the Federal Reserve Bank of Kansas, the Federal Reserve Bank of Minneapolis, the Federal Reserve Bank of Chicago, the Wharton School at the University of Pennsylvania, the University of Rochester, the Applications Workshop at the University of Chicago, Columbia Business School, the Banco de Mexico, the 2019 SED in St. Louis, the MM group in the 2019 NBER Summer Institute, the Bank of Canada, the Bank of International Settlements, the Federal Reserve Bank of Richmond, Penn State, Dartmouth, and UCLA. We further want to thank Libby Mishkin and other members of the San Francisco Uber policy group, and especially the Uber Mexico team for general support and assistance, programming, implementing the field experiments, and for countless queries of observational data and background information, in particular to Federico Ranero, Daniel Salgado, and Hector Argente. We thank Basil Halperin for his many contributions during the initial phase of the project. We also thank Francisca Sara-Zaror and Rafael Jimenez for excellent research assistance. None of the two authors are employees or consultants for Uber and have not received payments of any kind from Uber. David Argente is the brother of Hector Argente, who was the Research and Analytics Manager for Uber Latin America. First draft: March 2019.

†Email: f-alvarez1@uchicago.edu. Address: 1126 E. 59th St., Chicago, IL 60637

‡Email: dargente@psu.edu. Address: 403 Kern Building, University Park, PA 16801.

1 Summary and Introduction

In this paper we aim to contribute into the area of the money demand literature, in particular we estimate 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.[1] We use three large field experiments as well as several quasi-natural experiments to estimate the consumer surplus that would be lost if Uber riders in Mexico were not allowed to use cash as a means of payment. We find that the riders of this platform who use cash either sometimes or exclusively would suffer an average private cost is at least 50% of the expenditure on Uber rides paid in cash before the ban. Unsurprisingly, we find that the cost of the ban in cash would fall mostly on lower income households. We use a simple model in which riders choose the number of Uber trips that they take and view paying Uber in 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 methods. We allow for heterogeneity among riders in their preferences of paying for trips in cash or with credit on their preferences for composite trips relative to other goods, and in the cost they pay to register a credit card in the application. 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 cards) and about 50% of the expenditure is accounted by riders that use both cash and credit cards.[2] 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.

[1]Currently, there are more than 400 cities worldwide, and more than 40 cities in Mexico, where cash is available as means of payment for Uber trips. Mexico City is one of the ten largest metropolitan areas in terms of its number of Uber trips in the world.

[2]The greater Mexico City refers to Mexico's Metropolitan Area constituted by both Mexico City and adjacent municipalities in the State of Mexico. These statistics, and our estimates in general, refer to the part of the greater Mexico City that excludes Mexico City, where cash is not allowed which we also refer to as the State of Mexico.

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), or the model on multiple payment methods in Prescott (1987) as well as a many studies that follow them, such as Whitesell (1989), Lacker and Schreft (1996), Freeman and Kydland (2000), Lucas and Nicolini (2015), and Stokey (2019). There is also a related literature which follows the search theoretical literature of money as a payment method largely started by Kiyotaki and Wright (1989), and 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. As an example Rogoff's (2017) book 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.[3] Motivated by these recent policies, we estimate the effect on the consumer surplus of Uber riders by introducing cash as a payment method in a city where cash was not available and the loss caused by banning cash as a payment method in a city where it was available.

As we mentioned above, 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.[4] 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 for riders after cash is allowed 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 ignore the effect of the entry of cash (or the effect of the ban) in incumbent pure credit riders who never used cash in the application because we find no evidence of change

[3]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.

[4]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.

in price.[5] Thus, 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's 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. Using a conventional event study framework, we 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 taxis. Giving the lack of effect on prices, we conclude that the entry of cash has no effect on the pure credit riders' consumer surplus. The evidence for the event study 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 two different types of evidence for this paper. One type of evidence comes from quasi-natural experiments in which we can estimate the effect of the entry (or 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. The second type of evidence comes from field experiments (randomized control trials) in which we randomly give riders different prices for paying with cash, paying with credit, or paying with either payment method, as well as different rewards to register their credit cards in the application. We use both types of evidence to parameterize our model and estimate the loss in consumer surplus from a ban on the use of cash.

Entry of Cash Across Mexican Cities

We first turn to the three different quasi-natural experiments. For the entry of cash, we use two different data sets. One is an event study of the asynchronous entry of cash to 15 different cities where Uber had previously only accepted credit cards as the payment method. This part of the analysis is described in Section 4. We assume that the entry is quasi-random. Our

[5] While our study focuses on riders, the same reasons imply a small effect of the entry or ban on cash on drivers. We don't focus on the effect of cash as a method of payment on drivers because our evidence comes mostly from the event study of the non-synchronous entry of cash across Mexican cities served by Uber. Instead, in the case of riders we have additional evidence, such as the use of geolocalized trips between State of Mexico and the City of Mexico, and from three large field experiments or RCT's.

understanding of Ubers decision to introduce cash in these cities is that after the successful introduction of cash in May of 2015 in Hyderabad (India), Uber decided that cash could be introduced to all cities in developing countries where it was allowed. The difference in the timing reflects the difference in the local regulations.[6] We follow a standard design for the event study and estimate weekly effects of the outcome variables mentioned above for a period of about one year after the introduction of cash to each city. As standard, we include time and city fixed effects and time varying city level controls which we construct for this study.[7] We find statistically significant and economically large increases in the total number of trips and in the total fares after the entry of cash; both trips and fares more than doubled after a year. There are also large increases in the sign up of riders and drivers and in the number of active riders and drivers (those with positive trips in a week). The number and sign up of drivers is smaller than those estimated for riders, but we also find that drivers increase their weekly hours by approximately the same percentage as total fares. We find no statistically significant effects on prices (or the average surge) or on the average waiting times for Uber riders after the introduction of cash as well as no changes in the prices of taxis. Our interpretation of these findings is that the long-run supply of drivers per hour is very elastic, which is consistent with findings across US cities by Hall et al. (2017).

Entry of Cash in the Greater Mexico City

The second quasi-natural experiment we use is the introduction of cash to the metropolitan area of Mexico City, a city of more than 20 million people and one of the then largest city in terms of Uber trips in the world. This area includes both Mexico City (Cuidad de México) and the remaining part of the greater metropolitan area, which we refer to as the State of Mexico (Estado de México). Uber entered the greater Mexico City in 2013 but was unable to introduce cash until the end of 2016. In particular, Uber trips starting in the State of Mexico were allowed to be paid in cash, but not those starting in Mexico City. We geolocalized all the trips that took place in Greater Mexico City during August 2016, 2017, and 2018. We merge these trips with census information at the census block level. We use this data for three purposes. First, we find that the share of trips paid in cash in 2017-2018 in different census blocks of the State of Mexico decreases with any of the census block level observables related to the households' income level (such as average number of years of education, fraction of houses with internet connection, fraction of houses with a car, etc.).[8]

[6] Consistent with this hypothesis, after the Supreme Court's decision, Uber has decided to introduce cash in the cities where it was not previously allowed.

[7] We also construct city-level measures of income, unemployment, weekly rainfall, gas prices, and time since Uber has entered in the city but allowed payments only using credit cards.

[8] We find the same across the census blocks of the city of Puebla when cash was allowed.

Second, we match each census block in the State of Mexico with a “similar” census block in Mexico City using coarsened exact matching. We estimate the average treatment effect of the entry of cash on the growth rate of the total trips in the State of Mexico (relative to the matched census blocks in Mexico City) to be about 100%. Third, we complement this last estimate with a local treatment effect of the change in trips around the boundary between the State of Mexico and Mexico City. This last estimate has the advantage of controlling for unobservables, which vary continuously around the boundary. For this estimate we use a standard regression discontinuity design. We find that the growth rate of trips jumps 40% from one side to the other side of the city. We attribute the difference between the average treatment effect (100%) and this local treatment effect (about 40%) to the fact that the effect from the entry of cash is heterogeneous across census blocks in the State of Mexico. This heterogeneity is consistent with the distribution of observables –the poorer areas of the State of Mexico where cash has a greater impact are further away from the frontier with Mexico City. We describe these results in Section 5.

Ban of Cash in Puebla

The third quasi-natural experiment uses the ban on cash in the city of Puebla in December of 2017. In September of 2017 a young women, Mara Castilla, was kidnapped and subsequently killed, allegededly by a Cabify driver –Cabify is another ride-hailing company that matches drivers and riders using an app similar to Uber. As a consequence of the crime, a law was passed which temporarily suspended Cabify and also ended up banning the use of cash as a means of payment for Uber in Puebla. The ban entered into effect at the beginning of December of 2017. We use a synthetic control approach that considers many cities of Mexico which at that time had already adopted cash and credit as payment to create a counterfactual path for the trips by Uber in Puebla if the ban had not existed. As is standard in this method, the effect of the ban is estimated by comparing the actual behavior in Puebla with its counterfactual Puebla. We find that the ban immediately reduces the trips by more than 60% but in a short period of time, some of the previous cash users had registered a credit card. As a result, the total number of trips decreases by about 40%. We find similar results when we match each census block in Puebla with a “similar” census block in the State of Mexico and use coarsened exact matching to estimate the average treatment effect of the ban on cash. We also find that about 35% of those that were pure cash riders before the ban registered a card with Uber after the ban, in excess of the normal migration from cash to credit that was observed in the past. Additionally, consistently with cash and credit being substitutes, we found that riders that use cash more heavily before the ban, decrease the number of trips after the ban. To put these numbers in perspective and to compare them with the event study, we note that both Puebla and the State of Mexico are two cities with closer to the smallest share of trips paid in cash in Mexico (about 40%) among those where cash is allowed, with some other cities having a cash share twice as large. These estimates are described in Section 6.

Riders' Model and Consumer Surplus

Having established 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 its effect 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 by 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 them 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 them 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. Our baseline estimate is that the consumer surplus lost for pure cash and mixed riders amounts to about 50% of their expenditures on Uber rides paid in cash before then ban. 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.[9] We assume that a rider can register a credit card

[9]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

in the Uber 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 as opposed to increases. 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 7.

Field Experiments

The three randomized control experiments were conducted in the State of Mexico and included the population of active Uber riders with the majority of trips in the State of Mexico. These experiments are discussed in Section 8. 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. In the experiment with mixed riders, they were offered specific to the means of payment. In particular, the experiment had a total of six treatment groups of about 20,000 riders, each with a registered credit card, who received discounts of either 10% or 20% for paying for trips either in cash, for paying trips with credit, or regardless of the method of payment. 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 riders. We estimate price elasticities for miles as large as 1.1 evaluated at current prices.

We compare and complement the estimation of the price elasticity of Uber trips (and miles) with two other price experiments and with a quasi-natural experiment in Uber Panama. 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*. In addition, we use the data of two

more goods, some of them closer substitutes and some 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.

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.

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), as well as 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 steps. The first step is to distort the ideal choice of payment for Uber for a given number of trips, which depends on the elasticity of substitution between paying Uber in cash and paying with credit, as well as the share of trips paid in cash. This step can be summarized as the increase in the ideal price index for Uber trips caused by the cash ban. The second step is that given the increase in the ideal price index in which the magnitude of the loss in the consumer surplus depends on the increase as well as in 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 now discuss the remaining two experiments used 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 quasi-natural experiment in Puebla. 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, where we offer reward equivalents of about 3, 6, or 9 times the average weekly expenditure on Uber if they register a credit card in either less than a week, and the same reward 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 in one week it is hard to obtain a credit card in Mexico but in six weeks they can. Thus, the temporal migration patterns 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 make two findings from this experiment. The first is that the small incentives raises the rate of registering a credit card about twice as much as the one for the control group.[10] 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 finding we conclude that the migration from cash to credit for smaller 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 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 35% 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 45% of their expenditures on Uber.

[10] 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.

Contribution and Limitations of the Study

In summary, since 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.

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, we use both miles and trips for our definition of good service that also allows in principle for higher elasticity by changing the length of trips, and thus a lower consumer surplus. Similarly, 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 –the price at which the demand becomes zero. For instance, 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.[11]

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 find the low value of the elasticity of substitution between cash and credit, which we estimate to be about three, to be surprising. Our strategy does not identify the mechanism for this low elasticity. 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. For instance, Alvarez and Lippi (2017) construct a model in which cash and credit are used simultaneously and find some evidence consistent with the

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

proposed mechanism for developed countries. Also Deviatov and Wallace (2014) develop a model where a fraction of the population is unbanked and uses only cash, and because of that even those that are banked find convenient to hold cash. 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 90s 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.

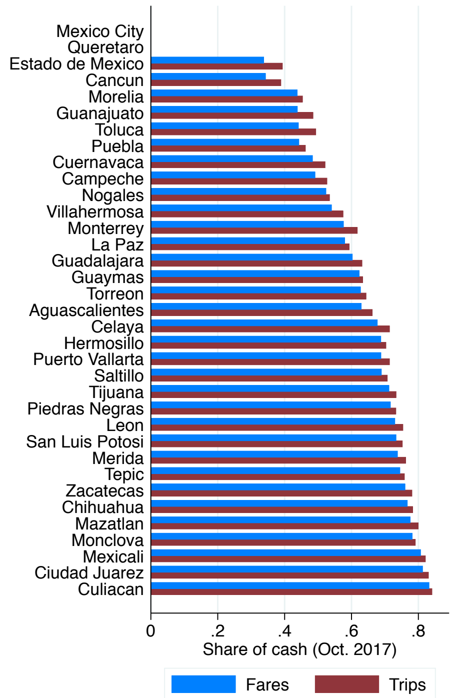
2.1 Uber Mexico

Uber was launched in Mexico in 2013. The first city with the service was the Greater Mexico City, which is composed by Mexico City and its adjacent municipalities in the State of Mexico. As of 2018, Uber was in more than 40 cities in Mexico. 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.[12]

A few local governments, nonetheless, prohibited cash as a payment method at first. Cash was not allowed in Mexico City (as defined by its political boundaries) at first even if it was

[12] 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

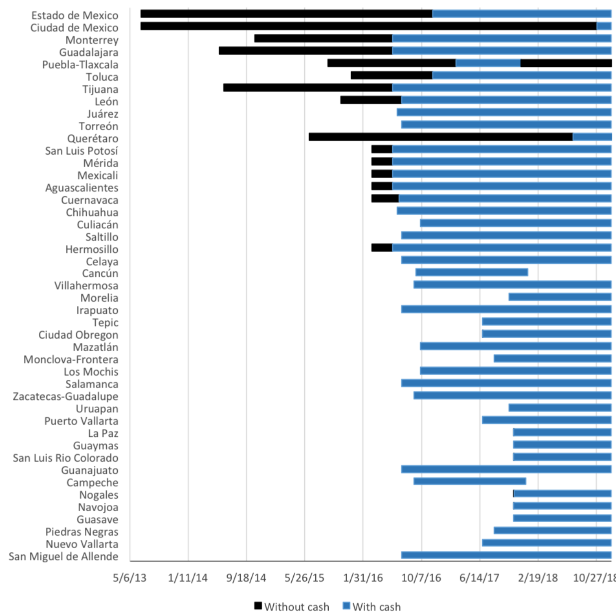


Note: The graph shows the share of trips and fares paid in cash in different cities in Mexico. The red bars show the fraction of trips paid in cash. The blue bars show the share of fares paid in cash. The sample of cities are those that were active in October of 2017.

allowed in all surrounding areas. In this case, the local government prohibited drivers from receiving any payments in cash, with 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 assassination of a young student allegedly by a driver of Cabify, 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.

Figure 2 shows the entry date of Uber in each of the cities in Mexico along with date of the introduction of cash. The black lines denote the periods in which the only payment available in the application was a credit card. The blue lines denote the periods when cash became available in each of the cities. The figure shows that cash became available in most cities where Uber was active in the middle of 2016. After that period, in each city where Uber launched its services, the application already offered the option of cash payment.[13]

Figure 2: Uber Mexico: timing of the introduction of cash as a payment method



Note: The figure shows the entry date of Uber in each of the cities in Mexico. The black parts of the bars indicate the period when only card payment is available to riders. The blue line shows the periods where both card and cash are available as payment methods. The cities are ordered from top to bottom by the size of their population.

2.2 Use of cash in Mexico

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. Some examples are: housing rent (90%), taxes (92%), public services (95%), private services (91%), and public transport (98%).[14] The lack of banking services throughout the population, particularly the poor, is potentially one of the explanations why people rely mainly on cash to pay for goods and services. Only 54% of the population between 18 and 70 years of age has a financial product (i.e. a bank account, some form of formal credit, retirement savings, etc.), less than 50% own

[13]Uber suspended service in December of 2017 in both Cancun and Campeche due to the threat and animosity of taxi cab unions and because of a tense relationship with regulators.

[14]Financial Inclusion Database (BDIF), Mexico 2018.

a debit card and less than 31% own a credit card. Since Uber can be paid by either a credit or a debit card, in the rest of the paper we refer to card payments as those conducted with either a debit or a credit card.

The availability of smartphones in Mexico is more widespread than that of financial products. Approximately 65% of the population owns a smartphone; this share is higher for students, high income individuals or those with higher levels of education. Appendix H provides a detailed decomposition of the demographics of individuals that both own a smartphone and a debit/credit card.

3 Data

We construct a panel at the daily level for all cities where Uber is active in Mexico since the company launched in each city until June of 2018. The data include information on the number of trips, fares, miles, active riders, active drivers, rider sign ups, driver sign ups, driver hours, as well as the average surge multiplier, the share of trips surged, the average estimated time arrival, and the cancellation rates. The data include information of each service Uber provides in Mexico (e.g. UberBlack). However, more than 97% of all trips in Mexico are done using the UberX service.

We also have geolocalized information of every trip taking in the Greater Mexico City during the months of August 2016, August 2017 and August 2018. As we describe below, we use these trips not only to obtain the demographic information of cash users from the census but also to be able to compare similar census blocks in Mexico City and in the State of Mexico before and after the introduction of cash. We also geolocalized information of the trips that took place in the city of Puebla in August 2016, August 2017 and August 2018 to explore the implications of the introduction and ban of cash in this city controlling for observable characteristics of the census blocks.

4 Event Study

We begin by studying the effect of the introduction of cash as a payment option in several cities of Mexico. We explore the impact cash on several outcome variables using an event study approach. Our sample covers the 15 cities where Uber was available before the introduction of cash. This allows us to have a pre-period before the introduction of cash to check for possible pre-trends. In addition, in our sample, cities like Queretaro and Mexico City do not experience the introduction of cash and, as a result, are useful to identify the time effects and serve as comparison group. For this analysis, our sample period covers from April 2016 to the beginning of December of 2017, the week cash was banned in the city of Puebla.

Let Y_{it} be an outcome variable for city i and time t (e.g. number of trips, total fares, average surge multiplier, number of active riders, number of active drivers, etc). Our specification is the following:

$$Y_{it} = \alpha + \sum_{k=-\infty}^{\infty} \gamma_k \mathbb{1}\left\{K_{it} = k\right\} + \theta_i + \lambda_t + \zeta X_{it} + \epsilon_{it} \tag{1}$$

where θ_i represents city fixed effects and λ_t are time effects. K_{it} denote the number of periods relative to the introduction of cash so that γ_k for $k < 0$ correspond to pre-trends and $k \geq 0$ to dynamic effects k periods after the introduction of cash. X_{it} represent a set of city-specific time varying controls such as the unemployment rate, the level of precipitation, the average income of the population in city i at time t, and the time elapsed since Uber has entered into the city.[15] Since the error term in could be serially and cross-sectionally correlated, we use Driscoll and Kraay standard errors.

Figure 3 and Figure 4 show the effect of the introduction of cash on our outcome variables. The graphs show that, conditional on city and time effects, there are no pre-trends in all our outcome variables at least 20 weeks before the introduction of cash. This pattern is consistent with the timing of the introduction of cash being randomly assigned conditionally on the city and time fixed effects. The identification assumption of this exercise is precisely that the entry of cash in these cities had no anticipatory behavior by Uber riders or drivers. The graphs also show that the number of trips and fares more than doubles after the introduction of cash. This is both due to an increase in the number of rider sign ups and also due to an increase in the number of trips of riders already using the application. Between 55-60% of the increase in trips is due to existing riders traveling more often than before once cash is introduced as a method of payment.

Panels (e) and (f) of Figure 3 show that there was also a large increase in the number of driver sign ups (40%) and in the number of driver hours per week (20%). Given that the increase in the number of drivers was not enough to fully cover the increase in the demand of rides, the existing drivers responded by driving more hours. As a result, both the number of active riders over drivers and the fares per active driver increased. Panels (a) and (b) of Figure 4 show that relative to before the introduction of cash the ratio of active riders over drivers increased by 20% and the fares per active driver increase by an average of 20 USD per week, an increase of 12-15% on the total weekly fares per driver. Nevertheless, the drivers' income per hour (total fares divided by total driver hours) does not change when cash is

[15] More details on the data sets used to construct the control variables can be found in Appendix I.

introduced, as shown in Figure B2 in the Appendix.

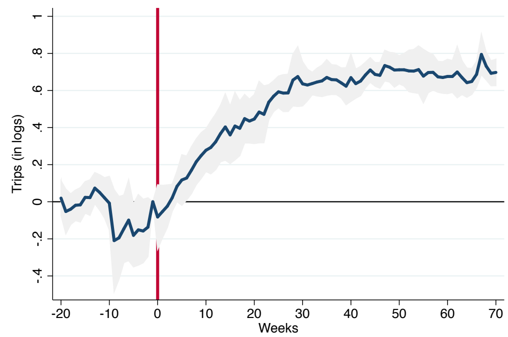
Interestingly, together, the increase in the number of drivers and the increase in the average weekly hours per driver fully compensate the increase in the demand for Uber trips. This can be seen by the path of the average prices of Uber trips after the introduction of cash. Panels (d) and (e) of Figure 4 show that the average price per trip and the average surge multiplier did not increase after the introduction of cash. Given that the effect on prices can be reflected not only in the monetary cost of a trip but also in the waiting cost paid by riders, we also study the patters of the estimated time of drivers' arrival. As shown by Panel (f), we do not find any significant increase in this variable either. Figure B1 in Appendix B shows that the average price of taxis in the cities where cash was introduced does not increase significantly.[16]

These findings are consistent with the presence of a very elastic supply curve for Uber rides and, as a result, a very low producer surplus. Hall et al. (2017), who also found that the driver supply of labor to ride-sharing markets is highly elastic, and argued that this is likely because drivers face no quantity restrictions on how many hours to supply and that new drivers face minimal barriers to entry. Consistent with the fact that prices remain unaffected after the introduction of cash, we find that the number of trips paid in credit remain virtually unaffected after the option of cash payments became available (Panel (c) in Figure 4).

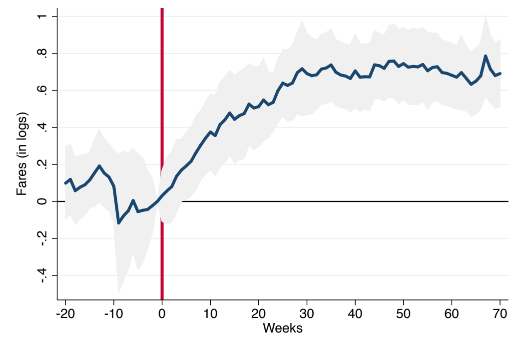
[16] Figure B1 in the Appendix also shows that the cancellation rate remains fairly constant after the introduction of cash.

Figure 3: Event Study: Extensive and Intensive Margin of Riders and Drivers

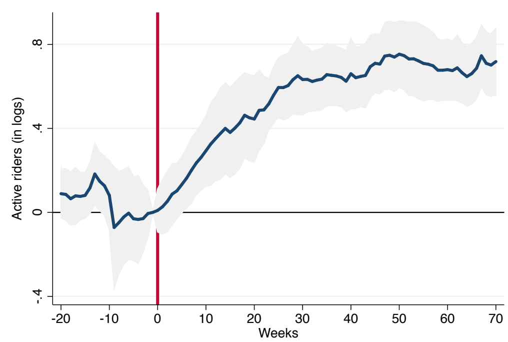
(a) Trips



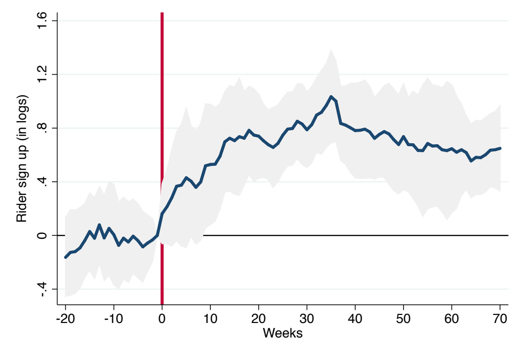
(b) Fares



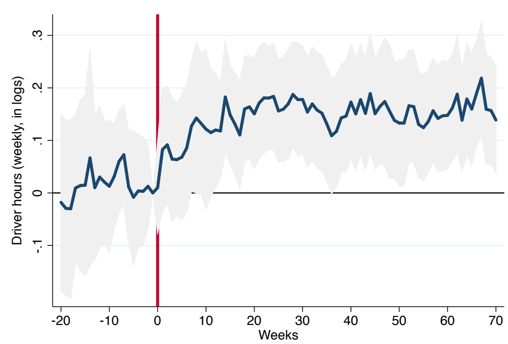
(c) Active Riders



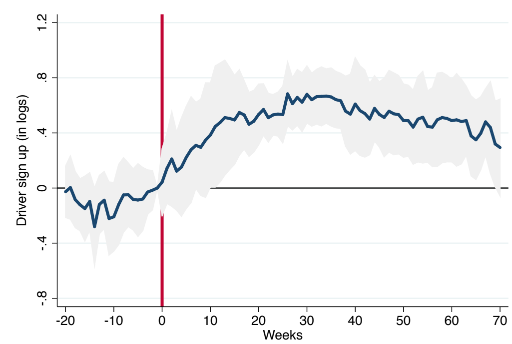
(d) Rider Sign Ups



(e) Driver Hours



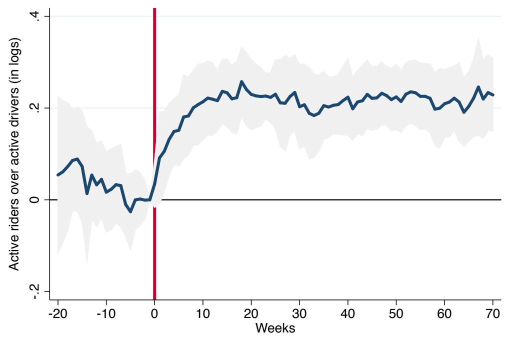
(f) Driver Sign Ups



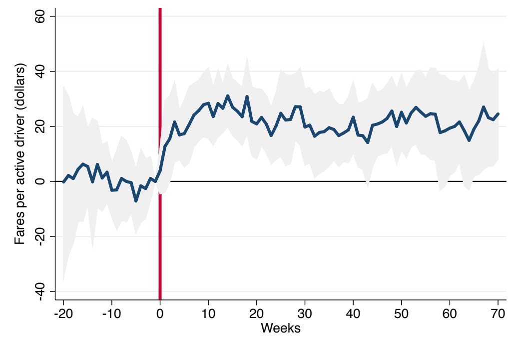
Note: The graph shows the evolution of the number of trips, total fares, active riders, rider sign ups, driver hours, and driver sign ups before and after the introduction of cash. The figure plots the coefficients of γ_k after estimating equation (1). The red line denotes the week of the introduction of cash as a payment method. The gray area 95% confidence interval computed using Driscoll and Kraay standard errors.

