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

Fernando Alvarez† David Argente‡
University of Chicago FRB Minneapolis

March 2019
Preliminary and Incomplete
PLEASE DO NOT CITE OR CIRCULATE WITHOUT PERMISSION

Abstract

We estimate the private benefits for Uber rides of using cash as a means of payment. We use three large field experiments as well as several quasi-natural experiments to estimate the consumer surplus that will be lost if Uber riders in Mexico will not be allowed to use cash as a means of payment, a policy that has been in place in several cities. We find that that riders of this platform that use cash as means of payment either partially or exclusively will suffer an average private cost of approximately 30% of their total expenditures on rides. The incidence of the cost of 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 thank Manual Amador, Andy Atkeson, Anmol Bhandari, Stephane Bonhomme, Doireann Fitzgerald, John List, Ellen Mc Grattan, Greg Kaplan, Juanpa Nicolini, Venky Venkateswaran for their comments and suggestions. We would like to thank the San Francisco Uber policy group, and especially the Uber Mexico team for general support and assistance, programming, and implementing the field experiments and for countless queries of observational data and background information, in particular to Federico Ranero and Hector Argente. We thank Basil Halperin for his many contributions during the initial phase of the project. We would like to thank Francisca Sara-Zaror and Rafael Jimenez for excellent research assistance. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System. None of the two authors are employees or consultants for Uber, and have not received payments from any kind from Uber. David Argente is the brother of Hector Argente, who is 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: david.argenteamaya@mpls.frb.org. Address: 90 Hennepin Ave, Minneapolis, MN 55401.

1 Summary and Introduction

In this paper, we estimate the private benefits for consumers of alternative means of payments. We consider the case of Uber rides 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 are not be allowed to use cash as a means of payment. We find that the riders of this platform that use cash either partially or exclusively would suffer an average private cost of about 30% of the value of their rides. Unsurprisingly, we find that the incidence of the cost of the ban in cash will fall mostly on lower income households.

The general area where our paper makes a contribution is the optimal choice of means of payments, which itself can be thought as a part of the study of money demand. Examples of earlier theoretical papers on the choice of means of payments are the cash-credit model in Lucas and Stokey (1987), or the multiple means of payment model in Prescott (1987), as well as a large literature that follows them. Recently the use of cash has been received considerable attention by policymakers, many times expressing 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 means of payment for Uber in Mexico, as well as in other countries such as Panama, has had severe restrictions. In particular, cash has been originally not allowed in several cities in Mexico (for example in the Mexico City or in the city of Queretaro), and even banned in the city of Puebla, a city where payment in cash was previously used by Uber. Only recently, the Mexican Supreme Court has rule as unconstitutional the prohibition of using cash by local jurisdictions as a means of payment.[2] Motivated by these recent policies, we will estimate the effect on the consumer surplus of Uber riders of the benefits of introducing cash as a means of payments in a city where cash was not available, as well as the lost in consumer surplus of banning cash as a means of payment in a city where it was available. We extend the estimates for the cost of the ban of cash on Uber rides in the entire country of Mexico, and even more speculatively, we extend the results to a ban of cash to *all* goods and services.

Our paper considers only private benefits for riders, so we don't take into account either networks effects or externalities. Yet we find that the size of the estimated benefits are very

[1] Currently, there are more than 450 cities worldwide, and more than 40 cities in Mexico, where cash is available as means of payment for Uber rides. Mexico city is a very large metropolitan area, with the third largest number of Uber trips in the world.

[2] 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.

large. We believe that public policies such as the ban on the use of cash should be based on credible estimates on the difference between the private and social benefits, and of course this difference should be commensurable with the lost of private benefits for the riders for the ban to be welfare improving. In conclusion, based on the evidence we present, we believe that banning cash as means of payments is a very costly public policy.

As we mentioned above, in 450 cities worldwide Uber allows its riders to select cash as a means of payment –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 as means of payment, then the rider will pay the driver the same way that the rider will pay a taxi.[3] We focus on estimating the change in the consumer surplus for riders after the entry of cash in a city. We distinguish between the effect on riders that can use *both* means of payments (we refer to them as mixed users), and the effect on riders that do *not* declare a credit card in the application (we refer to them as pure cash users). We ignore the effect of the entry of cash (or of the ban) in incumbent pure credit riders as well as on the drivers. We ignore these effects because we find no evidence that they are quantitatively. To see this, we find helpful to consider the entry of cash in a city as a demand shock for Uber rides. If we think of Uber as a platform merely connecting riders with drivers, the entry of cash can be analyzed as industry equilibrium after a demand shock which may lead to an increase in prices as well as quantities, whose magnitude will depend on the elasticities of demand from riders and the elasticity of supply from drivers. If prices increase, there will be an increase in the producer surplus for drivers, and a loss on consumer surplus for the previous riders, especially those that don't use cash (i.e the pure credit riders). On the other hand, new riders that either use cash exclusively, or that enter because the possibility of using cash –even if they have a different payment method, will benefit. Using a conventional event study framework we found no statistically significant effect of change on prices (or the average surge multiplier) or in the riders waiting times of arrival as a consequence of the entry of cash. At our estimated values it appears that the supply of riders (in terms of number of active drivers as well as hours worked per driver) is elastic enough at the relevant time interval so that we can disregard the effect on the riders' producer surplus and the effect on the previous pure cash users consumer surplus.

We use two different types of evidence for this paper. One type of evidence are quasi-natural experiments where we can estimate the effect of the entry (or the ban) of cash in 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, etc. The second type are field experiments (randomized control

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

trials) where riders face different prices or rewards to use alternative payment methods.

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 in 15 different cities where previously Uber has entered accepting credit as the only means of payment. We argue that the entry can be considered as quasi-random. Our understanding of the the decision of Uber to introduce cash is that, after it successful introduction of cash in may of 2015 in Hyderabad (India), it was decided that cash will be introduced in all cities in developing countries where it was allowed. We follow a standard event study design, estimating weekly effects of the outcome variables mentioned above for a period of about one year after the introduction of cash in each city. As standard, we include time and city fixed effects, and time varying city level controls which we construct for this study. We found statistically significant and very large increases in the total number of trips and in the total fares after the entry of cash, more than doubling them after a year. There are large increases in the sign up of riders and drivers, as well as in the number of active riders and drivers. The number and sign up of drivers is smaller than those estimated by riders, but we also found that drivers increase their weakly hours, so in total total weekly hours of drivers increase by approximately the same percentage as total fares. We found no statistically significant effects on prices or on average waiting times after the introduction of cash, as well as no changes in the price of taxis. As explained above, these finding motivate our focus on the consumer surplus of mixed riders and of pure cash riders.

The second quasi-natural experiment that we use is the introduction of cash in the greater metropolitan area of Mexico city, a very large city of more than 20 million in population and the third largest city in terms of Uber rides 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 in the Greater Mexico City in 2013, but it was able to introduce cash only by the end of 2016. In particular, Uber rides that started in the State of Mexico were allowed to be paid in cash, but no trips starting in Mexico City were allowed to be paid in cash. We geolocalized all the rides that took place in the Greater Mexico City during August of 2016, 2017 and 2018 (approximately 30 millions rides). We merge these trips with census information at the census block level. We use this data for three exercises. First, we find that the share of trips in cash in 2017 or in 2018 in different census blocks of the State of Mexico is decreasing in any of the census block level observables which measure household income level (such as average number of years of education, fraction of houses with internet connection, etc.).[4] Second, we match each census block of the State of Mexico with a "similar" census block in Mexico City –we

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

use coarsened exact matching using four continuous observables. We estimate the average treatment effect for growth rate of the total trips in the State of Mexico with 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 on trips around the boundary between the State of Mexico and Mexico City, which has the advantage of controlling for unobservables which vary continuously around the boundary. For this estimate we use a standard discontinuity design. We find that the growth rate of trips jumps the equivalent of 40% from one side to the other side of the city. We attribute the different between the average treatment effect (100%) and this local treatment effect (about 40%) to the fact that the effect of entry of cash is heterogeneous across census blocks of the State of Mexico. This heterogeneity is consistent with the distribution of observables –the poorer areas of the State of Mexico where cash has higher impact are further away from the frontier with Mexico City.

The third quasi-natural experiment uses the ban of cash in the city of Puebla in December of 2017. In September of 2017 a young women, Mara Castilla, was kidnapped and subsequently killed by a Cabify driver –Cabify is a taxi company which matches drivers and riders using an app similar to Uber. As a consequence of the crime, a law was passed which temporary suspended Cabify and ended up banning the use of cash at Uber in Puebla. The ban entered into effect at the beginning of December of 2017. We use a synthetic control approach utilizing the many cities of Mexico that at that time already have cash and credit as means of payments to create a counterfactual path for the trips and prices of Uber that Puebla would have have in absence of the ban, estimating the effect of the ban. We find that the ban immediately reduces the trips in more than 50%, but with time some of the previous cash users registered a credit card and the total number of trips decreases by almost 40%. We also found that about 35% of the previous cash users registered a card with Uber after the ban, in excess to the normal migration from cash to credit in the past. To put these numbers in perspective, we note that both Puebla and the State of Mexico are the two cities with the smallest share of trips in paid cash in Mexico (about 40%) among those where cash is allowed, with some other cities having a cash share twice as large.

Having established that there were large changes in quantities (such as the total number of trips) with the entry or the ban of cash for Uber as means of payment across Mexican cities, we turn to the estimation of its effect on consumer surplus. For that we need to estimate how Uber riders value the use of cash. To do so we use standard consumer demand theory and consider Uber paid in cash as a different good than Uber paid in credit. As long as the price of all other goods stays constant, the rider's consumer surplus of Uber cash paid in cash can be obtained by integrating the area under the demand for Uber paid in cash, starting with the current price up to the price at which the demand reaches zero. As the price of Uber paid in

cash increases, riders which have credit cards can substitute towards Uber paid with credit as well as towards other goods. Also, as the price of Uber paid in cash increases, riders without a credit card can substitute towards other goods as well as toward Uber paid in credit, if they obtain a credit card. In other words, we can consider both the intensive and extensive margin decisions if we can estimate the (entire) demand of Uber paid in cash. In principle we can estimate the demand for Uber paid in cash by designing a set of experiments with increasingly higher prices of Uber paid in cash. Unfortunately for our study we can't implement such experiments. Instead, we implemented three experiments in which we reduced prices (i.e. we offer discounts) to riders, two of the experiments are targeted to pure cash riders –those without a registered credit card in the Uber application, and one for mixed riders –those with registered credit card in the application. The two experiments for pure cash riders aim at estimating both intensive and extensive margin responses to incentive of riders. The one for mixed riders aims at measuring only intensive margin response to prices. We use these experiments to estimate a parametric model where we can compute the consumer surplus lost if cash where to be banned for these users. Below we outline the experiments and how we use their findings. Our baseline estimate is that the consumer surplus lost with a ban on the use of cash for all riders with use cash (either as their only method of payment or in conjunction with credit) amounts to about 30% of the total expenditure of these riders in Uber.

We consider a simple model of an Uber rider who is in a city where she can paid in cash or in credit. There are three goods in the model: Uber rides paid in cash, Uber rides paid in credit, and an outside good. We assume that the utility function is quasi-linear in the outside good, a simplification which we hope is a good approximation given the low budget share of Uber rides.[5] A rider can registered (or obtain) a credit card in the Uber app only after paying a fixed cost. Otherwise they can only ride paying cash. While in principle with enough randomized price increases we can identify the model without any parametric assumptions, we have limited number of experiments, and price decreases as opposed to decreases, so we will use parametric versions of the model to the the necessary extrapolation. Whenever we have to make a choice we take a conservative approach, such as in our choices for parametric forms and other auxiliary assumptions, i.e. we chose the versions that give the smaller consumer surplus of using cash.

The three randomized control experiments were conducted in the State of Mexico for a

[5]As it t well known quasi-linearity makes the consumer surplus, the compensating variation, and the equivalent variation identical. Additionally, even though we have only three goods, we can consider a set up with 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.

population of active Uber riders with a majority of trips started in the State of Mexico. For each rider we know their historical number of trips, the average price paid for their trips, the average miles per trips, whether they have registered a credit card in the application, the percentage trips in cash, and their tenure in Uber among other things. The experiment for mixed Uber rides randomized the price of Uber depending on the means of payment chosen by the rider for a period of a week. In particular there is a total of six treatment groups of about 20,000 riders each with a registered credit card which received discounts of either 10% or 20% for a trips paid by either cash, or using credit, or any method of payment. The control group are approximately 90,000 riders whom received no discounts. We estimate an elasticity of substitution between trips (or miles) paid in cash versus credit, using the price variation of the discounts for trips paid in cash or discounts paid in credit. We estimate the elasticity of substitution using a translog approximation for the share of cash trips, and use the historical share of trips paid in cash. We estimate the elasticity of substitution of trips paid in cash to trips paid in credit to be about 3. Additionally we use the discounts given regardless of the means of payment to estimate the price elasticity for Uber riders. We estimates price elasticities for miles as large as 1.1 evaluated a current prices.

We compare and complement the estimation of the price elasticity of Uber rides (and miles) with two other price experiments conducted in Uber and with a quasi-natural experiment coming from Uber Panama. The quasi-natural experiment in Panama is given by a sudden and very large change in the cost and licensing requirement for drivers, which allows us to estimate the price elasticity for Uber trips with large price *increases*. An independently conducted randomized price experiment in Uber allows us to compare the price elasticities we obtained in an experiment that lasted for a week, to the one where the discount lasting for four weeks, which presumably better approximate a permanent change. In both cases we found that the results are roughly similar to ours.

