Consumer Surplus of Alternative Payment Methods*

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Abstract

This paper estimates the consumer surplus from using alternative payment methods. We use evidence from Uber rides in Mexico, where riders have the option to use cash or cards to pay for rides. We design and conduct three large-scale field experiments, which involved approximately 400,000 riders. We also build a structural model which, disciplined by our new experimental data, allows us to estimate the loss of private benefits for riders when a ban on cash payments is implemented. We find that Uber riders who use cash as means of payment either sometimes or exclusively suffer an average loss of approximately 40-50% of their total trip expenditures paid in cash before the ban. The magnitude of these estimates reflects the intensity with which cash is used in the application, the shape of the demand curve for Uber rides, and the imperfect substitutability across means of payments. Welfare losses fall mostly on the least-advantaged households, who rely more heavily on the cash payment option.

JEL Classification Numbers: O1, O2, E4, E5
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1 Introduction

Some academics and policymakers have recently advocated for a cashless economy to address the prevalence of criminal activities and tax avoidance (e.g. Rogoff, 2017). For example, in India, a 2016 demonetization plan was enacted to, in part, remove certain large-denomination bills from circulation.[1] In Mexico, until a November 2018 ruling by the Supreme Court disallowing cash bans, several of the country's largest cities banned cash payments for app-based ridesharing firms like Uber.[2] Has the time come to phase out cash? This question is particularly relevant for low and middle income countries, where the least-advantaged households tend to use cash much more, and where policies that restrict the use of cash could limit economic access for the poor and could have important distributional consequences.

Despite the renewed attention to the role of cash in the economy, the debate over the consequences of phasing out cash is far from settled. In fact, it is challenging to estimate the private costs of policies limiting the use of cash. Such estimates would require detailed information on cash transfers and on people without access to banking services, especially in developing countries given their prevalence. They would also require both variation in prices, to estimate the elasticity of demand, and crucially, information about the functional form of the demand curve, since consumer surplus estimates are sensitive to the magnitude of choke prices. An accurate estimate of consumer surplus must also account for the costs of adopting cashless payment methods like debit or credit cards.

This paper builds a structural model and combines it with three large-scale field experiments to overcome these challenges and estimate the private benefits from using alternative payment methods. To do so, we use evidence from the effects of allowing for different payment methods in a ride-sharing app. In more than 400 cities worldwide, Uber allows its riders to select cash as a payment method—in the same way that their app allows riders to set more than one payment card as a means of payment. However, the use of cash to pay for Uber, in Mexico and other countries such as Panama and Uruguay, has encountered severe restrictions. Cash was originally not allowed in several cities in Mexico (for example in Mexico City or Querétaro) and was later banned in other cities, such as Puebla and San Luis Potosí. Motivated by these recent policies, we estimate the consumer surplus loss caused by banning cash as a payment method in a city where it was available.

We develop a model of an Uber rider in a city where she can purchase Uber trips paid in cash, Uber trips paid in card, an arbitrary number of other goods that might be complements

[1] See Chodorow-Reich et al. (2020) for a description and evaluation of its macroeconomic effects.

[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.

or substitutes of Uber, and an outside good.[3] We assume that the utility function is quasi-linear in the outside good, an assumption that we test and is not rejected by the data. We assume weak separable preferences so that we can define the demand for "composite Uber trips," an aggregate of both types of trips. Furthermore, we model both the extensive-margin choice of registering a card to gain access to both payment methods, and the intensive-margin choice of how many trips to take with each of the available payment methods. Thus, we distinguish between a ban's effect on riders that use both payment methods (mixed riders), and the effect on riders that do not register a payment card in the app (pure cash riders). We also allow for heterogeneity among riders in their preferences for paying with cash or card, and in the cost of registering a card in the application.

The calculation of consumer surplus is guided by a general result in demand theory: when prices of alternative options are held fixed, as documented in previous studies for this market after a ban or introduction of cash (e.g., Alvarez and Argente, 2022), cross-price elasticities and quantities demanded for these alternatives do not influence calculation.[4] This result enables us to estimate consumer surplus without the need to measure the quantities. The riders' consumer surplus from paying Uber in cash can be obtained by integrating the area under the demand curve, starting with the current price and up to the choke price at which the demand reaches zero. In theory, one could estimate the demand for Uber paid in cash by imposing increasingly higher prices until reaching the choke price. In practice, however, this exercise is almost impossible to implement using exclusively field experiments.[5] We overcome this challenge by using our theory to inform the design and implementation of three large-scale field experiments and a survey, involving over 400,000 riders in the State of Mexico. Our model allows us to extrapolate the demand curve from the variation in demand that we observed as prices were reduced.[6]

In the first experiment, we targeted *mixed riders* to estimate the elasticity of substitution between paying for trips with cash or with a card. We varied prices using discounts for trips paid in cash or discounts for trips paid with a card. The experiment had a total of six treatment groups, each with about 20,000 riders who had registered a card with Uber. These

[3]Since users can use either a credit or debit card to pay for Uber rides, in the rest of the paper we refer to card payments as those conducted with either a debit or a credit card.

[4]In other words, the supply of drivers is elastic at the relevant time horizon. According to Hall et al. (2023), following a base fare increase, driver hours worked increase on both the extensive and intensive margins. After about 8 weeks, there is no clear difference in the driver's gross average hourly earnings rate.

[5]While Uber allowed us to implement discounts in experiments, its policies did not permit an increase in absolute prices. Raising prices until demand reaches zero would likely harm its customer base. However, Uber did permit us to experiment with increasing relative prices. To the best of our knowledge, there is no research that conducts experiments by raising the price of a specific good or service as a treatment.

[6]Other recent examples of work integrating structural models with experimental evidence are Kaboski and Townsend (2011) and Buera et al. (2021a).

riders received discounts of either 10% or 20%. Some of them received discounts for paying with cash, some received discounts for paying with a card, while others received discounts regardless of their payment method. A control group of approximately 90,000 riders received no discounts. We estimate the elasticity of substitution to be about three. We also use the price discounts given regardless of the payment method to estimate the price elasticity for Uber rides for *mixed users*, which can be as large as 1.1, evaluated at current prices.

We combine these findings with our structural model to produce theoretically-based estimates of the consumer surplus for mixed riders. This is equivalent to increasing the price in cash from its current value to infinity—or to the choke price at which there will be no more trips paid in cash. The effect of this increase can be decomposed into two parts. The first part is the change in the choice of payment for a given number of trips, which depends on the elasticity of substitution between payment methods, as well as the share of trips paid in cash. The second part is given by the change in the ideal price index for Uber trips caused by the cash ban, which depends on the price elasticity of Uber trips. Integrating across all types of mixed users, we find that the consumer surplus of an Uber ride falls by more than 25% of mixed users' expenditures on Uber when cash payments are banned. These users represent approximately 50% of the total Uber customers in the State of Mexico.

Our second and third field experiments were intended to estimate the consumer surplus of *pure cash riders*, who account for about 25% of Uber's user base in the State of Mexico. In the event of a ban on cash payments, pure cash users must either cease to use Uber, and lose the entire consumer surplus of using the app, or register a card at some cost. The second experiment allows us to estimate the first part of this consumer surplus loss. We randomize the amount of the discount offered to pure cash riders, measuring the effect on purchases in terms of the length and number of trips. We use four treatment groups of 23,000 riders, each with discounts of 10%, 15%, 20%, and 25%, and a control group of 56,000 riders. The four treatments cover several price points so that we can learn about the shape of the demand curve. From this experiment, we find that the price elasticity for *pure cash riders* is about 1.3, evaluated at current prices.

We use the third experiment to estimate the distribution of fixed costs of adopting a card, in order to adjust the consumer surplus for pure cash users that decide to remain in the application in the event of a ban on cash. Pure cash users were offered a small reward of credit for future trips, contingent on registering a card in the application. This experiment included six treatment groups of about 20,000 riders each. In return for registering a payment card, we offered rewards equivalent to about three, six, or nine times a user's average weekly expenditure on Uber. The same reward was offered to one group of riders for registering a card in less than a week, and to another group of riders with a time limit of six weeks. We consider these two time frames to test for the hypothesis that riders may not register a card in the application *even if they have one*, because it is difficult to obtain a card in Mexico within one week, but reasonable within six. The temporal migration patterns across user types (e.g. pure cash riders becoming mixed riders) inform us about whether the likely margin of response is to register a card that the riders already have, or to obtain a new card. We find that the smallest incentives *double* the rate at which riders register a card, compared with the control group. We also find that only slightly more pure cash users register a payment card with a six-week window, as most excess migration to cards occurs in the first week. The latter finding suggests that migration from cash to card induced by small rewards is mostly driven by riders registering payment cards that they already own.

With the results of the second and third experiments targeting pure cash users and the elasticity of substitution between payment methods, we calculate the consumer surplus for pure cash users. This estimation also requires an estimate of the rate at which pure cash users *return* to the application after a ban on cash payments. We draw this estimate from a case study of such a ban in the city of Puebla, Mexico conducted by Alvarez and Argente (2022). In the most-extreme case, if no pure cash users register a payment card, then the effect of a cash-payment ban is to erase the entire consumer surplus these users enjoy when purchasing Uber rides, which we estimate to be at least as much as 47% of a user's *total expenditures* on Uber. We also know that roughly 30% of pure cash riders switch to using cards after a ban. With this figure and the above results, we estimate that a previously pure cash user who registers a card will see her consumer surplus decrease by about 44% of her Uber expenditures. Aggregating both groups, we find a ban on cash leads to a large loss in consumer surplus for pure cash riders, equal to about 46% of their total Uber expenditures. Given that lower-income households are more-likely to rely on cash as the primary mode of payment, the private costs of a ban on cash will fall disproportionately on such households.