Figure 4: Event Study: Riders over Drivers and Prices

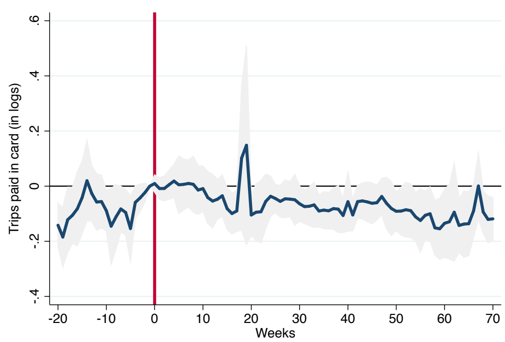
(a) Active Riders over Drivers



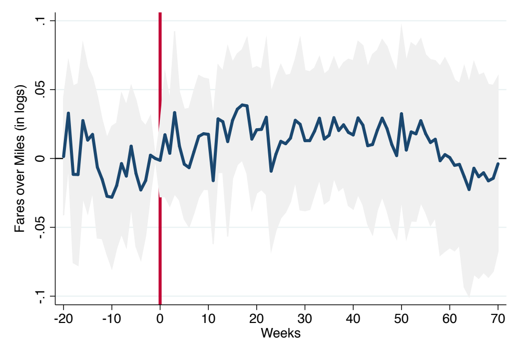
(b) Fares per Activer Driver



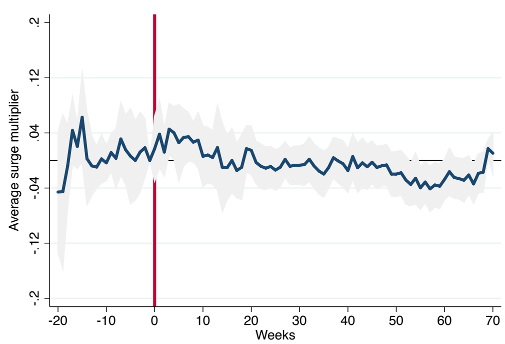
(c) Trips Paid in Credit



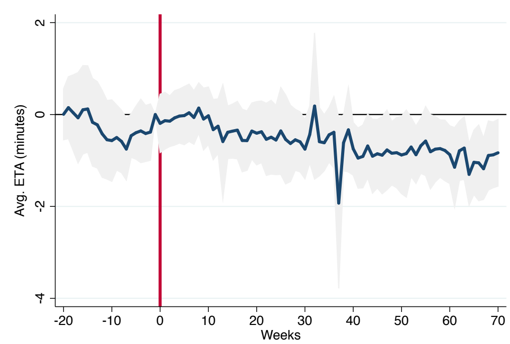
(d) Price



(e) Avg. Surge Multiplier



(f) Avg. ETA



Note: The graph shows the evolution of the ratio of active riders over drivers, fares per active driver, trips paid in cash, price, average surge multiplier, and average estimated time of arrival before and after the introduction of cash. The figure plots the coefficients of γ_k after estimating equation equation (1). The red line denotes the week of the introduction of cash as a payment method. The gray area 95% confidence interval computed using Driscoll and Kraay standard errors.

5 Greater Mexico City: Neighboring Regions Approach

In this section we provide further evidence of the impact of the introduction of cash as a payment method on the number of trips and riders using the application. We accomplish this by using geolocalized data to compare the outcomes of the State of Mexico, a region where cash was introduced in November of 2016, and Mexico City, a city that did not allow cash as a payment method until the ruling of the Supreme Court in November of 2018. Importantly, the municipalities in the State of Mexico that we examine belong to the Greater Mexico City and neighbor Mexico City. Between November of 2016 and November of 2018, cash trips could be requested within the limits of the State of Mexico but not within the limits of Mexico City. Approximately, 26% of the trips starting in the State of Mexico (cash enabled) end in Mexico City.

For this analysis, we use information of all the trips that took place in August 2016, August of 2017 and August of 2018. Our sample of users are those whose most frequent Uber city (i.e. most frequent city of origin for an Uber request) is the Greater Mexico City.[17] For the trips of these users we have information of the latitude and longitude of the origin and destination as well as information on the payment method for the trip.

Using the coordinates of each trip, we are able to assign them to the closest census block; the finest level of geographic aggregation provided by the Mexican census that consists of an area that is on average 80 m^2 (95 square yards). As a result, using the demographic information in the census, we are able to determine the average characteristics of the users that are more likely to pay in cash. Furthermore, we are able to compare, after controlling for observables, census blocks that experience the introduction of cash and those that did not.

We use two empirical approaches to determine the effect of the introduction of cash on the number of trips and fares. We use coarsened exact matching to find the proper counterfactual for each census block in the State of Mexico where cash was introduced. And, second, we use a regression discontinuity approach to compare census block located at the limit between Mexico City and the State of Mexico. This approach allows us to control for both observable and unobservable characteristics of the census block. Using these methodologies, we find an average treatment effect of about 100% of the introduction of cash on the number of trips. At the boundary, we find a local treatment effect of about 40% on the number of trips.

[17] In the case of an user having taken less than 3 trips or in the case of a tie, we use the sign up location of the user to determine their most frequent city.

5.1 Matching Trips to Census Blocks

The Mexican Census provides shape files containing the coordinates of the polygons surrounding each census block in the country.[18] The coordinates of each point of the polygon in the census are provided in the Lambert conformal conic projection (LCC). In order to match the geolocalized trips to census blocks, we first convert the Uber coordinates to the LCC (Elipsoide: GRS80).[19]

We use the longitude and latitude of the centroid of each census block as its location.[20] Then, we match each Uber trip to the closest (centroid) of the census block, by minimizing the Euclidean distance between the two. We use the latitude and longitude of the origin of the trip since that is what determines if the option of paying with cash is available. In order to minimize measurement error, we correct for the potential differences in the Uber's geofence (the polygon that defines the area of cash acceptance shown in Figure 5) and the actual political boundaries of the State of Mexico) using the shape files of the geofence generated by Uber. Figure C1 in the Appendix shows the distribution of distances between the trips and the centroids of the closest census blocks. The median distance of each trip to the centroid of the closest census block is 50 meters.

5.2 Demographics of Cash Users

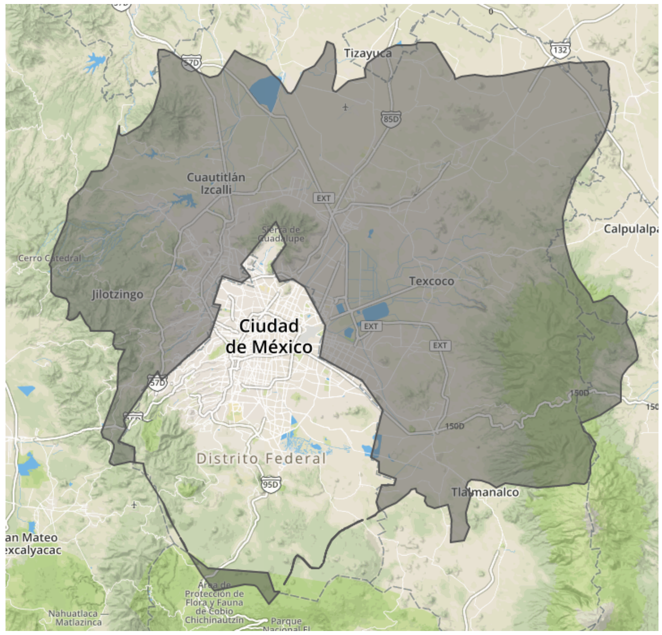
Using the demographic information available in the 2010 Mexican Census, we are able to compute the observable characteristic of each census block and the share of trips paid in cash. Figure 6 shows the share of cash as a function of four observables: the average education in the census block, the share of homes with access to internet, the share of homes with a cell phone, and the share of homes in a census block that own a car. These observables are correlated with the level of income of the households in the census block. The figure shows that the share of trips paid in cash is negatively correlated with all the variables. The negative correlation between the share of cash and different measures of proxies for income persists when we use the first principal component of these variables or the income per capita at the municipality level as shown in Appendix C.2. The share of trips paid in cash is larger in municipalities with lower levels of bankarization, as measured by the debit cards per capita, credits card per capita, bank branches per capita or ATMs per capita (Appendix C.3). It is

[18] Mexico has 32 federal entities (31 states plus Mexico City), 2456 municipalities, Basic Geostatistical Area (set of 1 to 50 census blocks), Locality (population greater than or equal 2500 inhabitants) or census tract, and census block. There are 2.3 million census blocks in the country, more than 100 thousand in the Greater Mexico City.

[19] Details can be found in Appendix C.1.

[20] The centroid of the polygon minimizing the sum of squared Euclidean distances between itself and each point in the set.

Figure 5: Mexico City: areas where cash is allowed



Note: The figure shows the geofence that limits cash payments in the area covering Greater Mexico City. Cash is allowed as a method of payment in the darker areas, outside the official limits of Mexico City.

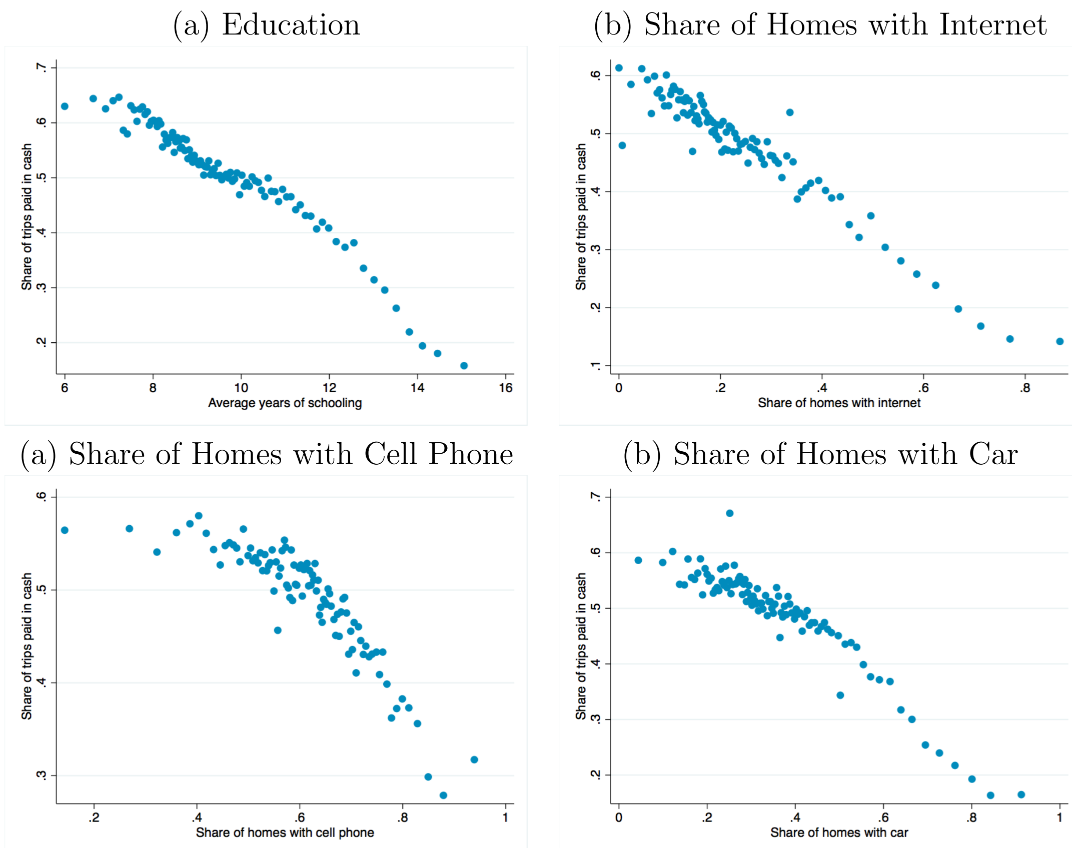
also larger in suburban regions of the State of Mexico (Appendix C.5) and in census blocks with less developed infrastructure measured by the availability of street lights, pavement, or whether the census blocks has access to public transport (Appendix C.4).

5.3 Coarsened Exact Matching (CEM)

To compare census blocks that experience the introduction of cash with those that did not, we use the fact that cash was introduced only in the State of Mexico. Given that the State of Mexico neighbors Mexico City, conditional on observables, we can use the census blocks of Mexico City as counterfactuals for those in the State of Mexico. To do so we use coarsened exact matching (CEM) to find the proper counterfactual for each census block where cash was introduced.[21] CEM is a matching method that allows us to choose the maximum imbalance between the treated and control groups ex ante. In other words, it coarsens each control variable for the purposes of matching. Then, it sorts all units into strata, each of which has

[21]In Appendix C.8 we conduct this analysis using ordinary least squares. The Appendix show results for trips and fares and decomposes the impact of the introduction of cash into both intensive margin (trips in census blocks that were active before the introduction of cash) and extensive margin (trips in census blocks that became active after the introduction of cash). The results using CEM and OLS are quantitatively very similar. The conclusions remain similar when we control for pairs of origin and destination at the basic geostatistical area level.

Figure 6: Share of fares paid in cash by demographics



(a) Education

(b) Share of Homes with Internet

(a) Share of Homes with Cell Phone

(b) Share of Homes with Car

Note: The figure shows the relationship between the share of trips paid in cash and several demographic variables from the Mexican Census. The share of trips paid in cash are those trips that took place in each census block in August of 2017, after the introduction of cash in the State of Mexico. The demographic variables included are the average years of schooling, the share of homes with internet, the share of homes with cell phone, and the share of homes with a car. The census blocks are grouped into 100 equal-sized bins.

the same values of the coarsened observable variables and prunes from the data set the units that do not include at least one treated and one control unit.

We use the share of homes with internet, the share of homes with a car, the share of homes with a cell phone, the number of retail banks, and the average years of educations at the census block level as observable characteristics for the matching. We choose a Sturges rule to coarsened each observable, which implies that each was coarsened in 20 bins. Approximately 94% of all census blocks were matched using this procedure.

Table 1 reports the average treatment effect of comparing blocks in the State of Mexico after the introduction of cash with those in Mexico City. The dependent variable is either the change in the number of trips (Columns 1-3) or the change in the total fares (Columns 4-6), each calculated as in Davis and Haltiwanger (1992), i.e. $2(y_t - y_{t-1})/(y_t + y_{t-1})$, to facilitate

Table 1: CEM: Effect of the Introduction of Cash on Trips and Fares

Note: The table reports the results of an OLS regression that estimates the effect of the introduction of cash in census blocks in the State of Mexico relative to those in Mexico City. The weights of the regression are computed using coarsened exact matching and a Sturges Rule. The observable characteristics used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, and the share of households that own a car. Columns (1)-(3) report the results using the change in the total number of trips and Columns (4)-(6) the results using the change in total fares as dependent variable. Columns (2) and (5) report changes in the intensive margin (trips and fares in census blocks that were active before the introduction of cash) and Columns (3) and (6) changes in the extensive margin (trips and fares in census blocks that became active after the introduction of cash).

	(1) $\Delta Trips$	(2) $\Delta Trips_I$	(3) $\Delta Trips_E$	(4) $\Delta Fares$	(5) $\Delta Fares_I$	(6) $\Delta Fares_E$
State of Mexico	0.657***	0.377***	0.280***	0.517***	0.237***	0.280***
	(0.006)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)
Observations	81,931	81,931	81,931	81,929	81,929	81,929
R-squared	0.137	0.081	0.026	0.088	0.031	0.026
Estimator	CEM	CEM	CEM	CEM	CEM	CEM
Rule	Sturges	Sturges	Sturges	Sturges	Sturges	Sturges
Margin	All	Intensive	Extensive	All	Intensive	Extensive

the study of census blocks becoming active or inactive after the introduction of cash.[22] The Table shows that after the introduction of cash the number increase doubled (a value of 0.66 in $2(y_t - y_{t-1})/(y_t + y_{t-1})$ corresponds to approximately 100% growth rate). Approximately 55% of this increase is explained by census blocks already using the application before the introduction of cash and 45% by census blocks that started using the application after cash was introduced.[23] The results using the change in the total fares as dependent variable are very similar.

These results are consistent with those found in previous sections which use an event study approach. Altogether these results show that, even controlling for census blocks observables, the effect of the introduction of cash on the number of trips and on the total fares is large. This is relevant since the State of Mexico does not have a particularly large share of trips paid in cash relative to other states as shown in Figure 1.

[22]This growth rate is symmetric around zero and it lies in the closed interval [-2,2] with census blocks activated after the introduction of cash corresponding to the right endpoint.

[23]The contribution of the intensive margin in Column (2) and that of the extensive margin in Column (3) add up to the total effect.

5.4 Regression Discontinuity

The second empirical approach leverages the RD design implicit in the introduction of cash to measure its impact on the changes in the number of trips on each side of Mexico City's borders. Specifically, we separately estimate the effect of the introduction of cash across each side of the border of Mexico city and test whether the introduction of cash caused discontinuous changes in the number of trips around the border. This allows to control for unobserved determinants of the number of trips that change continuously across the borders between Mexico City and the State of Mexico.[24] If the relevant assumption is valid, adjustment for a sufficiently flexible polynomial in distance from the border or a local linear regressions on either side of the border will remove all potential sources of bias.

Figure 7 illustrates the impact of cash at the border by showing the relationship between the growth in users and trips before and after the introduction of cash and the distance to Mexico City. As before, the changes in users are computed as in Davis and Haltiwanger (1992). The graphs shows that, allowing a flexible polynomial to differ on each side of the border yields a significant discontinuity at the border both in the change of the number of users (Panel (a)) and in the change in the number of trips (Panel (b)).[25] This is also the case when we examine the change in trips from 2016 to 2018 (Panel (a) of Figure 8). The graphs also show that regions farther away from Mexico City experience more significant increases in users and trips. Importantly, Panel (b) of Figure 8 shows that the discontinuity at the border does not exist if we examine the change in trips between 2017 and 2018, the years that followed the introduction of cash, when there where no further changes on the means of payments allowed occurred in both sides of the border.

We estimate the following equation to test for the impacts of the introduction of cash as a payment method in the State of Mexico:

$$\Delta y_i = \alpha + \beta \times StateMexico_i + f(d_i; \gamma^e) + StateMexico_i \times f(d_i; \gamma^d) + \lambda X_i + \epsilon_i \qquad (2)$$

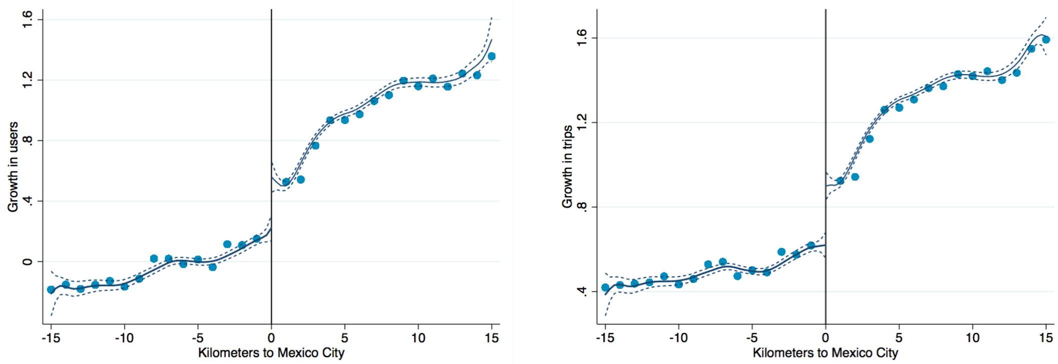
where i denotes a census block, Δy_i is the change in the outcome variable (e.g. trips, users, etc), and $StateMexico_i$ is an indicator variable equal to one if the census block is located in the State of Mexico. In other words, if $StateMexico_i$ equals one, cash was allowed as a payment method. $f(\cdot; \gamma)$ is a Kernel-weighted local polynomial in meters relative to the border between Mexico City and the State of Mexico that satisfies $f(0; \gamma) = 0$, X_i is a vector

[24] Appendix C.7 shows that there is no discontinuous change in observables variables, such as education and other variables related to income, at the border between the State of Mexico and Mexico City.

[25] In order to determine the growth of users in each census block, we assign each user to the census block where most of his or her trips originated. In case of ties we assigned users to the census block where the majority of her trips started in the morning (before noon) and where the majority of her trips ended at night (after 5 pm).

Figure 7: Percent change in the number of users and trips 2016-2017

(a) Change in Users (2016-2017) (b) Change in Trips (2016-2017)



Note: Panel (a) shows the relationship between the growth in users between 2016-2017 and the distance to Mexico City. Panel (b) shows the relationship between the growth in trips between 2016-2017 and the distance to Mexico City. Negative numbers in the x-axis indicate the census block is in Mexico City. Each bin corresponds to one kilometer. The dots show the average growth in users (trips) in each bin. The line is a kernel-weighted (epanechnikov) local polynomial of degree 3. The dashed lines are the 99% confidence intervals.

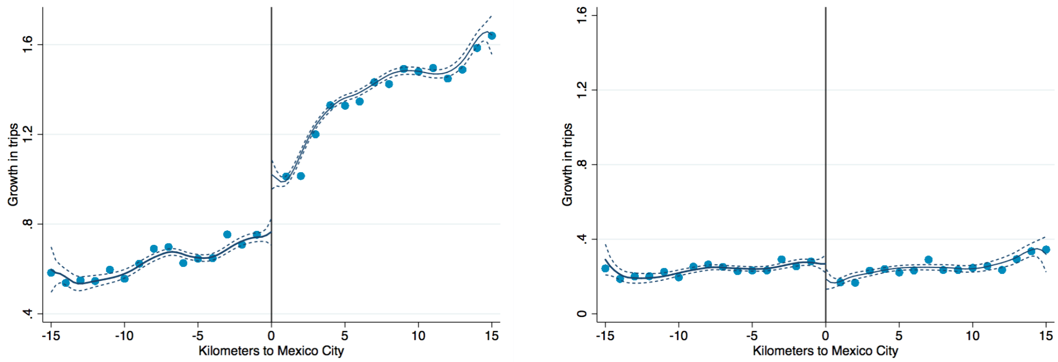
of the census block characteristics that could potentially affect the number of Uber trips, such as the average education of the block and the share of homes that own a cell phone. The parameter of interest is β, which provides an estimate of whether there is a discontinuity in outcomes at locations outside the border of Mexico City relative to locations inside Mexico City. If the RD assumptions hold, estimates of β will provide an unbiased estimate of the change in the number of trips and fares as a consequence of the introduction of cash.

The results are reported in Table 2 and Table 3 for the change in the number of trips and fares respectively. At the boundary we find a local treatment effect of 40% in the number of trips and a slightly lower effect for total fares. The tables also show that our results are robust if we use polynomials of different degrees and are not sensitive to the inclusion of controls. Table CI and Table CII in Appendix C.6 show that our results are also robust if we restrict the sample of census blocks on each side of the border to be within 5 kilometers of the border.[26]

[26] The trips are geolocalized based on the location where the driver started and ended the trip. As a result, we are able to detect and adjust our estimates for riders that might have requested a trip in the State of Mexico to be paid in cash but whose trip in fact started in Mexico City. On the other hand, it is possible that riders in Mexico City crossed to the State of Mexico to request trips in cash. Our results are very similar if we exclude trips that started less 100 mts from the border.

Figure 8: Percent change in the number of users 2016-2018 and 2017-2018

(a) Change in Trips (2016-2018) (b) Change in Trips (2017-2018)



Note: Panel (a) shows the relationship between the growth in trips between 2016-2018 and the distance to Mexico City. Panel (a) shows the relationship between the growth in trips between 2017-2018 and the distance to Mexico City. Negative numbers in the x-axis indicate the census block is in Mexico City. Each bin corresponds to one kilometer. The dots show the average growth in trips in each bin. The line is a kernel-weighted (epanechnikov) local polynomial of degree 3. The dashed lines are the 99% confidence intervals.

Table 2: Regression Discontinuity Approach: Effect on Trips

Note: The table reports the results for the coefficient of β after estimating equation (2). The estimates report the local treatment effect at the border between the State of Mexico and Mexico City of the introduction of cash as a payment method. Each column reports the results using a Kernel-weighted local polynomials of different degrees. The dependent variable is the change in the total trips of each census block.

	(1)	(2)	(3)	(4)	(5)
State of Mexico	0.390***	0.313***	0.216***	0.173***	0.239***
	(0.013)	(0.018)	(0.023)	(0.029)	(0.034)
Observations	87,036	87,036	87,036	87,036	87,036
R-squared	0.351	0.352	0.353	0.354	0.354
Controls	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All
Degree	1	2	3	4	5

Table 3: Regression Discontinuity Approach: Effect on Fares

Note: The table reports the results for the coefficient of β after estimating equation (2). The estimates report the local treatment effect at the border between the State of Mexico and Mexico City of the introduction of cash as a payment method. Each column reports the results using Kernel-weighted local polynomials of different degrees. The dependent variable is the change in the total fares of each census block.

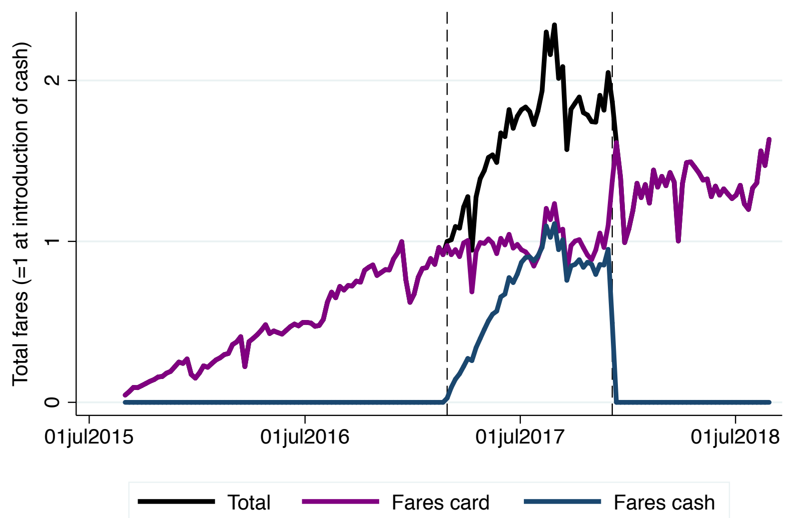
	(1)	(2)	(3)	(4)	(5)
State of Mexico	0.283***	0.245***	0.154***	0.118***	0.187***
	(0.011)	(0.016)	(0.021)	(0.026)	(0.031)
Observations	87,033	87,033	87,033	87,033	87,033
R-squared	0.249	0.250	0.251	0.251	0.251
Controls	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All
Degree	1	2	3	4	5

6 Ban on Cash

Uber launched in Puebla on September of 2015 but it did not introduce cash as a payment method until March of 2017. On September 15th of the same year, a student was kidnapped and subsequently assassinated, allegedly by a Cabify driver, another ride-hailing company operating in the city. In consequence, the local government decided to ban Cabify in the city as well as to ban cash as a payment method in ride-hailing companies. The announcement of the ban was made on October 31st and its implementation occurred on December 8th. Figure 9 shows the total fares in the city of Puebla after splitting by payment method. The graphs shows that the total fares almost doubled after the introduction of cash; although Puebla was one of the least cash intensive cities in the country, the total fares paid in cash were very close to those paid in credit before the ban.[27]

[27]A more recent ban on cash ocurred in the city of San Luis Potosí on Juy 17th, 2019. The ban was a consequence of changes in the local Transportation Law. In contrast to Puebla, San Luis Potosí was a cash intensive city, approximately 75% of the total fares were paid in cash. More details on the patters of fares in San Luis Potosí are provided in Appendix M.