Using the estimates of the elasticity of substitution of Uber paid in cash and Uber paid credit, the historic distribution of the share of expenditure of trips paid in cash, and the price elasticity of Uber trips (or miles) we can compute the consumer surplus lost by mixed riders if cash were to be banned. As discussed above, this is equivalent to increase the Uber price paid in cash from its current value to infinity. 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 depend on the elasticity of substitution between Uber paid in cash and Uber paid in credit, as well as the share of trips paid if cash. This step can be summarized as the increase on the ideal price index for Uber rides caused by the ban. The second step is that, given the increase in the Uber ideal price index, there is a lost consumer surplus, whose magnitude depends on the increase on the ideal price index as well as in the price elasticity

of Uber trips. Integrating across all type of mixed users we found that the lost on consumer surplus is larger than 25% of the total amount spent in Uber by these riders.

We now discuss the remaining two experiments used to estimate the consumer surplus of pure cash users. A ban in cash increase up to infinity the price of Uber paid in cash, which for a pure cash user means that either she registered (or obtain) a credit card and becomes a pure credit users, or she cease to use Uber. Thus to measure this lost we use two experiments. In the first we randomize the size of the discount faced by pure cash users for a week and measure the effect on their miles and 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 where we left the prices unaltered. From this experiment we estimate the demand for Uber rides for pure cash uses. For instance, we found price elasticity of miles smaller than 1.3 evaluated at current prices.

The second experiment on the pure cash users involves given them a reward (credit in their Uber account) if they register a credit card. We have six controls groups of about 20,000 each, where we offer rewards equivalents to about 3, 6, or 9 times the average weekly expenditure in Uber for pure cash users if they registered 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 them. Our understanding is that in one week is very hard to obtain a credit card in Mexico, but that six weeks will suffice. We have two findings from this experiments. The first is that we find that the small incentives to registered card makes the migration rate to credit is about twice as large as the one in the control group. The second is that the rate at which riders register credit card in six weeks is not very different from the rate for the case of one week, and indeed most of the excess migration to credit occurs in the first week.

We use the two experiments for cash users, together with the elasticity of substitution between Uber paid in cash and Uber paid in credit estimated for mixed users, and the rate at which pure cash users have become pure credit users after the ban in Puebla to estimate the parameters that we need to compute the consumer surplus lost in a ban of cash. Roughly speaking, if no cash users could become credit users 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 expenditure in Uber. On the other hand from the evidence in Puebla we know that there may be about 35% of pure cash users that became credit users. Using the second experiment for pure cash users, as well as the elasticity of substitution between cash and credit previously estimated from mixed users –which we assume will apply to pure cash users, we estimate a consumer surplus lost that for those that migrate to become pure

credit just below 40% of their expenditure in Uber. Aggregating both groups we obtain that the average lost consumer surplus in the case of a ban in cash for pure cash users is about 45% of their expenditure in Uber.

Summarizing, since in the State of Mexico there are about 25% of riders that are pure cash users, and 50% that are pure credit users, and aggregating them according to their expenditure, we obtain that the consumer surplus lost due to a ban in cash is about 30% of the total expenditure in Uber for those rider that use cash either as their some means of payment or together with credit.

2 Institutional Background

2.1 Uber Cash

Uber started accepting cash as a payment method in May of 2015. The company first rolled out the option into the application's payment options in Hyderabad, India. Following its success they extended the option to four more cities in India. By the end of the following year, the cash payment option became available in over 150 cities and in 2018, this number grew to over 400 cities and 51 countries.

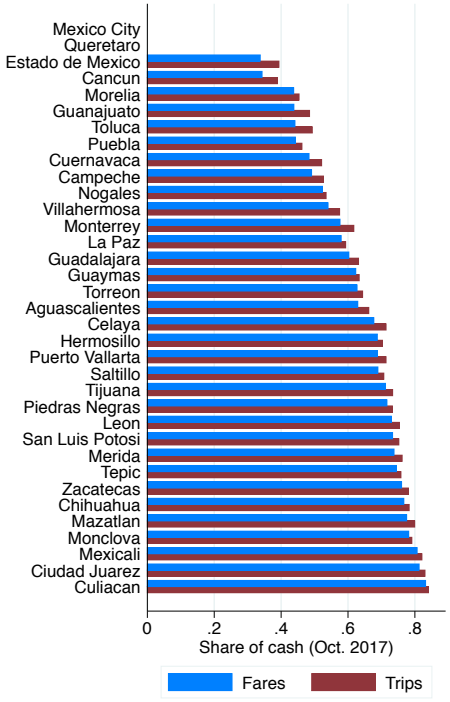
2.2 Uber Mexico

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. Today, Uber is in 43 cities. Mexico accounts for one third of all trips in Latin America and the Greater Mexico City is the third most active city 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. Cash as a payment methods was introduced in all the cities where Uber was operating at the time and quickly became the main payment method in these cities. 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.[6]

A few local governments, nonetheless, prohibit the introduction of cash as a payment method. Cash as a payment method is not allowed in Mexico City (as defined by its political boundaries) but it is permitted as soon as drivers cross into the surrounding State of Mexico. In this case, local government prohibit drivers to receive any payment with cash as well as

[6]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



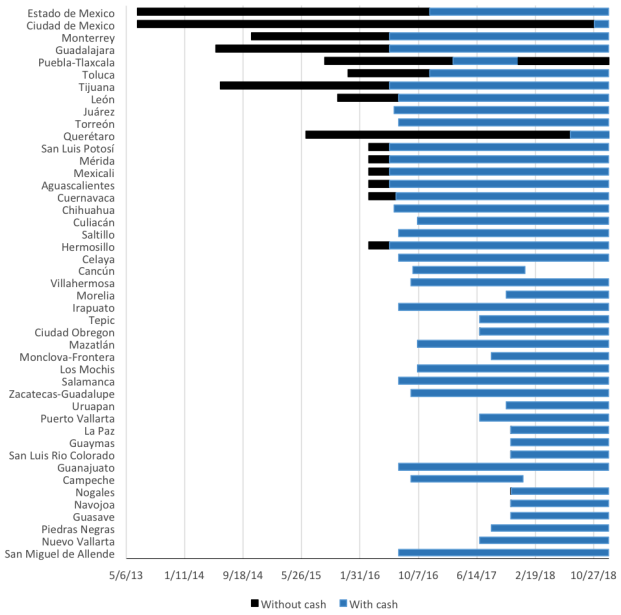
Note: The graph shows the share of trips and fares paid in cash in different cities in Mexico. The red bars show the fraction of trips paid in cash. The blue bars show the share of fares paid in cash. The sample of cities are those that were active in October of 2017.

with non-banking pre-paid cards or payment systems in convenience stores through electronic wallets. The same occurred in the city of Queretaro, a mid-size city close to Mexico City. In Puebla, payments were limited to electronic payments, but the government did not enforced this until the assassination of a young student 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, setting 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 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 was introduced already offering the option of cash payments.[7]

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.

2.3 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%), public transport (98%). 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 have a financial product (i.e. bank account, formal credit, retirement), less than 50% own 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.

[7] Uber suspended service in December of 2017 in both Cancun and Campeche. In both cases due to the threat and animosity from taxi cabs unions and for tense relationship with regulators.

The availability of smartphones in Mexico is more widespread than that of financial products. Approximately 65% of the population own a smartphone, this share is higher for students, high income individuals or those with higher levels of education. Appendix 14 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 use the geolocalized information of the trips that took place in the city of Puebla in August 2017 and August 2018 to explore the implications of the ban on 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. 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 driers, etc). We use the

following specification:

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

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, and the average income of the population in city i at time t. Since the error term in could be serially and cross-sectionally correlated, we use Driscoll and Kraay standard errors

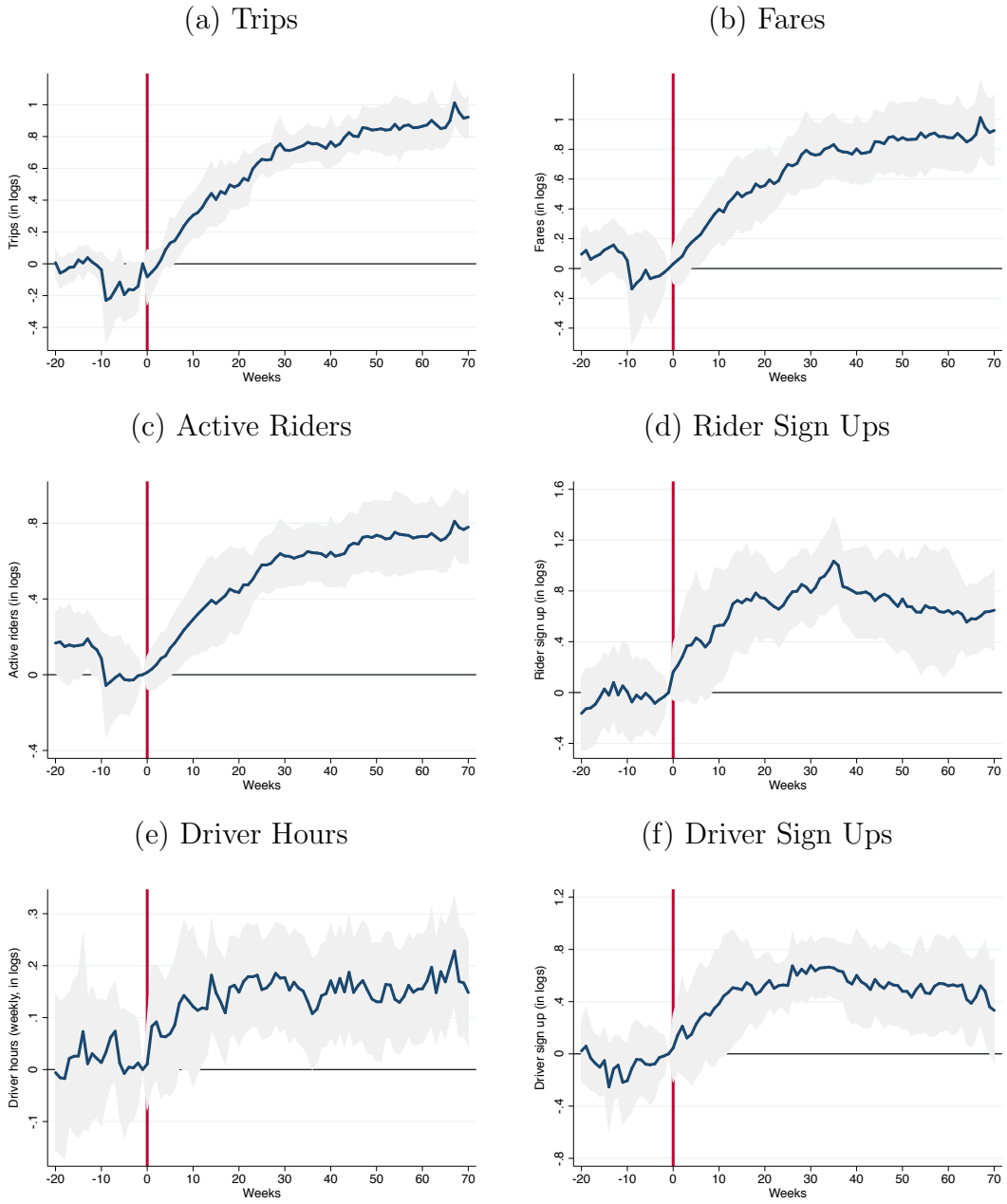
Figure 3 and 4 show the effect of the introduction of cash on our outcome variables. The graphs show that, conditional on city and time effects, there are no pre-trends in all our outcome variables at least 20 weeks before the introduction of cash. This is, the timing of the introduction of cash is close to randomly assigned conditionally on the city fixed effects. 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% and 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 shows 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 drove 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.

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 cost of a trip but also in the time drivers take to pick up a rider, 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. 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. These findings are relevant because first, they are consistent with the presence of a very elastic supply curve for Uber rides implying a very low producer surplus and, second, they indicate the pure credit users were not affected by the introduction of cash.

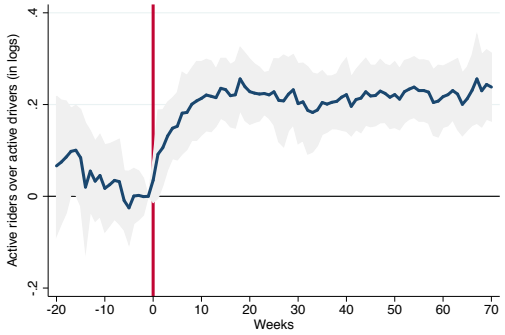
Figure 3: Event Study: Extensive and Intensive Margin of Riders and Drivers



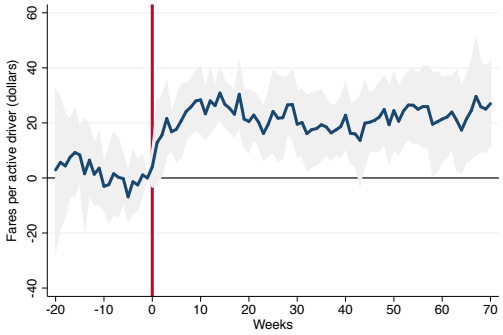
Note: The graph shows the evolution of the number of trips, total fares, active riders, rider sign ups, driver hours, and driver sign ups before and after the introduction of cash. The figure plots the coefficients of γ_k after estimating equation 1.