As a complement to our estimate of Uber trip price elasticity, we considered two *additional* independent price experiments conducted by Uber. These experiments were not designed for our specific purposes, yet the price elasticities observed align closely with our field experiment findings. Notably, one of these experiments involved longer-lasting discounts, which better approximate permanent price changes and yielded similar elasticities. To further validate our findings, we explored a quasi-natural experiment in Uber Panama, where prices increased significantly due to changes in costs and licensing requirements, resulting in a substantial reduction in driver supply. This event allowed us to estimate price elasticity for Uber trips with significant *price increases*, and our results aligned with those from our model. Additionally, we employed a survey instrument to gather evidence on users' choke prices. Over 6,000 users responded to this survey, sent almost a year after the experiments. They were asked about their responses to various price changes, including substantial increases. We found that the reported elasticities in the survey closely matched the revealed preference elasticities, and when comparing these reported choke prices to our model's estimates, they exhibited remarkable consistency, further validating our structural assumptions.[7]

Taken together, our results show that the loss in consumer surplus due to a ban in cash is large, at least 50% of total expenditures on Uber paid in cash or approximately 0.8% of annual per capita income in the State of Mexico.[8] The magnitude of our estimate reflects the following: First, we argue that any effect on riders who exclusively use cards before the ban on cash is likely to be small. Second, in the State of Mexico, pure cash riders account for 20% of total expenditures, and 50% of total expenditures are from mixed riders, who pay about 42% of their fares in cash. Third, while riders that use both means of payment do react to changes in the relative prices of the two payment methods, they view the payment methods as imperfect substitutes. Fourth, while riders without registered cards react to incentives, a significant fraction of them face large costs for registering a card. Fifth, we find that the demand for Uber trips is relatively inelastic, regardless of payment method. Importantly, consumer surplus losses fall mostly on the least-advantaged households, who rely more heavily on the cash payment option.

2 Related Literature and Contribution

While the literature has used *observational* data to document how the option for cash payment affects rides, prices, and the use of other payment methods (Alvarez and Argente, 2022), this paper is the first one to conduct consumer surplus evaluation. Consumer surplus evaluation is complex, as it must incorporate mixed users and pure cash users, and both intensive and extensive margins. The analysis of consumer surplus also demands building new structure and producing estimates from *experimental* data, which are at the core of this paper. In particular, to estimate the consumer surplus losses of pure cash users who drop from the application after the ban and lose the entire consumer surplus of using the service, we need *variation in prices* to estimate the elasticity of demand for Uber. To calculate the

[7] Our choice of the functional form for demand, featuring a constant semi-elasticity, *aligns* with the local convexity observed in the relationship between trips and prices, as well as with the presence of a finite choke price in the experimental and survey data.

[8] Cohen et al. (2016) use a discontinuity design based on the rounding of prices dictated by the surge algorithm to estimate the consumer surplus of Uber for three large U.S cities and find it to be about 1.6 of the expenditure of Uber riders. This difference is in large part explained by the different elasticity that they estimate for US riders versus users in the State of Mexico. In our case the price elasticity at the current equilibrium values is 1.3 for pure cash users, 1.1, for mixed users, and 0.7 for pure card users. In Cohen et al. (2016) the price elasticity is below 0.55.

consumer surplus of mixed users we need variation in prices by payment method to estimate the relevant elasticity of substitution. We also need variation to approximate the distribution of the cost to register a card in the application, as well as information of the appropriate *functional* form of the demand curve, since consumer surplus estimates are very sensitive to the magnitude of choke prices. All the former are obtained from the experimental undertaking in this paper, and are not present in any previous work.

The approach of this paper is closely related to recent studies that assess the welfare implications of policies in developing economies by combining randomized controlled trials and natural experiments with structural modeling (e.g. Kaboski and Townsend, 2011; Buera et al., 2021a). Buera et al. (2021b) review this literature and Townsend (2020) highlight how macroeconomic theory and empirical research can complement one another to improve macro development policy in payment systems. Our experimental design represents an innovation in *tailoring* such large-scale field experiments with a structural model in mind. This approach differs from previous related work, which relied solely on structural models (e.g. Alvarez and Lippi, 2017; Briglevics and Schuh, 2020; Alvarez et al., 2021), and it is closer in spirit to Chodorow-Reich et al. (2020), who use the Indian demonetization as a natural experiment.

The paper also contributes to the literature on money demand, with its focus on the effects of availability and optimal choices of means of payment. Examples of earlier theoretical studies on the choice of payment are the cash-credit model in Lucas and Stokey (1987), the model of multiple payment methods in Prescott (1987), and studies that followed: Whitesell (1989), Lacker and Schreft (1996), Freeman and Kydland (2000), Lucas and Nicolini (2015), Koulayev et al. (2016), and Stokey (2019).[9] Several mechanisms might explain the relatively inelastic substitutability between cash and cards. For instance, the popularity of paying for other goods with cash in Mexico encourages consumers to use cash for Uber rides, even those that own payment cards, as in Deviatov and Wallace (2014) and Alvarez and Lippi (2017).[10]

Our well-identified estimate of the elasticity of substitution between cash and card payments for a given good is, in itself, a contribution to the empirical study of money demand. To the best of our knowledge, ours is the first estimate of this parameter using experimental data.[11] Furthermore, the experimental variation used to estimate the elasticity of demand

[9]Other related work is the search-theoretical literature considering money as a payment method, largely started by Kiyotaki and Wright (1989), which incorporates credit payments as in Kocherlakota (1998), Lagos and Wright (2005), or Wang et al. (2019).

[10]According to the 2018 National Survey of Financial Inclusion (ENIF), cash is the primary payment method 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.

[11]Very few studies have considered the behavior of households when faced with a differential cost in means of payment. Klee (2008) estimates the transaction times needed for different payment methods in grocery stores using data from time-stamped cash registers; this study observed no variation in prices. Humphrey et al. (2001) use aggregate semiannual time series from Norway during the 1990s and observed variations price

for Uber rides in this paper also allows us to draw upon the quasi-natural experiments in Alvarez and Argente (2022), which provide information on the long-run elasticity of substitution across payment methods, given the estimates of the elasticity of demand obtained in this paper. This alternative estimate for the elasticity of substitution complements the estimates from experimental data, enabling us to provide a long-run estimate of the consumer surplus lost after a ban on cash payments, amounting to 38% of total cash expenditures.

Our paper is also related to research studying the adoption of debit and payment cards (e.g. Borzekowski et al., 2008, Yang and Ching, 2014), which has focused on identifying the determinants of consumers' adoption decisions. Our work contributes to this literature with experimental data about the distribution of adoption costs among consumers.

In summary, this paper develops and estimates a structural model suitable for the evaluation of different margins of adjustment across users and provides the first welfare estimates of alternative payment methods. Additionally, this paper conducts large-scale field experiments tailored to generate variation which is essential to estimate the relevant parameters for this calculation. These are the first experimental estimates of the elasticity of substitution across payment methods. We also provide estimates of the fixed cost of adopting or registering a payment-card. All these estimates can be used beyond our application for the analysis of policies attempting to encourage or discourage payment methods.[12] We also provide evidence that reported elasticities in a survey are informative about the revealed preference elasticities, which contributes to the recent literature examining the external validity of survey instruments as low-cost alternatives to experimental evidence.[13]

3 Institutional Background

At its launch in 2010, Uber was notable for offering users the ability to easily hail a car and pay for the ride with a credit or debit card registered in a mobile-phone app. As Uber expanded to cities across the globe, it began to accept cash payment during a 2015 pilot program in Hyderabad, India. This pilot program expanded Uber's user base by opening access to consumers who prefer to use cash, because they have no access to a bank or card or because they prefer not to register a card with Uber. Following the success of that pilot, Uber extended the option to four more cities in India. By the end of 2016, the cash-payment

across payment methods to estimate patterns of substitution between cash, checks, and debit cards. Ching and Hayashi (2010) estimate the effects of payment-card rewards on consumer choice of payment methods in retail stores. Amromin et al. (2006) use a one-time change in toll booth prices on a Chicago highway, which depended on whether payment is made using cash or a transponder.

[12] Section 6.4 analyzes a ban on *card* payments in Argentina.

[13] Examples include Karlan et al. (2016), Parker and Souleles (2019), Méndez and Van Patten (2021) and Hainmueller et al. (2015).

option was made available in over 150 cities (including Mexico City); by 2018 Uber users could pay using cash in 400 cities and 60 countries. Most Latin American countries are included in this list, including Brazil and Mexico, the two largest in terms of population.[14]

Uber began operations in Mexico in 2013, beginning with the Greater Mexico City area, which is composed of Mexico City and its adjacent municipalities in the State of Mexico. As of 2018, Uber operated in more than 40 of Mexico's cities. Greater Mexico City is one of the firm's top ten most-active cities in the world, in terms of rides taken. In August 2018, when our experiments took place, Uber had almost the entire market share in Mexico; Cabify, a Spanish ridesharing company, had a very low market share and Didi, the Chinese ride-hailing company, was not yet active.

Uber users can select the cash option in the payment tab of the application (e.g. Panel (a) of Figure 1). Drivers accept both cash and card payments and do not know the payment method chosen by the rider when a trip is requested. At the end of the trip, the customer hands over the amount shown in the application directly to the driver.[15] Panel (b) of 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 in the cities in which Uber accepts cash payment, the option is used heavily; almost half of the trips taken are paid for in cash and half of all fares are collected in cash.[16] In the State of Mexico, where we executed the experiments reported below, approximately 25% of users (approximately 30% of fares) only use card payments, 25% of users (20% of fares) only pay in cash, and 50% of users (50% of fares) pay with cash and card. The relevance of riders that use both payment methods actively informed the distinction between mixed users and pure cash users in our model and experiments.

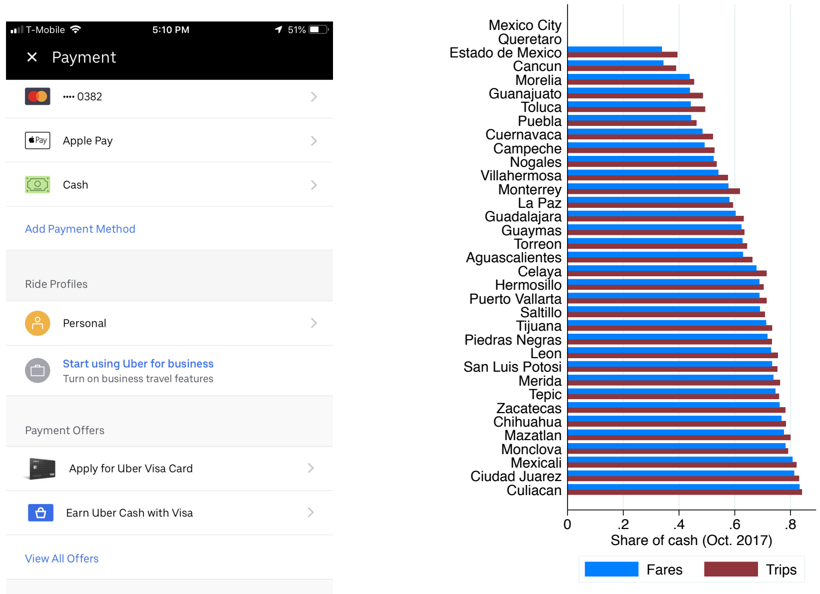
Although Uber is a service mostly consumed by middle- to high-income consumers, the cash option is largely used by low-income consumers. Panel (a) of Figure 9 shows the share of cash fares by income per capita at the municipality-level. In the State of Mexico, around 60% of fares in municipalities with low income per capita are paid with cash (e.g. Teoloyucan, Coyotepec), while less than 20% of fares in municipalities with high income per capita are paid with cash (e.g. Naucalpan de Juárez, Huixquilucan). Alvarez and Argente (2022) show, using demographic information from the 2010 Mexican Census, that this pattern holds for other variables correlated with income, such as education. A greater share of trips are paid for in cash in municipalities that have less access to banking services, as measured by debit

[14]Uber has been progressively expanding its cash-payment program, recently adding several high-income countries to the list: Germany, Spain, France, Czech Republic, Greece, Poland, Turkey and Chile.