Figure 9: Puebla: Total Fares by Payment Method



Note: The figure shows the evolution of the fares paid by users in the city of Puebla. The black line shows the total fares, the purple line shows those paid in card, and the blue the fares paid in cash. The dotted lines show the introduction and ban of cash as a payment method in the city. Total fares are normalized to equal 1 the period of the introduction of cash.

6.1 Synthetic Control

To study the effect of the ban on cash on total trips, we use the Synthetic Control Method proposed by Abadie and Gardeazabal (2003). We construct a weighted average of 32 cities in Mexico to mimic the patterns observed in the city of Puebla before the ban on cash. Let $J+1 \in \mathbb{N}$ be the total number of cities including Puebla observed during $T \in \mathbb{N}$ periods. The ban on cash affects only Puebla from period T_0+1 to period T, where $T_0 \in (1,T) \cap \mathbb{N}$. Let Y_{jt}^N be the potential outcome (e.g. number of trips, total fares) that would be observed for city j in period t if cash is not banned as a payment method and let Y_{jt}^I be the potential outcome that would be observed if city j faced a ban on cash. We define $\alpha_{jt} \equiv Y_{jt}^I - Y_{jt}^N$ as the effect of the ban for city j in period t. Then, the observed outcome for city j in period t is:

$$Y_{jt} \equiv Y_{jt}^N + \alpha_{jt} D_{jt}$$

where D_{jt} is a dummy variable that equals 1 if city $j=1$ (Puebla) faces the ban on cash in period t and 0 otherwise. We estimate Y_{1t}^N using the Synthetic Control Method to find the estimator $\alpha_{1,t}$ defined as $\hat{\alpha}_{1t} \equiv Y_{1t} - \hat{Y}_{1t}^N$.

We use daily city-level panel data from August of 2017 to March of 2018. The ban on cash occurred on December 8th, 2017. Our sample of cities includes the 32 cities in Mexico that were active the week of the ban on cash in Puebla after splitting Mexico City and the State of Mexico. We estimate the effect of the ban on the total number of trips per capita in Puebla as the difference between this variable and its synthetic counterpart the days following the ban. For the pre-ban characteristics we rely on variables related to the number of trips and the use of cash as a payment method: trips paid in cash per capita, total fares per trip, and the total trips per capita on August 15th and September 1st of 2017.[28] The synthetic Puebla is a weighted average of Guanajuato (0.453), State of Mexico (0.425), Mexico City (0.072), and Queretaro (0.051) with weights reported in parenthesis. All other cities are assgined zero weights. The root mean square prediction error (RMSPE) is 0.00152. Table 4 compares the pre-ban characteristics of Puebla to those of synthetic Puebla. Overall, the table shows that the synthetic Puebla is very similar to the actual Puebla in terms trips and fares.

Table 4: Predictor Balance with State of Mexico

Note: The table reports the average values of the predictors used to define the synthetic control for the city of Puebla. The variables reported in per capita terms are computed using the population of the city of Puebla in 2017.

	Puebla	Synthetic
Trips paid in cash per capita (daily)	0.0019	0.0019
Total fares per trip (daily)	3.4698	3.4748
Total trips per capita (Sept 1, 2017)	0.0220	0.0202
Total trips per capita (Aug. 15, 2017)	0.0148	0.0148

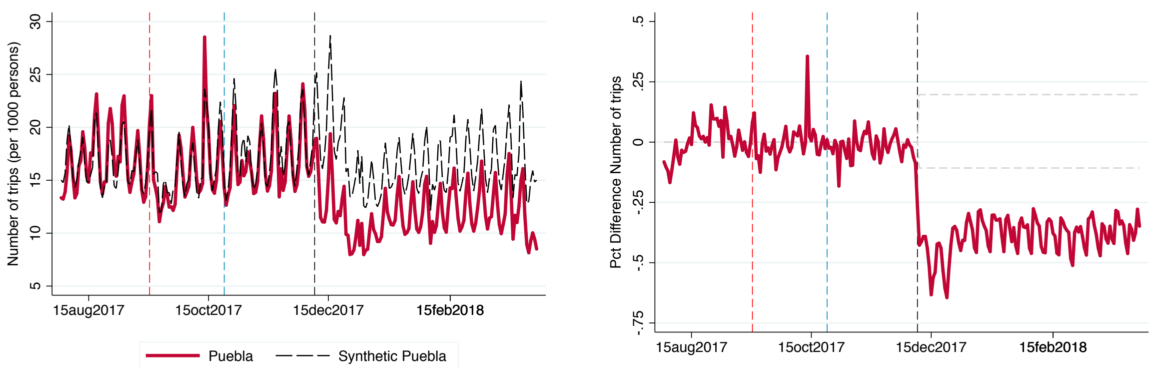
Panel (a) in Figure 10 shows the evolution of the daily trips before and after the ban in cash. The graph shows that our synthetic Puebla matches well daily fluctuations in the trips of the city of Puebla before the ban including the brief spikes in the number of trips that occur during the weekends. The figure also shows that after the ban on cash the trips decreased significantly. Panel(b) shows the difference (in percent) of the number of trips between the synthetic Puebla and the actual Puebla. The figure shows that on impact, the total number of trips decreased more than 60%. The number of trips rebounded after approximately four weeks, mainly due to cash users migrating to credit after the ban, but remained permanently lower than the level before the ban in cash. The dotted gray lines in Panel (b) show the 95% confidence interval of the change in the number of trips indicating that the change is

[28]Our results are unchanged when we include low frequency variables, such as the unemployment rate or the income level of the city, as pre-ban characteristics.

not only large but also significant relative to the distribution of the effects estimated for the cities that did not experience the ban. In Appendix D we describe our inference procedure, which follow the permutation tests described in Firpo and Possebom (2018) and analyze the size and the power of eleven different test statistics. In all the tests the change in the number of trips before and after the ban is statistically significant.

Figure 10: Puebla: Synthetic Control - trips

(a) Trips (b) Percent Change in Trips



Note: Panel (a) shows the evolution of daily trips per 1000 persons in the city of Puebla (dotted black line) and the evolution of trips of the synthetic Puebla constructed using the Synthetic Control Method (red line). Panel (b) shows the evolution percent difference in daily trips. The black dotted vertical line is the date of the ban on cash. The gray dotted lines in Panel (b) show the 95% confidence interval computed using permutation tests as in Firpo and Possebom (2018).

We have also repeated the exercise using data until prior dates to fit the weights of synthetic Puebla, such as until the date of the murder of Mara or the date of the passing of the law -both indicated in the graph in Figure 10.

6.2 Coarsened Exact Matching (CEM)

The effect of the ban on cash on the number of trips is similar if, instead of a Synthetic Control Method, we use a coarsened exact matching (CEM) procedure to compare each of the census blocks that experience the ban in Puebla with comparable blocks that did not in the State of Mexico.[29] For this analysis, we use geolocalized data of Puebla for the months of August 2017 and August 2018. Given that cash was banned in all the census blocks in Puebla, we use census blocks in the State of Mexico as counterfactuals. The State of

[29] Appendix D.5 shows the basic geostatistical areas in Puebla that experience larger changes in the number of trips after the introduction and ban of cash. The maps show that suburban areas, those farther away from the center of the city, experienced larger changes.

Mexico is a particularly useful counterfactual for Puebla since the two cities are both close geographically and had similar share of trips paid in cash before the ban –indeed State of Mexico had a large weight in the synthetic control.

As before, we use the share of homes with internet, the share of homes with a car, the share of homes with a cell phone, the number of retail banks, and the average years of educations as observable characteristics in the census block for the matching. In addition we include the total trips per capita in 2017 at the census block level. In this case, approximately 73% of approximately 20 thousand census blocks in Puebla were matched. Table 5 reports the average treatment effect of comparing blocks in the Puebla after the ban of cash with those in the State of Mexico. As before, the dependent variable is either the change in the number of trips (Columns 1-3) or the change in the total fares (Columns 4-6). Consistent with the findings of the previous section, there was a decrease in the number of trips and the total fares of more than 50%. In this case, however, most of the decrease is explained by the intensive margin given that in most census blocks, at least one user remained active in the application after the ban of cash.

Table 5: CEM: Effect of the Ban on Cash on Trips and Fares

Note: The table reports the results of an OLS regression that estimates the effect of the ban of cash in census blocks in Puebla relative to those in the State of Mexico. The weights of the regression are computed using coarsened exact matching and a Sturges Rule. The observable characteristics used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, the share of households that own a car, and the trips per capita in 2017. Columns (1) reports the results using the percent in the total number of trips, Column (2) the percent change in trips attributable to the intensive margin, and column (2) the percent change attributable to the extensive margin. Columns (4)-(6) reports the results using the percent change in total fares as dependent variable. Columns (2) and (5) report changes in the intensive margin (trips and fares in census blocks that were active before the introduction of cash) and Columns (3) and (6) changes in the extensive margin (trips and fares in census blocks that became active after the introduction of cash).

	(1) $\Delta Trips$	(2) $\Delta Trips_I$	(3) $\Delta Trips_E$	(4) $\Delta Fares$	(5) $\Delta Fares_I$	(6) $\Delta Fares_E$
Puebla	-0.493***	-0.460***	-0.032***	-0.491***	-0.459***	-0.032***
	(0.010)	(0.006)	(0.008)	(0.010)	(0.006)	(0.008)
Observations	51,991	51,991	51,991	51,987	51,987	51,987
R-squared	0.048	0.117	0.000	0.045	0.099	0.000
Estimator	CEM	CEM	CEM	CEM	CEM	CEM
Rule	Sturges	Sturges	Sturges	Sturges	Sturges	Sturges
Margin	All	Intensive	Extensive	All	Intensive	Extensive

6.3 Survival Function

The decrease in the total number of trips after the ban was in part attenuated by the fact that many pure cash users (those that use only cash as a payment method, approximately 30% of users) chose to adopt credit to remain using the application. Figure 10 shows, for example, that within 2 weeks the number of trips experienced a partial recovery after the sudden decline that occurred the week of the ban. To quantify the propensity of cash users to adopt credit after the ban in cash, we estimate survival functions of different cohorts of users. We use data starting on the week of March 6, 2016, when cash was introduced in the city. The last cohort of users considered are those that enter the week of the ban on cash, which took place on December 8th, 2017. We consider 39 cohorts of users before the ban on cash and 39 cohorts after.

Figure 11 shows the survival function for pure cash users and hazard rate of pure cash taking a trip and paying with a credit card for the first time as a function of the number of weeks since they first joined Uber. Panel (a) shows the survival function and Panel (b) the hazard rate. The graphs show that new pure cash users are more likely to adopt credit but the hazard of credit adoption remains mostly constant afterward. Moreover, the figure shows that the cohort of users that entered before the ban on cash are much more likely to adopt credit particularly the first few weeks after they first use the application. Overall, we find that between 35-40% of all the pure cash users ended up adopting credit after the ban on cash, in excess of the percentage that would have normally done so. The majority of those adopted credit the immediate weeks after the ban, suggesting that they already had a credit card available and had chosen not to register it in the application.

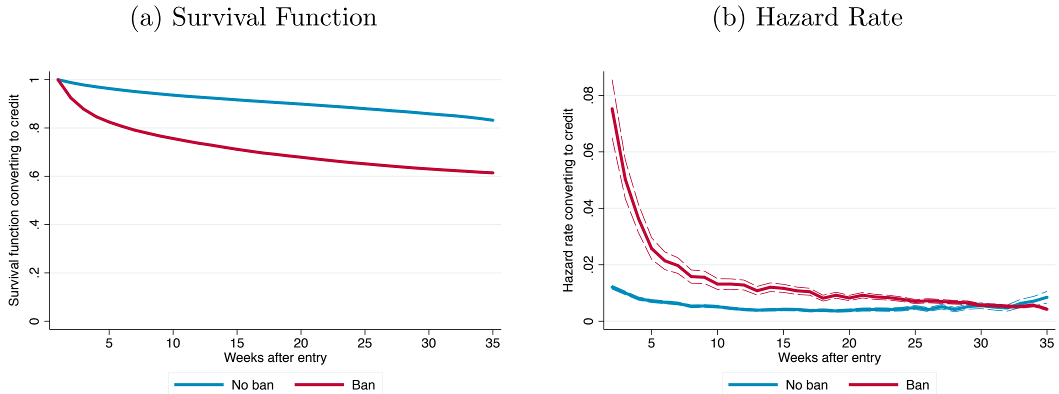
6.4 Mixed Users

The decrease in the number of trips after the ban did not come only from pure cash users but also from mixed users (those that have used both cash and credit as payment methods in the application). Almost half of the users in the city of Puebla were mixed users before the ban. We show that even users that had adopted credit before the ban decreased their trips after the ban in cash is in place. The effect on the ban on the number of trips is larger for those users whose share of fares paid in cash before the ban was larger.[30] We show this by estimating the following specification:

$$\Delta Y_j = \alpha + \sum_k \beta_k \text{ Share Cash Before}_{jk} + \lambda X_j + \epsilon_j \tag{3}$$

[30]The distribution of users over the share of fares paid in cash is close to uniform. We provide more details on the shape of this distribution in the next section.

Figure 11: Puebla: survival function and hazard rate before and after ban



Note: The graph shows the survival function and hazard rate of users using card as a payment method for the first time. Panel (a) shows the survival function and panel (b) the hazard rate. The data is for the city of Puebla and considers users that first used the application the week of March 6, 2016, when cash was introduced in the city. The last cohort of users considered are those that enter the week of the ban on cash, which took place on December 8th, 2017. We consider 39 cohorts of users before the ban on cash and 39 cohorts after. The dashed lines in Panel (b) show 99% confidence intervals.

where ΔY_j is the change in the average number of trips per week before and after the ban. The unit of observation j is a specific rider in the city of Puebla. Share Cash Before$_{jk}$ is an indicator that the share of fares paid in cash before the ban for rider j are in the k bin, and X_j is a vector of observables that include the cohort of the user (week the rider took her first trip in Uber) and the average weekly fares before the ban.

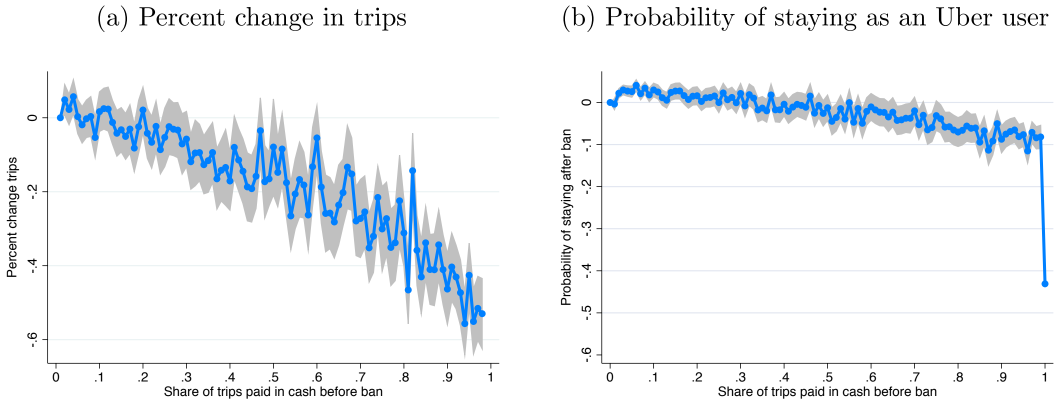
Figure 12 shows the estimates of β_k for different levels of the share of fares paid in cash before the ban.[31] The figure shows that there was a significant reduction in the average weekly trips of mixed riders after the ban. This reduction on the number of trips varies depending on how cash intensive the users were before the ban. Not surprisingly, the users that were more cash intensive before the ban decrease their trips more drastically.

Panel (b) shows the results when we estimate equation (3) using an indicator variable that equals one if the rider used the application after the ban as outcome variable. This specification allows us to estimate the propensity of users to use the application after the ban on cash. The graphs show that cash intensive users were also less likely to return to Uber, even if they had enabled credit as a payment method before the ban.[32]

[31] Appendix D.3 shows the estimated coefficients under several specifications.

[32] Figure D1 in Appendix D.4 shows the correlation between the probability of users returning to the application (after the ban) and several variables. Users in high income municipalities and in municipalities with wider availability of banking services are more likely to remain in the application after the ban.

Figure 12: Puebla: Intensive and Extensive margin adjustment to Ban given Past Cash Intensity



Note: Panel (a) shows the change in the average weekly trips of mixed users after the ban on cash as a function of the share of fares paid in cash of different users before the ban. Mixed users are defined as those whose share of fares paid in cash before the ban was between 1% and 99%. The panel plots the coefficient of β_k estimated using equation (3) for different shares of cash (indexed by k). Panel (b) shows the probability of staying as an Uber user after the ban on cash as a function of the share of fares paid in cash of the different users before the ban. The sample of users plotted in Panel (b) include pure credit users, pure cash users -which are the ones in the last bin- and mixed users. In both graphs the users considered are those that were active in 2017, the year before the ban on cash, and that had at least 10 trips that year.

7 Rider's Model and Consumer Surplus

We describe the model for 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, as we argue in Section 4 they are consistent with the available evidence in Mexico. Thus we ignore the potential cost for the drivers, or the benefits for the riders registered before the ban and that where not using cash both coming from price decreases. 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. we use that utility is quasi-linear. We distinguish as different goods Uber rides paid in cash from 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 to 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 assumption and the data we use to attempt to overcome them.

7.1 Intensive Margin Rider's Problem

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

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

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 the distribution of ϕ across riders.[33]

One advantage of quasi-linear preferences is its simplicity, since equivalent and compensated variations are the same. We also think that it is 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. Thus, 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 for 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

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

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:

$$v(p_a, p_c, p_2, \ldots, p_n; \phi) = \max_{a,c,x_2,\ldots,x_{n+1}} u\left(H\left(a, c; \phi\right)\right), x_2, \ldots, x_n; \theta) + x_{n+1} \tag{4}$$
$$\text{subject to } p_a a + p_c c + \sum_{i=2}^{n} p_i x_i + x_{n+1} = I$$

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 object 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 (4) 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 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:

$$\mathbb{P}(p_a, p_c; \phi) = \min_{a,c} p_a a + p_c c \text{ subject to } H(a, c; \phi) = 1 \tag{5}$$

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 (5) 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 that the elasticity of substitution to be larger than one.

7.2 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:

$$\mathcal{V}(p_a, p_c; \theta) \equiv \max \left\{ v\left(p_a, p_c; \phi\right) - \psi \, , \, v\left(p_a, \infty; \phi\right) \right\} \tag{6}$$

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 (6) 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 level 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.

7.3 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 it 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 (4). The prior decision of registering a card is summarized by $1_c(1,1;\theta)$, and the distribution of types F. The consumer surplus lost in the ban is:

$$
\begin{aligned}
\mathcal{CS}_{ban} = &\int 1_c(1,1;\theta)\,[v(1,1;\phi) - v(\infty,1;\phi)]\,dF(\theta) \\
&+ \int [1 - 1_c(1,1;\theta)]\,[v(\infty,1;\phi) - \mathcal{V}(\infty,1;\theta)]\,dF(\theta)
\end{aligned} \tag{7}
$$

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 costs 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 user. Their utility function flow value before the ban is $v(\infty,1;\phi)$. 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:

$$
\begin{aligned}
\mathcal{CS}(p_a,1) = &\int 1_c(1,1;\theta)\,[v(1,1;\phi) - v(p_a,1;\phi)]\,dF(\theta) \\
&+ \int [1 - 1_c(1,1;\theta)]\,[v(1,\infty;\phi) - \mathcal{V}(p_a,1;\phi)]\,dF(\theta)
\end{aligned} \tag{8}
$$

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 $p_a \geq 1$:

$$
A(p_a,1) = \int 1_c(1,1;\theta)\,\tilde{a}(p_a,1;\phi)dF(\theta) + \int (1 - 1_c(1,1;\theta))\,a^*(p_a,1;\theta)dF(\theta) \tag{9}
$$

Note that the definition of the aggregate demand breaks the integral into the same two groups of riders as in equation (8). 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

$$\mathcal{CS}_{ban} = \int_1^\infty A(p_a, 1) dp_a \tag{10}$$

Note that the demand that satisfies equation (10) 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 for g for the fixed cost to take care of the extensive margin.

7.4 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 keep 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 because 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. We combine this information with a structural model to produce theoretically based estimates of the consumer surplus. In particular we use a parametric version because our experiments contain limited amount of price points and rewards variation, due to the need to combine the information on the riders' intensive and extensive margin reaction to price decreases, and most importantly because our experiments have only price decreases. Below we explicitly write the assumptions we use for our estimation.

Our first result is to represent the problem for the Uber rider in two stages. This allows to us 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 $\{p_2, \ldots, p_n\}$.

$$U(X; \phi, p_2, \ldots, p_n) \equiv \max_{x_2, x_3, \ldots, x_n} u(X, x_2, \ldots, x_n; \phi) + I - \left[\sum_{i=2}^{n} p_i x_i\right] \tag{11}$$

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:

$$V(P; \phi) = \max_{x \geq 0} U(x; \phi) + [I' - Px] \tag{12}$$

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 (12)), for U defined as in equation (11), if and only if $x_1 = X$ solves:

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

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

$$v(p_a, p_c; \phi) = V(\mathbb{P}(p_a, p_c; \phi); \phi). \tag{13}$$

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

$$\tilde{a}(p_a, p_c; \phi) = a\left(\frac{p_a}{p_c}, 1; \phi\right) X(\mathbb{P}(p_a, p_c); \phi) \tag{14}$$

$$\tilde{c}(p_a, p_c; \phi) = c\left(\frac{p_a}{p_c}, 1; \phi\right) X(\mathbb{P}(p_a, p_c); \phi) \tag{15}$$

where a, c are the solutions of problem (equation (5)), and X is the solution of problem (equation (12)).

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 in our experiments –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 credit group, expect 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 (11) and from problem (equation (12)) that U is identified by observing how $\tilde{c}(p, p; \phi)$ and $\tilde{a}(p, p; \phi)$ changes 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 $\mathbb{P}(p_a, \infty; \phi) = p_a\,\mathbb{P}(1, \infty; \phi)$.[34] 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 flow rewards d to be obtained only if

[34] 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 E.3.

they registered a card. Then we can identify the distribution $\psi \sim g(\cdot|\phi)$ using the fraction that have registered card for different values of d. This follows from the inequalities implied in equation (6). 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 a interval of feasible values for the share α based upon the the experimental evidence and the observed behaviour or 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 users, from the estimates of excess migration from Puebla, and from the experiments on payments to migration to credit. They all apply 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 this 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:

$$\psi \geq v(1, 1; \phi) - v(1, \infty; \phi) \tag{16}$$

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:

$$\psi \leq v(\infty, 1; \phi) - v(\infty, \infty; \phi) \text{ for fraction } m_{ban} \text{ and} \tag{17}$$

$$\psi \geq v(\infty, 1; \phi) - v(\infty, \infty; \phi) \text{ for fraction } 1 - m_{ban} \tag{18}$$

The right hand side of these inequalities defines a value of ψ such that for higher values riders 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 haveL

$$0 < \tilde{a}(\infty, 1; \phi) \leq \tilde{a}(1, \infty; \phi) \tag{19}$$

4) *Experimental evidence on the excess migration due to incentives.* From our experiment pure cash riders are offered a once time payment d_k, from which we measure the induced (excess) migration of fraction m_k 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 k.

$$\psi \leq v(1, 1; \phi) - v(1, \infty; \phi) + \rho d_k \text{ for fraction } m_k \text{ and} \tag{20}$$

$$\psi \geq v(1, 1; \phi) - v(1, \infty; \phi) + \rho d_k \text{ for fraction } 1 - m_k \tag{21}$$

for each reward level k.

In Appendix K 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.

7.5 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 at 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:

$$\tilde{U}\left(H\left(a_i, c_i; \phi\right); \phi, \omega\right) \tag{22}$$

where $\tilde{U}(\cdot; \phi, \omega)$ has been described above in equation (11). 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:

$$\begin{gathered} U(a, c; \phi) \equiv \max_{a_i, c_i} \int \tilde{U}\left(H\left(a_i(\omega), c_i(\omega); \phi\right); \phi, \omega\right) \mu(d\omega|\phi) \qquad (23) \\ \text{subject to: } a = \int a_i(\omega)\, \mu(d\omega|\phi) \text{ and } c = \int c_i(\omega)\, \mu(d\omega|\phi)\,. \end{gathered}$$

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.

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 EI and Table EII in Appendix E.6. We found that all restrictions are satisfied for the two price experiments described below.

7.6 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

$$U(x;\phi) = -e^{(x+\bar{x})k}/k$$

so U has two parameters, $k >$ and $\bar{x} > 0$. The demand that solves the problem (equation (12)) 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:

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

The consumer surplus of a rider with this utility function

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

Note that the demand X is convex on P, a feature we 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 16 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, using a demand with constant elasticity would give a consumer surplus that can be an order of magnitude larger than with our semi-log demand. Additionally, Figure 16 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 E 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 E 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.

7.7 Assumptions

Now we are 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 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 characteristic.

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 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 $\mathbb{P}(1, \infty; \phi) = (1-\alpha)^{1/(1-\eta)}$.[35] Hence for each α for pure cash users we can identify all the parameters. Indeed the restrictions given by equation (16) and equation (17), 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.

8 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, 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.

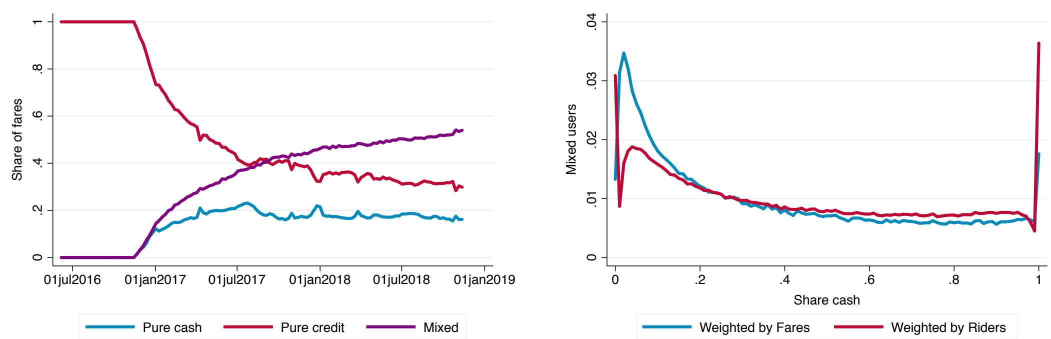
8.1 Experiment 1: Mixed Users

The experiment took place in the State of Mexico from August 21st to August 27th of 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 of 2018. Appendix FI 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 13 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.

[35] See the expression for $a^*(p_a, \infty; \phi)$ in Appendix E.3. This expression depends on $k, \bar{P}$ and $(1-\alpha)^{1/(1-\eta)}$.

Figure 13: 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 leas 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 the distribution weighted by riders.

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 remainder emails were sent (in the middle of the week and two days before the promotions expired).[36]

Table 6 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 6, we summarize our result as by saying that $\eta \approx 3$ or smaller. We compare the behavior of the share of trips paid in

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

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 F.2 for the derivation of the approximation. The first and second order approximations around $p_c/p_a = 1$ are:

$$s_c = \alpha - (\eta - 1)\alpha(1-\alpha)\ln\left(\frac{p_c}{p_a}\right) \text{ , and} \tag{24}$$

$$s_c = \alpha - (\eta - 1)\alpha(1-\alpha)\ln\left(\frac{p_c}{p_a}\right) + \frac{1}{2}(1-\eta)^2(1-\alpha)\alpha\left[1-2\alpha\right]\left(\ln\left(\frac{p_c}{p_a}\right)\right)^2 \tag{25}$$

In column (5) we use each mixed rider's historical trips in Uber to estimate α as the share of trips paid in credit s_c outside our experiment, i.e. when $p_a = p_c$, so that in 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 (24) by our estimate of $\alpha(1-\alpha)$ and run the regression:

$$\tilde{s}_c = 1/(1-\alpha) - (\eta - 1)\log(p_c/p_a) \tag{26}$$

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 specification with and without controls (historical fares and tenure in Uber), and with 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).[37]

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 single rider and as a function of her share parameter α and of the common elasticity of substitution η. In the Appendix F.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 (25) as the expected value of the share of credit trips. We let μ 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

[37]Other robustness checks can be found in Appendix F.3.4.