Figure 4: Event Study: Riders over Drivers and Prices

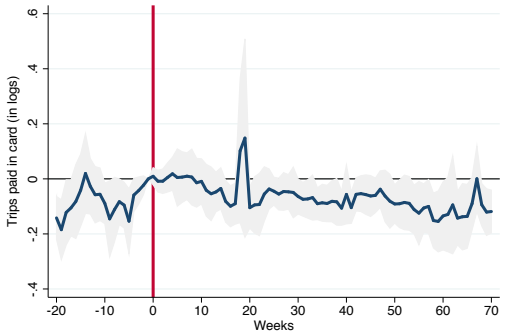
(a) Active Riders over Drivers



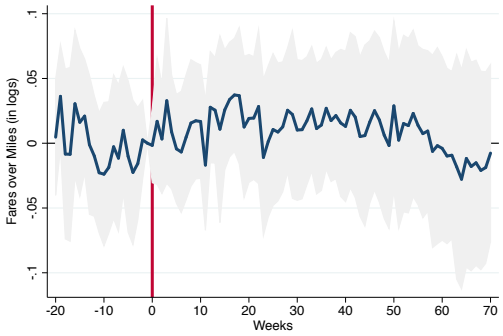
(b) Fares per Activer Driver



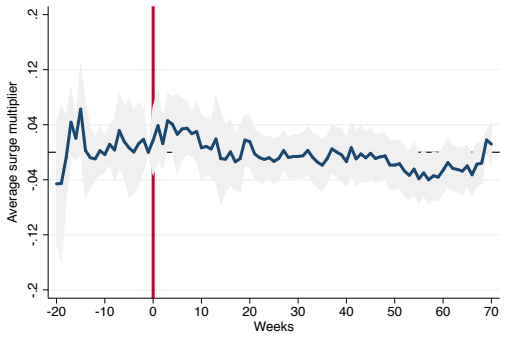
(c) Trips Paid in Credit



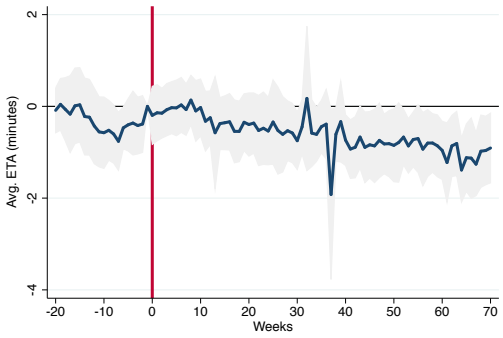
(d) Price



(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 1.

5 Greater Mexico City: Neighboring Regions Approach

In this section we use 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 on more than 30 million trips that took place in August (2016-2018). 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.[8] 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. 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 a two procedures to determine the effect of the introduction of cash on the number of trips and fares. First, we use coarsened exact matching to find the proper counterfactual for each census block in the State of Mexico, where cash was introduced. An, 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 of effect 100% of the introduction of cash on the number of trips. At the boundary, we find a local treatment effect of 40%.

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. A census block is on average 80 m^2.[9] The coordinates

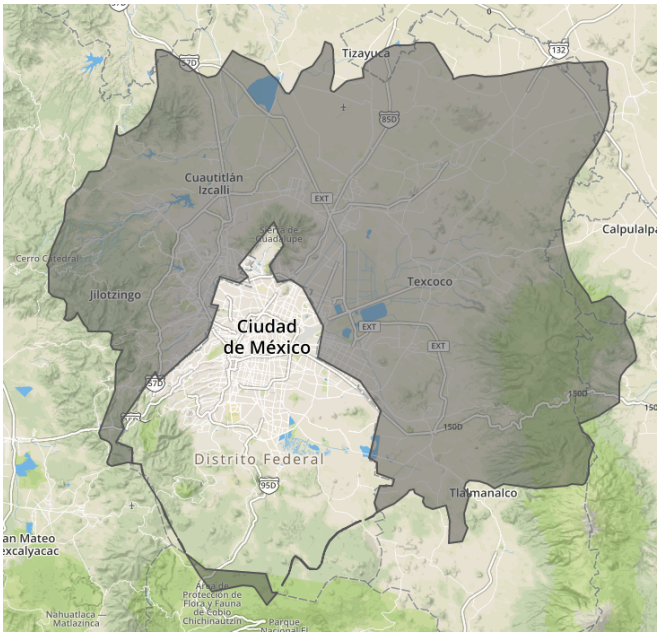
[8] In the case of an user having taken less than 3 trips or in the case of a tie, we use the sign up location of the user to determine their most frequent city.

[9] 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,

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).[10]

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. Then, we find the closest centroid for each Uber trip using the Euclidean distance. 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 boundaries of the State of Mexico) using the shape files of the geofence generated by Uber. Figure 18 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.

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.

and census block. There are 2.3 million census blocks in the country, more than 100 thousand in the Greater Mexico City.

[10]Details can be found in Appendix 11.2.1.

5.2 Demographics of cash users

In order to identify the demographic characteristics of cash users, we take advantage of the demographic information in the census and the fact that we are able to geolocate the origin each trip and assign it to a census block. As a result, we are able to compute the share of trips paid in cash as a function of the observable characteristic of each census block. 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. Each of these observables is 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 income persist when we use the first principal component of these variables or the income per capita at the municipality level as shown in Appendix 11.2.2. Furthermore, the share of trips paid in cash is larger in municipalities with lower levels of bancarization as measured by the debit cards per capita, credits card per capita, bank branches per capita or ATMs per capita (Appendix 11.2.3) or less developed infrastructure (11.2.4).

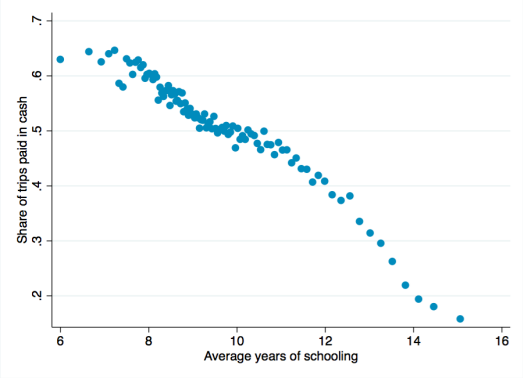
5.3 CEM

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. We use coarsened exact matching (CEM) to find the proper counterfactual for each census block where cash was introduced. 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 coarsen each control variable for the purposes of matching. Then, it sorts all units into strata, each of which has 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.

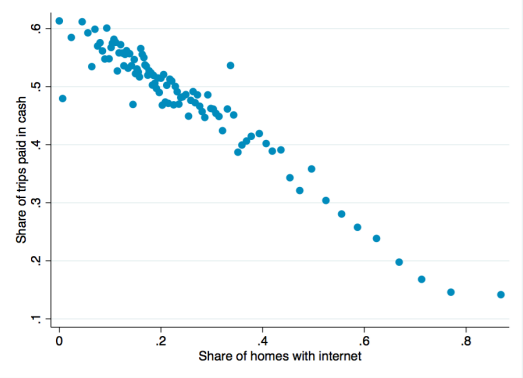
We use the share of homes with internet, the share of homes with a car, the share of homes with a cell phone, and the average years of educations as observable characteristics for the matching. We also choose a Sturges rule to coarsened each observable, which implies that each was coarsened in 20 bins. 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.

Figure 6: Share of fares paid in cash by education

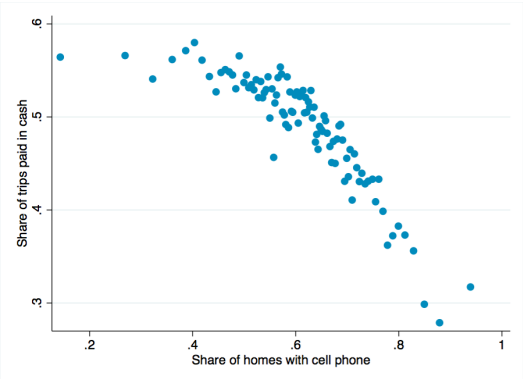
(a) Education



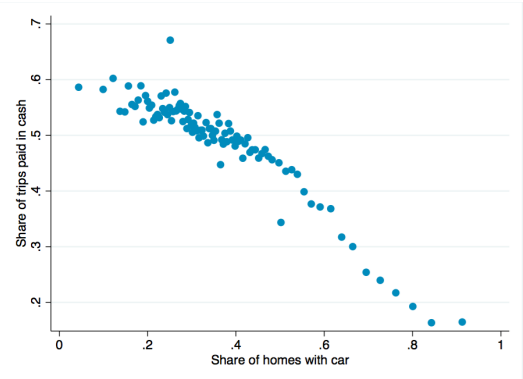
(b) Share of Homes with Internet



(a) Share of Homes with Cell Phone



(b) Share of Homes with Car



Note: The figure shows the binscatter plot of the share of trips paid in cash and the average years of schooling in each census block. The census blocks are grouped into 100 equal-sized bins. The data of Uber rides is from August of 2017 in the State of Mexico.

5.4 Regression Discontinuity

The second 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 test whether the introduction of cash caused discontinuous changes in the number of trips in the State of Mexico. The necessary assumptions are that any unobserved determinants of the number of trips change smoothly across the borders between Mexico City and the State of Mexico. If the relevant assumption is valid, adjustment for a sufficiently flexible polynomial in distance from the border or local linear regressions on either side of the border will remove all potential sources of bias and allow for causal inference.

Figure 7 illustrate this by showing the relationship between the growth in users and trips between 2016-2017 and the distance to Mexico City. Negative numbers indicate the census block is in Mexico City. Each bin corresponds to one kilometer. The dots show the average

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.

	(1) $\Delta Trips$	(2) $\Delta Trips$	(3) $\Delta Trips$	(4) $\Delta Fares$	(5) $\Delta Fares$	(6) $\Delta Fares$
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

growth in users in each bin. The line is a kernel-weighted (epanechnikov) local polynomial of degree 3. The graphs shows that, allowing the 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 and in the change in the number of trips. Panel (b) of Figure **??** shows that this is not the case if we examine the same variables from 2017-2018 years when the cash was already introduced in the State of Mexico.

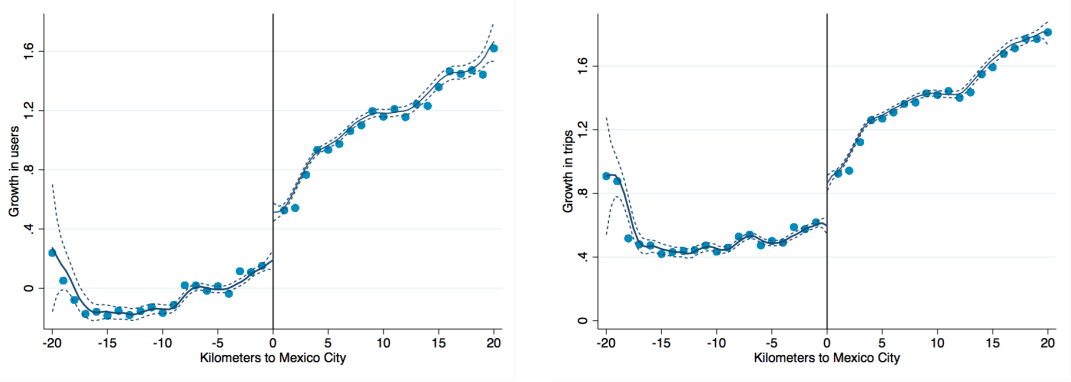
To quantify the size of the discontinuity, we estimate the following parametric equations to test for the impacts of the the introduction of cash as a payment method:

$$\Delta y_i = \alpha + \beta \times StateMexico_i + f(d_i) + StateMexico_i \times f(d_i) + \lambda X_i + \epsilon_i \tag{2}$$

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.[11] In other words, if $StateMexico_i$ equals one, cash was allowed as a payment method. $f(d_i)$ is a polynomial in meters relative to the border between Mexico City and the State of Mexico, X_i is a vector of the census block characteristics that could possible affect the number of Uber trips such as the average education of the block and the share of homes that own a cell phone.

[11] We compute growth rates for every variable y_{it} as follows: $\Delta y_{it} = \frac{y_{it} - y_{it-1}}{\frac{1}{2}(y_{it} + y_{it-1})}$.

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

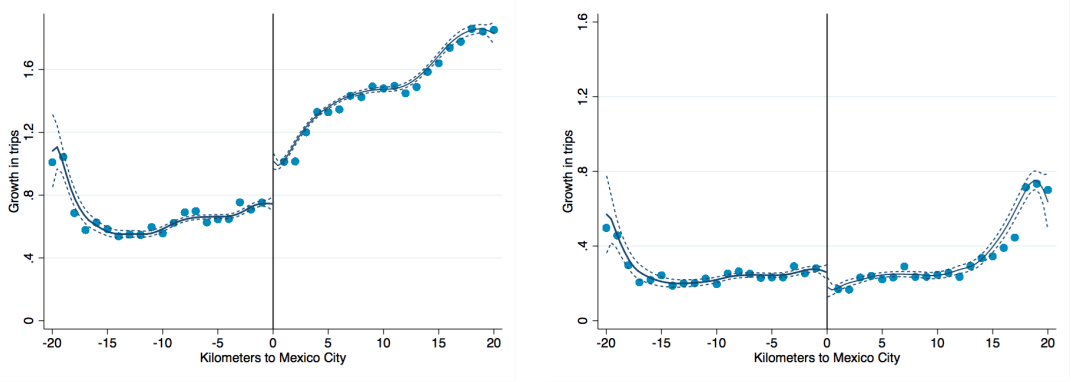


Note: The graphs show the relationship between the growth in users between 2016-2017 and the distance to Mexico City. Negative numbers indicate the census block is in Mexico City. Each bin corresponds to one kilometer. The dots show the average growth in users in each bin. The line is a kernel-weighted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

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 as a payment method.

The results are reported in Tables 2 and 3 for the change in the number of trips and fares. 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. Tables 5 and 6 in Appendix 11.2.5 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.

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



Note: The graphs show the relationship between the growth in trips between 2016-2018 and the distance to Mexico City. Negative numbers 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 reports 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.