[15]If the user cancels a trip and is charged a cancellation fee, this amount is added to her next trip's fare, which can also be paid using cash.

[16]Cash-fare trips are shorter on average. 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



(a) Paying with Uber with Cash (b) Share of Cash by City

Note: Panel (a) illustrates how users select the cash option in the payment tab of Uber's mobile application. Panel (b) shows share of trips and fares paid in cash in different cities in Mexico. The red bars show the fraction of trips and the blue bars the share of fares paid in cash. The sample of cities are those that were active in October 2017.

cards per capita, credit cards per capita, bank branches per capita, or ATMs per capita.[17] The share of cash trips is also larger in suburban regions of the State of Mexico and in municipalities with less-developed infrastructure, as measured by the availability of street lights, pavement, or whether the municipality has access to public transport.

Several local governments prohibited cash payments for Uber rides at first. Cash fares were not allowed within the city limits of Mexico City, whose local government prohibited drivers from receiving any payments in cash, non-banking pre-paid cards, or payment systems hosted by convenience stores through electronic wallets. Queretaro, a mid-size city close to Mexico City, enacted similar policy. In Puebla, ride-hailing fares were limited to electronic payments, but the government did not enforce the policy until a young student was allegedly murdered by a driver working under the auspices of Cabify, another ride-hailing firm. Puebla

[17] In Mexico, the use of debit cards is much more prevalent than that of credit cards. Panel (a) of Figure G6 shows that, conditional on using cards as the most frequent payment method, more than 80% of households report using debit cards for payments below 20 USD, which covers the majority of Uber rides. Panel (b) of Figure G6 shows the number of debit cards per capita and the number of credit cards per capita in the State of Mexico. The figure shows that the number of debit cards per capita exceeds the number of credit cards per capita, especially in municipalities where more cards are available, which coincides with those with more active Uber riders.

banned cash payments for ride-hailing services in December of 2017.[18] This decision was also motivated by the taxi-drivers' union's lobbying of the state government, complaining that cash fares for Uber rides represented unfair competition with traditional taxi services.[19] In fact, during the ban on cash, the local government launched its own ride-hailing application "Pro-taxi", which connected mobile-phone users with traditional taxis; cash payments were *allowed* for that app.[20] In November of 2018, the Mexican Supreme Court struck down a state ban on cash fares for ride-hailing firms, setting a national precedent that allows Uber and other ride-hailing firms to accept cash payments. By a vote of 8-3, the court ruled that the small western state of Colima's ban on cash fares was unconstitutional. After the court's decision, Uber began accepting cash payments in Mexico City, Querétaro, and Puebla.

4 Rider's Model and Consumer Surplus

The model is centered on a general utility function for $n+1$ goods where good 1 is "composite Uber trips", goods $2, .., N$ are close substitutes for Uber, and good $n+1$ represents all other goods with constant marginal utility, such that utility is quasi-linear. Uber rides paid in cash and those paid in card are distinguished as distinct sub-goods that together comprise composite Uber trips. This intensive-margin choice is complemented with the choice of choosing to register a payment card, which we assume is subject to a fixed cost, so that agents have access to Uber trips paid in card only if they pay a fixed cost.

We assume that while a ban on cash payments is in effect, the prices for all goods remain constant. This assumption simplifies the problem and is documented extensively for the case of Mexico and Panama by Alvarez and Argente (2022). They find that the availability of cash payments has a substantial effect on the quantities of rides, but no effects on prices including: prices of Uber rides, average surge multiplier, waiting times for Uber rides, price of taxis, waiting times for taxis, prices of other ride-hailing companies, waiting times for other ride-hailing companies, and time to location of public transport.[21] These findings hold for both the entry and ban of the cash option, and suggest that the supply of drivers is elastic

[18] Unfortunately, we do not have access to data of crimes committed by riders and/or drivers and cannot quantify the social benefits of such policy. Alvarez and Argente (2022) do not find evidence that the cash option in Uber affected city-level crime levels. Alvarez et al. (2021) measure the social benefits of restricting the use of cash on crime in Mexico. They find that the private costs of heavily taxing the use of cash outweigh the social benefits.

[19] According to the ENIF, approximately 90% of respondents, who own a debit or a credit card, report cash as their most frequently used payment method for transportation services (e.g. taxi, bus).

[20] Pro-taxi was launched almost 10 months after the ban on cash in the city of Puebla. It became inactive 3 months later for lack of financial resources.

[21] Section H shows that cancelation rates did not change significantly either.

at the relevant time horizon.[22] The lack of effect on prices allows us to ignore the effects of a cash-payment ban on pure card riders and on drivers' producer surplus, since both effects are likely to be small. Moreover, this evidence allows us to apply general results from demand theory to estimate the consumer surplus of cash Uber fares without needing to measure the quantities of other goods. The model, therefore, focuses on the choice faced by consumers who potentially encounter different prices for Uber rides depending on the payment method, holding prices for other goods constant.

We consider the welfare cost for riders in the case of a ban on cash as means of payment for Uber rides. Before the ban on cash payments, riders face the same price for Uber rides paid in cash and Uber rides paid in card. Facing equal prices, heterogeneous riders then face the choice of whether to register a payment card or not. We then estimate the change in a rider's welfare, in dollars, if the price cash-fare for Uber rides increases to infinity (i.e. a ban on cash payments). This welfare loss equals the area under the demand curve for cash-fare Uber rides. This measure takes both the intensive and extensive margins into account.

4.1 Intensive-Margin Choice

We assume that a rider's utility function is given by $u\left(x_1, x_2, \ldots, x_n; \phi\right) + x_{n+1}$, where x_1 are composite Uber rides and the goods or services $x_2, x_3, \ldots, x_n$ are close substitutes for and/or complements to Uber (e.g. taxis). The good x_{n+1} represents the rest of the goods and services. Preferences are quasi-linear, with the marginal utility of income normalized to one. We assume that $u(\cdot; \phi)$ is strictly concave and increasing in its n arguments. We let ϕ index the preferences of different riders, and let K be the distribution of ϕ across riders. We use ϕ to refer to types defined by variables that we can observe.

Assuming a quasi-linear utility function subject to idiosyncratic shocks at the rider level is reasonable, given the small share of each consumer's overall expenditures allocated to Uber rides (Vives, 1987). These preferences offer two key advantages. First, they significantly simplify the analysis, as equivalent and compensated variations coincide. Second, they aggregate to a quasi-linear utility for a group of ex-ante identical riders with the same observable characteristics. Consequently, we can test all the restrictions implied by our experimental data on that aggregate utility function, with the null hypothesis being that the experimental data was generated by some quasi-linear utility function at the aggregate level. In Section A.2, we apply the test proposed by Allen and Rehbeck (2018) and confirm that all restrictions hold for the two price experiments used to quantify Uber riders' consumer surplus.[23]

[22] Drivers' income per hour was unchanged. For an in-depth analysis of Uber drivers' labor supply with varying compensation schemes, see Angrist et al. (2021).

[23] To the best of our knowledge, our work is the first to apply this type of statistical test to experimental

Composite Uber rides, x_1, follow a constant returns-to-scale function, such as constant elasticity of substitution (CES), represented as $x_1 = H(a, c; \phi)$, where a denotes Uber rides paid in cash, and c Uber rides paid with a card. This framework, in line with Lucas and Stokey (1987), provides a tractable framework for a welfare analysis of restrictions on cash usage. The function H captures consumer preferences between paying with cash or card.

It is convenient to have a specific notation for the price of Uber rides paid in cash, for which we use p_a, and Uber rides paid with card, for which we use p_c. We let $p_2, ..., p_n$ denote the prices of the rest of the goods. Thus, the intensive-margin problem for the rider is:

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

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

where we assume that the total income of rider I is large enough so that consumption of good $n+1$ is always positive. We have normalized $p_{n+1} = 1$, so that we can interpret the numeraire as dollars (or Mexican pesos). The indirect utility function v is the focus of our theory, since we will use it to estimate consumer surplus. We omit the prices $\{p_2, \ldots, p_n\}$ from most expressions since we keep them fixed in our applications given the evidence discussed above.

Our weakly separable specification allows us to isolate the choice between means of payment from the overall demand for Uber rides. Given the assumption that H is homogeneous of degree one, a rider's choice to pay for an Uber trip with cash depends only the rider's type ϕ and the ratio of cash and card prices p_a/p_c, but it does not depend on the rider's income I or any feature of the utility function u. On the other hand, if prices are equal for riders that have access to both means of payment, $p_a = p_c = P$, the demand for composite Uber rides depends only on the common price P and on the utility function u; demand is independent of the function H. We can use H to define the ideal price for one composite Uber ride:

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

We normalize the units of $H(\cdot; \phi)$ so that $H(p, p; \phi) = p$ for any $p > 0$.[24] We assume that H is such that $\mathbb{P}(\infty, 1; \phi)$ and $\mathbb{P}(1, \infty; \phi)$ are both finite (i.e. allows for finite choke prices for pure cash users and pure card users). For instance, since H is given by a CES function, we require the elasticity of substitution to be greater than one.

data with price variation across individuals.