Table 6: 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 (26) 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 (26) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (24). Column (6) estimates the elasticity using the CES second order approximation in equation (25). 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 (24) 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

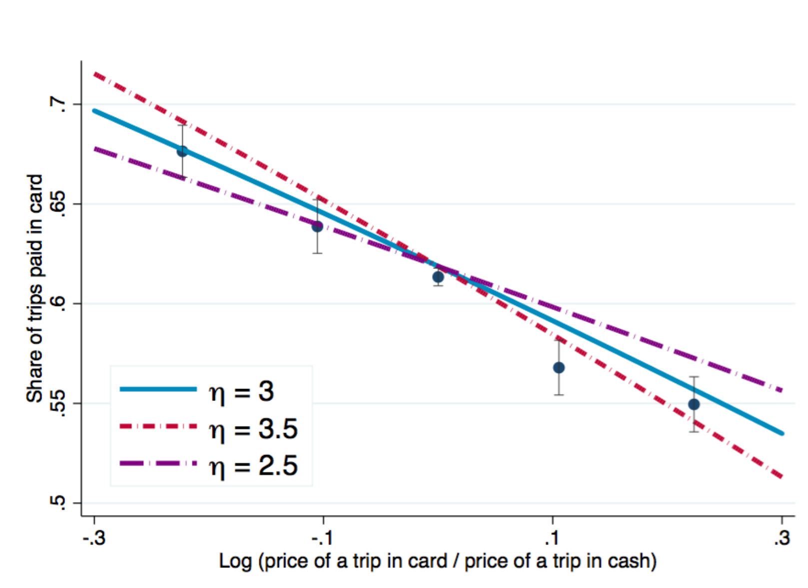
riders– and they do so with weights proportional to the probability of having a trip within a week. Control and treatment groups differ only on the randomly allocated prices p_c/p_a, so the the expected value of $\bar{s}_c(p_c/p_a)$ is given by:

$$\bar{s}_c\left(\frac{p_c}{p_a}\right) = m_1 - (\eta-1)m_2 \ln\left(\frac{p_c}{p_a}\right) + m_3\,(1-\eta)^2\left(\ln\left(\frac{p_c}{p_a}\right)\right)^2 \tag{27}$$

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

We estimate μ by using the distribution of the share of credit prior to the experiment for the 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 14 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 (27), 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 6. 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 five dots are arranged in at almost linear segment. Third, a value of $\eta = 3$ gives a very good fit.

Figure 14: 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 erro bands. The solid and dotted lines are the theoretical prediction for the expected credit share displayed in equation (27) 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 ride 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 experiment's week on the log of the price and a constant, as shown in Table 7. We find that the elasticity ϵ, evaluated a current prices, is approximately 1.1 or smaller, which correspond to the first two columns of Table 7 labelled AA. We also include the results of two other independently conducted experiments by Uber. Interesting, the experiment labelled Mandin had price variation that lasted four weeks and the elasticities are similar to ours–see Section 8.2.1 for more details. Appendix F.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 15 using our functional form for U and h and 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 of lost in a ban of cash of about 25% of the total fares paid by mixed users.[38] Since the average cash share of mixed users is 0.37, the consumer surplus lost by mixed users is about 68% of their expenditure on trips paid in cash.[39] 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 13.

Table 7: Elasticity of Demand: Mixed Users (Miles)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (50) 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

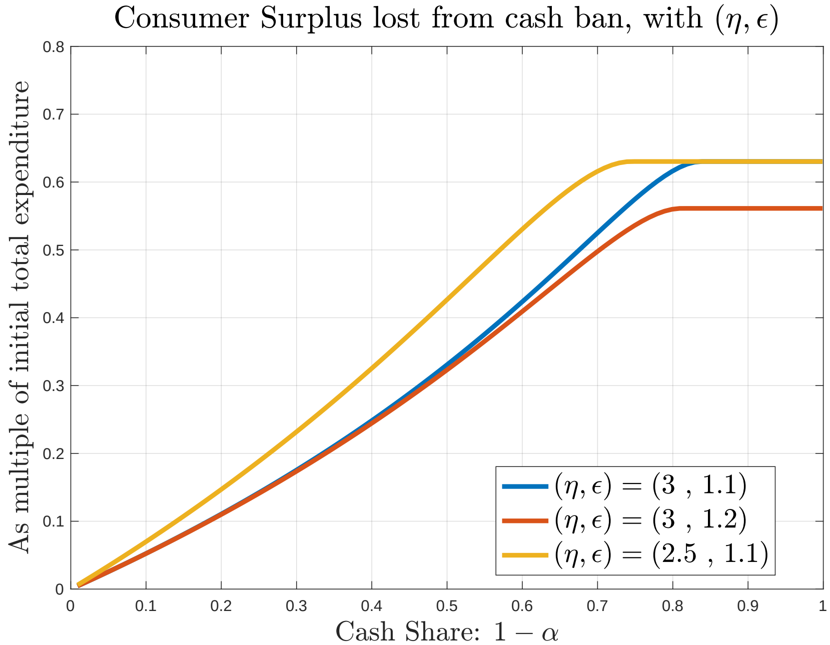
8.2 Experiment 2: Pure Cash Users

The second experiment took place in the State of Mexico during the same week of the previous experiment (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 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

[38] 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.

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

Figure 15: 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 graphs 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.

are 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 remainder emails were sent (in the middle of the week and two days before the promotions expired).[40]

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.

[40]Examples can be found in Appendix F.5.

Our baseline case is the semi-log demand corresponding to our functional form specification. Table 8 display the estimates under columns AA, as well as estimates using the same specification for two independently run experiments discussed in Section 8.2.1. Other specifications and further robustness exercises can be found in Appendix F.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 8: Elasticity of Demand: Pure Cash Users (Miles)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (50) 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.

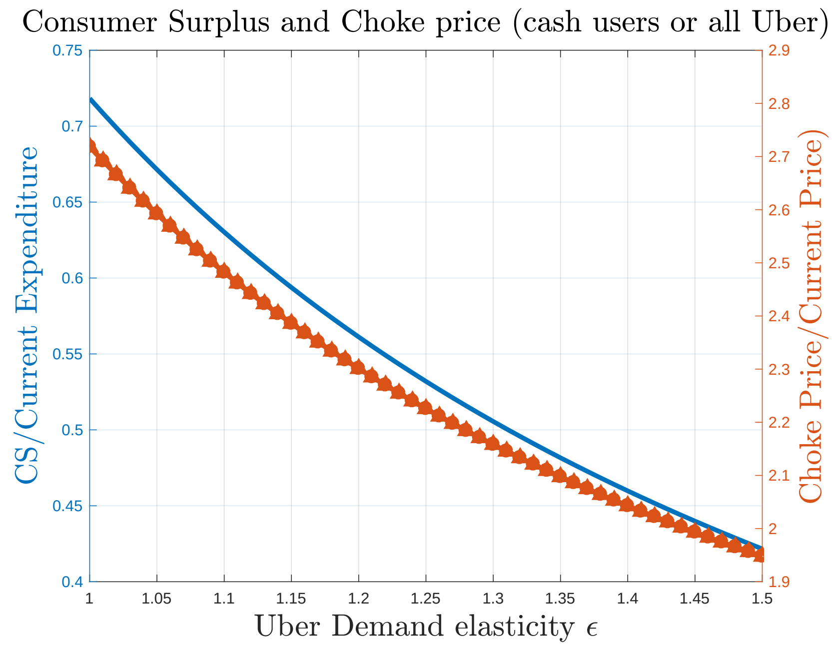
	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Elasticity	1.375***	1.383***	1.113***	0.813**
	(0.101)	(0.078)	(0.165)	(0.414)
Observations	138,725	138,725	4,279	3,569
Controls	No	Yes	Yes	Yes

Figure 16 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 16 are, 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 8.3 provides more details.

8.2.1 Other experiments: Ubernomics, Mandin, and Panama

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

Figure 16: 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.

not originally designed to estimate the elasticity and the curvature of the demand function of mixed users and pure cash users as is the case in our experiments. Nonetheless, we are able to select the riders that meet the same criteria as our experiments and, using their historical data, we are able to construct control variables to make the samples comparable. 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.

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 FII 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 F.3 shows the estimates of the elasticity of demand for pure cash users (Table 8) and mixed users (Table 7). 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%), East (15%). Furthermore, they segmented riders according to the number of trips they took during the last year in the following categories: Remain (Trips $\leq$ 10), Regular (10 $<$ Trips $\leq$ 20), Mid (20 $<$ Trips $\leq$30), Power (30 $<$ Trips $<$ 50), and Rockstar (Trips $\geq$ 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 FIII 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 long-run elasticity of Uber rides are very similar.

Panama

Uber launched in Panama on 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. Uber is active 3 provinces: Panama City, Panama West and Colon. 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.[41]

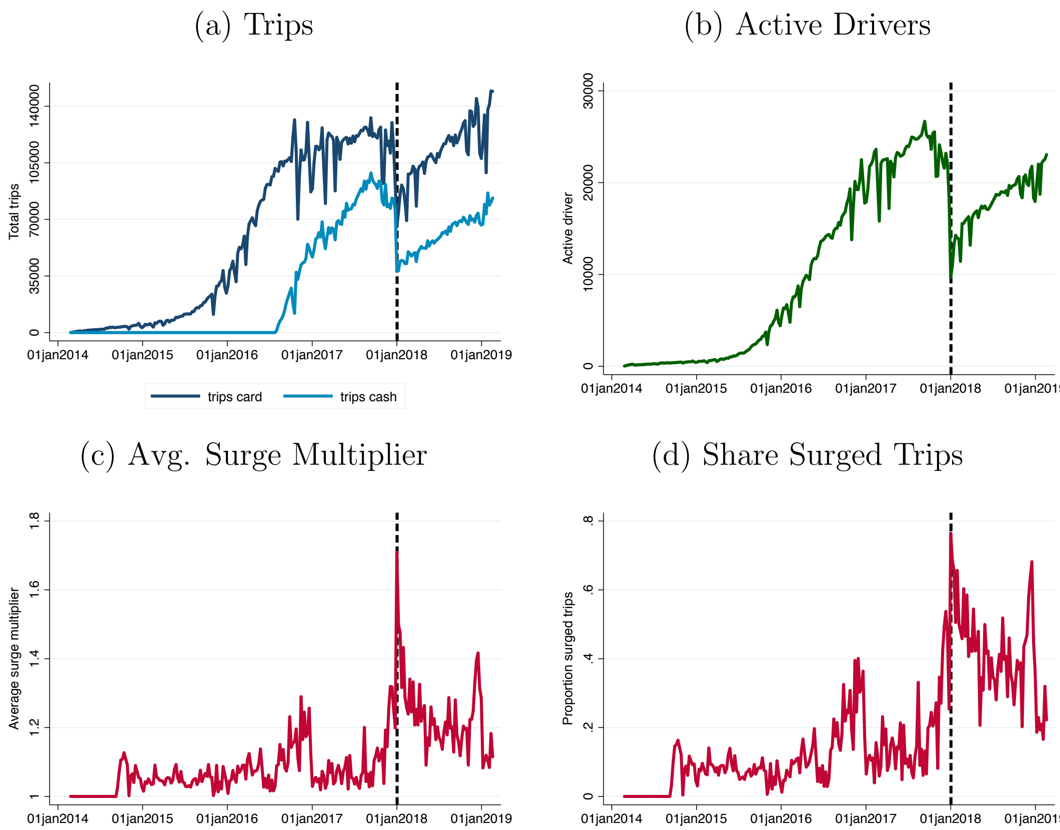
In October of 2017 a decree imposing restrictions on Uber was put in place. The decree includes a prohibition on cash as a payment method for trips taken in Uber. In addition, the decree requires a special license for drivers (i.e. an "E1" type), which only nationals over 21 can obtain. The license has 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 decree went into effect in January 2, 2018. Uber negotiated an extension of the deadline for the ban on cash. The extension expires on May 2019, and it was renewed until October 2019. The rest of the decree went into effect, in particular, the restrictions involving drivers. A total of 83% of all Uber drivers did not have the E1 license and were disconnected from the application. The total number of drivers signing up into the application was approximately 8 thousand per week before the decree. At the end of 2018, a year after the decree went into effect, total number of drivers sign up is only about 4.5 thousand drivers. 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 17 also shows that the share of trips in cash also decreased drastically from more

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

Figure 17: Panama: Trips, Fares, and Drivers

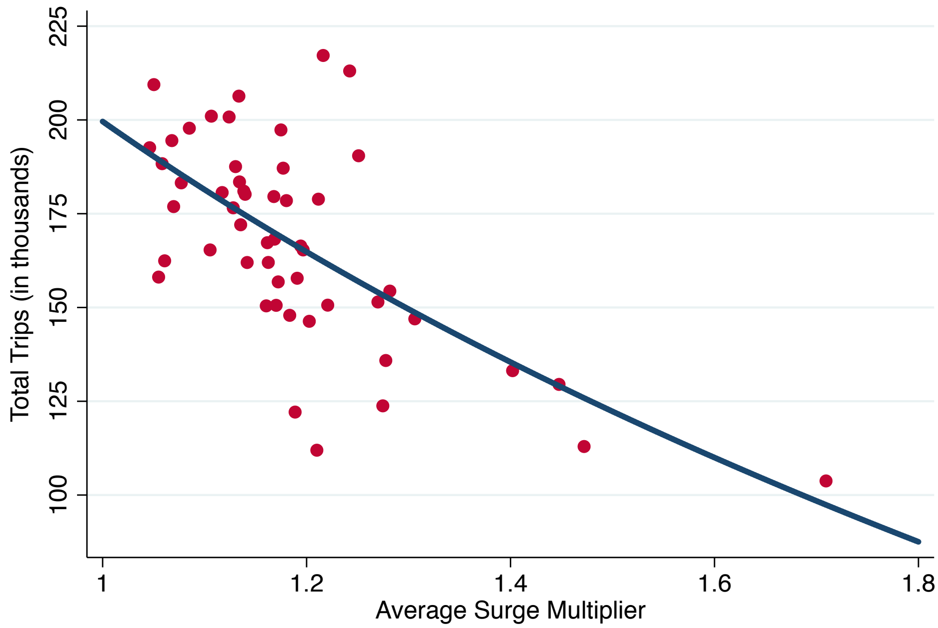


Note: The figure shows the evolution of trips, active drivers, the average surge multiplier and the share of surged trips in Panama. The frequency of the data is weekly. The black dotted line denotes the date the decree by the government restricting the supply of drivers went into effect.

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. We believe that the demand for Uber trips paid in cash is more elastic for trips paid with credit card.

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 18 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 remarkably well the patterns of total trips and prices. 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 pay in cash we estimate a

Figure 18: 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.

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.[42]

8.3 Experiment 3: Extensive Margin

The third experiment took place in the State of Mexico from September 17th to October 23rd, 2018. It is 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 are 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.

[42] We provide details on these estimates in Section G.

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 or 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 treatment 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 9: 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

Table 9 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 4.4%, which is statistically significantly larger than the one corresponding to 5.2 USD, which is 3.3% –see column (3) of the Table.

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 FXXVIII shows that users under our treatment groups were more likely to use credit as a payment method more than 6 months after the 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 FXXIX in Appendix F.4 shows the 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 9.

8.4 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 7.6, with their implications for demand derived in Appendix E.3, the corresponding indirect utility functions derived in Appendix E.4, and the conditions that fixed cost and indirect utility has to satisfy for the optimal registration/adoption of credit cards, as described in equation (17) and equation (20). On the evidence we 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 it applies to cash users), the migration rates under each of the incentive levels described in Section 8.3 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 –see Figure 11 and Figure 12. 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 lost. Appendix K goes over details of these calculations.

According to our evidence from Puebla, about 65% of the pure cash riders stop using Uber after the ban of cash.[43] From Table 8 our estimated elasticities at pre-ban prices are just below 1.4 for this group, so their consumer surplus lost is almost 0.47 of their yearly expenditure in Uber. For the remaining 35% of riders the losses are smaller.[44] For instance, for those with the smaller losses, i.e. for those with the smallest fixed cost among those that adopt/obtain a credit card, we obtain a lower bound on the consumer surplus lost of approximately 0.35 of their yearly expenditure in Uber. Using the information from Experiment III we obtain a lower bound for net consumer surplus lost for pure cash users of about 0.45 of the yearly expenditure in Uber. Appendix K shows the detailed calculations for this lower bound.

9 Conclusion: Ban on Cash and Beyond

We combine experimental evidence with three quasi-natural 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 in 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 at least 45% 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 a our 50% headline figure for the lower bound of the consumer surplus lost in a ban on cash.[45]

[43] Given that the State of Mexico is slightly poorer and have less banking penetration the fraction of pure cash users that will migrate in the case of a ban may be smaller than in Puebla. In Appendix J we try to estimate the difference and conclude that it may be of the order of 1% smaller. We ignore this difference to continue the spirit of obtaining a lower bound for the consumer surplus.

[44] Indeed, in Appendix J we correct this estimate to take into account observable differences between Puebla and the State of Mexico, which may lower this estimate up to 34%. In the spirit of obtaining a lower bound on the consumer surplus lost, we keep the 35% figure.

[45] The calculation for the consumer surplus lost in cash is the average of the consumer surplus relative to the expenditure in cash for pure cash users and the one for the mixed cash users relative to their expenditure in cash, weighted by their share on the total cash expenditure: $0.45 \times \frac{0.20}{0.2+0.5\times 0.37} + 0.68 \times \frac{0.5\times 0.37}{0.2+0.5\times 0.37} =$

We have several other findings which we believe are of independent interest. For instance, using three quasi-natural experiments we found extremely large effects on the number of trips and the number of riders both in the entry of cash and inversely in the ban on cash. 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 card when riders are given incentives, a reward of 15 USD increases the adoption rate in less than 5%, largely accounted for registering 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, since mid July of 2019 a ban on cash is in effect in the state of San Luis Potosí, Mexico, where one can see a sharp decreases in trips -see Appendix M. Our results are also relevant for Panama. While in Panama cash is accepted as means of payment everywhere Uber is operating, its legal status is precarious. Cash has been originally banned, but the application of the ban has been temporarily suspended by three consecutive decrees from the government. We have estimated price elasticities for riders of different types in Panama that are similar than those in the Sate of Mexico, as well as similar share of trips in cash –see Section 8.2.1 and Appendix G. Thus, assuming the rest of the parameters are as in the State of Mexico, a ban in cash in Panama, as the one that will occur as the decree takes effect, will cause a consumer surplus lost of approximately 50% of the trips currently paid in cash in Panama. Finally, our estimates are relevant for policies applied in the southern cone. For instance, cash is banned in all cities of Uruguay, except on Punta del Este. In Argentina, the municipal government of the city of Buenos Aires, as a way to curtail the use of Uber, has issued a prohibition on the processing of credit cards payments, which had the implication that credit card are not accepted in the entire country, and hence riders can 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 L for details. We found that the consumer surplus lost of a ban in credit is about 0.80 the expenditure on Uber paid in credit before the ban. This lost is higher than the one for a ban in cash because for pure credit users it is fully equivalent to a ban on Uber, then they have larger expenditure and they are more inelastic. Moreover, for mixed users their share of credit is 63%, so they are more affected in a ban of credit, than in a ban on cash.

$0.5605 > 0.5$.

References

Abadie, A., Gardeazabal, J., 2003. The economic costs of conflict: A case study of the basque country. American Economic Review 93 (1), 113–132.

Allen, R., Rehbeck, J., 2018. Assessing misspecification and aggregation for structured preferences. Manuscript, Working Paper.

Alvarez, F., Lippi, F., 2017. Cash burns: An inventory model with a cash-credit choice. Journal of Monetary Economics 90 (C), 99–112.

Amromin, E., Jankowski, C., Porter, R. D., April 2006. Inducing more efficient payment on the Illinois Tollway. Chicago Fed Letter (225).

Chodorow-Reich, G., Gopinath, G., Mishra, P., Narayanan, A., December 2018. Cash and the economy: Evidence from india's demonetization. Working Paper 25370, National Bureau of Economic Research.

Cohen, P., Hahn, R., Hall, J., Levitt, S., Metcalfe, R., September 2016. Using big data to estimate consumer surplus: The case of uber. Working Paper 22627, National Bureau of Economic Research.

Davis, S. J., Haltiwanger, J., 1992. Gross job creation, gross job destruction, and employment reallocation. The Quarterly Journal of Economics 107 (3), 819–863.

Deviatov, A., Wallace, N., April 2014. Optimal inflation in a model of inside money. Review of Economic Dynamics 17 (2), 287–293.

Firpo, S., Possebom, V., 2018. Synthetic control method: Inference, sensitivity analysis and confidence sets. Journal of Causal Inference 6 (2).

Freeman, S., Kydland, F. E., 2000. Monetary aggregates and output. The American Economic Review 90 (5), pp. 1125–1135.

Hainmueller, J., 2012. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. Political Analysis 20 (1), 25–46.

Hall, J., Horton, J., Knoepfle, 2017. Labor market equilibration: Evidence from uber. accessed november 19, 2017.

Humphrey, D. B., Kim, M., Vale, B., 2001. Realizing the gains from electronic payments: Costs, pricing, and payment choice. Journal of Money, Credit and Banking 33 (2), 216–234.

Kiyotaki, N., Wright, R., August 1989. On Money as a Medium of Exchange. Journal of Political Economy 97 (4), 927–954.

Klee, E., 2008. How people pay: Evidence from grocery store data. Journal of Monetary Economics 55 (3), 526–541.

Kocherlakota, N., 1998. Money is memory. Journal of Economic Theory 81 (2), 232–251.

Lacker, J. M., Schreft, S. L., August 1996. Money and credit as means of payment. Journal of Monetary Economics 38 (1), 3–23.

Lagos, R., Wright, R., 2005. A unified framework for monetary theory and policy analysis. Journal of Political Economy 113 (3), 463–484.

Lucas, Robert E, J., Stokey, N. L., 1987. Money and interest in a cash-in-advance economy. Econometrica 55 (3), 491–513.

Lucas, R. E., Nicolini, J. P., 2015. On the stability of money demand. Journal of Monetary Economics 73 (C), 48–65.

Prescott, E. C., 1987. A multiple means-of-payment model. New Approaches to Monetary Economics, 42–51.

Rogoff, K. S., 2017. The Curse of Cash: How Large-Denomination Bills Aid Crime and Tax Evasion and Constrain Monetary Policy. Princeton University Press.

Stokey, N., 2019. Means of payment. Working paper, University of Chicago.

Wang, L., Wright, R., Qian, L., January 2019. Money and credit: Theory and applications. forthcoming, International Economic Review.

Whitesell, W. C., 1989. The Demand for Currency versus Debitable Accounts: Note. Journal of Money, Credit and Banking 21 (2), 246–251.

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 $1_c\left(1, 1; \theta\right) = 1$. Note

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 $\mathcal{CS}(p_a, 1)$:

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

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:

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

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:

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

and using the derivative of the indirect utility function:

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

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

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

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

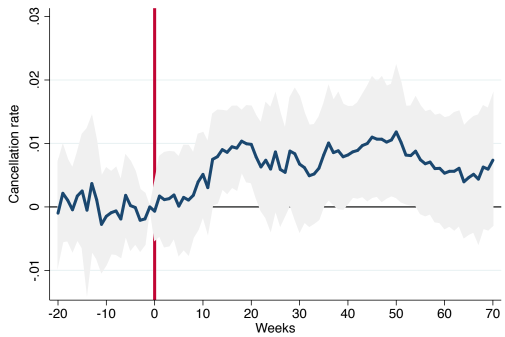
$$\mathcal{CS}(p_a,1)=\int_1^{p_a}A(p,1)dp\,.$$

□

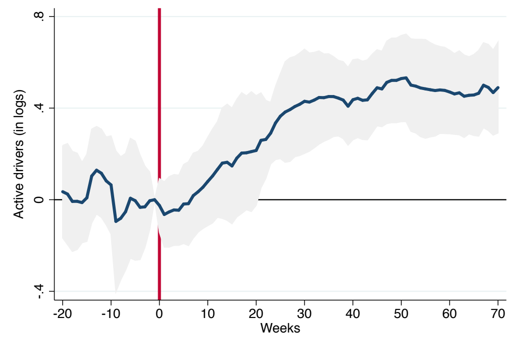
B Event Study

Figure B1: Event Study: Additional Results

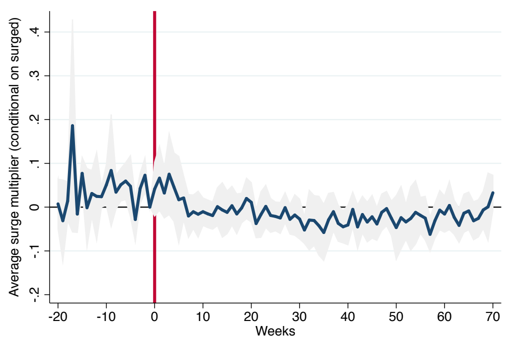
(a) Cancellation Rate



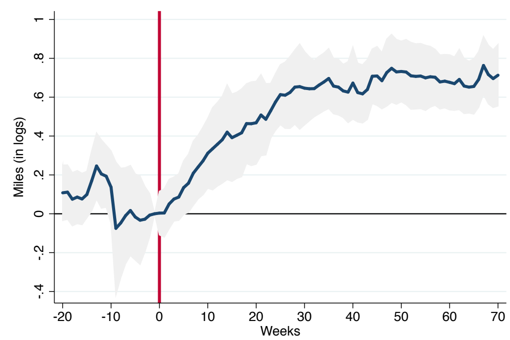
(b) Active Drivers



(c) Avg. Surge Multiplier Conditional on Trip



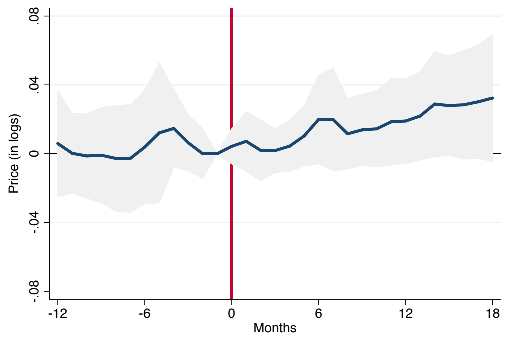
(d) Miles



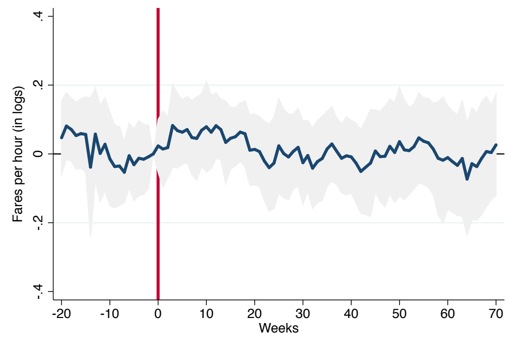
Note: The graph shows the evolution of the number of active drivers, the cancellation rate, the average surge multiplier conditional on the trip being surged, and the total miles before and after the introduction of cash. The figure plots the coefficients of γ_k after estimating equation (1). The red line denotes the week of the introduction of cash as a payment method. The gray area 95% confidence interval computed using Driscoll and Kraay standard errors.