	(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

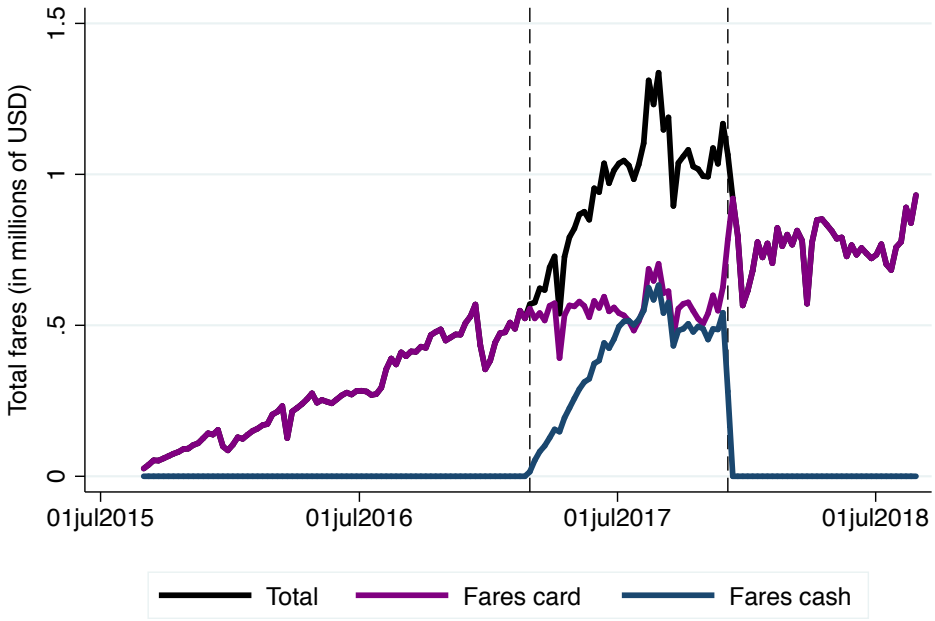
Note: The table reports the results for the coefficient of β after estimating equation 2. The estimates reports the local treatment effect at the border between the State of Mexico and Mexico City of the introduction of cash as a payment method. Each column reports the results using polynomials of different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

	(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. Cash as a payment method was introduced on March of 2017. On September 15th of the same year, a student was kidnapped and subsequently assassinated in a Cabify, another ride-hailing company operating in the city. On October 31st the local government announced a ban on cash to be implemented on December 8th. Figure 9 shows the total fares in the city of Puebla after splitting by payment method. The graphs shows that, although Puebla before the ban 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.

Figure 9: Puebla: Total Fares



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.

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 several cities in Mexico to mimic the patterns observed in the city of Puebla before the ban on cash. Our data include information of $J+1 \in \mathbb{N}$ cities including Puebla and $T \in \mathbb{N}$ 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) that would be observed for city j in period t if there were no intervention for $j \in \{1,...,J+1\}$ and $t \in \{1,...,T\}$. Let Y_{jt}^I be the potential outcome that would be observed for city j in period t if city j faced the ban on cash at period t. 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 is 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 $\alpha_{1,t}$ for each $t \in 1, ..., T$ as follows

$$\hat{\alpha}_{1t} \equiv Y_{1t} - \hat{Y}_{1t}^N$$

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

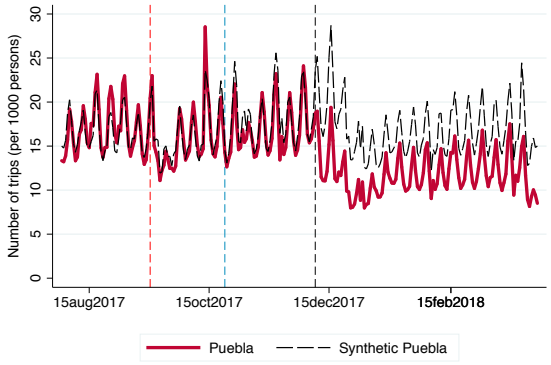
Our pool of cities includes the 32 cities in Mexico that were active the week of the ban on cash in Puebla after splitting Mexico City and the State of Mexico. The synthetic cohort weights we find are: 0.425 (Estado de Mexico), 0.453 (Guanajuato), 0.072 (Mexico City), 0.051 (Queretaro) and the root mean square prediction error (RMSPE) is 0.00152. 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. The graph 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 but remained permanently lower than before in cash for the subsequent periods.

6.1.1 Inference

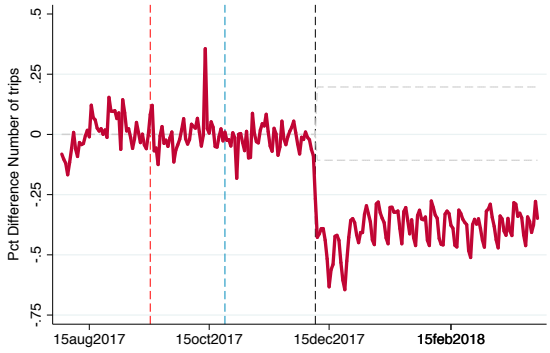
Our inference procedure examines whether or not the estimated effect of the ban is large relative to the distribution of the effects estimated for the cities that did not experience the ban. To do so we run permutation tests where each city is assumed to be treated and estimate $\hat{\alpha}_{jt}$ for 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:

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 line) and the evolution of trips of the synthetic Puebla constructed using the Synthetic Control Method. Panel (b) shows the evolution percent difference in daily trips. The black dotted vertical line is the date of the ban on cash.

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

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

$$p \equiv \frac{\sum_{j=1}^{J+1} \mathbb{1}\left[RMSPE_j \geq RMSPE_1\right]}{J+1} \leq \gamma \tag{3}$$

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 $\mathrm{f} : \{1, ..., T\} \to \mathbb{R}$, the test statistic RMSPE is given by equation 3. Following this inference procedure we estimate γ-confidence intervals for the effect of the ban as

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

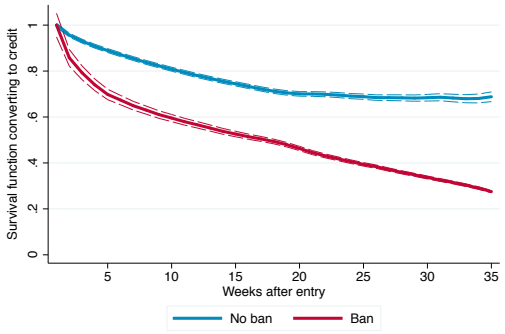
where $c \in \mathbb{R}$ and $\gamma \in (0, 1)$. We assume that there is a constant effect of the ban and estimate the empirical distribution of RMSPE following Firpo and Possebom (2018) to perform inference.

6.2 Survival Function

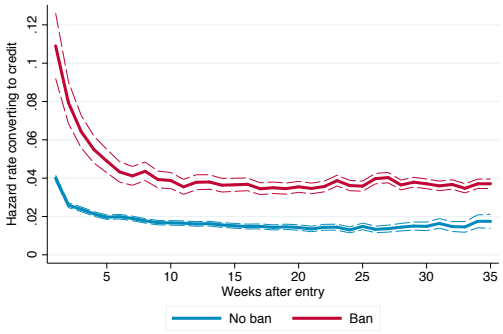
To quantify the propensity of users to adopt credit as a payment method after a ban in cash, we use the natural experiment that took place in the city of Puebla to estimate survivial functions of different cohorts of users. Figure 11 shows the survival function and hazard rate of users using card as a payment method for the first time as a function of the number of weeks they since they first joined Uber. Panel (a) shows the survival function and panel (b) the hazard rate. 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. The graphs shows that new 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 more likely to adopt credit.

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

(a) Survival Function



(b) Hazard Rate



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 confidence dashed line shows 99% confidence intervals.

6.3 Mixed Users

Before the ban on cash, almost half of the users had used both payment methods to pay for Uber rides. Here, we show that even users that had adopted credit before the ban decrease their trips as a consequence of the ban. We show this using the following specification:

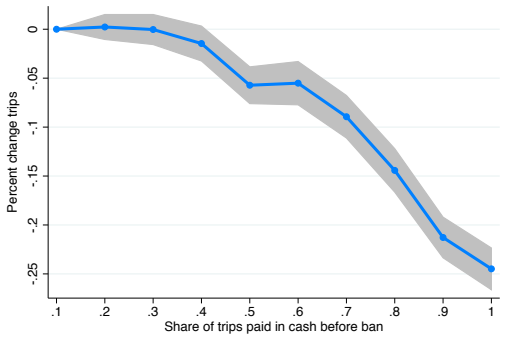
$$\Delta\, Trips_j = \alpha + \beta ShareCashBefore_j + \lambda X_j + \epsilon_j$$

where j is a rider in Puebla that had trips before and after the ban on cash, $\Delta Trips$ is the change in the average weekly trips by rider j before and after the ban, $ShareCashBefore_j$ is the share of fares paid in cash before the ban, and X_j is a vector of observables that include the cohort (week the rider took her first trip in Uber) and the average weekly fares.

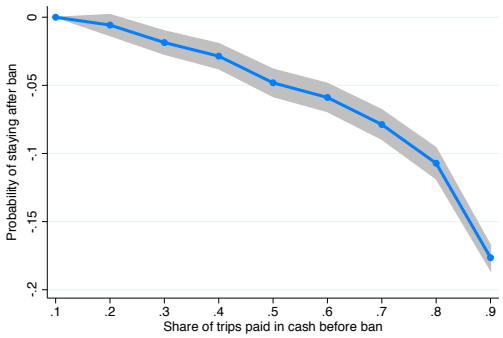
Figure 12 shows the estimates of β for different levels of the share of fares paid in cash before the ban. The figure shows that there was a significant reduction in the average weekly trips of mixed riders after the ban. This reduction on the number of trips varies depending on how cash intensive the 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 that these users also were less likely to return to Uber after their main payment method is banned.

Figure 12: Puebla: change in trips given past cash intensity

(a) Percent change in trips



(b) Probability of staying as an Uber user



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. The panel plots the coefficient of β estimated using equation 4 for different shares of cash. Panel (b) shows the probability of staying as a 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.

7 Model

7.1 General Set-Up

The rider is characterized by a strictly concave and increasing utility of composite Uber rides $U : \mathbb{R}_+ \to \mathbb{R}$, a strictly positive marginal utility of income $\lambda > 0$, and a strictly increasing, and strictly quasi-concave, constant returns to scale sub-utility $H : \mathbb{R}^2_+ \to \mathbb{R}_+$ of the cash (a) and credit (c) trips: $H(a, c)$. We treat λ as a fixed parameter, so that the utility of composite Uber rides is quasi-linear. We let the cash and credit price of an Uber trip be p_a, p_c respectively.

We write the problem for the Uber rider in two stages. The first is the choice of the means of payment. Without loss of generality we write this problem for subject to obtaining one util of composite rides.

$$\begin{aligned} \mathbb{P}(p_a, p_c) = \min_{a,c \geq 0} p_a a + p_c c \\ \text{subject to } H(a, c) \geq 1 \end{aligned} \tag{4}$$

We let $a(p_a, p_c)$ and $c(p_a, p_c)$ so the choices that attain the minimun 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 homogenous of degree zero in (p_a, p_c) while $\mathbb{P}$ is homgeneous of degree one in (p_a, p_c). The ideal price index is given by $\mathbb{P}(p_a, p_c)$. The function $\mathbb{P}$ is also increasing in convex in (p_a, p_c). If we define the minimum cost of X utils instead of one, we just multiply the functions a, c and $\mathbb{P}$ by X.

Now we consider the second stage, choosing the optimal number of trips. This problem take as given a price for the composite trip P.

$$V(P) = \max_{x \geq 0} U(x) + \lambda \left[I - Px \right] \tag{5}$$

We let the optimal solution be $X(P)$, with first oder condition $U'(X(P)) = \lambda P$ if $X(P) > 0$ and $U'(X(P)) \leq \lambda P$ otherwise.

We can now write the complete solution of the problem with cash and credit trips given by by $a^*(p_a, p_c)$ and $c^*(p_a, p_c)$. They are given by:

$$a^*(p_a, p_c) = a\left(\frac{p_a}{p_c}, 1\right) X\left(\mathbb{P}(p_a, p_c)\right) \tag{6}$$

$$c^*(p_a, p_c) = c\left(\frac{p_a}{p_c}, 1\right) X\left(\mathbb{P}(p_a, p_c)\right) \tag{7}$$

We also define the indirect utility:

$$v(p_a, p_c) \equiv V\left(\mathbb{P}\left(p_a, p_c\right)\right) \tag{8}$$

7.2 Extensive Margin Choice

We assume that each rider facing prices (p_a, p_c) has to pay a fixed cost ψ to be able to use credit. Thus the full indirect utility function corresponding to the rider problem that incorporates the intensive and extensive margin is:

$$\mathcal{V}(p_a, p_c) = \max\left\{\frac{1}{\rho}\frac{v(p_a, \infty)}{\lambda}\ ,\ \frac{1}{\rho}\frac{v(p_a, p_c)}{\lambda} - \psi\right\} \tag{9}$$

where ρ is the effective discount rate on the flow indirect utility functions v, which takes into account discounting as well as the life-span of the credit card. We have divided the indirect utility function by λ to denote everything in dollars. In the first branch the agent cannot use credit. In the second she is able to use credit but it has to pay the fixed cost ψ.

7.3 Distribution of cost ψ and α for pure cash users

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

Cash users. We use ψ for the (flow) cost of becoming a mixed/credit users. We also let $v(p_a, p_c; \alpha)/\lambda$ be the indirect utility function of a rider that have access to Uber paying p_a in cash and p_c in credit. This agent has credit share parameter α and marginal utility of income λ.

We describe a set on conditions on (ψ, α) so that the model is consistent with 1) the behaviour of the pure cash users, 2) the excess migration from cash to credit after the ban in Puebla, and 3) the experimental evidence on the excess migration due to incentives.