[24] We let $a(p_a, p_c)$ and $c(p_a, p_c)$ be the choices that attain the minimum in equation (2) so that $\mathbb{P}(p_a, p_c) = p_a a(p_a, p_c) + p_c c(p_a, p_c)$. The functions a and c are homogeneous of degree zero in (p_a, p_c) while $\mathbb{P}$ is homogeneous of degree one in (p_a, p_c). The ideal price index is given by $\mathbb{P}(p_a, p_c)$, and is increasing in the convex function of (p_a, p_c).

4.2 Extensive-Margin Choice

We assume a rider can pay with a card only after incurring a fixed cost $\psi \geq 0$.[25] We use the vector $\theta = (\psi, \phi)$ to fully specify the rider's type. The complete problem for the rider is:

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

The first option is to pay the fixed cost ψ and face ride prices (p_a, p_c). The rider can also save the fixed cost ψ, but will then only have access to the cash price; we represent this limited access by setting the card price to infinity: $p_c = \infty$.

Let $\tilde{a}$ and $\tilde{c}$ be the demand functions for Uber rides paid in cash and cards, respectively. Also, let $1_c\left(p_a, p_c; \theta\right) \in 0, 1$ be an indicator that equals one if the optimal decision in equation (3) is to register a payment card with Uber and zero otherwise.[26] We can now define the rider's demands for cash or card Uber rides for any type of rider $\theta = (\psi, \phi)$, taking the intensive and extensive margins into account:

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

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

4.3 Welfare Costs and Consumer Surplus

Given our assumption of quasi-linearity, we can aggregate the riders' welfare level and measure it in units of the numeraire. We normalize the units that quantify trips so that the price of a trip is 1 when both means of payment are available, i.e. we normalize the length of each ride so that the cash and card prices are $p_a = p_c = 1$. We denote the consumer surplus lost in the ban of cash by CS_{ban}, which we define as follows. We assume that riders have access to both cash and a payment card before the ban and that they have already made their optimal choice regarding registering a card by solving the problem in equation (1). The prior decision

[25]We express the fixed cost with its equivalent-flow value. This notation converts the fixed cost to units comparable with $v\left(p_a, p_c; \phi\right)$. Later on, we introduce a discount rate ρ which converts the flows into stocks. The discount rate ρ incorporates pure-time discounting and the expected duration for the registration of the payment card and/or the expected duration of the Uber service.

[26]See Section A.5 for a full characterization of the demand functions.

about registering a card is summarized by $1_c(1,1;\theta)$ and the distribution of types F. The consumer surplus cost of the ban is, therefore:

$$\mathcal{CS}_{ban} = \int 1_c(1,1;\theta)\left[\underbrace{v(1,1;\phi)}_{\text{mixed}} - \underbrace{v(\infty,1;\phi)}_{\text{pure card}}\right] dF(\theta) \\ + \int [1 - 1_c(1,1;\theta)]\left[\underbrace{v(1,\infty;\phi)}_{\text{pure cash}} - \underbrace{\mathcal{V}(\infty,1;\theta)}_{\text{pure card vs no Uber}}\right] dF(\theta) \tag{4}$$

The first term counts the riders that registered a card before the ban, denoted by the indicator $1_c(1,1;\theta)$. These riders are either pure card users or mixed users. Before the ban, their net utility flow is $v(1,1;\phi)$. These users have paid the fixed cost to register a card, which is a sunk cost. After the ban these riders face a much higher cash price for Uber ride, i.e. their utility flow value is $v(\infty,1;\phi)$. The second term counts the riders that were pure cash users before the ban. Their utility-function flow before the ban is $v(1,\infty;\phi)$. After the ban, these riders must choose between paying the fixed cost and becoming pure card users, which gives the utility flow of $v(1,\infty;\phi)-\psi$, or ceasing to use Uber, which corresponds to the net utility flow $v(\infty,\infty;\phi)$. This last choice is accounted for with the term $\mathcal{V}(\infty,1;\theta)$.[27]

Following standard arguments from demand theory, the consumer surplus lost after a cash-payment ban can be computed as the area below the aggregate demand for cash-fare Uber rides. First, we define the aggregate demand in a city that initially allows cash payments, where the cash price unexpectedly increases to $p_a \geq 1$:

$$A(p_a,1) = \int 1_c(1,1;\theta)\,\tilde{a}(p_a,1;\phi)dF(\theta) + \int (1 - 1_c(1,1;\theta))\,a^*(p_a,1;\theta)dF(\theta) \tag{5}$$

Note that this definition of aggregate demand breaks the integral into two groups of riders, as in equation (4). The first group has already registered a card, according to the decision at the original prices $(p_a,p_c)=(1,1)$, for which $1_c(1,1;\theta)=1$. The second are the remaining riders, which have not registered a card and, hence, they may consider to do it optimally.

Proposition 1. *Assume that $G(\cdot|\phi)$ has continuous density, and that almost all riders θ have sufficiently large income I to consume the outside good. Then*

$$\mathcal{CS}_{ban} = \int_1^{\infty} A(p_a,1)dp_a \tag{6}$$

The demand satisfying equation (6) is the *aggregate* demand. A proof of Proposition 1

[27]More generally, we can define for any $p_a \geq 1$ the consumer surplus cost that follows an increase in the price of cash from 1 to $p_a \geq 1$ as $\mathcal{CS}(p_a,1)$. The ban is represented as $\lim \mathcal{CS}(p_a) = \mathcal{CS}_{ban}$ as $p_a \to \infty$.

is provided in Section A.1, relying on the envelope theorem for the intensive-margin and assuming a density g for the fixed cost to account for the extensive-margin of adoption.

Other means of transportation. Proposition 1 states that the consumer surplus depends only on the prices/quantities of Uber rides. We assume that the prices of taxis and other substitutes (complements), remain constant after a ban on cash payments, an assumption supported by ample empirical evidence. These findings allow us to evaluate the consumer surplus for cash-fare Uber rides *without* measuring the impact on the quantities of other goods. In fact, the availability of this information does not impact or improve the consumer surplus calculations. This is a general result of demand theory.[28] In Section C.1 we use demand theory to show that when the prices of substitutes (or complements) are fixed, cross-price elasticities and quantities demanded of these goods do not affect the calculation of consumer surplus. Section C.2 develops a closed-form example to illustrate these results from demand theory, and Section I summarizes the empirical evidence on the price response of other means of transportation following a ban or the introduction of cash. Nevertheless, if the prices of other modes of transportation were increase in response to a ban on Uber rides, our consumer surplus estimates, which turn out to be large, would be a lower bound.

4.4 Identification and Functional Forms

In theory, based on Proposition 1, we could trace out the demand curve for Uber rides by increasing the cash price permanently. Repeating this exercise until the cash price reaches the choke price, we could directly estimate the consumer surplus of cash-fare Uber trips. In practice, however, Uber's policies render this exercise impossible. We overcome this challenge with large-scale field experiments in which we trace out the demand curve by reducing, rather than increasing prices, as well as bringing to bear information from the reaction of riders to the ban in Puebla. In concert with the structural model described above, we extrapolate from this data to estimate the consumer surplus. We use a parametric version of the model because our experiments contain a limited amount of price points and rewards variation.

We first divide an Uber rider's consumption problem into two stages to clarify the features of the indirect utility function that are identified by each experiment. As a preliminary step, we define the utility function $U(\cdot;\phi,p_2,\ldots,p_n):\mathbb{R}_+\to\mathbb{R}$ to embed all the information of the utility function u in a simple set up, for fixed prices of the related goods $\{p_2,\ldots,p_n\}$:

[28] See Hausman (1981), who shows that one can recover an expenditure function whose derivative provides the appropriate compensated demand curve for the good whose price has changed, which enables the exact calculation of compensating variation and equivalent variation, which coincide under quasi-linearity.

Table 1: Functional Forms and Main Equations

Note: The table shows the functional forms assumed in the model. It also shows the experiments that identify each of the parameters required to estimate the consumer surplus and the key equations used for the calculation of the consumer surplus.

	Model	Identification
Preferences	$u\left(H\left(a,c;\phi\right)\right), x_2, \ldots, x_n; \phi) + x_{n+1}$	Test using experimental data (Section A.2)
Extensive	$\mathcal{V}(p_a, p_c; \theta) \equiv \max\left\{v\left(p_a, p_c; \phi\right) - \psi\,,\, v\left(p_a, \infty; \phi\right)\right\}$	ψ: Experiment 3 (Section 5.3) and Puebla
Utility	$U(x;\phi) = -k\exp\left(-\left(x+\bar{x}\right)/k\right)$	$\epsilon(P_0)$: Experiments 1 and 2 (Section 5), Panama (Section 5.2.1), Survey (Section 5.2.2)
Intensive	$H(a,c) = \left[\alpha^{\frac{1}{\eta}} c^{\frac{\eta-1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} a^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$	η: Experiment 2 (Section 5.2), α: Data
	Consumer Surplus	**Derivation**
Pure Cash	$\epsilon(P_0)\left[\exp\left(\frac{1}{\epsilon(P_0)}\right) - 1\right] - 1$	Indirect Utility Comparisons (Section A.4) Details in equation (11)
Pure Cash (adj.)	$\int_{\underline{\widehat{\psi}}}^{\max\{\widehat{\underline{\psi}}, \widehat{\psi}_{ban}\}} \left[\psi - \underline{\widehat{\psi}}\right] \widehat{g}(\psi) d\psi$	Net Consumer Surplus Lost (Section A.7) Details in equation (39)
Mixed	$\epsilon(P_0)[-\frac{1}{\epsilon(P_0)} - 1 - \alpha^{\frac{1}{1-\eta}}(\log(\alpha^{\frac{1}{1-\eta}}) - \frac{1}{\epsilon(P_0)} - 1)]$	Indirect Utility Comparisons (Section A.4) Details in equation (29)

$$U(X;\phi,p_2,\ldots,p_n) \equiv \max_{x_2,x_3,\ldots,x_n} u\left(X, x_2, \ldots, x_n; \phi\right) + I - \left[\sum_{i=2}^{n} p_i x_i\right] \tag{7}$$

This problem establishes a utility function for composite Uber rides, in which X serves as the main argument by maximizing out the remaining related goods 2 to n, at prices $\{p_2, \ldots, p_n\}$.[29] Using U, we can define the following indirect utility function $V(\cdot;\phi) : \mathbb{R} \to \mathbb{R}$ in the problem for a rider choosing the number of composite rides X at price P:

$$V(P;\phi) = \max_{x \geq 0} U(x;\phi) + [I' - Px] \tag{8}$$

Note that we are using that preferences are quasi-linear. We let the optimal solution be $X(P)$, with the first-order condition $U'(X(P)) = P$ if $X(P) > 0$ and $U'(X(P)) \leq P$ otherwise. These results will aid the below discussion of the assumptions needed to compute $\mathcal{CS}_{ban}$.