Figure B2: Event Study: Average Price of Taxis and Earnings per Hour

(a) Taxi Prices



(b) Fares per Hour



Note: Panel (a) shows the evolution of the average price of taxis before and after the introduction of cash. The frequency of the variable is monthly. The data for the average price of taxis comes from the Mexican Consumer Price Index at the city level. Panel (b) shows the patterns of the drivers' income per hour computed as the total fares earned over total hours. The figure plots the coefficients of γ_k after estimating equation (1). The red line denotes the week of the introduction of cash as a payment method. The gray area 95% confidence interval computed using Driscoll and Kraay standard errors.

C Greater Mexico City

C.1 Geolocalization

We use the latitude, ϕ, and longitude, λ, of an Uber ride and transform them into xy grid coordinates that follow the Lambert Conformal Conic (LCC) map projection. A LCC map projection is defined by two ellipsoidal parameters a and f, grid origin (ϕ_0, λ_0), latitude of the north standard parallel, ϕ_N, and south standard parallel, ϕ_S, false easting, E_0, and false northing, N_b. We use the following three functions:[46]

$$W(\phi) = \sqrt{1 - e^2 \sin^2(\phi)} \tag{28}$$

$$M(\phi) = \frac{\cos(\phi)}{W(\phi)} \tag{29}$$

$$T(\phi) = \sqrt{\left(\frac{1-\sin(\phi)}{1+\sin(\phi)}\right)\left(\frac{1+e\sin(\phi)}{1-e\sin(\phi)}\right)} \tag{30}$$

The remaining zone constants are:

$$w_1 = W(\phi_S) \tag{31}$$

$$w_2 = W(\phi_N) \tag{32}$$

$$m_1 = M(\phi_S) \tag{33}$$

$$m_2 = M(\phi_N) \tag{34}$$

$$t_0 = T(\phi_0) \tag{35}$$

$$t_1 = T(\phi_S) \tag{36}$$

$$t_2 = T(\phi_N) \tag{37}$$

$$n = \sin(\phi_0) = \frac{\ln(m_1) - \ln(m_2)}{\ln(t_1) - \ln(t_2)} \tag{38}$$

$$F = \frac{m_1}{n t_1^n} \tag{39}$$

$$R_b = aFt_0^n \tag{40}$$

Given the geodetic coordinates of an Uber ride, the northing (y), easting (x), scale, k,

[46] An ellipsoid is defined by the length of its semi-major axis, a, and its flattening factor, f. The GRS 80 ellipsoid used by the Mexican census has defining parameters $a = 6,378,137.0$ m and $f = 1/298.257222101$. The first eccentricity is computed as $e = \sqrt{2f - f^2}$. In addition, the Mexican census indicates the following grid origin $\phi_0 = 102°00'00''$ W, $\lambda_0 = 12°00'00''$ N, $\phi_N = 17°30'$ N, $\phi_S = 29°30'$ N, $E_0 = 2500000$, $N_b = 0$. We use the Mexican Geostatistical Framework of June 2018.

and convergence angel, γ, of the point are computed as:

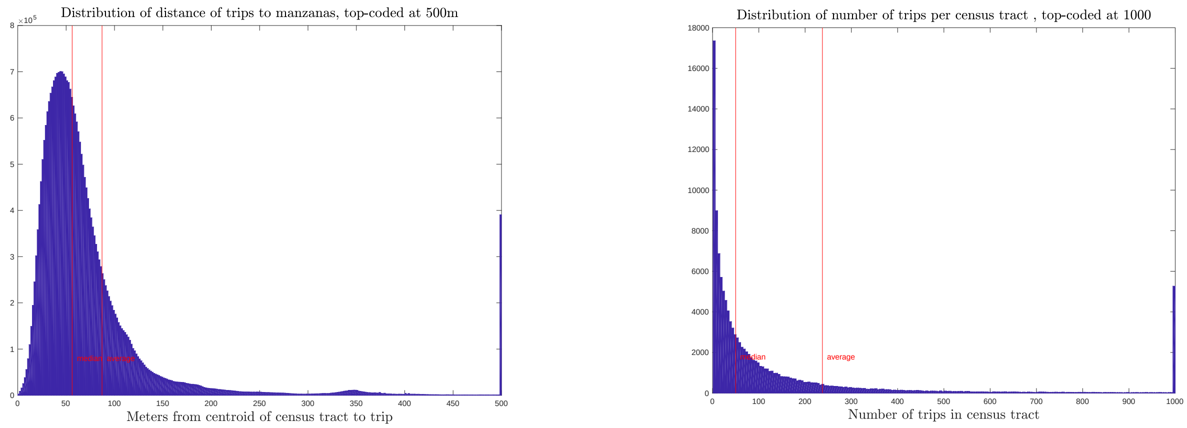
$$t = T(\phi) \tag{41}$$
$$m = M(\phi) \tag{42}$$
$$R = aFt^n \tag{43}$$
$$\gamma = (\lambda - \lambda_0)n \tag{44}$$
$$E = R\text{sin}(\gamma) + E_0 \tag{45}$$
$$N = R_b - R\text{cos}(\gamma) + N_b \tag{46}$$
$$k = \frac{Rn}{am} \tag{47}$$
$$\tag{48}$$

Next, we find the centroid of the polygon around each census block by minimizing the sum of squared Euclidean distances between itself and each point in the set. The centroid of a finite set k points $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k$ in $\mathbb{R}^n$ is:

$$\mathbf{C} = \frac{\mathbf{x}_1 + \mathbf{x}_2 + \cdots + \mathbf{x}_k}{k}$$

To find the closest centroid for each Uber trip, we compute the Euclidean distance between the trip and the centroid of each census block. Lastly, we correct for differences in Uber's geofence (the polygon that defines the area for cash acceptance) and the political boundaries of the State of Mexico. We use the shape files of the geofence generated by Uber and redefine the boundaries of the State of Mexico so that it is consistent with their geofence. After geolocalizing the trips with a grid using centroids of census tracts, the average of a trip to a centroid using our methodology is 60 meters (median 50 meters) as shown in Figure C1.

Figure C1: Distance of Trips to Census Block and Number of Trips per Census Block

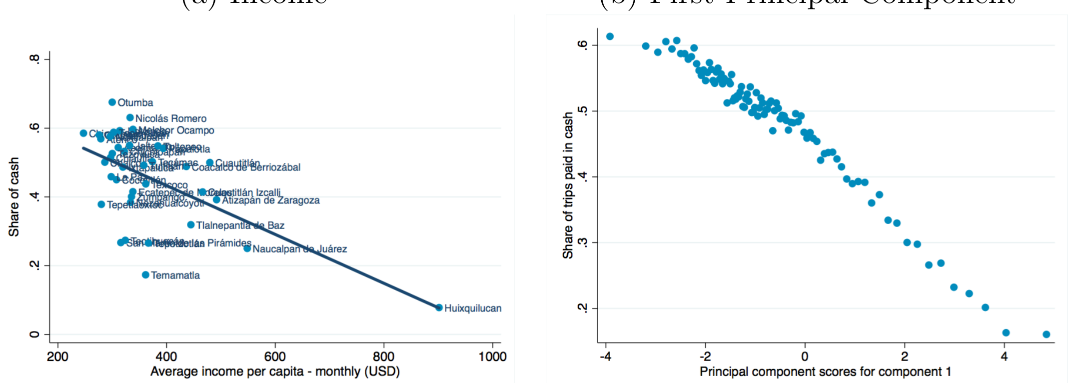


Note: The figure shows the distribution of distance of trips to the closest census block, top-coded at 500m. The coordinates are those of the origin of the trips. The red lines show the median and the mean distance. The median is approximately 60 meters. The figure shows the distribution of number of trips per census block for August 2016, August 2017, and August 2018. The red lines show the median and the mean number of trips. The median is approximately 50 trips per census block.

C.2 Income

Figure C2: Share of Fares paid in Cash by Income per Capita (Municipality)

(a) Income (b) First Principal Component

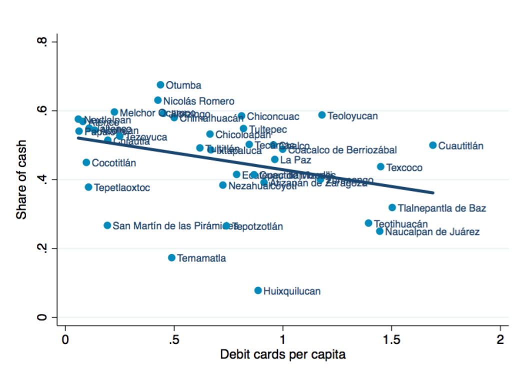


Note: Panel (a) shows the share of fares paid in cash and the average income per capita per month in USD. The income data comes from individuals that report labor income surveyed in the Intercensal Survey of 2015. The data of Uber rides are from August of 2017 in the State of Mexico. Panel (b) shows the relationship between the share of trips paid in cash and the first principal component of the following demographic variables: average years of schooling, share of homes with internet, share of homes with cell phone, and share of homes with a car. The census blocks are grouped into 100 equal-sized bins. The source of the demographic variables is the Mexican Census.

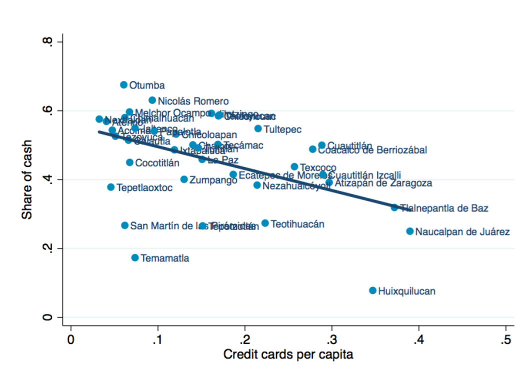
C.3 Banking services

Figure C3: Share of Fares Paid in Cash - Banking Services

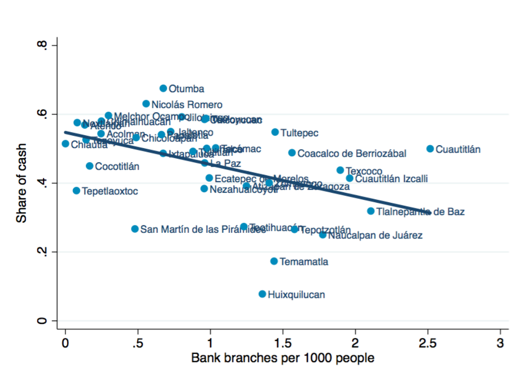
(a) Debit Cards



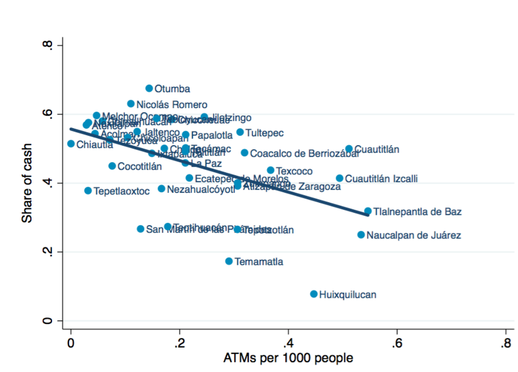
(b) Credit Cards



(c) Bank Branches

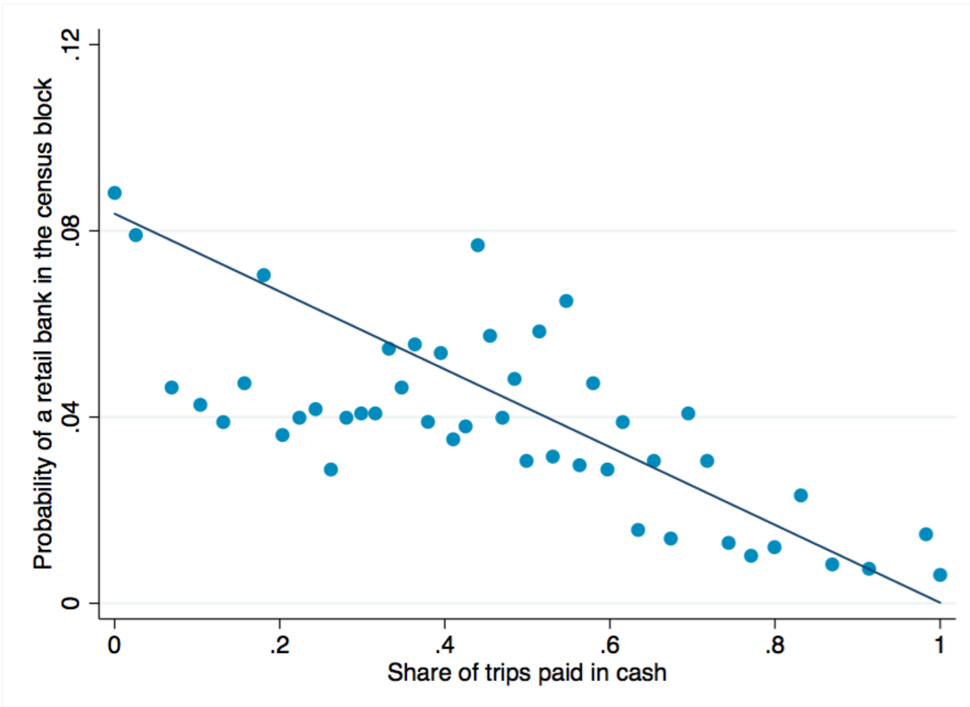


(d) ATMs



Note: The figure shows the share of fares paid in cash and several measures of the availability of banking services in each municipality of the State of Mexico, where Uber trips were taken in August 2017. The data on debit cards, credit card, bank branches, and ATMs comes from the Financial Inclusion Database (BDIF). The figure shows the average for 2017.

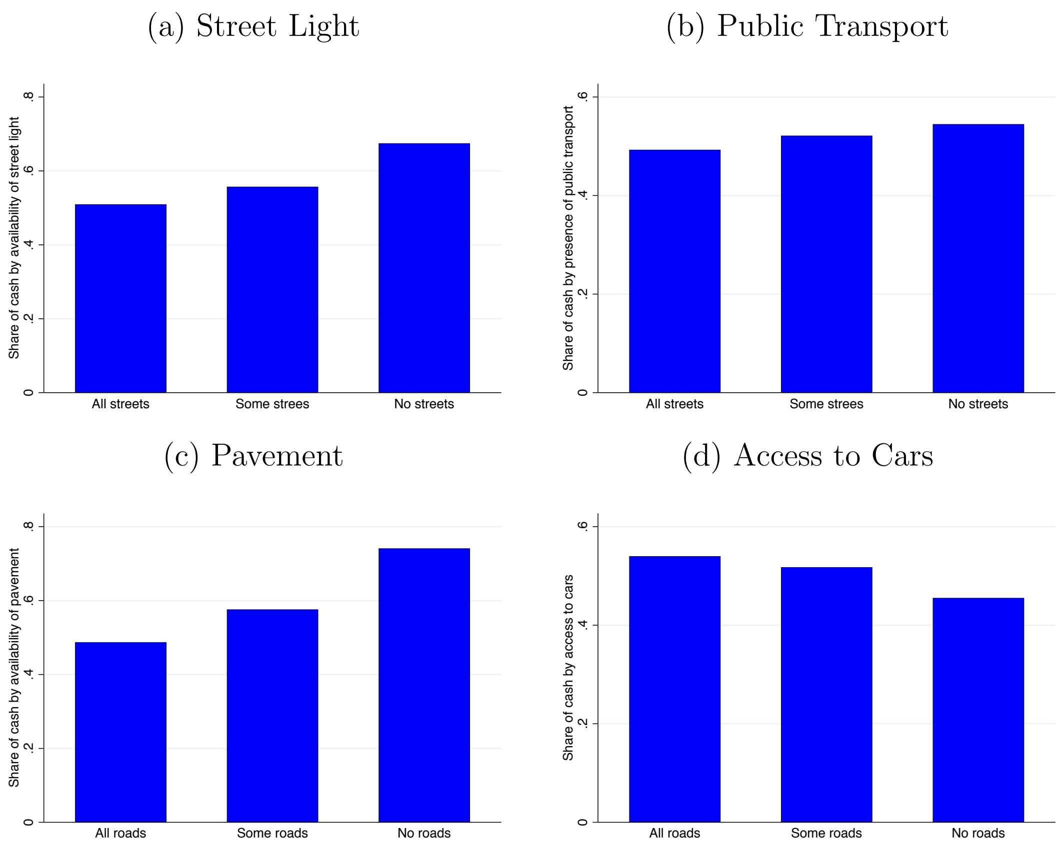
Figure C4: Share of Fares Paid in Cash - Probability of a Retail Bank in the Census Block



Note: The figure shows the binscatter plot of the probability a census block has a retail bank and the share of trips paid in cash in that census block group into 50 equal-sized bins. The data for retail bank branches comes from the National Statistical Directory of Economic Units (DENUE), geolocalized data of all establishments in Mexico. The data for Uber rides is from August 2017 in the State of Mexico.

C.4 Infrastructure

Figure C5: Share of Cash by Availability of Public Infrastructure

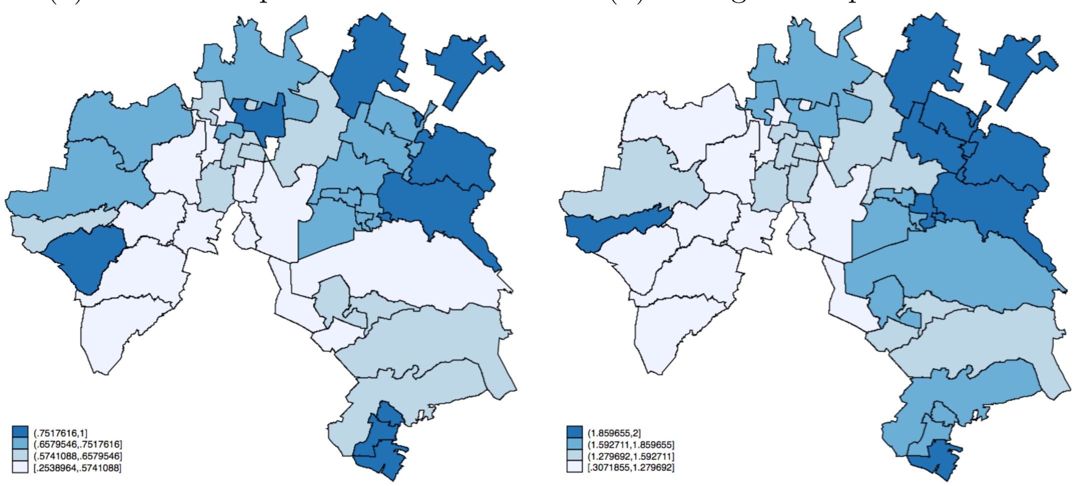


Note: The figure shows the share of fares paid in cash if the streets in the census block have public infrastructure. The date period is August 2017 and the census blocks are those located in the State of Mexico. "All streets" refers to census blocks where all the streets have public infrastructure. "No streets" refers to census blocks that do not have infrastructure. The public infrastructure considered are street light, public transport, pavement, and access to cars. The infrastructure information was collected through the Survey of Urban Enviroment (Cuestionario de Entorno Urbano y de Localidad) applied in the census blocks of census tracts with more than 5 thousands inhabitants or in the census tracts that registered less than 5 thousands inhabitants according to the last population count.

C.5 Maps: Urban and Suburban Regions

Figure C6: Share of Trips Paid in Cash and Change in Trips (State of Mexico)

(a) Share of Trips Paid in Cash (b) Change in Trips 2016-2017



Note: Panel (a) shows the number of total Uber rides in each municipality in the State of Mexico in August of 2017. Darker colors represent a larger share of trips paid in cash. Panel (b) shows the change in the number of trips in each municipality before and after the introduction of cash as payment method. Darker colors represent a larger change in trips.

C.6 Regression Discontinuity: Robustness

Table CI: Regression Discontinuity Approach: Effect on Trips (less than 5 km)

Note: Note: The table reports the results for the coefficient of β after estimating equation (2). The estimates report the local treatment effect at the border between the State of Mexico and Mexico City of the introduction of cash as a payment method. Each column reports the results using polynomials of different degrees. The dependent variable is the change in the total trips of each census block. The results consider only the sample of census blocks that are less than 5 kilometers from the border.

	(1)	(2)	(3)	(4)	(5)
State of Mexico	0.238***	0.218***	0.272***	0.215***	0.190***
	(0.021)	(0.031)	(0.043)	(0.054)	(0.067)
Observations	37,744	37,744	37,744	37,744	37,744
R-squared	0.255	0.255	0.255	0.255	0.255
Controls	Yes	Yes	Yes	Yes	Yes
Distance	<5 Km	<5 Km	<5 Km	<5 Km	<5 Km
Degree	1	2	3	4	5

Table CII: Regression Discontinuity Approach: Effect on Fares (less than 5 km)

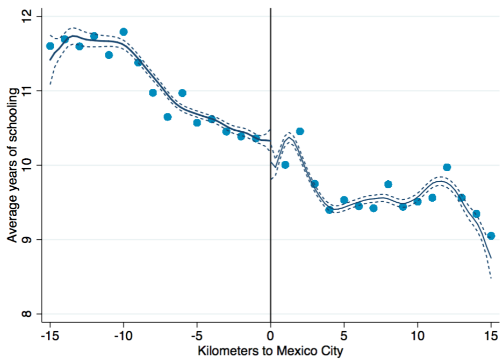
Note: The table reports the results for the coefficient of β after estimating equation (2). The estimates report the local treatment effect at the border between the State of Mexico and Mexico City of the introduction of cash as a payment method. Each column reports the results using polynomials of different degrees. The dependent variable is the change in the total fares of each census block. The results consider only the sample of census blocks that are less than 5 kilometers from the border.

	(1)	(2)	(3)	(4)	(5)
State of Mexico	0.174***	0.163***	0.212***	0.159***	0.148**
	(0.018)	(0.028)	(0.038)	(0.048)	(0.061)
Observations	37,744	37,744	37,744	37,744	37,744
R-squared	0.180	0.180	0.180	0.180	0.181
Controls	Yes	Yes	Yes	Yes	Yes
Distance	<5 Km	<5 Km	<5 Km	<5 Km	<5 Km
Degree	1	2	3	4	5

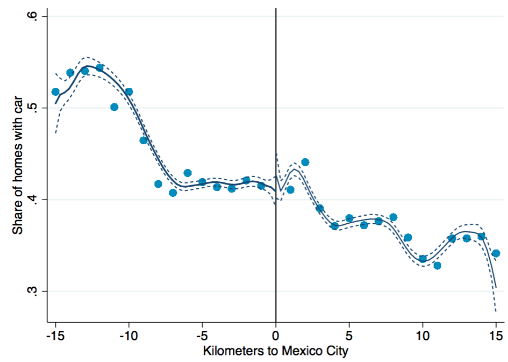
C.7 Regression Discontinuity: Observables

Figure C7: Observables Characteristics at the Border

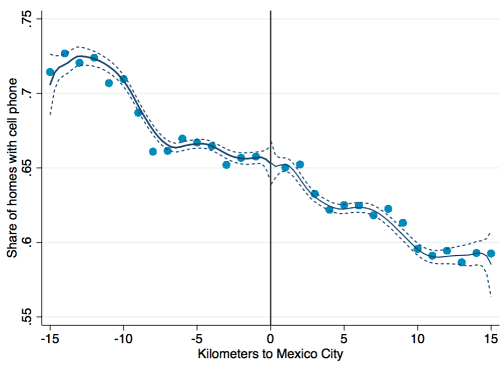
(a) Education



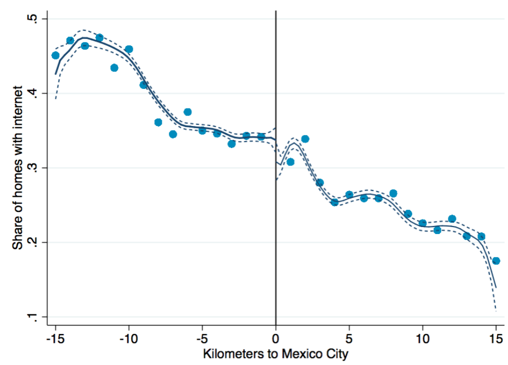
(b) Share of Homes with Car



(a) Share of Homes with Cell Phone



(b) Share of Homes with Internet



Note: The graphs show the relationship between several observables variables in each census block and the distance to Mexico City. The observable variables plotted are the average years of education, the share of homes with car, the share of homes with cell phone, and the share of homes with internet. Negative numbers in the x-axis indicate the census block is in Mexico City. Each bin corresponds to one kilometer. The dots show the average level of each variable in each bin. The line is a kernel-weighted (epanechnikov) local polynomial of degree 3. The dashed lines are the 99% confidence intervals.

C.8 OLS: Additional Results

Table CIII: OLS: Effect of the Introduction of Cash on Trips (State of Mexico)

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the number of trips of all census blocks, both those that were active in Uber before the introduction of cash (intensive margin) and those that were not (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block. Columns (3) and (4) consider census blocks at less than 5 kilometers and less than 1 kilometer from Mexico City respectively.

	(1)	(2)	(3)	(4)
State of Mexico	0.824***	0.615***	0.460***	0.294***
	(0.005)	(0.009)	(0.011)	(0.023)
Observations	108,272	87,036	37,744	7,702
R-squared	0.227	0.326	0.245	0.142
Controls	No	Yes	Yes	Yes
Distance	All	All	<5Km	<1Km

Table CIV: OLS: Effect of the Introduction of Cash on Fares (State of Mexico)

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the total of fares of all census blocks, both those that were active in Uber before the introduction of cash (intensive margin) and those that were not (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block. Columns (3) and (4) consider census blocks at less than 5 kilometers and less than 1 kilometer from Mexico City respectively.

	(1)	(2)	(3)	(4)
State of Mexico	0.665***	0.471***	0.347***	0.223***
	(0.005)	(0.008)	(0.010)	(0.020)
Observations	108,269	87,033	37,744	7,702
R-squared	0.156	0.230	0.174	0.105
Controls	No	Yes	Yes	Yes
Distance	All	All	<5Km	<1Km

Table CV: OLS: Effect of the Introduction of Cash on Trips (State of Mexico) - Heterogeneous Effects

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the number of trips of all census blocks, both those that were active in Uber before the introduction of cash (intensive margin) and those that were not (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block.

	(1)	(2)	(3)	(4)	(5)	(6)
State of Mexico	0.615***	0.846***	1.316***	0.924***	1.009***	0.904***
	(0.010)	(0.014)	(0.038)	(0.040)	(0.031)	(0.017)
Bank	-0.028***					
	(0.010)					
State of Mexico x Bank	-0.027					
	(0.025)					
Internet		-0.279***				
		(0.038)				
State of Mexico x Internet		-0.726***				
		(0.035)				
Education			-0.020***			
			(0.003)			
State of Mexico x Education			-0.068***			
			(0.004)			
Econ. Active				-0.022		
				(0.050)		
State of Mexico x Econ. Active				-0.703***		
				(0.087)		
Cell phone					0.364***	
					(0.039)	
State of Mexico x Cell phone					-0.603***	
					(0.046)	
Car						0.339***
						(0.030)
State of Mexico x Car						-0.693***
						(0.034)
Observations	87,036	87,036	87,036	87,036	87,036	87,036
R-squared	0.326	0.334	0.333	0.327	0.328	0.333
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All	All

Table CVI: OLS: Effect of the Introduction of Cash on Trips (State of Mexico) - Intensive Margin

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the number of trips of census blocks that already were already active using Uber before the introduction of cash (intensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block. Columns (3) and (4) consider census blocks at less than 5 kilometers and less than 1 kilometer from Mexico City respectively.