Cash users. First we impose a constrain in ALL cash users: they prefer not to switch to become mixed/credit users. The condition that ensures that pure cash users prefer not to become credit/mixed users:

$$\psi \geq \frac{1}{\rho}\left[\frac{v(1, 1; \alpha)}{\lambda} - \frac{v(1, \infty; \alpha)}{\lambda}\right] \tag{10}$$

where the RHS is increasing in α. The parameter ρ convert the one time payment of the

fixed cost into a flow payment comparable with the flow units on v.

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:

$$\psi \leq \frac{1}{\rho}\left[\frac{v(\infty,1;\alpha)}{\lambda} - \frac{v(\infty,\infty;\alpha)}{\lambda}\right] \text{ for fraction } m_{ban} \text{ and} \tag{11}$$

$$\psi \geq \frac{1}{\rho}\left[\frac{v(\infty,1;\alpha)}{\lambda} - \frac{v(\infty,\infty;\alpha)}{\lambda}\right] \text{ for fraction } 1 - m_{ban} \tag{12}$$

The RHS of these inequalities are increasing in α.

Experimental evidence on the excess migration due to incentives. From our experiment we have that given a once time payment d, we have induce an (excess) migration of m_d riders from cash to credit/mixed. We have this for three values of d_k, i.e. $0 < d_1 < d_2 < d_3$.

$$\psi \leq \frac{1}{\rho}\left[\frac{v(1,1;\alpha)}{\lambda} - \frac{v(1,\infty;\alpha)}{\lambda}\right] + d_k \text{ for fraction } m_{d_k} \text{ and} \tag{13}$$

$$\psi \geq \frac{1}{\rho}\left[\frac{v(1,1;\alpha)}{\lambda} - \frac{v(1,\infty;\alpha)}{\lambda}\right] + d_k \text{ for fraction } 1 - m_{d_k} \tag{14}$$

for $i = 1, 2, 3$. The RHS of each of these inequalities are increasing in α.

Suppose we assume that all pure-cash users have the same α and denote it by $\hat{\alpha}$. Let $F : [\underline{\psi}, \bar{\psi}] \to [0, 1]$ be the CDF for the cost ψ. We can write the previous four equations as requiring that $\hat{\alpha}$ and the cdf F satisfy:

$$\begin{aligned}
\underline{\psi} &= \frac{1}{\rho}\left[\frac{v(1,1;\hat{\alpha})}{\lambda} - \frac{v(1,\infty;\hat{\alpha})}{\lambda}\right] \\
m_{ban} &= F\left(\frac{1}{\rho}\left[\frac{v(\infty,1;\hat{\alpha})}{\lambda} - \frac{v(\infty,\infty;\hat{\alpha})}{\lambda}\right]\right) \\
m_{d_k} &= F\left(\frac{1}{\rho}\left[\frac{v(1,1;\hat{\alpha})}{\lambda} - \frac{v(1,\infty;\hat{\alpha})}{\lambda}\right] + d_k\right) \text{ for } k = 1, 2, 3.
\end{aligned}$$

8 Experiments

In what follows we specialize the utility function to be exponential $U(x) - kexp(-(x + \bar{x})/k$. This functional form is convex in price and has constant semi-elasticity k. We choose this specification since our experiments, summarized below, indicate that the demand of Uber rides is convex but it also yields a lower bound of the consumer surplus given that its shape is close to a linear demand function. In addition, we use CES for $H(a, c)$. The credit share

of each mixed and pure credit user α is observable.[12]

Experiment 1 estimates the the elasticity of substitution between cash and credit η using experimental data of changes of the relative prices p_a/p_c. Experiment 2 estimates the elasticity of Uber rides $\epsilon(P)$ by exploiting exogenous variation in the price of Uber rides. Lastly, experiment 3 estimates the distribution of the fixed cost of adopting credit ψ by providing different incentives to pure cash users to register a credit card in the application.

8.1 Experiment 1: Mixed Users

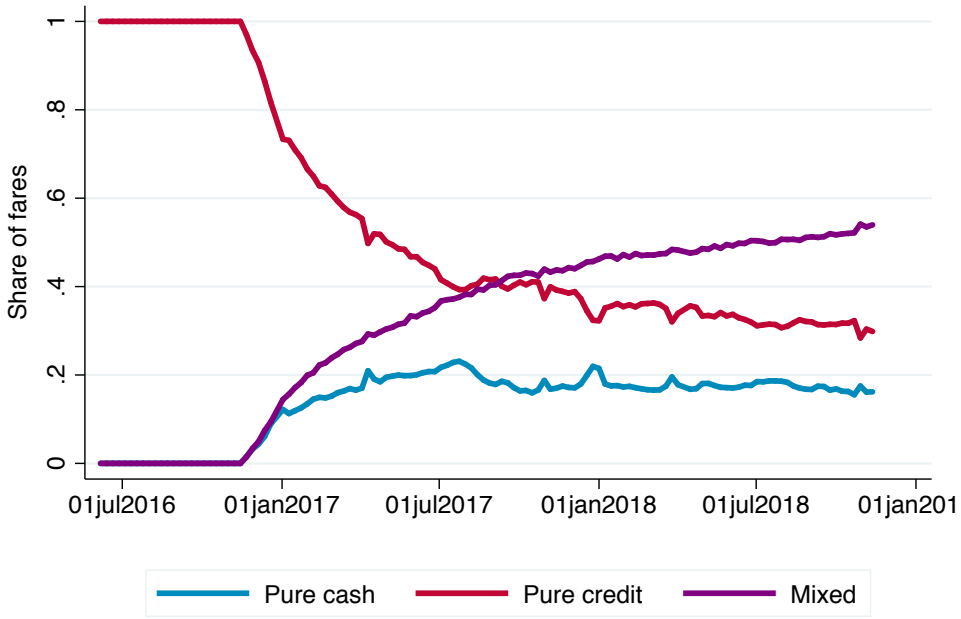
The experiment took place in the State of Mexico from August 21st to August 27th of 2018. Our sample of users are those who sign up in the State of Mexico and whose most frequent city is the State of Mexico. They also must have a card on file not banned by Uber, a verified mobile, and not subject to 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. 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. 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.

We have six treatment groups each compose of approximately 11 thousand riders and a control group of 90 thousand riders. The treatment and control groups were chosen to be 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 the entire week. 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).

Using the structure of the model, we estimate an elasticity of substitution between cash and credit of $\eta \approx 3$ using a separable translog and controlling for historical fares.[13] The composite Uber elasticity ϵ of mixed users is approximately 1.1, estimated using Uber prices

[12] More details of the model can be found in Appendix 12.
[13] Details can be found in Appendix 13.1.

Figure 13: State of Mexico: Share of fares by type of user



Note: The graph 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.

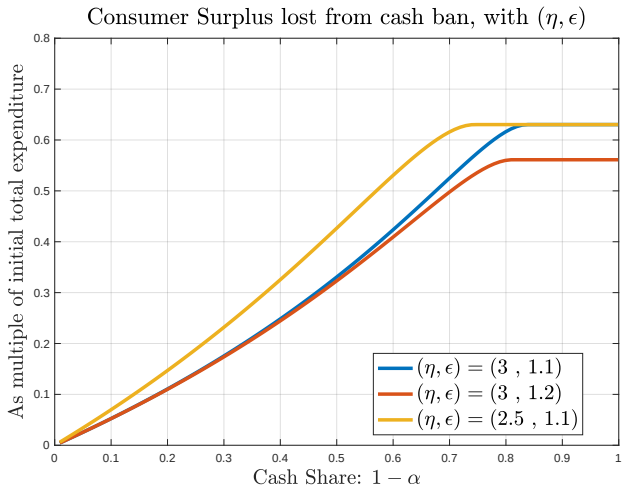
$P = p_a = p_c$. Figure 14 shows the consumer surplus estimates under this parameters for different share of cash fares. We estimate a consumer surplus of approximately 25% of total fares per year in the State of Mexico, using that the share of cash fares there is around 40%.

9 Experiment 2: Pure Cash Users

The experiment took place in the State of Mexico from August 21st to August 27th of 2018. Our sample of users are those who sign up in the State of Mexico and whose most frequent city is the State of Mexico. Since this experiment is targeted to pure cash users, we focus on users that have not registered a cash 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.

We have four treatment groups each compose of approximately 20 thousand riders and

Figure 14: Consumer Surplus: Mixed Users



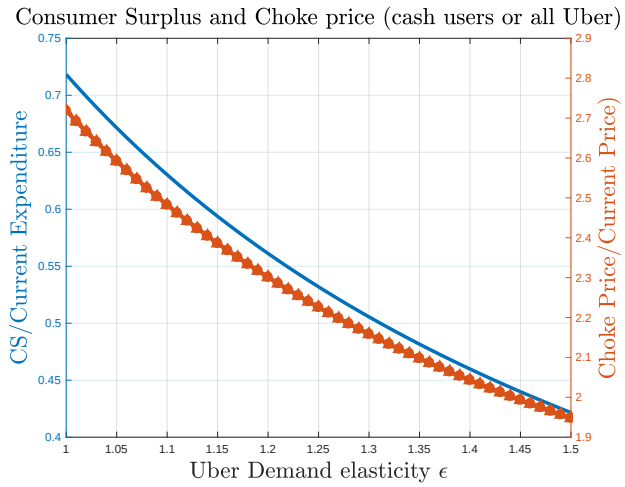
Note: The figure shows the model estimates of the consumer surplus (as a multiple of initial total fares) as a function of the cash share of users. The graphs plots the estimates for different combinations of the elasticity of demand ϵ and the elasticity of substitution between cash and credit η. The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

a control group of 56 thousand riders. The treatment and control groups were chosen to be 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 regardless of the payment method. 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).

Using the miles traveled during the week of the experiment as dependent variable, we estimate an elasticity of demand of 1.3. 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).

Figure 15 shows the estimated consumer surplus for pure cash users for different elasticity estimates. Using 1.3 as our elasticity measure, we estimate a consumer surplus of approximately 50% of the total fares per year for each rider. This is, however, an upper bound estimate given that, after a large price increase, some users might decide to migrate to credit rather than leaving Uber completely. In fact, in Puebla, only 65% of the users left after a ban on cash. To adjust the consumer surplus of these riders, we conduct a third experiment to estimate the fixed cost of adopting credit. Section 9.1 provides more details.

Figure 15: Consumer Surplus: 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.

9.0.1 Other experiments: Ubernomics, Mandin, and Panama

In this section, we validate our estimates of the elasticity of demand by using experimental data collected by Uber in the past. These experiments were not designed to estimated the elasticity and the curvature of the demand function of pure cash users as is the case on our experiment. Nonetheless, they are useful to validate our estimates since we are able to select the riders that meet the same criteria as our experiment and, using their historical data, we are able to construct control variables to make the samples comparable. In addition, we use a natural experiment that occurred in the country of Panama where the supply of drivers was suddenly restricted by the government. Given that the price of Uber rides increased substantially after the goverment regulation went into effect, we can use it to compute another estimate of the elasticity of demand. In all of these exercises we obtain an elasticity between 1.1 and 1.3.

Ubernomics

The experiment took place in Mexico City and lasted one week. The treatment groups received 10% and 20% off in all rides taken the week of the experiment. Sunday before the experiment, riders in the treatment were emailed and shown an in-app notification informing them of the relevant price change. The promotion will go live Monday at 4 am local time

and last 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 we use we consider riders whose most frequent city is the Greater Mexico City as in our 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). Our sample consists of 3,178 riders in the control group, 816 in the first treatment group and 875 in the second. The elasticity we find for this riders is: 1.124181.

Mandin

The 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 level 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 ≤ 10), Regular ($10 <$ Trips ≤ 20), Mid ($20 <$ Trips ≤ 30), Power ($30 <$ Trips < 50), and Rockstar (Trips ≥ 50).

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

To guarantee that the sample in this experiment is comparable to the one we use we consider riders whose most frequent city is the Greater Mexico City as in our experiment. 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 1.23, which is within the range of the one we estimated in our experiment. Importantly, given that this experiment lasted four weeks, we consider this findings as evidence that the short-run elasticity and the long-run elasticity of Uber rides is similar.

Panama

Uber was 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. [14]

In October of 2017, a decree that imposes restrictions on Uber was published. The decree includes on prohibition on cash as a payment method for trips taken in Uber. In addition, the decree requires a special licence for drivers (i.e. E1), 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.

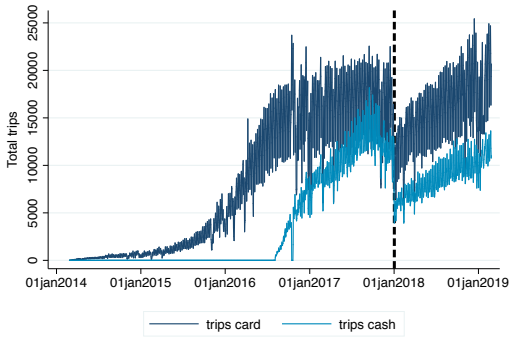
The decree went into effect in January 2, 2018. Uber negotiated an extension of the deadline for the ban on cash. The extension expires on May 2019. The rest of the decree went into effect, in particular, the restrictions involving drivers. A total of 83% of all Uber drivers did not have the E1 licence and were disconnected from the application. The total number of drivers signing up to the application per week, before the decree went into effect, was approximately 8 thousand drivers. At the end of 2018, a year after the decree went into effect, total number of drivers 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.

Importantly, the share of trips in cash also decreased drastically from more than 50% in 2017 to less than 35% in 2018. The number of trips paid in cash decreased more, relative to those paid in card for two reason. First, there was a substantial price increase due to the reduction in the supply of drivers. And, second, the demand for Uber trips is more elastic for trips paid in cash. As a result, the demand for trips paid in cash decreased more than that of trips paid in card. Interpreting this natural experiment as an exogenous decrease in the supply of drivers, we estimate an elasticity of demand of 1.2 for all trips and of 1.3 for trips paid in cash.