Cash-card choice utility H. For a given rider type ϕ, given that H is homogeneous of degree one, we can identify H if we observe the ratio of the choices $\tilde{a}(p_a, p_c; \phi)/\tilde{c}(p_a, p_c; \phi)$ as we vary p_a/p_c exogenously. Equivalently, we can identify H by tracing the share of trips paid in cash $p_a\tilde{a}/(p_a\tilde{a} + p_c\tilde{c})$ as a function of p_a/p_c (see Experiment 1 below). For $H(\cdot;\phi)$ we use a CES function described by two parameters:

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

[29] As before, we omit the dependence of prices $\{p_2, \ldots, p_n\}$.

where η is the elasticity of substitution and the observable rider-specific parameter α represents the share of payments made with a card for mixed users. To be precise, if $p_a = p_c = p$ for any p, the optimal demand gives $p_c c/(p_c c + p_a a) = \alpha$ and $p_a a/(p_c c + p_a a) = 1 - \alpha$. The parameters (α, η) are contained in the type ϕ.[30]

Uber ride utility U. The definition of U in equation (7) and equation (8) make clear that U is identified by observing how $\tilde{c}(p, p; \phi)$ and $\tilde{a}(p, p; \phi)$ change as the price of an Uber ride with either payment method $p = p_a = p_c$ changes, since $p = \mathbb{P}(p, p; \phi)$. Moreover, for pure cash riders, we can also identify U by varying the price of trips paid in cash p_a, which gives $\mathbb{P}(p_a, \infty; \phi) = p_a \, \mathbb{P}(1, \infty; \phi)$ (see Experiments 1 and 2 below).[31] Importantly, we use the functional form of U, and its associated demand for rides X, to extrapolate the shape of the indirect utility function V estimated using experimental variation in prices. We let

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

such that U is described by $k >$ and $\bar{x} > 0$. The demand that solves equation (8) is:

$$X(P; \phi) = -k \log P + k \log \bar{P} \tag{9}$$

so k and $\bar{P}$ are indexed by ϕ. This demand has constant semi-elasticity $k \geq 0$. Note that the price elasticity of this demand function is:

$$\epsilon(P) \equiv -\frac{P}{X(P)} \frac{\partial X(P)}{\partial P} = \frac{1}{\log\left(\bar{P}/P\right)}. \tag{10}$$

The consumer surplus of a rider with this utility function at initial price P_0 is[32]

$$C(P_0; \phi) = \int_{P_0}^{\bar{P}} X(p; \phi) dp \qquad \text{and} \qquad \frac{C(P_0; \phi)}{P_0 X(P_0; \phi)} = \epsilon(P_0) \left[\exp\left(\frac{1}{\epsilon(P_0)}\right) - 1\right] - 1. \tag{11}$$

This semi-log demand curve has a finite choke price $\bar{P}$ (i.e. $X(\bar{P}; \phi) = 0$) given by $\bar{P} = e^{-\bar{x}/k}$ and is convex. These two features are *consistent* with our experimental and survey data. The ratio of the choke price to the current price for the demand function with constant semi-elasticity is $\bar{P}/P = \exp(1/\epsilon(P))$. For instance, at $\epsilon = 1.3$ the choke price is about 2.1 times greater than the price at which we evaluate the elasticity.[33] The convexity

[30]As usual, the price of a composite Uber ride is $\mathbb{P}(p_a, p_c; \phi) = \left[\alpha p_c^{1-\eta} + (1-\alpha) p_a^{1-\eta}\right]^{1/(1-\eta)}$.

[31]If we decrease p_a, we can also disregard pure cash riders' incentives toward registering a card. Also, if the constant $\mathbb{P}(1, \infty; \phi)$ is unknown, then we can identify U up to a constant; see case 4 of Section A.5.

[32]P_0 refers to the initial price at which the consumer surplus is to be evaluated, e.g., the elasticity of demand is not constant, and its value depends on the point at which it is evaluated. Since we normalize the length of each ride to make cash and card prices equal to 1, we use $P_0 = 1$.

[33]In Section A.5 and Section A.6, we derive expressions for the different demand curves for cash and

of the demand curve implies a larger consumer surplus (relative to expenditures) compared to a linear demand curve, as the latter lacks local convexity and has lower choke prices. Considering a demand curve with constant elasticity would also not be reasonable due to the magnitude of choke prices, leading to a substantially larger consumer surplus.[34]

Distribution of fixed cost g. We assume that the indirect utility functions $v(p, \infty; \phi)$ and $v(p, p; \phi)$ are known and that pure cash riders are faced with different levels flow rewards d that can be obtained only if they register a card (see Experiment 3 below). Then, we can identify the distribution $\psi \sim g(\cdot|\phi)$ using the fraction of riders that have registered a card for different values of d.[35] The distributions of ψ and ϕ must also be consistent with the behavior of pure cash users. Here, we list the relevant constraints:

1. *The choice of pure cash users not to start using a payment card as long as cash payments are allowed.* The condition that ensures this is:

$$\psi \geq v(1, 1; \phi) - v(1, \infty; \phi) \tag{12}$$

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

2. *The observed excess migration of pure cash users to pure card users after the ban in Puebla.* For the second condition we use that fraction m_{ban} of pure cash users in Puebla migrated to card after the ban on cash, in excess to those that migrated before the ban:

$$\psi \leq v(\infty, 1; \phi) - v(\infty, \infty; \phi) \text{ for fraction } m_{ban} \text{ and} \tag{13}$$
$$\psi \geq v(\infty, 1; \phi) - v(\infty, \infty; \phi) \text{ for fraction } 1 - m_{ban} \tag{14}$$

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

3. *The change in trips for pure cash users that became pure card users after the ban in Puebla.* In Puebla, we keep tract of the number of trips for pure cash users that become

card fares: $a(p_a, p_c; \phi), \tilde{a}(p_a, p_c; \phi), c(p_a, p_c; \phi), \tilde{c}(p_a, p_c; \phi)$, the indirect utility function $v(p_a, p_c; \phi)$, and other comparisons between indirect utility functions used in the computation of the consumer surplus.

[34] Specifically, the consumer surplus relative to expenditures with linear demand is $\frac{1}{2}\frac{1}{\epsilon(P_0)}$. Under a demand function with constant elasticity the consumer surplus relative to expenditures is $\frac{1}{\epsilon-1}$. This value can grow very large for elasticities closer to 1, as those we estimate below.

[35] We assume that the density g of the distribution of fixed costs for registering a card ψ is the same for all pure cash users. This assumption is verified in Section F. Figure F4 shows that migration rates are independent of historical trips, a variable capturing heterogeneity among cash users.

pure card users after the ban. In the data, these users decreased their number of trips. Thus, for those values of ϕ, we must have

$$0 < \tilde{a}(\infty, 1; \phi) \leq \tilde{a}(1, \infty; \phi) \tag{15}$$

4. *The experimental evidence on the excess migration for different reward levels.* In our experiment (Experiment 3 below), pure cash riders are offered a one time payment d_j, from which we measure the induced (excess) migration of fraction m_j of pure cash riders to become card/mixed riders by registering a card. We index each level incentives as well as each fraction of the treatment group that migrate by j.

$$\psi \leq v(1, 1; \phi) - v(1, \infty; \phi) + \rho d_j \text{ for fraction } m_j \text{ and} \tag{16}$$

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

Although we do not know α for pure cash riders, given that they have not been faced with interior choices for card prices, there is a small interval of α's consistent with all these inequalities. In Section A.7, we find the remaining parameters of U and G and compute the consumer surplus lost in a ban on cash by pure cash users for each feasible value of α. Below, we aim to be conservative and report estimates using the value of α that is consistent with a *lower bound* of the net consumer surplus lost by pure cash users who switch to card payments after the ban. We also report estimates consistent with an *upper bound* of the consumer surplus lost by pure cash users assuming riders do not switch to card payments after a ban on cash. Our estimates show that both lower and upper bounds are very close.

Consumer surplus calculation. All the relevant functional forms for our analysis and expressions used for the consumer surplus calculation are listed in Table 1. The calculation of the consumer surplus is straightforward; here, we recap the steps. For pure cash users, we integrate the demand for Uber rides up to the choke price. After normalizing by total fares, the calculation only requires plugging in the empirical estimate $\epsilon(P_0)$ into equation (11) at the initial price $P_0 = 1$. For pure cash users who switch to cards after the ban, the consumer surplus has to be adjusted by subtracting the fixed cost of registering a card, $\psi \sim g(\cdot|\phi)$, estimated using the experimental and observational evidence described below. Lastly, for mixed users, the consumer surplus has to be adjusted for the share of payments made with a card α and the elasticity of substitution η. In this case, the calculation for the consumer surplus, normalized by total fares, requires plugging in α, which is observed, as well as our estimates for $\epsilon(P_0)$ and η into equation (29): $\epsilon(P_0)[-\frac{1}{\epsilon(P_0)} - 1 - \alpha^{\frac{1}{1-\eta}}(\log(\alpha^{\frac{1}{1-\eta}}) - \frac{1}{\epsilon(P_0)} - 1)]$, representing the difference between the indirect utility of mixed users and pure card users relative to total fares of mixed users.

Discrete choice model. Section B describes a discrete choice model of Uber ridership and the choice of means of payment, which gives rise to the same demand system described above. In each subperiod of the discrete choice model, agents choose whether to take an Uber trip or to use an alternative mode of transportation, and, conditional on choosing to ride with Uber, they decide the means of payment they will use (i.e., cash or card). As standard, in each subperiod agents draw a set of random variables that indicate the values of these choices. Using particular distributional assumptions of these random variables, we obtain our functional forms. In Section R, we also discuss how to estimate the discrete choice model using sequential GMM.

5 Experiments

This section describes the three field experiments that let us identify the parameters in our model and estimate the consumer surplus lost after cash payment is banned. The experiments took place in the State of Mexico between August and September of 2018. The sample includes users who signed up in the State of Mexico and whose most-frequent city for Uber trips is within the State of Mexico. All users have a verified mobile number and are not subject to other experiments simultaneously. The users in our sample took at least 2 trips in 2018 and took at least one trip since April 1st of 2018.