	(1)	(2)	(3)	(4)
State of Mexico	0.368***	0.400***	0.400***	0.364***
	(0.004)	(0.008)	(0.011)	(0.023)
Observations	108,272	87,036	37,744	7,702
R-squared	0.084	0.115	0.143	0.141
Controls	No	Yes	Yes	Yes
Distance	All	All	<5Km	<1Km

Table CVII: OLS: Effect of the Introduction of Cash on Trips (State of Mexico) - Extensive Margin

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the number of trips of census blocks that were not active in Uber before the introduction of cash (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block. Columns (3) and (4) consider census blocks at less than 5 kilometers and less than 1 kilometer from Mexico City respectively.

	(1)	(2)	(3)	(4)
State of Mexico	0.456***	0.215***	0.060***	-0.070***
	(0.005)	(0.011)	(0.013)	(0.022)
Observations	108,272	87,036	37,744	7,702
R-squared	0.074	0.112	0.060	0.032
Controls	No	Yes	Yes	Yes
Distance	All	All	<5Km	<1Km

Table CVIII: OLS: Effect of the Introduction of Cash on Trips (State of Mexico) - Intensive Margin, Heterogeneous Effects

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the total number of trips of all census blocks that were active in Uber before the introduction of cash (intensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block.

	(1)	(2)	(3)	(4)	(5)	(6)
State of Mexico	0.395***	0.337***	0.181***	0.005	0.303***	0.347***
	(0.008)	(0.015)	(0.044)	(0.038)	(0.031)	(0.018)
Bank	-0.032***					
	(0.008)					
State of Mexico x Bank	0.210***					
	(0.025)					
Internet		-0.261***				
		(0.031)				
State of Mexico x Internet		0.197***				
		(0.043)				
Education			-0.016***			
			(0.003)			
State of Mexico x Education			0.021***			
			(0.004)			
Econ. Active				-0.135***		
				(0.041)		
State of Mexico x Econ. Active				0.897***		
				(0.085)		
Cell phone					0.012	
					(0.032)	
State of Mexico x Cell phone					0.148***	
					(0.046)	
Car						-0.119***
						(0.029)
State of Mexico x Car						0.126***
						(0.039)
Observations	87,036	87,036	87,036	87,036	87,036	87,036
R-squared	0.116	0.116	0.116	0.117	0.115	0.115
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All	All

Table CIX: OLS: Effect of the Introduction of Cash on Trips (State of Mexico) - Extensive Margin, Heterogeneous Effects

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the number of trips of census blocks that were not active in Uber before the introduction of cash (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block.

	(1)	(2)	(3)	(4)	(5)	(6)
State of Mexico	0.220***	0.508***	1.135***	0.919***	0.706***	0.557***
	(0.011)	(0.021)	(0.052)	(0.049)	(0.041)	(0.024)
Bank	0.004					
	(0.008)					
State of Mexico x Bank	-0.237***					
	(0.023)					
Internet		-0.019				
		(0.038)				
State of Mexico x Internet		-0.924***				
		(0.044)				
Education			-0.004			
			(0.003)			
State of Mexico x Education			-0.089***			
			(0.004)			
Econ. Active				0.113***		
				(0.044)		
State of Mexico x Econ. Active				-1.600***		
				(0.103)		
Cell phone					0.352***	
					(0.038)	
State of Mexico x Cell phone					-0.751***	
					(0.055)	
Car						0.459***
						(0.032)
State of Mexico x Car						-0.819***
						(0.039)
Observations	87,036	87,036	87,036	87,036	87,036	87,036
R-squared	0.113	0.127	0.127	0.118	0.117	0.124
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All	All

Table CX: OLS: Effect of the Introduction of Cash on Fares (State of Mexico) - Heterogeneous Effects

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the total of fares of all census blocks, both those that were active in Uber before the introduction of cash (intensive margin) and those that were not (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block.

	(1)	(2)	(3)	(4)	(5)	(6)
State of Mexico	0.472***	0.673***	1.098***	0.770***	0.815***	0.718***
	(0.009)	(0.014)	(0.035)	(0.038)	(0.030)	(0.015)
Bank	-0.025***					
	(0.009)					
State of Mexico x Bank	-0.030					
	(0.023)					
Internet		-0.217***				
		(0.036)				
State of Mexico x Internet		-0.636***				
		(0.032)				
Education			-0.018***			
			(0.003)			
State of Mexico x Education			-0.060***			
			(0.003)			
Econ. Active				-0.010		
				(0.048)		
State of Mexico x Econ. Active				-0.680***		
				(0.082)		
Cell phone					0.318***	
					(0.037)	
State of Mexico x Cell phone					-0.526***	
					(0.043)	
Car						0.280***
						(0.029)
State of Mexico x Car						-0.592***
						(0.031)
Observations	87,033	87,033	87,033	87,033	87,033	87,033
R-squared	0.230	0.237	0.237	0.231	0.232	0.236
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All	All

Table CXI: OLS: Effect of the Introduction of Cash on Fares (State of Mexico) - Intensive Margin

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the number of trips of census blocks that already were already active using Uber before the introduction of cash (intensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block. Columns (3) and (4) consider census blocks at less than 5 kilometers and less than 1 kilometer from Mexico City respectively.

	(1)	(2)	(3)	(4)
State of Mexico	0.210***	0.256***	0.287***	0.293***
	(0.004)	(0.008)	(0.011)	(0.021)
Observations	108,269	87,033	37,744	7,702
R-squared	0.027	0.043	0.071	0.089
Controls	No	Yes	Yes	Yes
Distance	All	All	<5Km	<1Km

Table CXII: OLS: Effect of the Introduction of Cash on Fares (State of Mexico) - Extensive Margin

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the total fares of census blocks that were not active in Uber before the introduction of cash (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block. Columns (3) and (4) consider census blocks at less than 5 kilometers and less than 1 kilometer from Mexico City respectively.

	(1)	(2)	(3)	(4)
State of Mexico	0.455***	0.215***	0.060***	-0.070***
	(0.005)	(0.011)	(0.013)	(0.022)
Observations	108,269	87,033	37,744	7,702
R-squared	0.074	0.112	0.060	0.032
Controls	No	Yes	Yes	Yes
Distance	All	All	<5Km	<1Km

Table CXIII: OLS: Effect of the Introduction of Cash on Fares (State of Mexico) - Intensive Margin, Heterogeneous Effects

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the total fares of census blocks that already were already active using Uber before the introduction of cash (intensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block.

	(1)	(2)	(3)	(4)	(5)	(6)
State of Mexico	0.251***	0.165***	-0.036	-0.148***	0.110***	0.161***
	(0.008)	(0.015)	(0.042)	(0.038)	(0.031)	(0.018)
Bank	-0.029***					
	(0.009)					
State of Mexico x Bank	0.207***					
	(0.025)					
Internet		-0.198***				
		(0.031)				
State of Mexico x Internet		0.288***				
		(0.041)				
Education			-0.014***			
			(0.003)			
State of Mexico x Education			0.028***			
			(0.004)			
Econ. Active				-0.123***		
				(0.043)		
State of Mexico x Econ. Active				0.919***		
				(0.084)		
Cell phone					-0.034	
					(0.033)	
State of Mexico x Cell phone					0.224***	
					(0.045)	
Car						-0.179***
						(0.029)
State of Mexico x Car						0.227***
						(0.036)
Observations	87,033	87,033	87,033	87,033	87,033	87,033
R-squared	0.044	0.045	0.045	0.045	0.043	0.044
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All	All

Table CXIV: OLS: Effect of the Introduction of Cash on Fares (State of Mexico) - Extensive Margin, Heterogeneous Effects

Note: The table reports the results of estimating the effect of the introduction of cash in the State of Mexico. The dependent variable is the change in the total fares of census blocks that were not active in Uber before the introduction of cash (extensive margin). The controls used are the average education of each census block, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the census block.

	(1)	(2)	(3)	(4)	(5)	(6)
State of Mexico	0.220***	0.508***	1.134***	0.919***	0.705***	0.557***
	(0.011)	(0.021)	(0.052)	(0.049)	(0.041)	(0.024)
Bank	0.004					
	(0.008)					
State of Mexico x Bank	-0.237***					
	(0.023)					
Internet		-0.019				
		(0.038)				
State of Mexico x Internet		-0.923***				
		(0.044)				
Education			-0.004			
			(0.003)			
State of Mexico x Education			-0.089***			
			(0.004)			
Econ. Active				0.113***		
				(0.044)		
State of Mexico x Econ. Active				-1.599***		
				(0.103)		
Cell phone					0.352***	
					(0.038)	
State of Mexico x Cell phone					-0.750***	
					(0.055)	
Car						0.459***
						(0.032)
State of Mexico x Car						-0.818***
						(0.039)
Observations	87,033	87,033	87,033	87,033	87,033	87,033
R-squared	0.113	0.127	0.127	0.118	0.117	0.124
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Distance	All	All	All	All	All	All

Table CXV: OLS: Effect of the Introduction of Cash by Origin and Destination

Note: The table reports the effects of estimating the change in trips and fares before and after the introduction of cash by origin-destination pairs. Each observation in the regression is an origin and destination pair at the basic geostatistical area level (AGEB). The dependent variables are the change in trips (columns 1-2 and 5-6) and the change in fares (columns 3-4 and 7-8) from 2016 to 2017 (columns 1-4) and from 2017 to 2018 (columns 5-8). The independent variables are indicator variables of origin-destination pairs. "SM to SM" are pairs of AGEBs where the origin is in the State of Mexico and the destination as well. For "SM to MC" the origin of the trip is in the State of Mexico and the destination is in Mexico City and for "MC to SM" the origin is in Mexico City and the destination is the State of Mexico. The omitted pair is "MC to MC", trips within Mexico City. The estimates with controls include the average education of each AGEB, the share of households with cell phones, the share of households with internet access, the share of economically active population, share of households that own a car, and an indicator variable that equals one if a bank is present in the AGEB.

	(1) Δ Trips	(2) Δ Trips	(3) Δ Fares	(4) Δ Fares	(5) Δ Trips	(6) Δ Trips	(7) Δ Fares	(8) Δ Fares
SM to SM	0.786***	0.414***	0.742***	0.369***	0.034***	-0.069***	0.044***	-0.050***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SM to MC	0.274***	0.330***	0.238***	0.299***	-0.031***	0.231***	-0.028***	0.239***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
MC to SM	0.063***	0.358***	0.034***	0.327***	-0.025***	0.365***	-0.021***	0.370***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	2,582,361	1,846,123	2,582,322	1,846,088	3,011,395	1,975,550	3,011,335	1,975,521
R-squared	0.033	0.115	0.030	0.108	0.000	0.061	0.000	0.059
Controls	N	Y	N	Y	N	Y	N	Y
Year	2017	2017	2017	2017	2018	2018	2018	2018

D Synthetic Control: Inference

D.1 Confidence Sets

Our inference procedure examines whether or not the estimated effect of the ban is large relative to the distribution of the effects estimated for the cities that did not experience the ban. To do so we run permutation tests where each city is assumed to be treated and estimate $\hat{\alpha}_{jt}$ for each $j \in 2, ..., J+1$ and $t \in \{1, ..., T\}$. Following Firpo and Possebom (2018), we use the empirical distribution of a summary statistic:

$$RMSPE_j \equiv \frac{\sum_{t=T_0+1}^{T} \left(Y_{jt} - \hat{Y}_{jt}^{N}\right)^2 / (T - T_0)}{\sum_{t=1}^{T_0} \left(Y_{jt} - \hat{Y}_{jt}^{N}\right)^2 / (T_0)}$$

which is known as the ratio of the mean squared prediction errors. We calculate the a p-value as follows:

$$p \equiv \frac{\sum_{j=1}^{J+1} \mathbb{1}\left[RMSPE_j \geq RMSPE_1\right]}{J+1} \leq \gamma \tag{49}$$

where γ is some pre-specified significance level.

We want to test

$$\mathrm{H}_0 : Y_{jt}^{I} = Y_{jt}^{N} + \mathrm{f}(t)$$

where for a given intervention function is $\mathrm{f} : \{1, ..., T\} \rightarrow \mathbb{R}$, the test statistic RMSPE is given by equation (49). Following this inference procedure we estimate γ-confidence intervals for the effect of the ban as

$$\mathrm{CI}_{\gamma,\theta} \equiv \left\{\mathrm{f} \in \mathbb{R}^{\{1,...,T\}} : \mathrm{f}(t) = \mathrm{c} \text{ and } p_{\theta^{\mathrm{c}}} > \gamma\right\}$$

where $\mathrm{c} \in \mathbb{R}$ and $\gamma \in (0, 1)$. We assume that there is a constant effect of the ban and estimate the empirical distribution of RMSPE following Firpo and Possebom (2018) to perform inference. The effect of the ban on cash on the percent change in the number of trips per capita is significant at the 99% confidence level.

D.2 Size and Power

We also analyze the size and the power of eleven different test statistics and report them in Table DI. Overall, the effect of the ban on cash on the number of trips is significant under each of the tests statistics. Let $\tilde{j}$ be the city that is assumed to face the intervention permutation.

- $\theta^1 \equiv \text{mean}\left(\left|\hat{\alpha}_{\tilde{j}t}\right| | t \geq T_0 + 1\right)$
- $\theta^2 \equiv \text{RMSPE}$
- θ^3 is the absolute value of the statistic of a t-test that compares the estimated average post-ban effect against zero. As follows:

$$\theta^3 \equiv \left| \frac{\bar{\alpha}_{\text{post}}/T - T_0}{\hat{\sigma}/\sqrt{T - T_0}} \right| |$$

where $\bar{\alpha}_{\text{post}} \equiv \frac{\left(\sum_{t=T_0+1}^{T} \hat{\alpha}_{\tilde{j}t}\right)}{(T-T_0)}$ and $\hat{\sigma} \equiv \frac{\left(\sum_{t=T_0+1}^{T}\left(\hat{\alpha}_{\tilde{j}t} - \bar{\alpha}_{\text{post}}\right)\right)}{(T-T_0)}$

- $\theta^4 \equiv \left| \text{mean}\left(Y_{\tilde{j}t} | t \geq T_0 + 1\right) - \frac{\sum_{t=T_0+1}^{T} \sum_{j \neq \tilde{j}} Y_{jt}}{(T-T_0) \times J} \right|$
- θ^5 is the coefficient of the interaction term in a differences-in-differences model.

  $$Y_{jt} = \eta_1 \times \mathbb{1}[j = \tilde{j}] + \eta_2 \times [j = \tilde{j}] \times \mathbb{1}[t \geq T_0 + 1] + Z_{jt} \times \zeta + \xi_j + \mu_t + \epsilon_{jt}$$

  where ξ_j and μ_t are region and time effects and $\hat{\theta}^5 = |\hat{\eta}_2|$.

- $\theta^6 \equiv \left|\text{mean}\left(\hat{\alpha}_{\tilde{j}t} | t \geq T_0 + 1\right)\right|$
- $\theta^7 \equiv \text{mean}\left(\hat{\alpha}_{\tilde{j}t}^2 | t \geq T_0 + 1\right)$
- $\theta^8 \equiv \left|\text{median}\left(\hat{\alpha}_{\tilde{j}t} | t \geq T_0 + 1\right)\right|$
- $\theta^9 \equiv \text{median}\left(\hat{\alpha}_{\tilde{j}t} | t \geq T_0 + 1\right)$
- $\theta^{10} \equiv \text{median}\left(\hat{\alpha}_{\tilde{j}t}^2 | t \geq T_0 + 1\right)$
- $\theta^{11} \equiv \min\left(\hat{\alpha}_{\tilde{j}t} | t \geq T_0 + 1\right)$

Table DI: Synthetic Control: Inference

Note: The table reports the size and the power of different test statistics. The first column, θ, reports the statistics excluding cities were promotions were implemented the week of the ban on cash in Puebla (i.e. Aguascalientes, Cuernavaca, Mazatlán, Torreón). The second column, θ_{all}, includes all the cities. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	θ	θ_{all}
1	$0.0690^{\star}$	$0.0938^{\star}$
2	$0.0345^{\star\star}$	$0.0312^{\star\star}$
3	$0.0345^{\star\star}$	$0.0312^{\star\star}$
4	$0.0714^{\star}$	$0.0625^{\star}$
5	$0.0714^{\star}$	$0.0625^{\star}$
6	$0.0690^{\star}$	$0.0938^{\star}$
7	$0.0690^{\star}$	$0.0938^{\star}$
8	$0.0690^{\star}$	$0.0625^{\star}$
9	$0.0690^{\star}$	$0.0625^{\star}$
10	$0.0690^{\star}$	$0.0625^{\star}$
11	$0.0345^{\star}$	$0.0312^{\star}$

D.3 Puebla: Mixed Users

Table DII: Puebla: Change in the Number of Trips (Mixed Users)

Note: The table reports the results of estimating equation (3) using the change in average weekly trips (before and after the ban) as dependent variable. The sample considers all mixed users, including those not observed after the ban. Mixed users are defined as those that had used both payment methods before the ban. The regression is at the user level and includes controls for the log total fares before the ban and for the entry cohort of the user. Column (1) does not restrict the minimum number of trips a user must have taken to enter the sample. Column (2)-(4) considers only users with a certain minimum of trips before and after the ban. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Δ Trips				
Share cash (t-1)	-0.292***	-0.314***	-0.336***	-0.377***
	(0.012)	(0.012)	(0.013)	(0.015)
Log fares (t-1)	-0.019***	0.031***	0.027***	0.017***
	(0.003)	(0.003)	(0.004)	(0.005)
Observations	128,135	117,875	106,482	82,135
R-squared	0.034	0.040	0.040	0.040
Cohort	Yes	Yes	Yes	Yes
Min. Trips	No	At least 3	At least 5	At least 10

Table DIII: Puebla: Change in the Number of Trips in Credit (Mixed Users)

Note: The table reports the results of estimating equation (3) using the change in average weekly trips paid in credit (before and after the ban) as dependent variable. The sample considers all mixed users, including those not observed after the ban. Mixed users are defined as those that had used both payment methods before the ban. The regression is at the user level and includes controls for the log total fares before the ban and for the entry cohort of the user. Column (1) does not restrict the minimum number of trips a user must have taken to enter the sample. Column (2)-(4) considers only users with a certain minimum of trips before and after the ban. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Δ Trips Credit				
Share cash (t-1)	0.834***	0.784***	0.743***	0.678***
	(0.016)	(0.016)	(0.017)	(0.020)
Log fares (t-1)	0.084***	0.134***	0.127***	0.109***
	(0.004)	(0.004)	(0.004)	(0.005)
Observations	128,135	117,875	106,482	82,135
R-squared	0.033	0.037	0.035	0.030
Cohort	Yes	Yes	Yes	Yes
Min. Trips	No	At least 3	At least 5	At least 10

Table DIV: Puebla: Probability of Returning After Ban (Mixed Users)

Note: The table reports the results of estimating equation (3) using an indicator that equals one if the user had trips before and after the ban. The regression is at the user level and includes controls for the log total fares before the ban and for the entry cohort of the user. The sample of users includes pure cash users and mixed users (defined as those that had used both payment methods before the ban). Column (1) does not restrict the minimum number of trips a user must have taken to enter the sample. Column (2)-(4) considers only users with a certain minimum of trips before and after the ban. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Survived				
Share cash (t-1)	-0.235***	-0.235***	-0.235***	-0.239***
	(0.004)	(0.004)	(0.004)	(0.004)
Log fares (t-1)	0.066***	0.066***	0.066***	0.057***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	98,044	98,044	98,044	94,353
R-squared	0.083	0.083	0.083	0.076
Cohort	Yes	Yes	Yes	Yes
Min. Trips	No	At least 3	At least 5	At least 10

Table DV: Puebla: Change in the Number of Trips (Mixed Users - Intensive Margin)

Note: The table reports the results of estimating equation (3) using the change in average weekly trips (before and after the ban) as dependent variable. The sample considers only users that had trips before and after the ban. The regression is at the user level and includes controls for the log total fares before the ban and for the entry cohort of the user. Column (1) does not restrict the minimum number of trips a user must have taken to enter the sample. Column (2)-(4) considers only users with a certain minimum of trips before and after the ban. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Δ Trips	(1)	(2)	(3)	(4)
Share cash (t-1)	0.086***	0.011*	-0.031***	-0.075***
	(0.005)	(0.006)	(0.006)	(0.007)
Log fares (t-1)	-0.252***	-0.302***	-0.328***	-0.370***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	227,609	175,768	148,132	103,242
R-squared	0.174	0.196	0.219	0.260
Cohort	Yes	Yes	Yes	Yes
Min. Trips	No	At least 3	At least 5	At least 10

Table DVI: Puebla: Change in the Number of Trips in Credit (Mixed Users - Intensive Margin)

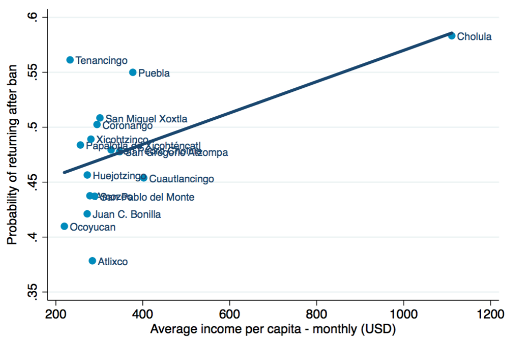
Note: The table reports the results of estimating equation (3) using the change in average weekly trips paid in credit (before and after the ban) as dependent variable. The sample considers only users that had trips before and after the ban. The regression is at the user level and includes controls for the log total fares before the ban and for the entry cohort of the user. Column (1) does not restrict the minimum number of trips a user must have taken to enter the sample. Column (2)-(4) considers only users with a certain minimum of trips before and after the ban. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Δ Trips Credit	(1)	(2)	(3)	(4)
Share cash (t-1)	1.964***	2.045***	2.030***	1.968***
	(0.008)	(0.007)	(0.007)	(0.007)
Log fares (t-1)	-0.216***	-0.225***	-0.243***	-0.286***
	(0.002)	(0.002)	(0.002)	(0.003)
Observations	138,033	113,607	98,312	71,719
R-squared	0.593	0.621	0.633	0.644
Cohort	Yes	Yes	Yes	Yes
Min. Trips	No	At least 3	At least 5	At least 10

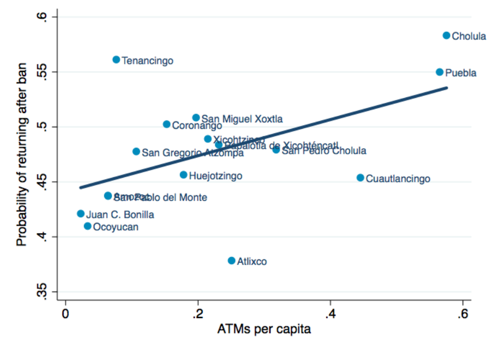
D.4 Puebla: Probability of Returning After the Ban

Figure D1: Probability of Returning After the Ban - Income and Banking Services

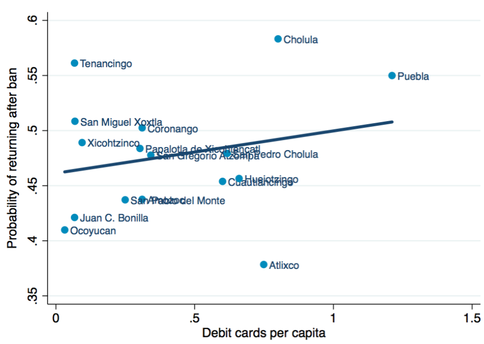
(a) Income



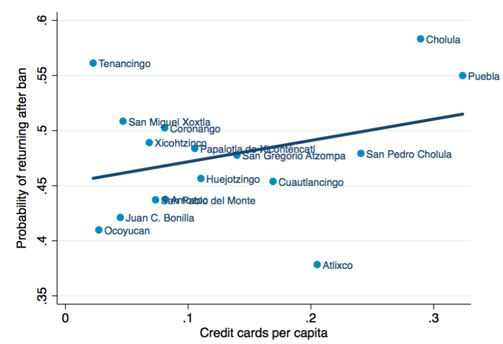
(b) ATMs



(c) Debit Cards



(d) Credit Cards

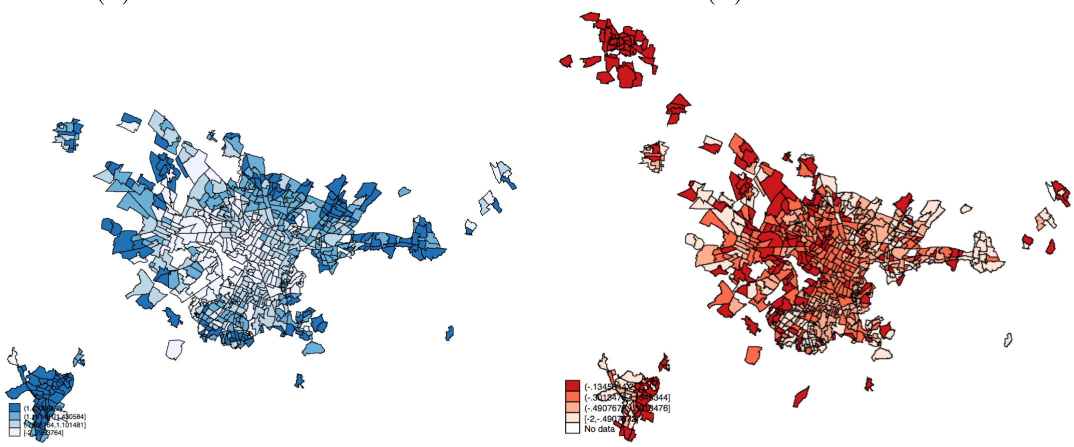


Note: The figure shows the probability of users' using the application again after the ban on cash in the city of Puebla as a function of the income per capita, debit cards per capita , credit cards per capita, and ATMS per capita in each municipality in the city of Puebla. The users are those that took trips in October and November of 2017. The data on debit cards, credit card, and ATMs comes from the Financial Inclusion Database (BDIF). The figure shows the average for 2017. The income data comes from Inter-censal Survey of 2015.

D.5 Puebla: Maps

Figure D2: Puebla: Changes in Trips (Introduction and Ban of Cash)

(a) Introduction of Cash (b) Ban of Cash



Note: The figure shows the changes in percent change in the number of trips in each basic geostatistical area of Puebla. The map on the left shows the changes in the number of trips before and after the introduction of cash (2016-2017). The map on the right shows the changes in the number of trips before and after the ban on cash (2017-2018).

E Details on the Rider's Model

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

E.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:

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

E.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:

$$X(P) = -k \log P + k \log \bar{P} \tag{50}$$

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.

E.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. We use the formulas derived above.

We consider several 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 $p_a = \infty$.

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

At the end of the document we include some notes with the algebra for these cases.