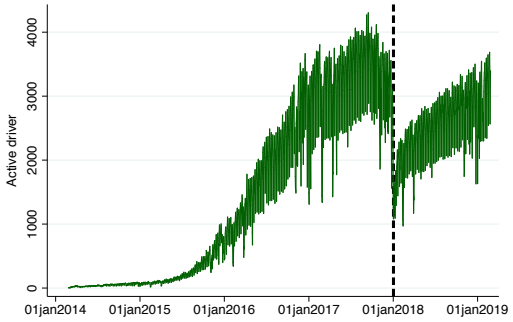
[14] Cabify is also present in Panama since June of 2016, however, as in Mexico, their market share is very still very low.

Figure 16: Panama: Trips, Fares, and Drivers

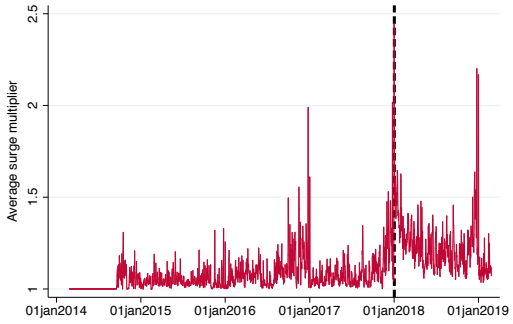
(a) Trips



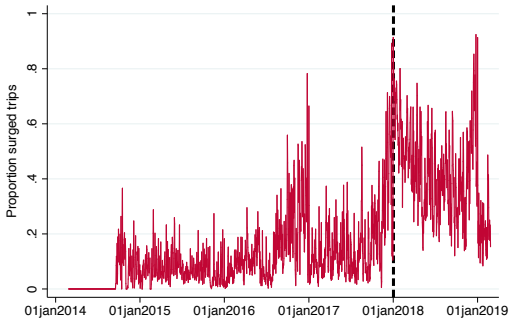
(b) Active Drivers



(c) Avg. Surge Multiplier



(d) Share Surged Trips



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

9.1 Experiment 3: Extensive Margin

The experiment took place in the State of Mexico from August 21st to August 27th of 2018. Our sample of users are those who sign up in the State of Mexico and whose most frequent city is the State of Mexico. Since this experiment is targeted to pure cash users, we focus on users that have not registered a cash 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.

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 an average of 3, 6, and 9 times their average weekly fares (approximately 1, 2 and 3 average trips). Given that pure cash users might or might not

have a credit card already, the experiment has two different horizons. The first lasts only one week and targets users that might already have a credit card but have not registered it in the application. The second lasts 6 weeks in order to allow users to obtain a credit card in case they do not have one. 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.

We find that users respond to the incentives provide by registering their cards. We observe larger migration to credit the larger the incentive, consistent with the presence of a fixed cost of adopting credit. We do not find any significant difference between the migration rate of those in groups where the experiment lasted one week and those in the groups where it lasted six weeks. This indicates, that although our incentives are enough to encourage migration for the marginal users, it is not enough to incentivize users that do not own a credit card already.

We use four moments to estimate the distribution of the cost of adopting credit ψ. The migration rates under each of the incentive levels along with the total migration observed in the city of Puebla after the ban on cash. Using the estimated distribution and the structure of our model, we estimate a consumer surplus of approximately 45% of the total fares per year for pure cash users. Note that is is lower than that of pure cash users that left Uber completely after the ban on cash. This is because, for 35% of the users, it is more convenient to adopt credit than giving up Uber completely.

10 Conclusion

We combine experimental evidence with three natural experiments in Mexico to estimate the consumer surplus of using cash as a payment method in Uber. We estimate large increases in the number of trips, fares, miles, riders, and drivers after the introduction of cash as a payment method. In particular, the increase is larger in suburban areas, less bancarized areas, and for low-income riders.

By estimating the Uber's elasticity of demand, the elasticity of substitution between cash and credit, and the fixed cost of adopting credit for pure cash users, we estimate a consumer surplus of approximately 30% of total fares per year paid by pure cash and mixed users. For the State of Mexico, the place where we conducted our experiments, this amount to approximately 50 USD million per year. This estimate is potentially ten times larger when estimated for the entire country.

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.

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.

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

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

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

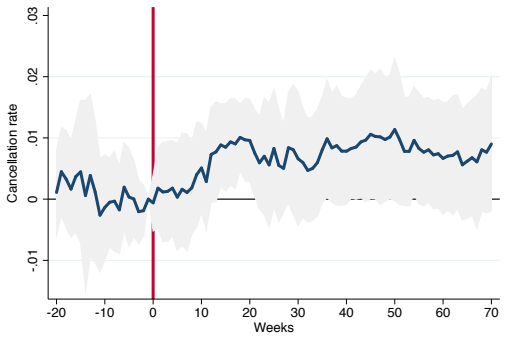
Rogoff, K. S., 2017. The Curse of Cash: How Large-Denomination Bills Aid Crime and Tax Evasion and Constrain Monetary Policy. Princeton University Press.

11 Appendix

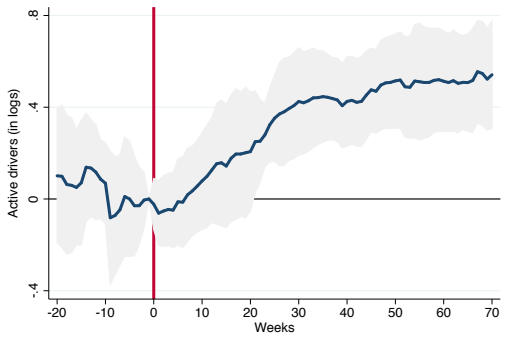
11.1 Event Study

Figure 17: Event Study: Additional Results

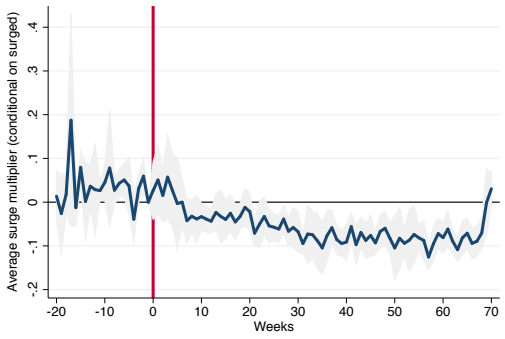
(a) Cancellation Rate



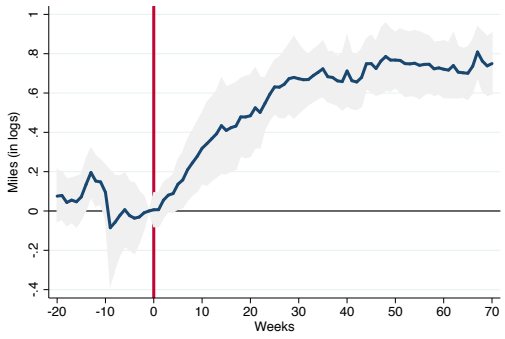
(b) Active Drivers



(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.

11.2 Greater Mexico City

11.2.1 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:[15]

$$W(\phi) = \sqrt{1 - e^2 sin^2\phi} \tag{15}$$

$$M(\phi) = \frac{cos(\phi)}{W(\phi)} \tag{16}$$

$$T(\phi) = \sqrt{\left(\frac{1 - sin\phi}{1 + sin\phi}\right)} \left(\frac{1 + esin\phi}{1 - esin\phi}\right) \tag{17}$$

The remaining zone constants are:

$$w_1 = W(\phi_S) \tag{18}$$

$$w_2 = W(\phi_N) \tag{19}$$

$$m_1 = M(\phi_S) \tag{20}$$

$$m_2 = M(\phi_N) \tag{21}$$

$$t_0 = T(\phi_0) \tag{22}$$

$$t_1 = T(\phi_S) \tag{23}$$

$$t_2 = T(\phi_N) \tag{24}$$

$$n = sin\phi_0 = \frac{lnm_1 - lnm_2}{lnt_1 - lnt_2} \tag{25}$$

$$F = \frac{m_1}{nt_1^n} \tag{26}$$

$$R_b = aFt_0^n \tag{27}$$

Given the geodetic coordinates of an Uber ride, the northing (y), easting (x), scale, k, and convergence angel, γ, of the point are computed as

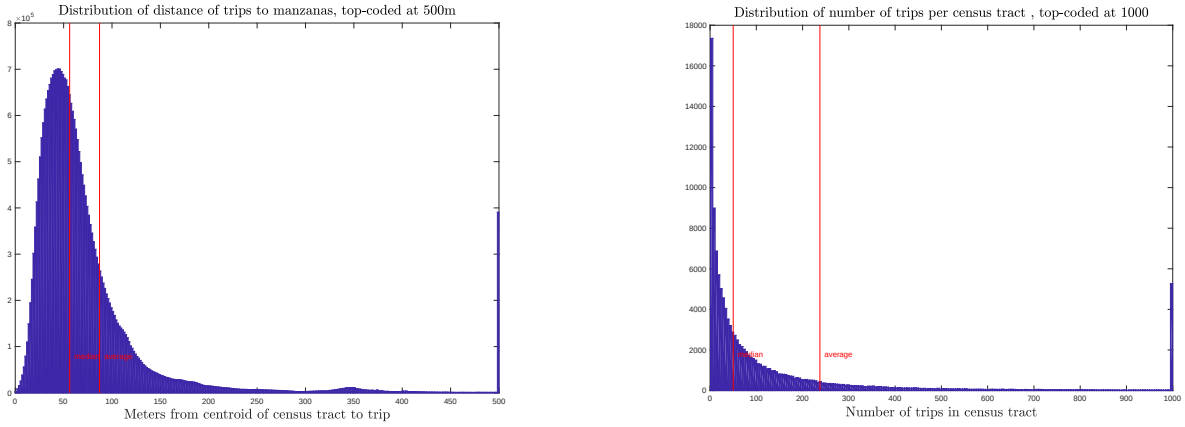
[15]The GRS 80 ellipsoid used by the Mexican census has defining parameters of a = 6,378,137.0 m and f = 1/298.257222101). In addition the Mexican census indicates the following grid origin $\phi_0 = 102°00'00''$ W, $\lambda_0 = 12°00'00''$ N, $\phi_N = 17°30'$ N, $\phi_S = 29°30'$ N, $E_0 = 2500000$, $N_b = 0$.

$$t = T(\phi) \tag{28}$$
$$m = M(\phi) \tag{29}$$
$$R = aFt^n \tag{30}$$
$$\gamma = (\lambda - lambda_0)n \tag{31}$$
$$E = Rsin\gamma + E_0 \tag{32}$$
$$N = R_b - Rcos\gamma + N_b \tag{33}$$
$$k = \frac{Rn}{am} \tag{34}$$
$$\tag{35}$$

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. Find closest centroid for each UBER trip using Euclidean distance. Lastly, we correct for difference in geofence from Uber and geolocalization of trips (due to the difference between the polygon that defines are for cash acceptance of Uber and EdoMex) using the shape files of the geofence generated by Uber.

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 as shown in Figure 18.

Figure 18: Distance of trips to census block and number of trips per census block



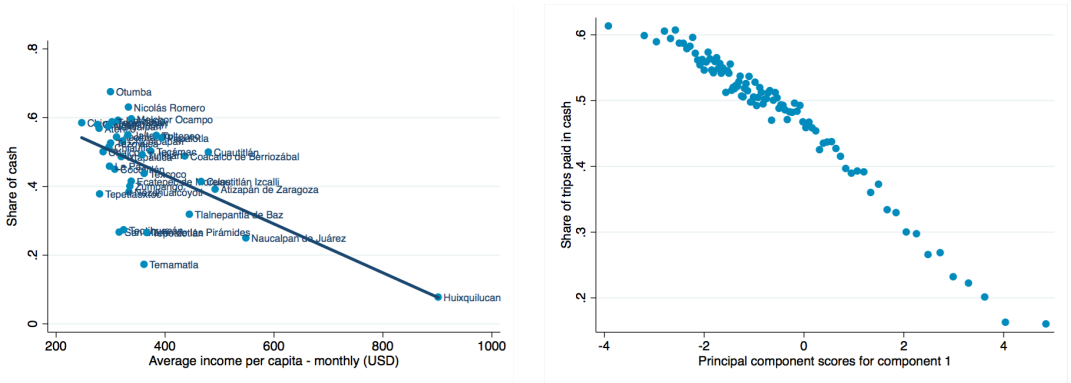
Note: The figure shows the distribution of distance of trips to the closes census block, top-coded at 500m. The coordinates are those of the origin of the trips. The red lines show the median and the mean distance. The median is approximately 60 meters. The figure shows the distribution of number of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

11.2.2 Income

Figure 19: Share of fares paid in cash by income per capita (municipality)

(a) Income

(b) First Principal Component

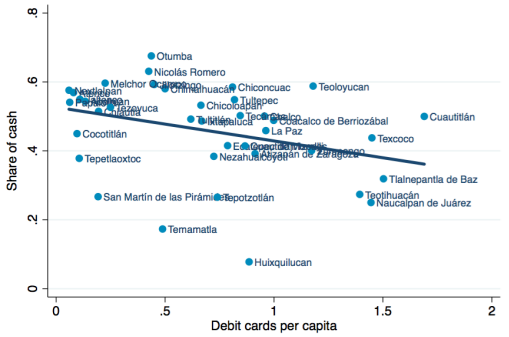


Note: The figure shows the share of fares paid in cash and the average income per capita per month in USD. The income data comes from individuals that report labor income surveyed in the Intercensal Survey of 2015. The data of Uber rides is from August of 2017 in the State of Mexico.