In Experiment 1, we vary the prices of cash and/or card for mixed users to estimate the elasticity of substitution between cash and card payments η, as well as the price elasticity of demand $\epsilon(P)$. In Experiment 2, we vary the price p_a for pure cash users to estimate the price elasticity of demand $\epsilon(P)$. Lastly, in Experiment 3 we present pure cash users with different incentives toward registering a payment card to estimate the distribution of the fixed cost g.

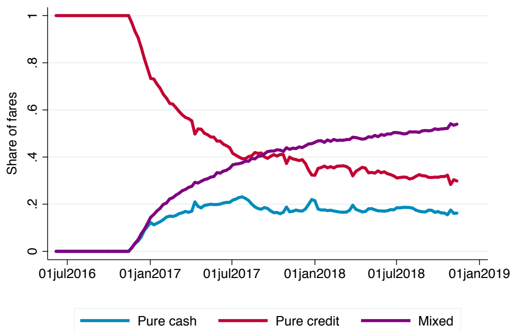
Table D1 shows descriptive statistics for the users in our sample including averages of variables such as fares, trips, fares paid in cash, trips paid in cash, share of fares paid in cash, and tenure. Mixed users pay higher fares per week than pure cash users ($5.29 USD vs. $1.43 USD) and travel more (1.11 trips per week vs. 0.36).

5.1 Experiment 1: Consumer Surplus - Mixed Users

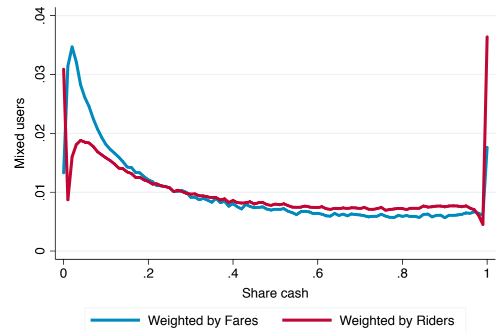
This experiment focuses on mixed users, who have paid for at least one trip using both cash and card in their rider history before the experiment began.[36] Panel (a) of Figure 2 shows the

[36]Users in the sample must have a card on file that is not banned by Uber.

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



(a) Share of Fares by User Type



(b) Distribution Mixed Users

Note: Panel (a) shows the share of total fares paid by different types of users in the State of Mexico. The red line shows the share of fares paid by pure card users, those that have never paid for an Uber ride with cash. The blue line shows the share of fares for pure cash users, those who have not registered a card in the application. The purple line shows the share of fares of mixed users, those who have at least one trip paid in cash and at least one paid using a card. The cash payment option was introduced in November, 2016. Panel (b) shows the distribution of mixed users as a function of the share of fares paid in cash. The sample includes users with at least 4 weeks of tenure that had used both methods of payment and that took at least 5 trips after becoming mixed users. The blue line shows the distribution of mixed users weighted by fares and the red line shows the distribution weighted by riders.

share of fares paid by mixed users over time in the State of Mexico. Mixed users account for approximately half of the fares paid in the State of Mexico. Panel (b) shows the distribution of mixed users over their share of fares paid in cash.

We have six treatment groups, each composed of approximately 11,000 riders and a control group of 90,000 riders. The treatment and control groups were balanced in the following observables: average weekly historical trips, average weekly historical fares, log tenure (in weeks), and average weekly historical fares paid in cash. Riders in the treatment groups were presented with the following promotional offers: 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. Note that this design includes both decreases and *increases* in relative prices. The discounts were applied to all trips taken by the riders in each treatment group during the entire week. At the beginning of the week, riders received an introductory email describing the promotion. At the same time, the promotion appeared on their phone's main screen once they opened the application. Two reminder emails were sent (in the middle of the week and two days before the promotion expired).[37]

We concentrate on the share of card payments, $s_c \equiv p_c c/(p_c c + p_a a)$, among mixed riders with positive trips during the week of the experiment in treatments facing different relative

[37]Examples of the emails sent communicating the promotions can be found in Section O.

prices p_a/p_c. For a given α, this is a function of relative prices faced by riders. We choose s_c, as opposed to the ratio $\frac{c}{a}$, because it is well-defined even if a rider makes only one trip during the week of the experiment. Indeed, in a discrete choice model, where taking a trip or not is a probabilistic event, the comparison of the average value of s_c between the treatment and control gives the equation to estimate η. In Section B we derive such a discrete time model, and in Section R we derive the moment conditions to estimate η.

To simplify the presentation and use regression analysis, we linearize the optimal choice of the share of card payments s_c for a CES function H, as a function of the relative prices p_a/p_c, the share parameter α, and the elasticity of substitution η.[38] The first- and second-order approximations around $p_c/p_a = 1$ are:

$$s_c = \alpha - (\eta - 1)\alpha(1-\alpha)\ln\left(\frac{p_c}{p_a}\right) \text{ , and} \tag{18}$$

$$s_c = \alpha - (\eta - 1)\alpha(1-\alpha)\ln\left(\frac{p_c}{p_a}\right) + \frac{1}{2}(1-\eta)^2(1-\alpha)\alpha\left[1-2\alpha\right]\left(\ln\left(\frac{p_c}{p_a}\right)\right)^2 \tag{19}$$

In our empirical implementation, we begin by using the first order approximation. We observe the share of payments made with a card, $\hat{\alpha}^i$, for $p_c = p_a$ in our data (i.e. equation (18) becomes linear for $p_a = p_c$). However, $\hat{\alpha}^i$ could be measure with measurement error since it is estimated using riders' historical data, which depends on the number of trips riders have taken. We mitigate this concern by dividing each side of equation (18) by our estimate of $\alpha(1-\alpha)$ so that $\tilde{s}_c \equiv \frac{s_c}{\alpha(1-\alpha)}$:

$$\tilde{s}_c = 1/(1-\alpha) - (\eta - 1)\log(p_c/p_a). \tag{20}$$

As a result, we run the following regression at the rider i level for data generated during the week of the experiment:

$$\tilde{s}^i_c = \varphi_0 + \varphi_1 \log(p^i_c/p^i_a) + \epsilon^i \tag{21}$$

where φ_0 is a constant, our estimate of η is obtained from φ_1 (i.e. $\hat{\eta} = 1 - \hat{\varphi}_1$), and ϵ^i is an error term that contains potential approximation and sampling errors. Prices are rider-specific given that riders are assigned to either treatment or control groups. This regression has the advantage of moving the measurement error on α to the left-hand-side variable, thereby mitigating the attenuation bias that such measurement error may cause. We refer to this specification as the transformed-share case. Table 2 shows our estimates of η, the elasticity of substitution between Uber rides paid in cash and Uber rides paid in card.[39] In

[38]In Section K.1 we show that the first-order approximation is highly accurate, and the second-order approximation is nearly exact. Our normalization on the length of each ride implies that the cash and card prices faced by the control group are $p_a = p_c = 1$.

[39]Our baseline specification includes mexed users with more than 1% of their fares paid in cash and less

these specifications, columns (1)-(3), we find an elasticity of substitution of approximately 3. In column (4), we include the constant $1/(1-\alpha)$ specified in equation (20) as a regressor using each mixed rider's historical trips to estimate $\hat{\alpha}^i$ and find similar results. In column (5), we go back to equation (18) and use our estimates for $\hat{\alpha}^i$ to construct $\Gamma^i \equiv \hat{\alpha}^i(1-\hat{\alpha}^i)\ln(p_c^i/p_a^i)$. Then, we estimate:

$$s_c^i = \varphi_0 + \varphi_1 \Gamma^i + \epsilon^i.$$

In column (6), we follow a similar procedure using the second-order approximation to construct the second order term $\left(\Gamma^i\right)^2 \equiv \frac{1}{2}(1-\hat{\alpha}^i)\hat{\alpha}^i\left[1-2\hat{\alpha}^i\right]\left(\ln\left(p_c^i/p_a^i\right)\right)^2$ and estimate

$$s_c^i = \varphi_0 + \varphi_1 \Gamma^i + \varphi_2 \left(\Gamma^i\right)^2 + \epsilon^i.$$

In column (7), we instrument α, to reduce potential bias introduced by measurement error. First, we compute the predicted share of fares paid in card using all the control variables. Then, we estimate equation (18), as in column (5), using the predicted share. Our preferred estimates are in columns (5) and (7). While the point estimates vary across the different specifications displayed in Table 2, we find $\eta \approx 3$ or smaller throughout.[40]

For robustness, we tested specifications with and without controls (historical fares and tenure in Uber), specifications that split price increases and price decreases, and specifications that use different thresholds to define the set of mixed users (those with more than 5% and less than 95% of their fares paid in cash, etc). These robustness checks can be found in Section K.2. We find that the estimates for η are similar for *price increases* and price decreases (Table K32). In Table K33, we futher confirm that similar estimates are obtained using the second-order term of the CES function's second-order approximation, φ_2 (i.e. $\hat{\eta} = 1-(\hat{\varphi}_2)^{\frac{1}{2}}$). Importantly, we find that the estimates for η are independent of observables such as share of rides paid with cash, total fares, total fares in cash, and riders' tenure (Figure F1), all of which are highly correlated with riders' income. These additional results provide additional portability to our estimates for this parameter and our structural specification.

An alternative estimate for the elasticity of substitution can be obtained by aggregating the decision about the share of card-payment trips across riders. For this purpose, we write the second-order approximation for this choice s_c as a function of the prices faced by a single rider and as a function of her share parameter α and of the common elasticity of substitution η.[41] We interpret equation (19) as the expected value of the share of card trips. We let μ be

than 99% of their fares paid in cash. We present robustness checks with mixed users with more than 5% of their fares paid in cash and less than 95% of their fares paid in cash.

[40]Throughout, we estimate the standard errors using the Delta Method. Our results are unchanged if instead we use robust standard errors.

[41]In Section K.1, we show that for the range of the parameter of interest the first-order approximation is very accurate and the second-order approximation is nearly exact.