E.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:

$$\frac{v(1,1)-v(\infty,1)}{(c^*(1,1)+a^*(1,1)))}=\begin{cases} \frac{1}{\log\bar{P}}\left[-\log(\bar{P})-1+\bar{P}\right] & \text{if } \alpha^{\frac{1}{1-\eta}}\geq\bar{P}\\ \frac{1}{\log\bar{P}}\left[-\log(\bar{P})-1-\alpha^{\frac{1}{1-\eta}}\left(\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right)-1\right)\right] & \text{otherwise}\end{cases} \tag{51}$$

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

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

E.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:

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

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

$$\log P_i = \frac{\beta_{0i}}{\beta_1}$$

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:

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

E.6 Random Quasi-linear Utility Test

Table EI: 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 EII: 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

F Experiments

F.1 Descriptive Statistics: Experiments

Table FI: 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 FII: 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 FIII: 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

F.2 CES

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

$$\frac{p_a a}{p_c c} = \left(\frac{1-\alpha}{\alpha}\right)\left(\frac{p_a}{p_c}\right)^{1-\eta} \tag{52}$$

using the identity

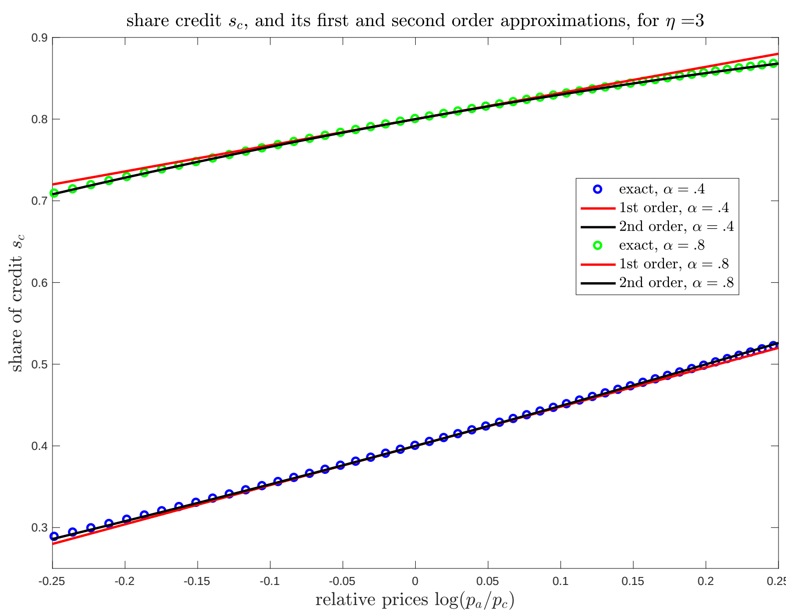
$$s_c = \frac{p_c c}{p_a a + p_c c} = \frac{1}{1 + (p_a a)/(p_c c)} \tag{53}$$

thus

$$s_c = \frac{1}{1 + \left(\frac{1-\alpha}{\alpha}\right)\left(\frac{p_a}{p_c}\right)^{1-\eta}} \tag{54}$$

A first order approximation of s_c around $\log(p_a/p_c) = 0$ gives equation (24). A second order approximation of s_c around $\log(p_a/p_c) = 0$ gives equation (25). Note that the second order approximation can be convex or concave depending on whether $\alpha \geq 1/2$ or not. Figure F1 plots the exact expression given by equation (54) and its first and second order approximation given by equation (24) and equation (25) 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 F1 we conclude that for this range of parameters the first order approximation is very accurate and the second order approximation is almost exact.

Figure F1: 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.

F.3 Estimation of Elasticities

F.3.1 Elasticity of Demand: Pure Cash Users

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

Note: The table reports the semi-elasticity of demand of pure cash users estimated using equation (50) 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 FV: 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 (50) 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 FVI: 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 (50) 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 FVII: Elasticity of Demand: Pure Cash Users (Trips)

Note: The table reports the elasticity of demand of pure cash users estimated using equation (50) 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 FVIII: Semi-Elasticity of Demand: Pure Cash Users (Trips)

Note: The table reports the semi-elasticity of demand of pure cash users estimated using equation (50) 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 FIX: 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

F.3.2 Elasticity of Demand: Mixed Users

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

Note: The table reports the semi-elasticity of demand of mixed users estimated using equation (50) 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 FXI: 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 (50) 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 FXII: 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 (50) 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 FXIII: Elasticity of Demand: Mixed Users (Trips)

Note: The table reports the elasticity of demand of mixed users estimated using equation (50) 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 FXIV: Semi-Elasticity of Demand: Mixed Users (Trips)

Note: The table reports the semi-elasticity of demand of mixed users estimated using equation (50) 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) AA	(2) AA	(3) AA	(4) Mandin	(5) 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 FXV: 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) AA	(2) AA	(3) AA	(4) Mandin	(5) 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

F.3.3 Elasticity of Demand: Pure Credit Users

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

Note: The table reports the elasticity of demand of pure cash users estimated using equation (50) 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 FXVII: Semi-Elasticity of Demand: Pure Credit Users (Miles)

Note: The table reports the semi-elasticity of demand of pure credit users estimated using equation (50) 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 FXVIII: 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 (50) 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 FXIX: 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 (50) 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 FXX: Elasticity of Demand: Pure Credit Users (Trips)

Note: The table reports the elasticity of demand of pure credit users estimated using equation (50) 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 FXXI: Semi-Elasticity of Demand: Pure Credit Users (Trips)

Note: The table reports the semi-elasticity of demand of pure credit users estimated using equation (50) 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 FXXII: 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

F.3.4 Elasticity of Substitution: Cash-Credit

Table FXXIII: 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 (26) 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 (26) 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 FXXIV: 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 (26) 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 (26) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (24). Column (6) estimates the elasticity using the CES second order approximation in equation (25). 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 (24) 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 FXXV: 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 (26) 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 (26) 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 FXXVI: 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 (26) 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 (26) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (24). Column (6) estimates the elasticity using the CES second order approximation in equation (25). 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 (24) 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 FXXVII: 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 (26) 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 (26) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (24). Column (6) estimates the elasticity using the CES second order approximation in equation (25). 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 (24) 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

F.4 Experiment Extensive Margin: Robustness

Table FXXVIII: 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 FXXIX: 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

F.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 Body.

[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, podras disfrutar de 10% de descuento en tus viajes de menos de $200 MXN*.

Tu descuento se aplicará automaáticamente, sólo solicita tu viaje que esta 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.

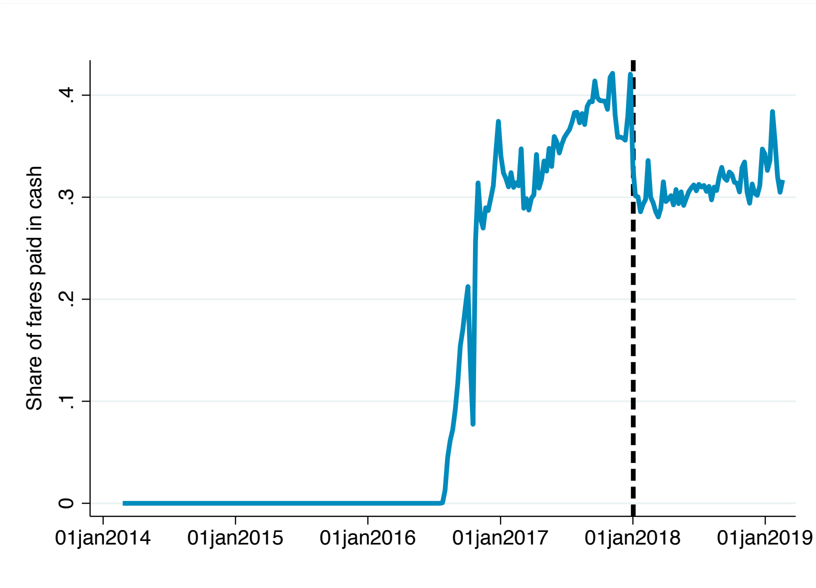
Despus de ingresar la tarjeta, espera un periodo de 8 horas para poder utilizar el descuento. Recuerda que podrás disfrutar de esta promoción sin importar el método de pago que elijas para los siguientes viajes.

*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.

G 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 G1: 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 GI: Elasticity of Demand: Panama (Trips)

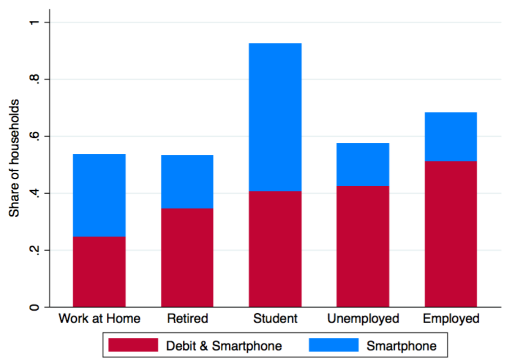
Note: The table reports the elasticity of demand estimated using equation (50) using trips as dependent variable for Panama. Each observation is a week in 2018; the year after the decree by the government restricting the supply of drivers went into effect. Column (1) reports the estimates using aggregated 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

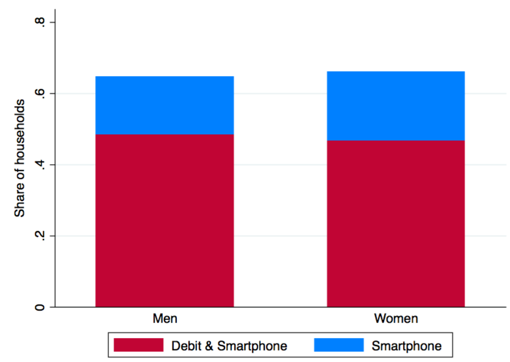
H Demographics in Mexico

Figure H1: Availability of Debit Card and Smartphone

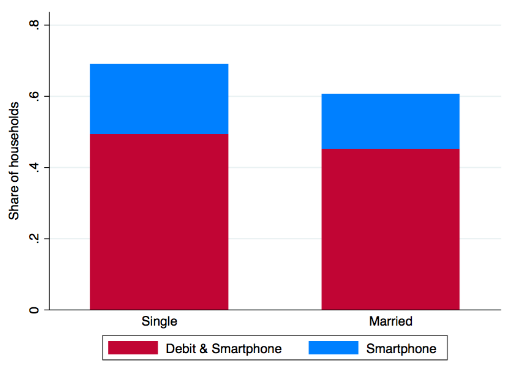
(a) Work



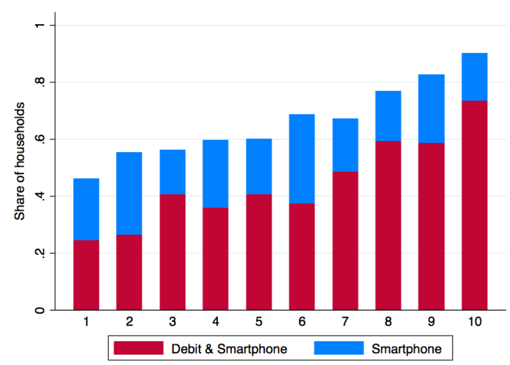
(b) Sex



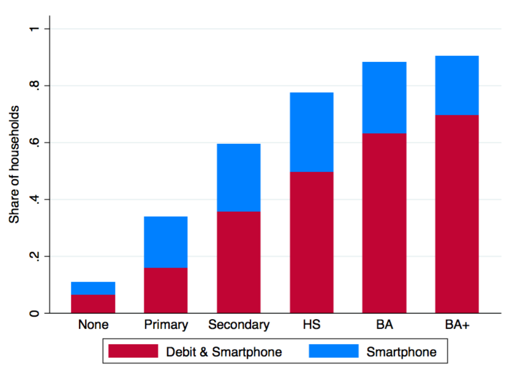
(c) Marital Status



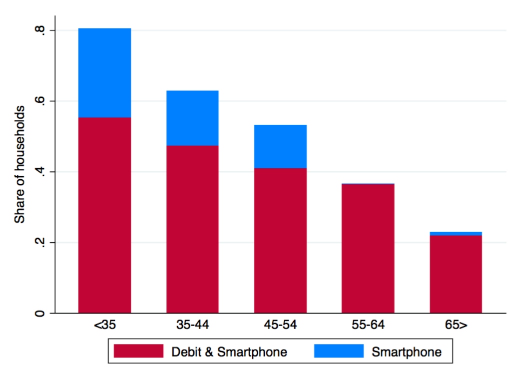
(d) Income



(e) Education

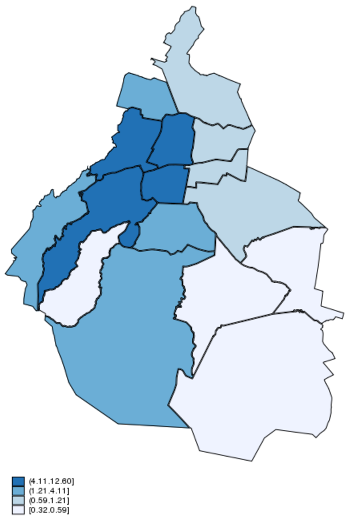


Age

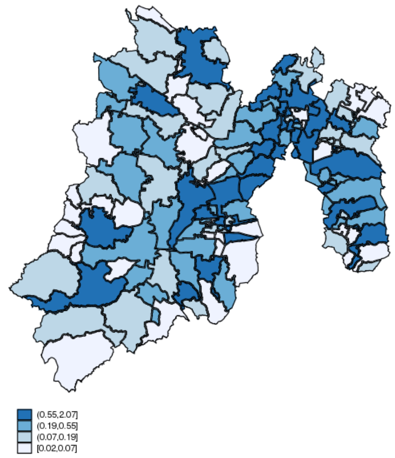


Note: The figure shows the share of households in Mexico who have used a debit card in the last three months (from the time they were surveyed) and that own a smartphone by work status. The data comes from the 2015 National Survey of Financial Inclusion (ENIF).

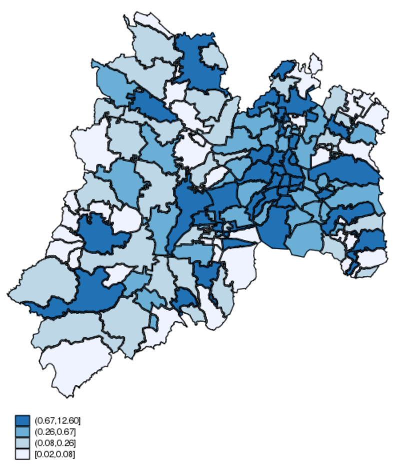
Figure H2: Debit Cards per Capita by Municipality



(a) Mexico City



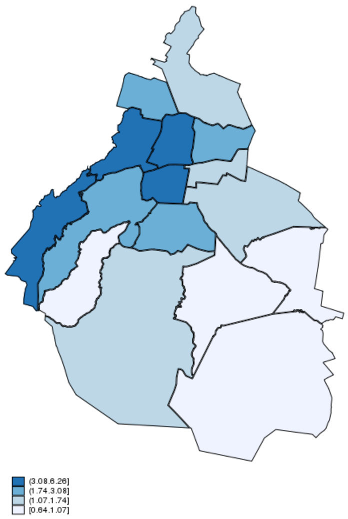
(b) State of Mexico



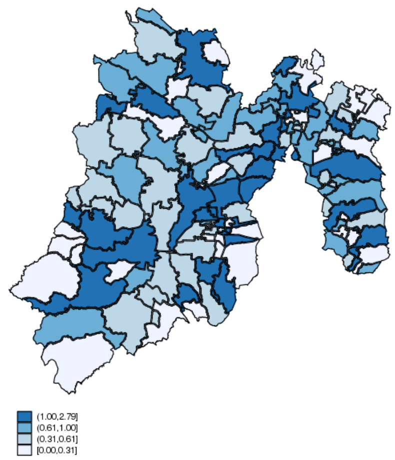
(c) State of Mexico and Mexico City

Note: Figure maps the number of debit cards per inhabitant by municipality in 2017. Darker colors represent a higher number of debit cards per capita. Data come from the Financial Inclusion Databases from the National Banking and Securities Commission.

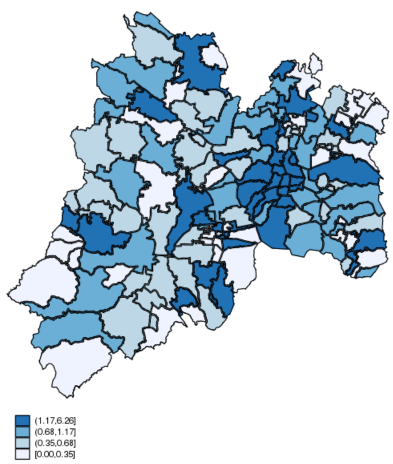
Figure H3: Bank Branches per 10,000 Inhabitants by Municipality



(a) Mexico City



(b) State of Mexico



(c) State of Mexico and Mexico City

Note: Figure maps the number of bank branches per 10,000 inhabitants by municipality in 2017. Darker colors represent a higher number of branches per capita. Data come from the Financial Inclusion Databases from the National Banking and Securities Commission.

I Other Data Sets

Financial Inclusion Database (BDIF)

The Financial Inclusion Databases (BDIF in Spanish) from the National Banking and Securities Commission (CNBV) consist on quarterly data gathered from commercial banks and other financial entities related to financial inclusion. The databases include variables such as bank branches, ATMs, point-of-sale terminals (POS), bank accounts and debit and credit cards. Data is disaggregated at the state and municipality level. The data gathered for this paper corresponds to the period 2012-2017.

National Survey of Household Income and Expenditure (ENIGH)

The National Survey of Household Income and Expenditure (ENIGH in Spanish) is a biannual household survey representative at the National level gathered by the National Institute of Statistics and Geography (INEGI). It gives information on the characteristics of housing units and socio-demographic and economic characteristics of the household members. It provides detailed information about expenditures, such as the type of goods purchased and the method of payment, which are gathered using a diary. We use the latest survey corresponding to 2016.

National Survey of Financial Inclusion (ENIF)

The National Survey of Financial Inclusion (ENIF in Spanish) is a triannual household survey representative at the National level gathered by INEGI. It provides information about access and use of payment methods, saving products, loans and other financial products. We use the latest survey corresponding to 2016.

Census and Inter-censal Survey

The Census of Population and Housing Units is conducted every 10 years by INEGI—with the latest data available corresponding to 2010. It provides information about housing units and socio-demographic characteristics of households and individuals. Some population variables are publicly available at the block level (which is the lowest level of aggregation). The Intercensal Surveys are carried to update some socio-demographic information at the midpoint between censuses. It provides information at the municipality level and at the town level for towns with population bigger than 50 thousand people.

National Statistical Directory of Economic Units (DENUE)

The National Statistical Directory of Economic Units (DENUE) provided information on identification, location, economic activity and size the universe of active economic units in Mexico. The data allow the identification of the economic units by the type of juridical organization (individual or legal entity), by its economic activity and/or by its size (stratum of employees), as well as locating them in the Mexican territory by regions, localities, blocks and streets. The Directory also provides the geographical coordinates for the location of establishments.

National Employment Survey (ENOE)

The National Employment Survey (ENOE), conducted by the National Institute of Statistics and Geography (INEGI), is the main source of statistical information on occupational characteristics of the population nationwide. The data gathered by the survey on a quarterly basis and it is representative at the level of locations of less than 2.500 inhabitants. The economically active population, used as control in some of our estimations, includes people who during the reference period carried out or had an economic activity (employed population) or actively sought to carry out one at some moment of the month prior to the day of the interview (unemployed population).

Precipitation Data

The Precipitation Data are gathered on a daily basis by the National Water Comission (CONAGUA). The database used in this project contains daily precipitation levels, between 2013-2018, for each group of pluviometric stations integrated by the Hydrological Information System (SIH). A group of pluviometric stations is identified by a geographical coordinate (i.e., latitude and longitude).

J Adapting Puebla's Evidence to the State of Mexico

In this section we adapt the evidence 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. Recall that in our counterfactual analysis of the ban in Puebla using synthetic control method, we 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 obtained using the actual ban in Puebla to the evaluation of an hypothetical ban in the State of Mexico. In our analysis of the ban in Puebla in Section 6.3 we found an excess migration rate of about 35% 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 our 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 JI displays statistics at the census block level for Puebla and the State of Mexico. Table JII 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 JIII 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. [47]bThe 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 Sate of Mexico than in Puebla, but that correction is smaller than 1%, i.e. it is given by $(0.74-0.59)\times 0.0095+(9.95-8.88)\times 0.0056 = 0.0074$.

[47]This sample is smaller than the universe used in Section 6.3. The smaller size of the sample is due to the fact that we need to geolocalize all these trips.

Table JI: 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 JII: 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 JIII: 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

K 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:

$$
\begin{aligned}
CS_{ban,a} &\equiv v(1, \infty; \phi) - \int \max\{v(\infty, 1; \phi) - \psi, v(\infty, \infty; \phi)\} g(\psi) d\psi \qquad (55)\\
&= v(1, \infty; \phi) - \int_{\underline{\psi}}^{\psi_{ban}} [v(\infty, 1; \phi) - \psi] \, g(\psi) d\psi - \left[1 - \int_{\underline{\psi}}^{\psi_{ban}} g(\psi) d\psi\right] v(\infty, \infty; \phi)
\end{aligned}
$$

where g is the distribution of fixed cost among the pure cash users before the ban, $\underline{\psi}$ 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.

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 $\phi = (\eta, \alpha, k, \bar{P})$, as well as for two critical values of the cost ψ, the lower bound of the support of g given by $\underline{\psi}$, and the value ψ_{bar} for which pure cash riders are indifferent between not using Uber and paying this fixed cost and becoming pure credit users. This set of values 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 7.4.

   (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:

$$\beta_0 = k(1-\alpha)^{\frac{1}{1-\eta}}\left[\log\left(\frac{\bar{P}}{(1-\alpha)^{\frac{1}{1-\eta}}}\right)\right] \tag{56}$$

$$\beta_1 = -k(1-\alpha)^{\frac{1}{1-\eta}} \tag{57}$$

(c) Pure cash users that become pure credit users take fewer rides after the ban. In term of the model it means that $\tilde{a}(1,\infty;\phi) > \tilde{a}(\infty,1;\phi) > 0$. This was shown panel (a) of Figure 12 in Section 6.4 in our analysis of Puebla. Using the expression in Appendix E.3 we have:

$$\alpha \leq 1/2 \tag{58}$$

(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 (56) and equation (57) enforce that the demand of pure cash users is positive. Using the expressions in Appendix E.3 we have:

$$\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}} \leq 1 \tag{59}$$

(e) 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:

$$\begin{aligned}\underline{\psi} &= v(1,1;\phi) - v(1,\infty;\phi) \\ &\equiv -k(1+\log\bar{P}) - k(1-\alpha)^{\frac{1}{1-\eta}}\left[\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right]\end{aligned} \tag{60}$$

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

(f) The lower bound $\underline{\psi}$ is smaller than the cost ψ_{ban} which triggers that no pure cash users want to registered a card:

$$\psi_{ban} = v(\infty,1;\phi) - v(\infty,\infty;\phi) \equiv k\alpha^{\frac{1}{1-\eta}}\left[\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] + k\bar{P} \tag{61}$$

Overall we have four equations, namely equation (56), equation (57), equation (60) and equation (61) and five unknowns (k, α, $\bar{P}$, $\underline{\psi}$, ψ_{ban}) and the three inequalities $\alpha \leq 1/2$, $\alpha > \bar{P}^{1-\eta}$, and $\psi_{ban} \geq \underline{\psi}$. Using the estimated values of β_0, β_1, η we obtain an interval for α and for each value in this interval we obtain the corresponding values of $(\underline{\psi},\, \psi_{ban},\, k,\, \bar{P})$.

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

   (a) The value of $\int_{\underline{\psi}}^{\psi_{ban}} g(\psi)d\psi$ is given by our estimate of the excess migration of pure cash riders to pure credit riders in Puebla after the ban. We use $\int_{\underline{\psi}}^{\psi_{ban}} g(\psi)d\psi = 0.35$ as estimated in Section 6.3.

   (b) 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 (20) 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.

We summarize the conclusion from the first step in the following proposition.

Proposition 3. Assume that $\eta > 1$ and $\beta_1 < 0$. The set of values for α what satisfy all the conditions described in step 1 above is contain in an interval $[\underline{\alpha}, 1/2]$ where $\underline{\alpha} > 1/\left[1 + \exp\left((1-\eta)\beta_0/\beta_1\right)\right]$. At $\alpha = \underline{\alpha}$, then $\psi_{ban} = \underline{\psi}$. For an open interval of values smaller than $\alpha = 1/2$, then $\psi_{ban} > \underline{\psi}$. The values of $\bar{P}$ and k for each α are given by

$$\bar{P} = (1-\alpha)^{\frac{1}{1-\eta}} e^{-\beta_0/\beta_1} \text{ and } k = \frac{-\beta_1}{(1-\alpha)^{\frac{1}{1-\eta}}}\,. \tag{62}$$

Proof. (of Proposition 3) The proof proceeds in four steps.

(i) We find an expression for $\bar{P}$ and k given an arbitrary α using equation (61) and equation (60). Dividing β_0 by $-\beta_1$ we get:

$$\frac{\beta_0}{-\beta_1} = \log\left(\frac{\bar{P}}{(1-\alpha)^{\frac{1}{1-\eta}}}\right) = \log\left(\bar{P}\right) - \log\left((1-\alpha)^{\frac{1}{1-\eta}}\right)$$

Rearranging and exponentiating:

$$\bar{P} = (1-\alpha)^{\frac{1}{1-\eta}} e^{-\beta_0/\beta_1}\,. \tag{63}$$

Also, dividing β_0 by $-\beta_1$, and multiplying and dividing the expression inside by k we get:

$$\frac{\beta_0}{-\beta_1} = \log\left(\frac{k\bar{P}}{k(1-\alpha)^{\frac{1}{1-\eta}}}\right) = \log\left(\frac{k\bar{P}}{-\beta_1}\right) = \log\left(k\bar{P}\right) - \log\left(-\beta_1\right)$$

or $k\bar{P} = -\beta_1 \exp\left(-\beta_0/\beta_1\right)$. Dividing the expression for $k\bar{P}$ by $\bar{P}$ we get the expression for k.

(ii) We find an expression for the value of α at which the inequality (equation (59)) holds with equality. We label this value as α_0. Combining equation (63) with (equation (59)) holding as equality we have:

$$\alpha_0 = \frac{1}{\exp\left((1-\eta)\beta_0/\beta_1\right) + 1} \tag{64}$$

Note that $\alpha_0 < 1/2$ as long as $(1-\eta)\beta_0/\beta_1 > 0$.

(iii) We use equation (61) to define $\tilde{\psi}(\theta)$ as follows

$$\psi_{ban} = (k\bar{P})\left[\theta\left(\log(\theta) - 1\right) + 1\right] \text{ where } \theta \equiv \frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}} = \left(\frac{\alpha}{1-\alpha}\right)^{\frac{1}{1-\eta}} e^{\beta_0/\beta_1}$$

where $k\bar{P} = -\beta_1 \exp\left(-\beta_0/\beta_1\right)$. Note $\psi'_{ban}(\theta) = k\bar{P}\log(\theta)$. Thus the function ψ_{ban} attains at minimum at $\theta = 1$, with $\tilde{\psi}(1) = 0$, and it is strictly convex, so it is strictly increasing for $\theta > 1$ and strictly decreasing for $\theta < 1$. Since $\eta > 1$, then θ is a monotonically decreasing function of α. Note that the requirement that riders that become pure credit users have positive rides implies that $\bar{P} > \alpha^{1/(1-\eta)}$ as indicated in inequality (equation (59)), and hence the relevant segment are the values for $\theta < 1$ where ψ_{ban} is strictly decreasing in θ and hence strictly increasing in α.