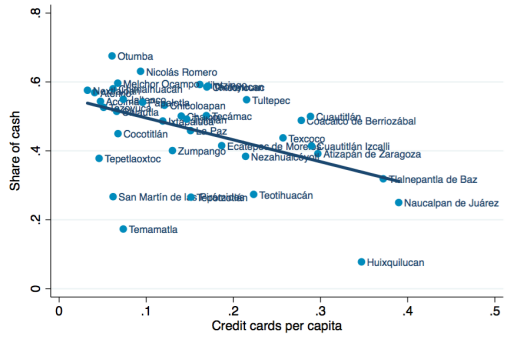
11.2.3 Banking services

Figure 20: Share of fares paid in cash - debit card per capita

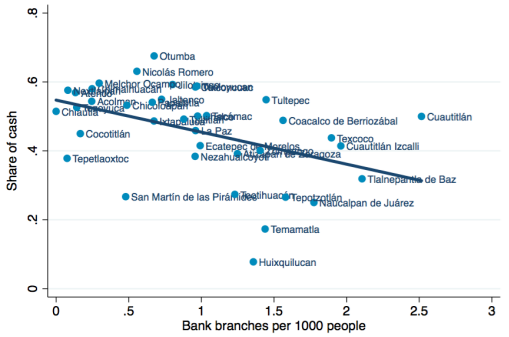
(a) Debit Cards



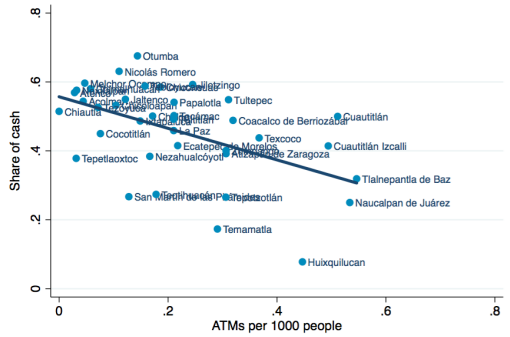
(b) Credit Cards



(c) Bank Branches

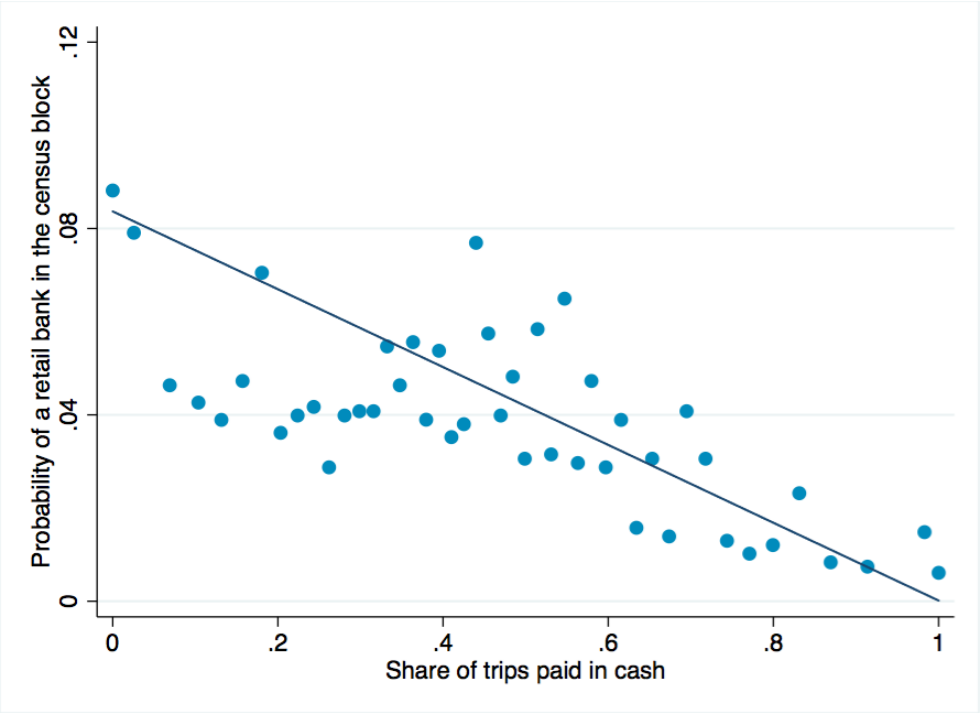


(d) ATMs



Note: The figure shows the share of fares paid in cash and the debit cards per capita in each municipality of the State of Mexico where Uber trips were taken in August 2017. The data on debit cards comes from the Financial Inclusion Database (BDIF). The figure shows the average for 2017.

Figure 21: Share of fares paid in cash - Probability of a retail bank in the census block



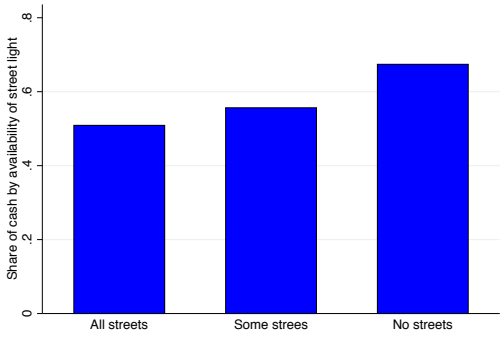
Note: The figure shows the binscatter plot of the probability a census block has a retail bank and the share of trips paid in cash in that census block group into 50 equal-sized bins. The data for retail bank branches comes from the National Statistical Directory of Economic Units (DENUE), geolocalized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

11.2.4 Infrastructure

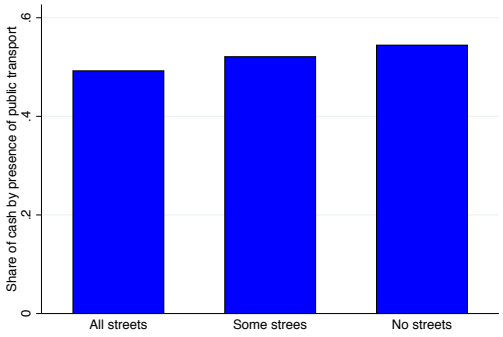
The 2010 Mexican Census collected information on the infrastructure and socioeconomic conditions of each census block. The information was collected through the Survey of Urban Enviroment (Cuestionario de Entorno Urbano y de Localidad) applied in the census blocks of census tracts with more than 5 thousands inhabitants or in the census tracts that registered less thant 5 thousands inhabitants according to the last population count.

Figure 22: Share of cash by availability of public infrastructure

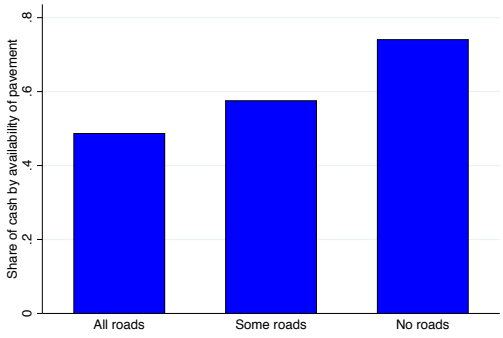
(a) Street Light



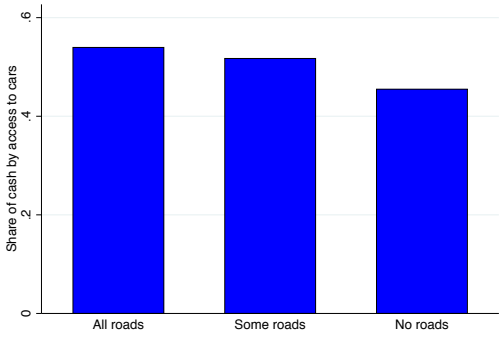
(b) Public Transport



(c) Pavement



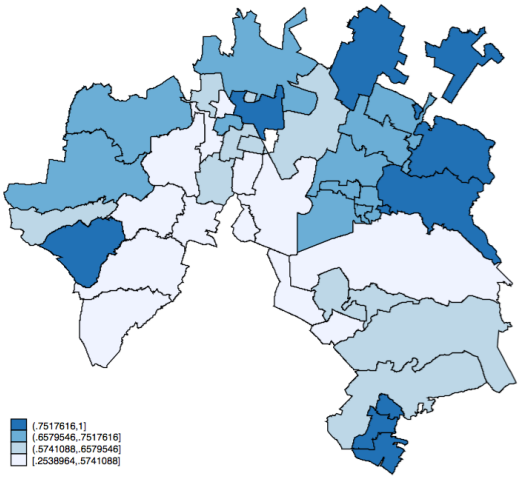
(d) Access to Cars



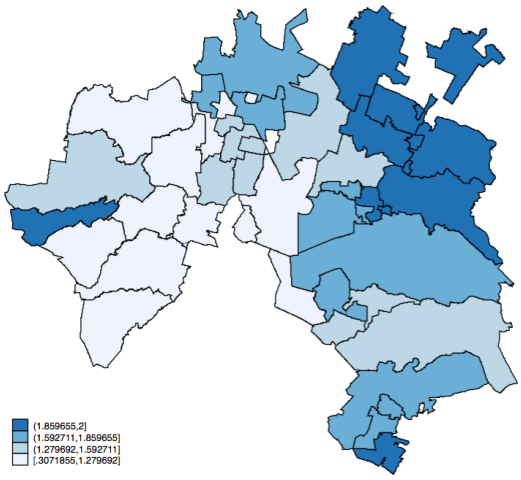
Note: The figure shows the share of fares paid in cash if the streets in the census block have public infrastructure. The date period is August 2017 and the census blocks are those located in the State of Mexico. "All streets" refers to census blocks where all the streets have street light. "No streets" refers to census blocks where no street has street light.

Figure 23: 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: The figure shows the number of total Uber rides per municipality in the State of Mexico in August of 2017. Darker colors represent a larger number of trips.

11.2.5 Regression Discontinuity: Robustness

Table 5: 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 reports 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 6: Regression Discontinuity Approach: Effect on Fares (less than 5 km)

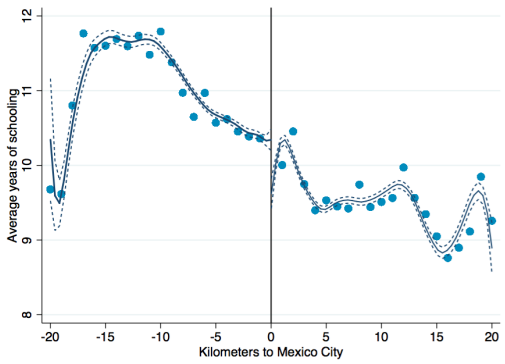
Note: The table reports the results for the coefficient of β after estimating equation 2. The estimates reports the local treatment effect at the border between the State of Mexico and Mexico City of the introduction of cash as a payment method. Each column reports the results using polynomials of different 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

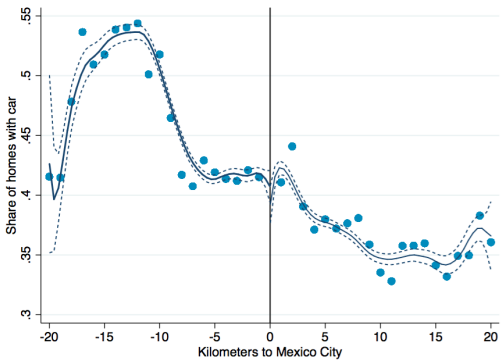
11.2.6 Regression Discontinuity: Observables

Figure 24: Percent change in the number of trips 2016-2017 - education

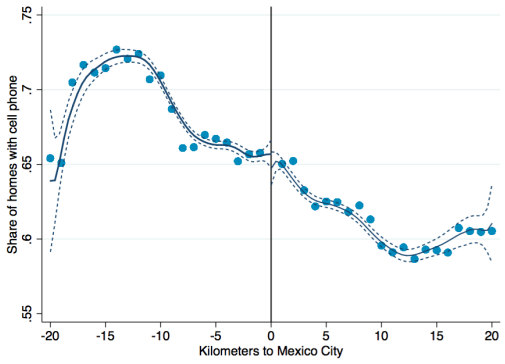
(a) Education



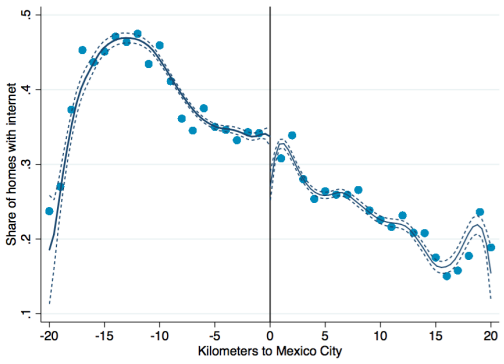
(b) Share of Homes with Car



(a) Share of Homes with Cell Phone



(b) Share of Homes with Internet



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

11.2.7 OLS: Additional Results

Table 7: 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.

	(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 8: 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.

	(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 9: 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 10: 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.

	(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 11: 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.

	(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 12: 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 13: 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 14: 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 15: 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.

	(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 16: 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.

	(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 17: 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 18: 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

11.3 Synthetic Control: Inference

We analyze the size and the power of eleven different test 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 $\hat{\theta}^5 = |\hat{\eta}_2|$.

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

Table 19: 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	$0.0690^{\star}$	$0.062^{\star}5$
10	$0.0690^{\star}$	$0.0625^{\star}$
11	$0.0345^{\star}$	$0.0312^{\star}$

12 Model

12.1 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:

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

12.2 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:

$$U'(x) = P\lambda$$

or

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

In general:

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

The choke point is:

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

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

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

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:

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

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.

12.3 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-utillity 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 $p = p_a = p_c$:

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

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

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

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

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

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

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

5. Pure credit users, i.e. credit demand when facing arbitrary p_c but infinite cash price

$p_a = \infty$.