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

Note: The table reports estimates of the elasticity of substitution between cash and card payments for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between card and cash payments for each user the week of the experiment and the independent variable is the relative price for cash and card trips. Column (1) reports the results after using the transformed-share specification in equation (20) and including mixed users with more than 1% of their fares paid in cash and less than 99% of their fares paid in cash. Column (2) reports the same specification including controls. The controls included for each user are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95% of their fares paid in cash. Column (4) includes the constant specified in equation (20) as a regressor. Column (5) estimates the elasticity using the CES first-order approximation in equation (18). Column (6) estimates the elasticity using the CES second-order approximation in equation (19). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predicted share of fares paid in card (i.e. $\hat{\alpha}$) using all the control variables. Then, we estimate equation (18) using the predicted share. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

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

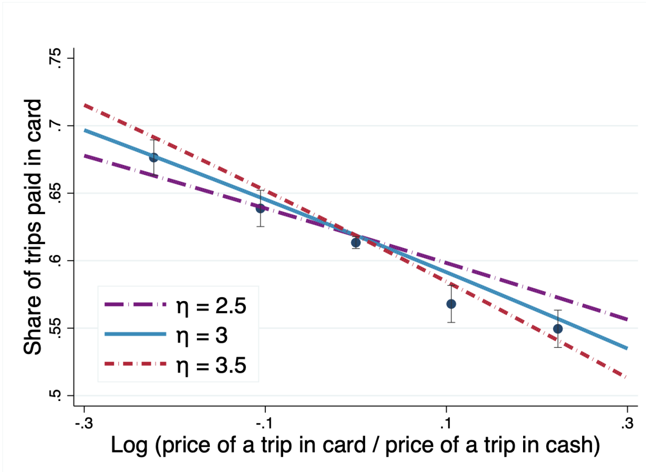
the distribution of α across the experiment's population. Riders enter into this population if they satisfy the conditions to be in the experiment –such as being active mixed riders– and they do so with weights proportional to the probability of taking a trip within a week. Control and treatment groups differ only in the randomly allocated prices p_c/p_a, so the the expected value of $\bar{s}_c(p_c/p_a)$ is given by:

$$\bar{s}_c\left(\frac{p_c}{p_a}\right) = m_1 - (\eta - 1)m_2 \ln\left(\frac{p_c}{p_a}\right) + m_3\left(1-\eta\right)^2\left(\ln\left(\frac{p_c}{p_a}\right)\right)^2 \tag{22}$$
$$m_1 = \int \alpha\mu(d\alpha),\ m_2 = \int \alpha(1-\alpha)\mu(d\alpha),\ \text{and } m_3 = \frac{1}{2}\int(1-\alpha)\alpha\left[1-2\alpha\right]\mu(d\alpha)$$

We estimate μ by using the distribution of the share of card payments prior to the experiment for 54,470 riders with positive trips during the experiment. The estimated values for the three moments are $\hat{m}_1 = 0.6187, \hat{m}_2 = 0.1349$ and $\hat{m}_3 = -0.0081$, with very small standard errors.

In Figure 3, we plot the actual average share across riders for each of the four treatment groups (10% and 20% cash discount and 10% and 20% card discounts) and for the control group, including its 95% confidence interval. We also plot three versions of the theoretical prediction equation (22), using the estimated moments $(\hat{m}_1, \hat{m}_2, \hat{m}_3)$. Each line corresponds to a different value of the elasticity of substitution, namely $\eta = 2.5, \eta = 3$ and $\eta = 3.5$, a range of values suggested by the regressions on Table 2. We note that given the small value of $\hat{m}_3$ the relationship between $\bar{s}$ and $\log(p_c/p_a)$ is almost linear, i.e. the first order

Figure 3: Experiment I and Elasticity of Substitution η



Note: The dots are the average card share for control and treatment groups with the corresponding relative price. The vertical lines are 95% standard error bands. The solid and dotted lines are the theoretical prediction for the expected card share displayed in equation (22) using the estimated values of $\hat{m}_1, \hat{m}_2$ and $\hat{m}_3$. The lines differ in the value of the parameter η.

approximation for the expected share is very accurate. Second, the dots, which correspond to the average card share for control and treatment groups for each price, are arranged in a nearly linear segment. Third, the value of $\eta = 3$ gives a very good fit, providing further validation to our previous estimates.[42] Lastly, in Section R we estimate the discrete choice version of our model and provide an alternative estimate for the elasticity of substitution, η. We again obtain estimates around 3 or smaller using sequential GMM.

We also estimate the composite Uber price elasticity ϵ for mixed users under our functional assumption of constant semi-elasticity, using the treatments where the cash and card prices $P = p_a = p_c$ are the same. These estimates are essentially regressions of the miles during the week of the experiment on the log of the price and a constant, following equation (9).[43] We find that the elasticity ϵ, evaluated at current prices, is approximately 1.1 or smaller, which corresponds to the first two columns of Table 3, labeled AA.

We also include the results of two other experiments conducted independently by Uber, labeled as Mandin and Ubernomics. We use these experiments to provide external validity to our estimates of the elasticity of demand for cash and mixed users. These experiments were not explicitly designed to give estimates of the elasticity and curvature of the demand function, but their results allow estimates of these parameters. We are able to select riders and

[42] Alvarez and Argente (2022) propose a mechanism for the simultaneous use of cash and cards and for the imperfect substitutability across payment methods. They show that mixed users are more likely to pay with cash whenever they have it available; in particular, they are more likely to pay with cash after they get paid.

[43] The normalization on the length of each ride implies that using miles as dependent variable is equivalent to using total fares.

Table 3: Elasticity of Demand: Mixed Users (Miles)

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

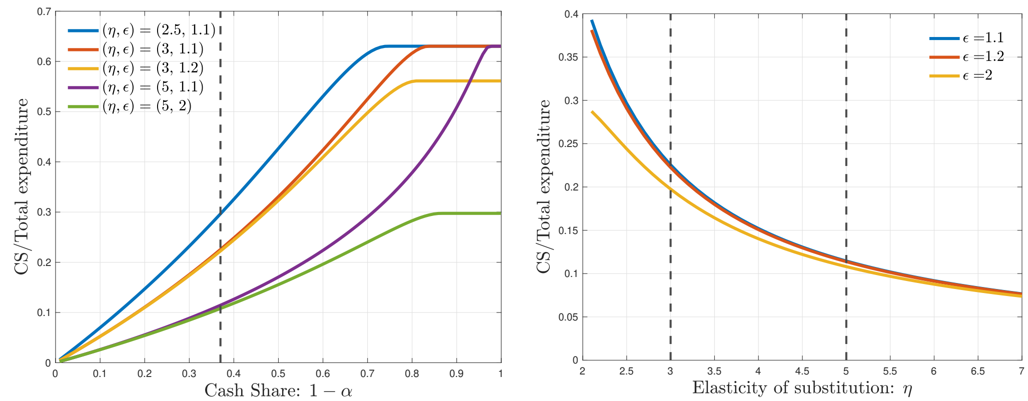
	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Elasticity	1.082***	1.030***	1.096***	1.278***	1.452***
	(0.103)	(0.086)	(0.093)	(0.075)	(0.296)
Observations	109,365	109,365	98,773	11,660	4,306
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

construct control variables to make the samples comparable using historical data. These confirmatory exercises return elasticities similar those found in our experiments.[44] The Mandin experiment is particularly relevant, since it had price variation that lasted four weeks. Thus, Uber riders were less likely to miss the promotion (avg. Uber rider in the State of Mexico takes 2.6 trips per month) and the experimental variation better approximates a permanent change in prices. Section K.2 contains several other robustness exercises that complement our estimated elasticities, including estimates of the semi-elasticity of demand, the elasticity of demand of number trips, the elasticity of demand for users that have taken at least 5 trips, the elasticity of demand in logs, the Poisson regression specification, and the Poisson pseudo maximum likelihood specification.

We next use the estimated values of η and ϵ to calculate the consumer surplus enjoyed by mixed users. Using these elasticities, the observed distribution of the share of cash trips, and the observed distribution of total fares, we implement equation (29). We aggregate riders weighting them by their fares paid in cash (i.e. Figure 2) so that the aggregate consumer surplus is the total surplus of the cash option over total expenditures. Figure 4 displays the consumer surplus as the share of a user's expenditure on Uber, where the horizontal axis shows the share of cash fares. Each line corresponds to different parameter values for ϵ and η. We estimate the consumer surplus lost after a ban on cash payments to be 25% what mixed

[44] The Ubernomics experiment took place in the Greater Mexico City from May 15th to May 22nd of 2017, only a few months after the introduction of cash in the State of Mexico. The treatment groups received discounts of 10% and 20% off in all rides taken the week of the experiment. The sample includes 4,869 pure cash users and 4,306 mixed users. The Mandin experiment took place in all areas of the Greater Mexico City in June 2018 and lasted four weeks. The treatment groups received discounts of 10%, 20%, and 30% off for all rides taken during the weeks of the experiment. The sample includes 5,668 pure cash users and 20,914 mixed users. More details on both experiments can be found in Section P.

Figure 4: Consumer Surplus: Mixed Users



Note: Panel (a) shows the model estimates of the consumer surplus (as a multiple of initial total fares) as a function of the share of a user's cash trips. The graph plots the estimates for different combinations of the elasticity of demand ϵ and the elasticity of substitution between cash and card payments η. The consumer surplus estimates are for mixed users, those who have paid for at least one trip using a payment card and for at least one trip in cash. Panel (b) shows the model estimates of the consumer surplus (as a multiple of initial total fares) as a function of the elasticity of substitution, η, for three different values of the elasticity of demand, ϵ. The expression used for the consumer surplus calculations is: $\epsilon(P_0)[-1/\epsilon(P_0) - 1 - \alpha^{\frac{1}{1-\eta}}(\log(\alpha^{\frac{1}{1-\eta}}) - 1/\epsilon(P_0) - 1)]$.

users spend on Uber rides.[45] Recall that mixed users account for about 50% all expenditures on Uber rides in the State of Mexico. Since the average mixed user pays for 37% of rides with cash, their consumer surplus decrease by 67% of their expenditures on trips paid in cash.[46] For $\eta = 5$, the consumer surplus lost for mixed users is 42.6% of cash fares.[47] Panel (b) shows that for $\eta \geq 5$, the consumer surplus lost is very similar for different values of ϵ.

5.2 Experiment 2: Consumer Surplus - Pure Cash Users

This experiment was targeted to pure cash users in order to understand their card adoption patterns. We focus on users that have not registered a card with Uber. We have four treatment groups each composed of approximately 20,000 riders and a control group of 56,000 riders. The treatment and control groups were balanced in the following observables: average

[45] The average of the ratio of consumer surplus to total Uber expenditures, using $\eta = 3$, $\epsilon = 1.1$, and the distribution of the α, weighted by fares, is 0.2463. This figure describes mixed riders who have taken more than five trips and have more than four weeks of tenure.