(iv) For $\alpha = 1/2$ we have that $\psi_{ban} > \underline{\psi}$. To see this set $\alpha = 1/2$ in equation (61) and equation (60) we have:

$$\begin{aligned}
\psi_{ban} - \underline{\psi} &\equiv k\,.5^{\frac{1}{1-\eta}}\left[\log\left(\frac{.5^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] + k\bar{P} - \left(k(1+\log\bar{P}) - k\,.5^{\frac{1}{1-\eta}}\left[\log\left(\frac{.5^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right]\right) \\
&= k\bar{P} - k(1+\log\bar{P}) \geq k\bar{P} - k\bar{P} = 0
\end{aligned}$$

where the inequality follows from the concavity of $\log\bar{P}$.

(v) For any ϕ with $\alpha \in (0,1)$, we have that $v(1,1;\phi) > v(1,\infty;\phi)$, hence $\underline{\psi}(\alpha)$, as defined by the left hand side of equation (60) is strictly positive.

Thus $\underline{\psi} > 0 = \psi_{ban}$ at $\alpha = \alpha_0$ and $\underline{\psi} < \psi_{ban}$ at $\alpha = 1/2$. By the intermediate value theorem, there must exist a $\underline{\alpha} \in (\alpha_0, 1/2)$ at which $\psi_{ban} = \underline{\psi}$. If there are several such values, take the smallest one.

$\square$

Next, we note that the consumer surplus lost for those with $\psi \geq \psi_{ban}$ is independent of α. This is the quantity plotted in Figure 16 (as a fraction of expenditure) and it is a function of β_0, β_1. Note that using equation (56) and equation (56) and the expression derived for $k\bar{P}$ we have

$$
\begin{aligned}
v(1,\infty;\phi) - v(\infty,\infty;\phi) &= k(1-\alpha)^{\frac{1}{1-\eta}} \left[\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\log \bar{P}}\right) - 1\right] + k\bar{P} \\
&= -\beta_0 + \beta_1 - \beta_1 \exp\left(-\beta_0/\beta_1\right) \qquad (65)
\end{aligned}
$$

In particular, from Table FIV we obtain obtain the following point estimates $\beta_1 = -2.044$ and $\beta_0 = 1.478$ for the miles specification. We use the mile specification because the price of a trip has been normalized to one, as in the theory. Also note that this corresponds to an elasticity of 1.38. Additionally, in our aim to be conservative, this is the largest elasticity, which gives the lowest consumer surplus. Using these values we get $v(1,\infty;\phi) - v(\infty,\infty;\phi) = 36.8$ per year or 0.467 of the expenditure before the ban, just as in Figure 16.

Recall that for pure cash riders with $\psi = \psi_{ban}$ we have that the consumer surplus lost is equal to:

$$v(1,\infty;\phi) - [v(\infty,1;\psi) - \psi_{ban}] = v(1,\infty;\phi) - v(\infty,\infty;\psi)$$

Thus for pure cash riders with $\psi \in [\underline{\psi}, \psi_{ban})$ we have that the consumer surplus lost is:

$$v(1,\infty;\phi) - [v(\infty,1;\psi) - \psi] = v(1,\infty;\phi) - v(\infty,\infty;\psi) + \psi - \psi_{ban}$$

Thus a lower bound for the consumer surplus lost for all the riders that migrate from cash to credit after the ban is:

$$v(1,\infty;\phi) - [v(\infty,1;\psi) - \psi] \geq v(1,\infty;\phi) - v(\infty,\infty;\psi) + \underline{\psi} - \psi_{ban} \qquad (66)$$

Integrating this expression with respect to the distribution g of ψ and using the definition of

$CS_{ban.a}$ in equation (55) we obtain the following lower bound:

$$
\begin{aligned}
CS_{ban,a} &= v(1,\infty;\phi) - v(\infty,\infty;\psi) - \int_{\underline{\psi}}^{\psi_{ban}} \left[\psi - \underline{\psi}\right] g(\psi)d\psi \\
&= \left[-\beta_0 + \beta_1 - \beta_1 \exp\left(-\beta_0/\beta_1\right)\right] - \int_{\underline{\psi}}^{\psi_{ban}} \left[\psi - \underline{\psi}\right] g(\psi)d\psi \\
&\geq \left[-\beta_0 + \beta_1 - \beta_1 \exp\left(-\beta_0/\beta_1\right)\right] - \left[\psi_{ban} - \underline{\psi}\right] \int_{\underline{\psi}}^{\psi_{ban}} g(\psi)d\psi \qquad (67)
\end{aligned}
$$

Using the estimated β_0 and β_1 we obtain a consumer surplus lost by the pure cash users that do *not* migrate after the ban, i.e. $v(1,\infty;\phi) - v(\infty,\infty;\psi) \approx 36$ USD per year, or about 0.47 of the yearly expenditure on rides paid in cash.

The inequalities developed in the first step above and the Proposition 3 give that $\alpha \in [0.38, 0.5]$. The difference $\psi_{ban} - \underline{\psi}$ is increasing in α within this interval, ranging between $\psi_{ban} - \underline{\psi} = 0$ at $\alpha = 0.38$ and and $\psi_{ban} - \underline{\psi} = 8.3$ USD per year at $\alpha = 0.5$. Thus we can use the lower bound on the consumer surplus lost is given by selecting $\alpha = 0.5$ and using the formula for the lower bound we obtain $CS_{ban,a} \geq 33$ USD per year or about 0.43 of the yearly expenditure of cash rides in Uber. For this lower bound we have used $\int_{\underline{\psi}}^{\psi_{ban}} g(\psi)d\psi = 0.35$, bases on Puebla.

We can use the results of Experiment 3 to obtain a better estimate of $\int_{\underline{\psi}}^{\psi_{ban}} \psi g(\psi)d\psi$. 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 9, 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:

$$
\begin{aligned}
&\int_{\underline{\psi}}^{\psi_{ban}} \left[\psi - \underline{\psi}\right] g(\psi)d\psi \\
&\leq 1 \times 0.033 + 2.1 \times (0.039 - 0.033) + 3.6 \times (0.047 - 0.039) + (8.3 - 3.6) \times (0.35 - 0.047) \\
&= 1.5 \leq 0.35 \times 8.3 = 2.9
\end{aligned}
$$

In this case we obtain $CS_{ban,a} \geq 36 - 1.5 = 34.5$ USD per year or about 0.45 of the yearly expenditure on Uber paid in cash by pure cash riders. This calculation is our headline number for pure cash users.

L Ban on the Use of Credit: Argentina

Motivated by the current legal framework in Argentina, where local credit cards cannot 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 current situation in Argentina is that Uber riders cannot pay using credit cards whose payments are processed by one of the two local firms processing credit card payments. This is due to an initial injunction issued by a public attorney of the City of Buenos Aires, even though it has been now reversed in appeal. The reason the ban is nationwide, even though the initial injunction was for the city of Buenos Aires, is that the credit card processors cannot distinguish the location where the charges of riders were originated. Uber riders using credit card whose payments are processed abroad, such as most international tourists, are 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 13, 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.

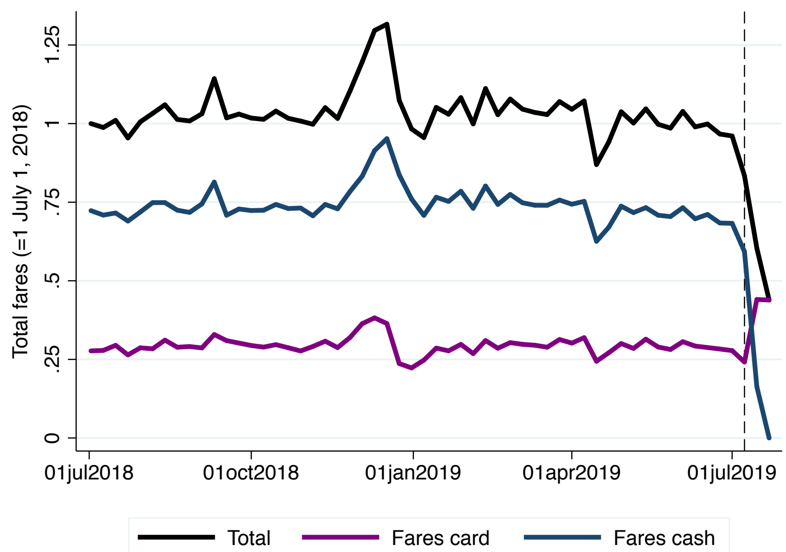
The ban on credit has a large effect on the pure credit riders. Given our assumption of no fixed cost to use cash, we rationalize that rider does not use cash (i.e. that she is a pure credit rider) as having a value of $\alpha \approx 1$. This means that pure credit riders will stop using Uber altogether 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 they 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 F.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 USA data and a different identification scheme, which is 1.66. Recall that in that US only credit is available as a means of payment.

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.

M Ban on the Use of Cash: San Luis Potosí

The Transportation Law in San Luis Potosí prohibits ride-hailing companies from receiving payments in cash. Uber had requested a suspension of the established norm but a judged did not grant the suspension and, as a result, cash was turn off from the application on July 17th 2019. Figure M1 shows the evolution of the total fares paid in San Luis Potosí by payment method. Importantly, before the ban on cash, around 75% of total fares in the city were paid in cash. The week after the ban on cash, as the total fares paid in cash dropped to zero, the fares paid in credit increased 60%; nonetheless, the total fares in the city decreased 60% after the ban. [48]

Figure M1: San Luis Potosí: Total Fares by Payment Method

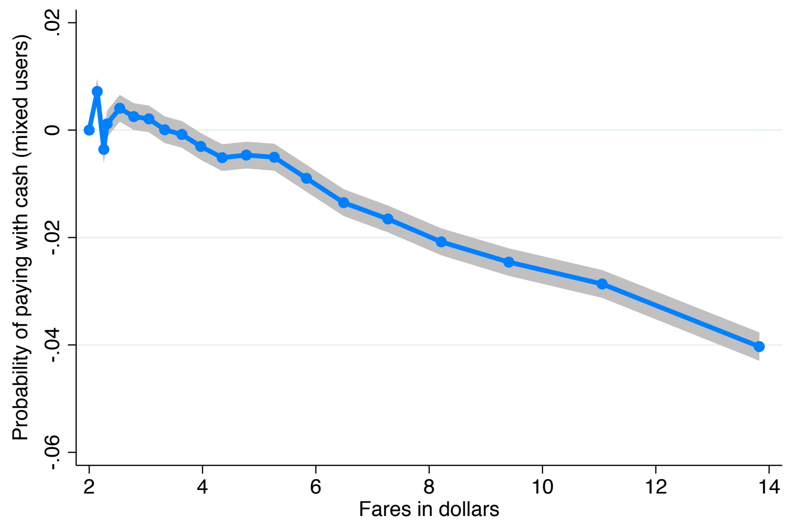


Note: The figure shows the evolution of the fares paid by users in the city of San Luis Potosí. The black line shows the total fares, the purple line shows those paid in card, and the blue the fares paid in cash. The dotted lines show the date of the ban on cash as a payment method in the city. Total fares are normalized to equal 1 on July 1st 2018.

[48]Unfortunately, the ban took place at the end of the time periods covered by our data; we are thus unable to extend the figure to more recent periods.

N Mixed Users: Individual Level Effects

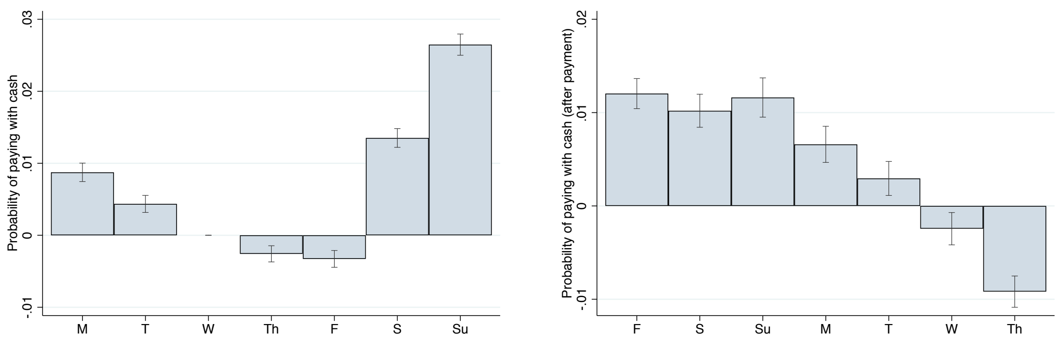
Figure N1: Mixed Users: Probability of Paying with Cash by Fare Size



Note: The figure shows probability paying with cash as a function of the fare size. The data used is a the trip level for the months of August 2017 and August 2018 in the State of Mexico. The sample of users includes only mixed users: those that have used both payment methods at least once and that have at least 5 trips and at least 4 weeks of tenure in Uber. The dependent variable is an indicator that equals to one if the trip was paid in cash. The dependent variable are percentiles of the fare paid per trip distribution. The figure shows the estimates after controlling for individual and time effects at the daily level. The shaded area shows the 95% confidence intervals.

Figure N2: Mixed Users: Probability of Paying with Cash by Day of the Week

(a) Change in Users (2016-2017) (b) Change in Trips (2016-2017)



Note: Panel (a) shows the probability of paying with cash (relative to Wednesdays) for a given user. The data used is a the trip level for the months of August 2017 and August 2018 in the State of Mexico. The sample of users includes only mixed users: those that have used both payment methods at least once and that have at least 5 trips and at least 4 weeks of tenure in Uber. The dependent variable is an indicator that equals to one if the trip was paid in cash. The dependent variable are the days of the week. The figure shows the estimates after controlling for individual effects and the fares paid in the trip. Panel (b) shows the estimates after interacting the days of the week with an indicator that equals one the days after a bi-weekly payment takes place. The bands indicate 95% confidence intervals.

O Survey

In order to obtain more evidence about the elasticities that we estimate in our experiment as well as the choke prices for different users, we sent surveys to riders asking how would they respond to different changes in prices. We design 6 different surveys each with 3 questions in order to minimize the time it took to complete a survey but also being able to explore several potential 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...". However, 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%. This design is helpful to bound the elasticities from the survey and being able to compare them with those obtained from our experimental design.

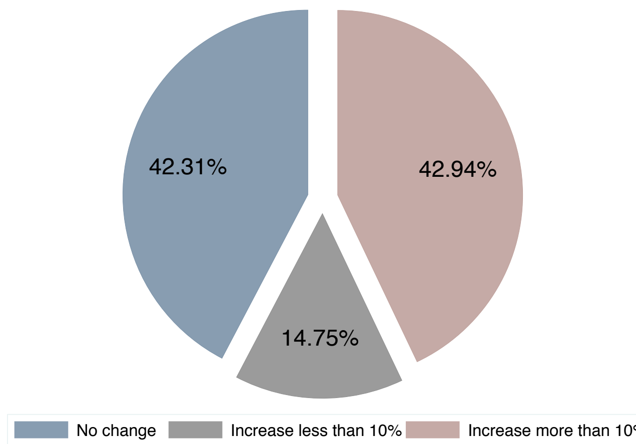
The surveys were sent through email on July 9th, 2019 and they were open until July 16th, 2019. The surveys were sent to all users that participated in experiment 1 and experiment 2. A total of 433,356 users received a survey, 287,233 participated in experiment 1 (mixed and pure credit users) and 146,123 participated in experiment 2 (pure cash users). We randomize the 6 surveys within each of the treatment 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 survey 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 an average of 1056 responses per survey. After dropping bad responses (often people wrote long comments to Uber instead of only answering the questions) and duplicates our total sample contains an average of 933.5 responses per survey.[49]

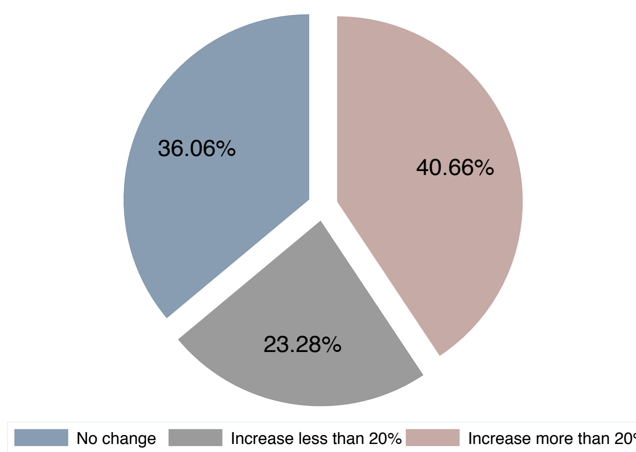
Next, we adjust the covariate distribution of the survey respondents by reweighting such that it becomes more similar to the covariate distribution of the entire population that participated in our experiments. We implement entropy balancing, a multivariate reweighting method described in Hainmueller (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 survey questions and responses are described below:

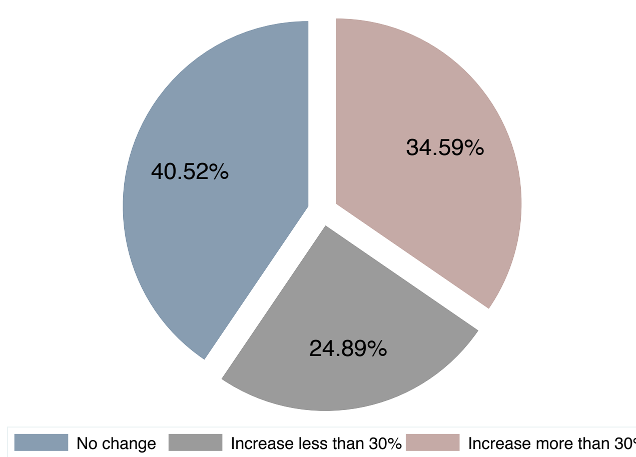
[49] If a given user responded the survey more than once we kept the response with less missing answers or, in case of a tie, we kept their last response.

O.1 Pure Cash Users

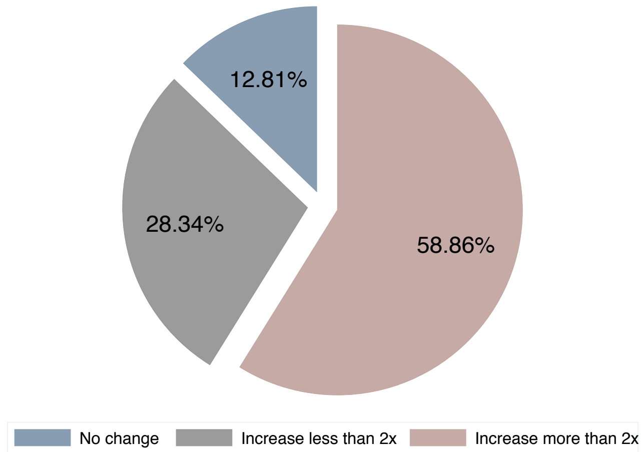
Question 1: If your receive a 20% discount for one week, how would you change your trips...



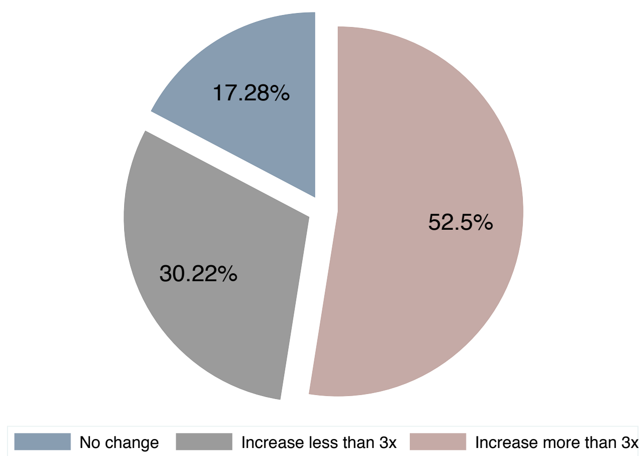




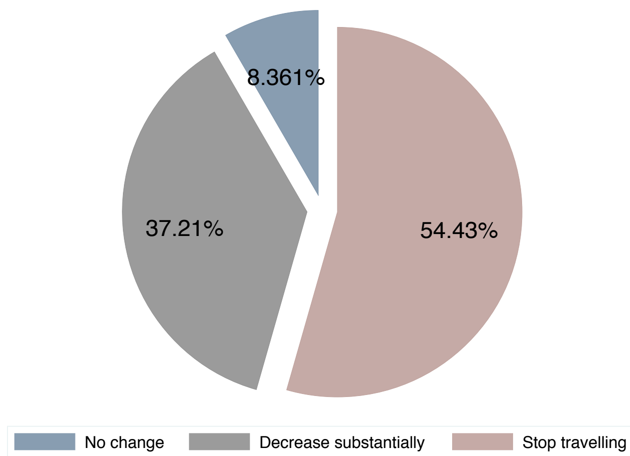
Question 2a: If the price of trips is permanently reduced by half, how would you change your trips...



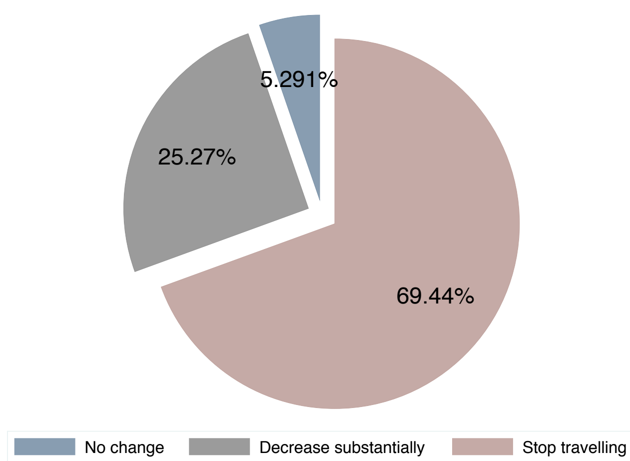
Question 2a: If the price of trips is permanently reduced to a third, how would you change your trips...



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

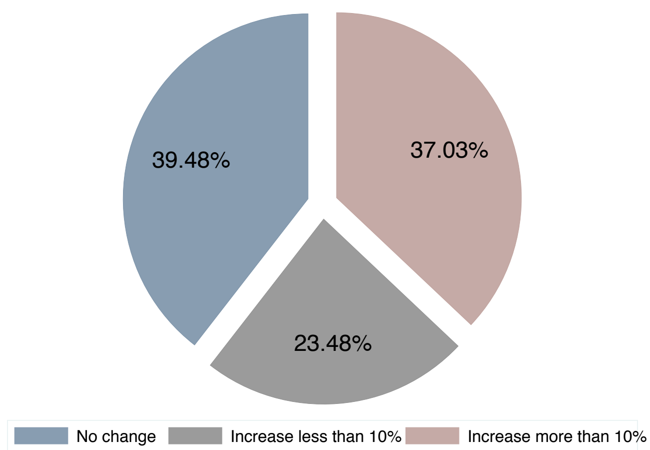


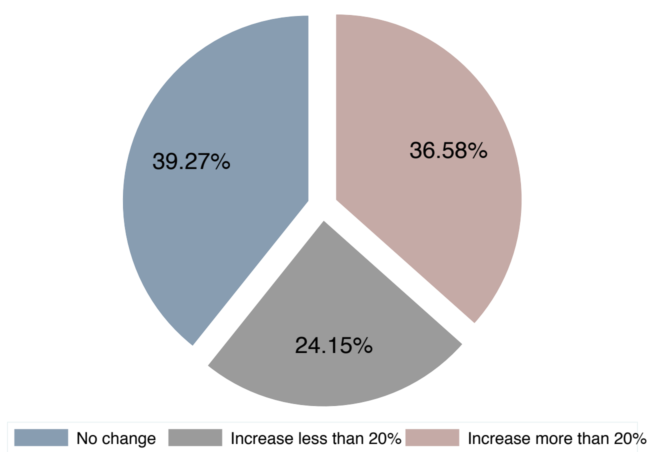
Question 3b: If the price of trips is permanently tripled, how would you change your trips...

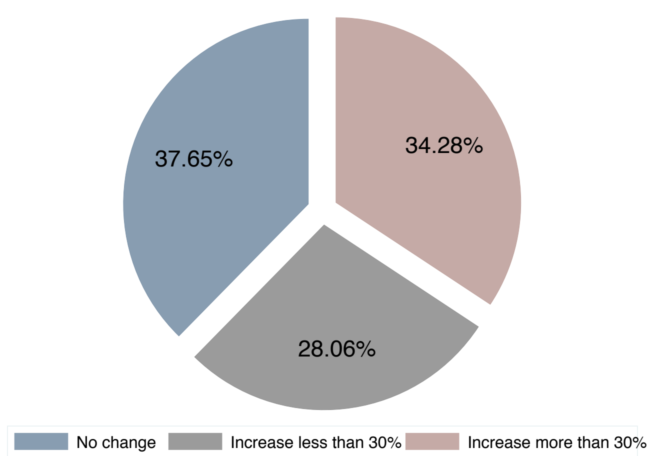


O.2 Mixed Users

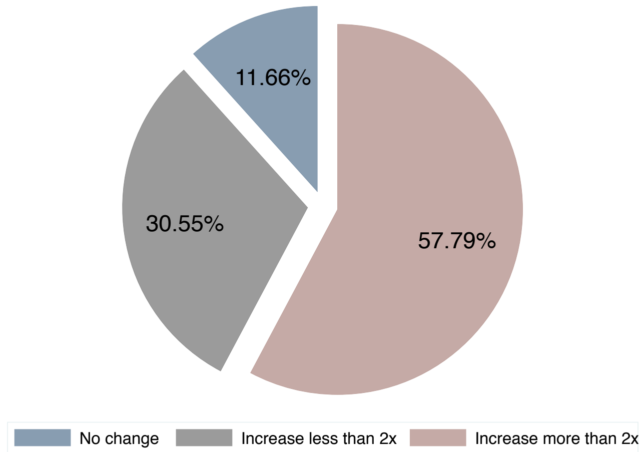
Question 1: If your receive a 20% discount for one week, how would you change your trips...



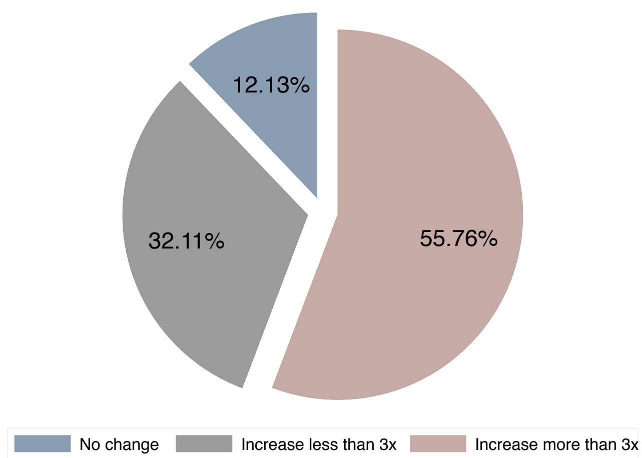




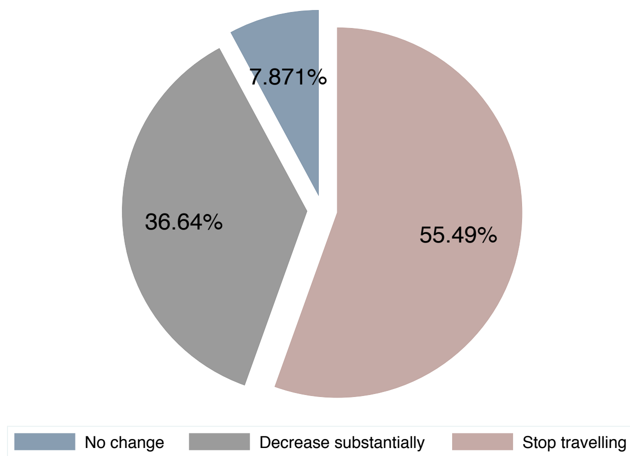
Question 2a: If the price of trips is permanently reduced by half, how would you change your trips...



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