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

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

12.4 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

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

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

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

Thus the indirect utility, in terms of the numerarire:

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

Indirect Utilities for selected cases:

1. Mixed user
$$\frac{v(1,1)}{\lambda} = -k + kI - k\log\bar{P}$$

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

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

4. Non-Uber user

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

Indirect Utility Comparisons:

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

$$\frac{v(1,1)-v(\infty,1)}{\lambda\ (c^*(1,1)+a^*(1,1)))} = \begin{cases} \frac{1}{\log \bar{P}}\left[-\log(\bar{P})-1+\bar{P}\right] & \text{if } \alpha^{\frac{1}{1-\eta}} \geq \bar{P} \\ \frac{1}{\log \bar{P}}\left[-\log(\bar{P})-1-\alpha^{\frac{1}{1-\eta}}\left(\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right)-1\right)\right] & \text{otherwise} \end{cases} \tag{36}$$

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

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

and

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

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

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

and

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

4. Indirect utility of Mixed Users vs Pure cash Users

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

and

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

12.5 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 randominzation 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:

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

13 Experiments

13.1 Translog

Ideal price index for two goods $i = c, a$:

$$\ln P(p_c, p_a) = \alpha \ln p_c + (1-\alpha)\ln p_a - \frac{1}{2}\sum_{i=c,a}\sum_{j=c,a}\gamma_{ij}\ln p_i \ln p_j - \ln C$$

where $\alpha > 0$ and $(1-\alpha) > 0$ and the matrix $(\gamma_{ij})_{i,j=c,a}$ is symmetric and positive semidefinite, and the following normalizations hold:

$$\alpha + (1-\alpha) = 1, \quad \gamma_{ic} + \gamma_{ia} = 0$$

The corresponding demand system is given by

$$x_i = \frac{h}{p_i}\left(\delta_i - \gamma_{ii}\ln p_i - \sum_{c\neq a}\gamma_{ij}\ln p_j\right)$$

using that $\gamma_{cc} = -\gamma_{ca} = \gamma$

$$x_i = \frac{h}{p_i}\left(\delta_i - \gamma\ln p_i + \gamma \ln p_j\right) = \frac{h}{p_i}\left(\delta_i - \gamma\ln\left(\frac{p_i}{p_j}\right)\right) \tag{37}$$

Let $w = \ln(p_c/p_a)$ and $z = \ln(x_c/x_a)$. Then, z can be written as

$$z = -w + \ln(\alpha - \gamma w) - \ln((1-\alpha) + \gamma w)$$

and

$$\frac{\partial z}{\partial w} = -1 - \frac{\gamma}{\alpha - \gamma w} - \frac{\gamma}{(1-\alpha) + \gamma w}$$

At $w = 0$

$$\frac{\partial z}{\partial w} = -1 - \frac{\gamma}{\alpha} - \frac{\gamma}{(1-\alpha)} = -1 - \frac{\gamma}{\alpha(1-\alpha)}$$

Estimation Elasticity of Demand

To estimate γ we use equation 37:

$$s_c = \frac{x_c p_c}{h} = \alpha - \gamma \ln\left(\frac{p_c}{p_a}\right) \tag{38}$$

where s_c is the share of credit.

Estimation Elasticity of Substitution

For mixed users we can estimate:

$$\frac{s_c}{\alpha(1-\alpha)} = \frac{1}{(1-\alpha)} - \frac{\gamma}{\alpha(1-\alpha)} \ln\left(\frac{p_c}{p_a}\right) \tag{39}$$

where s_c is the share of credit.

13.2 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],

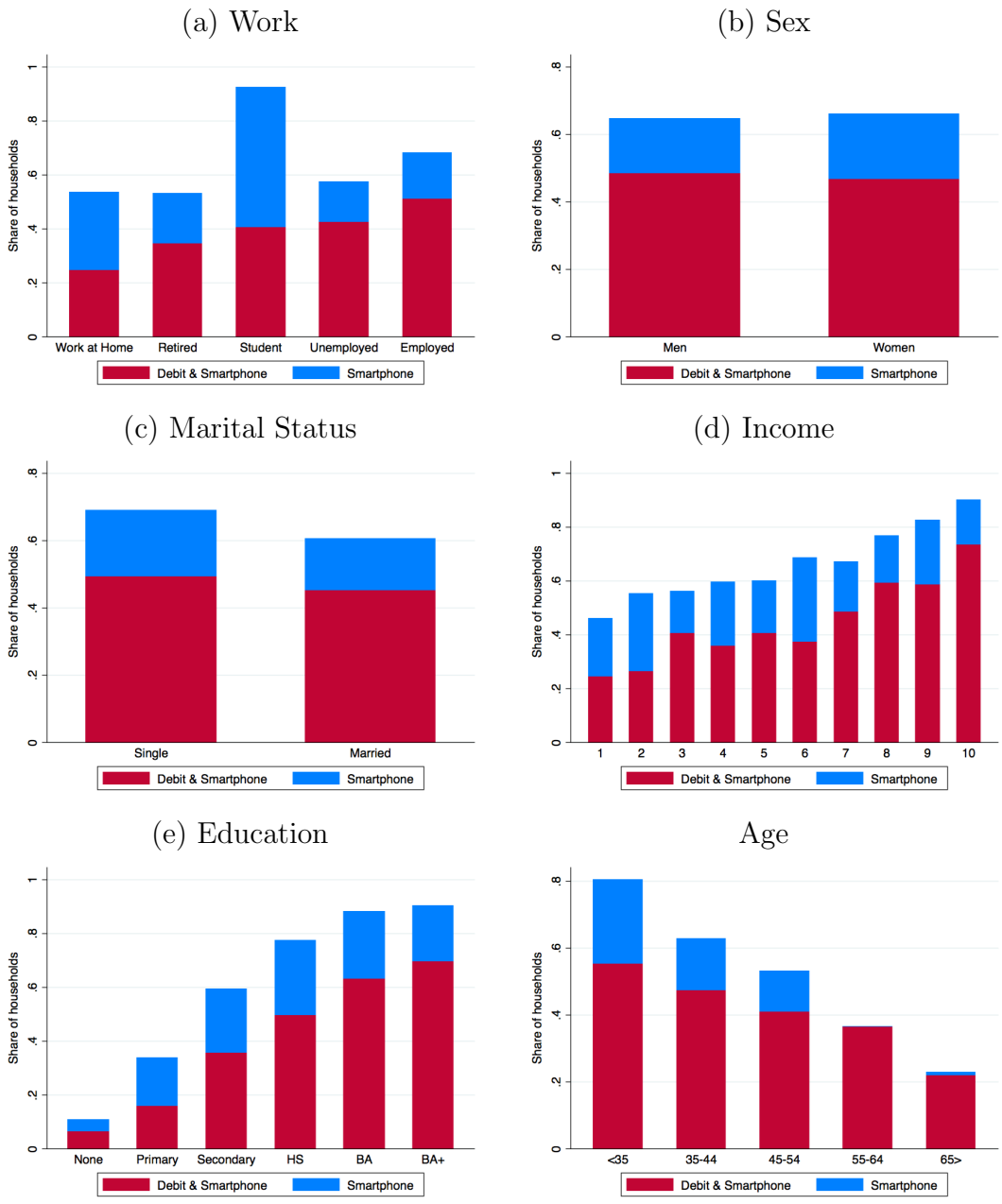
Tenemos una promoción especial para ti con la que podrás obtener 2 viajes con descuento por hasta $50 MXN cada uno. Lo único que tienes que hacer es ingresar una tarjeta de crédito o débito a tus métodos de pago en tu cuenta.

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.

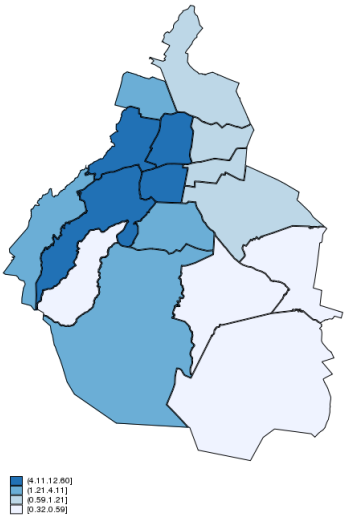
14 Demographics in Mexico

Figure 25: Availability of debit card and smartphone

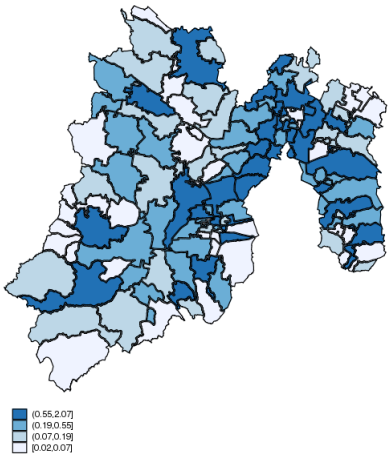


Note: The figure shows the share of households in Mexico who have used a debit card in the last three months (from the time they were surveyed) and that own a smartphone by work status. The data comes from the 2015 National Survey of Financial Inclusion (ENIF).

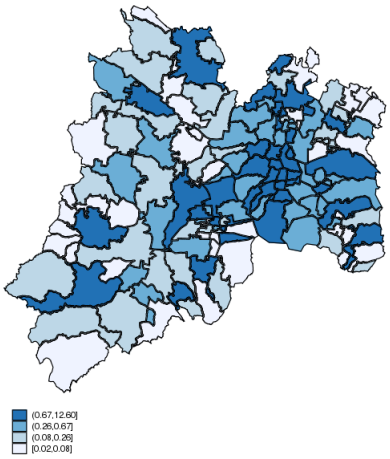
Figure 26: Debit cards per capita by municipality



(a) Mexico City



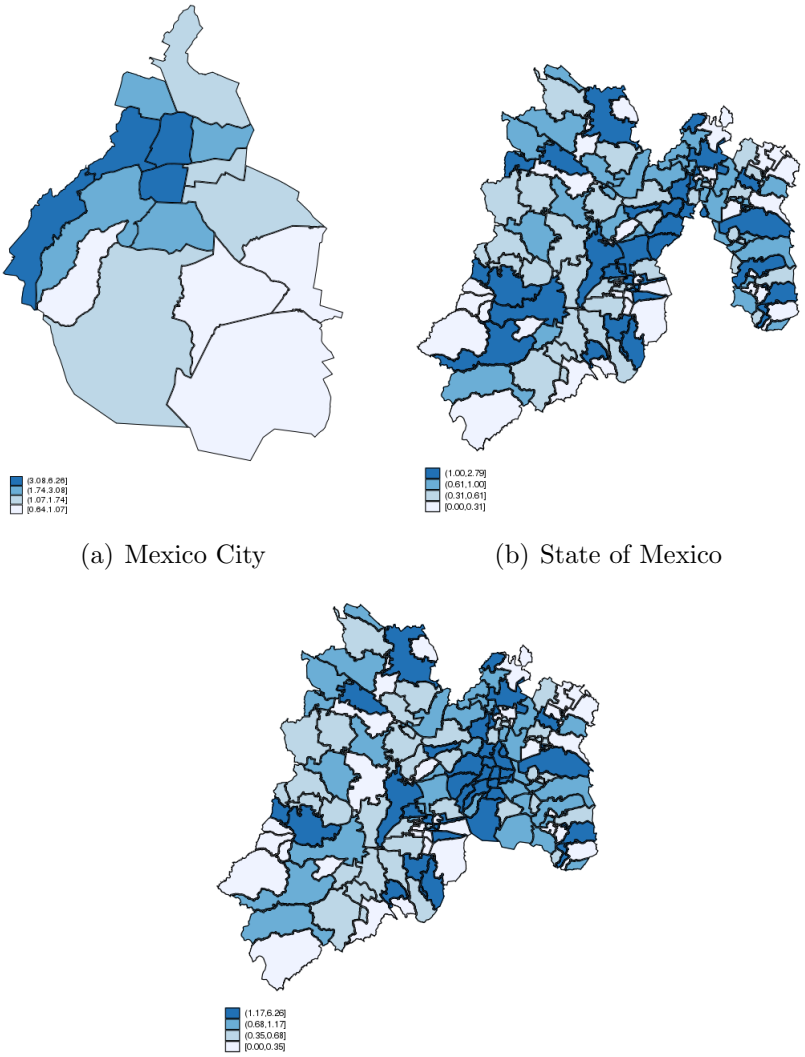
(b) State of Mexico



(c) State of Mexico and Mexico City

Notes: 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 27: 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.

15 Other data sets

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.

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 sociodemographic 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.

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 Intercensal 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 sociodemographic 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 sociodemographic 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.

DENUE

The National Statistical Directory of Economic Units (DENUE) provided information on identification, location, economic activity and size of 5,078,737 active economic units in Mexico. The data is updated continuously by authorized informants, who can update or complement their business data and incorporate commercial information online, through the application found in the data sheet of each economic unit. This information is previously validated by the National Institute of Statistics and Geography (INEGI). The data provided

by DENUE allows 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, so they can be visualized in cartography.

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 allows us to construct the following variables on a quarterly basis with representativeness at a highly disaggregated geographical level (locations of less than 2.500 inhabitants):

- Total population (by gender)
- Economically active population: 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).
- Non-economically active population: people who during the reference period did not carry out and did not have an economic activity, nor did they seek to have one at any time during the month prior to the day of the interview.
- Population by level of education (15 years and over): incomplete primary education, complete primary education, secondary education, and high school or more.
- Employed population by position: salaried workers, employers, self-employed workers, and unpaid workers.
- Employed population by income level: earns less than 1, between 1 and 2, between 2 and 3, between 3 and 5, and more than 5 minimum wages.
- Average income of employed given positive wage.
- Employed by employment benefits: no benefits, health benefits only, access to health and other benefits, access to other benefits but health, and unspecified benefits.
- Employed in the informal sector: employed population that works for a non-agricultural economic unit that operates from the resources of the household, but without forming

itself a company, so that the income, materials and equipment used for the business are not independent and/or distinguishable from those of the household.

The survey is conducted daily and it is designed in such a way that some indicators can be computed monthly but with state-level representativeness. In particular, it is possible to obtain estimates of the mentioned variables but expressed as shares or rates, depending on each case.

Precipitation

The Precipitation Data is 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).