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

[47] An alternative research design would have been to only use the changes in cash prices to estimate the consumer surplus lost for mixed users (e.g. using the same four discounts as we use in Experiment 2). This alternative design has the advantage of yielding a more-direct measure of the curvature of mixed users' demand for cash trips and does not require an estimate of η. Figure D1 in Section D.2 shows that our implied functional form captures the shape of the mixed user's demand for cash trips in the data, which validates both the model and our parameter estimates. We opt for modeling payment choices for mixed users instead of following this alternative approach because it allows us to *increase relative prices* and estimate the elasticity of substitution η, which we believe is a parameter of interest that can be used for several counterfactuals.

Table 4: Elasticity of Demand: Pure Cash Users (Miles)

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

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

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. Note that, since the treatments cover several price points, the experiment is designed to provide information about the local convexity of the demand curve, which we use to inform our structural assumptions on the constant semi-elasticity demand function. 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. Two reminder emails were sent (in the middle of the week and two days before the promotions expired).[48]

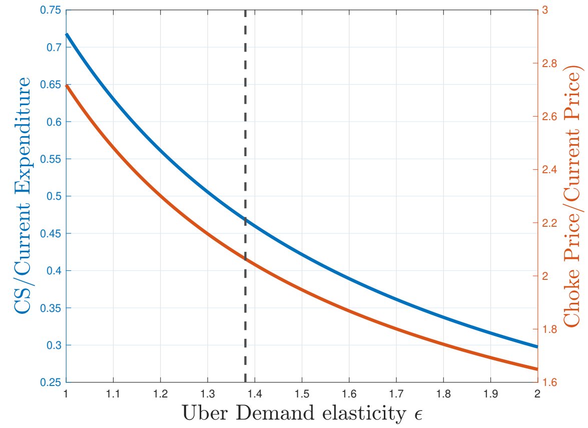
Using the miles traveled during the week of the experiment as the dependent variable, we estimate the price elasticity of demand, ϵ, to be approximately 1.38, when evaluated at current prices. Our baseline case is the semi-log demand corresponding to our functional form specification. Table 4 displays the estimates under columns AA, as well as estimates using the same specification for the Ubernomics and Mandin experiments. 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).[49]

Using the estimated price elasticity and our demand specification we next estimate the consumer surplus for pure cash users. Figure 5 displays our estimates for different elasticity estimates. Using 1.38, we estimate the consumer surplus to be approximately 47% of the total fares per year. The consumer surplus lost displayed in Figure 5 is, however, an *upper bound* estimate given that, some users might decide to begin using a card rather than leaving

[48] Examples can be found in Section O.

[49] Other specifications and further robustness exercises can be found in Section K.2 including estimates of the semi-elasticity of demand, the elasticity of demand of number trips, the elasticity of demand for users that have taken at least 5 trips, the elasticity of demand in logs, the Poisson regression specification, and the Poisson pseudo maximum likelihood specification.

Figure 5: Consumer Surplus and Choke Price: Cash Users



Note: The figure shows the model estimates of the consumer surplus (as a multiple of initial total fares) as a function of the elasticity of demand ϵ. The graphs also shows the model estimates of the choke point, the price at which the demand for Uber trips is zero as a function of ϵ. The estimates are for pure cash users, those that never registered a card in the application. The expression used for the consumer surp.us calculations is: $\epsilon(P_0)\left[\exp\left(1/\epsilon(P_0)\right)-1\right]-1$.

Uber completely after a large price increase. In fact, when the cash option was banned in Puebla, only 70% of the users left the platform. To adjust the consumer surplus of these riders we use both the experience in Puebla, as well as a third experiment to estimate the fixed cost of adopting a card payments. Section 5.3 provides more details.

The right axis of the figure displays the corresponding choke price implied by our functional form as a multiple of the current price. The choke prices corresponding to our preferred estimate for price elasticity are about double the current prices. We choose a demand function with constant semi-elasticity because it is consistent with the local convexity we found in the experimental data and because it implies a finite choke price. This implication is relevant because consumer surplus estimates are sensitive to the shape of the demand curve at very high prices, which are rarely explored in field experiments. For example, Table 5 reports estimates for pure cash users for different demand specifications using our estimated elasticity of demand. The table shows that our baseline specification predicts a consumer surplus 30% higher than the linear specification but at least 5.5 times smaller than the log-log specification. To go further in confirming our results, in the next subsection we use a natural experiment in the country of Panama and a survey instrument to validate the functional-form assumptions for the demand curve at very high prices.

5.2.1 Panama: Large Price Increase

We use data from a natural experiment in Panama, where the government abruptly limited the supply of drivers, to validate our functional-form assumptions and derive an additional

Table 5: Consumer Surplus Cash Users: Functional Forms

Note: The table displays estimates of the consumer surplus relative to expenditures for different functional forms at initial price P_0=1. The table shows the equations used for the calculation and the estimates for $\epsilon = 1.2$, $\epsilon = 1.38$, and $\epsilon = 2$. Our baseline estimates are under the semi-log specification and $\epsilon = 1.38$.

	CS relative to expenditures	$\epsilon = 1.2$	$\epsilon = 1.38$ (baseline)	$\epsilon = 2$
Linear	$\frac{1}{2}\frac{1}{\epsilon(P_0)}$	0.42	0.36	0.25
Semi-log (baseline)	$\epsilon(P_0)\left[\exp\left(\frac{1}{\epsilon(P_0)}\right)-1\right]-1$	0.56	0.47	0.30
Log-log (constant elasticity)	$\frac{1}{\epsilon-1}$	5	2.6	1

estimate of demand elasticity. These data is particularly informative about the demand curve's shape at elevated prices, as the cost of Uber rides nearly doubled following the government regulation.

Uber launched in Panama in February 2014, initially operating in three provinces: Panama City, Panama West, and Colon.[50] Panama City is the most active province in terms of rides. In August 2016, due to the low penetration of credit card use, cash payments were introduced nationwide. Within a year, over half of all trips were paid with cash.[51] Panama's government imposed restrictions on Uber in October 2017. The decree included a ban on cash payments for Uber rides, mandated a special license ("E1" type) for drivers, costing around $200 USD and obtainable only by nationals over 21, following a 36-hour seminar. The decree also introduced a fleet cap of two cars and geographic limitations, allowing Uber to operate in only four out of Panama's ten provinces. Driver restrictions took effect on January 2, 2018.[52] As a result, 83% of Uber drivers were disconnected from the application due to lacking the E1 license. The unexpected reduction in driver supply led to a surge in surge-priced trips, increasing from an average of 16% in 2017 to 45% in 2018. As shown in Figure 6, the share of cash-fare trips notably decreased from over 50% in 2017 to less than 35% in 2018. This decline in cash payments exceeded that of card payments, consistent with our findings that the demand for Uber trips paid in cash is more elastic than for card payments.

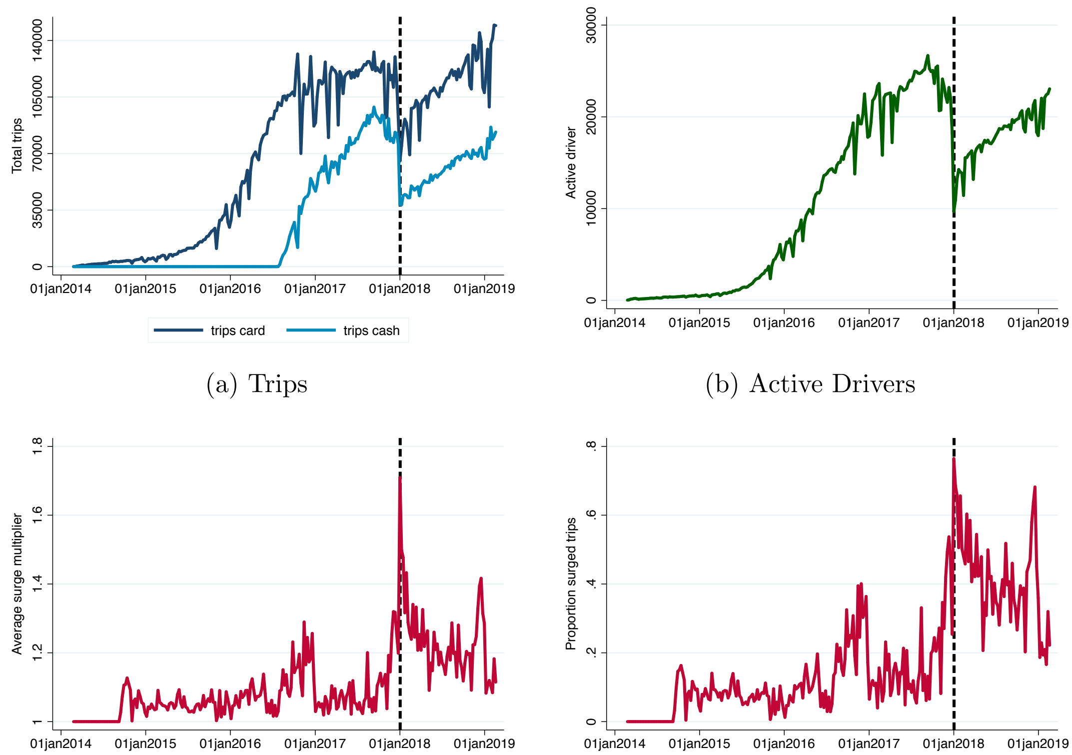
Interpreting this natural experiment as an exogenous reduction in driver supply, we use data on total trips and average surge multipliers to trace the Uber demand function in Panama. In Figure 7, we show the number of trips plotted against prices for each of the 52 weeks in 2018 following the driver supply restriction. The blue line illustrates the fit of the semi-log demand function implied by our chosen functional forms. Under this specification,

[50]A recent Supreme Court decision has allowed Uber to extend its services to more provinces.

[51]Cabify, present in Panama since June 2016, still holds a low market share.

[52]Uber negotiated an extension for the cash ban deadline until May 2019, later renewed until October 2019. Cash payments were temporarily banned in February 2020.

Figure 6: Panama: Trips, Fares, and Drivers



(a) Trips

(b) Active Drivers

(c) Avg. Surge Multiplier

(d) Share Surged Trips

Note: The figure shows the evolution of trips, active drivers, the average surge multiplier and the share of surged-price trips in Panama. The frequency of the data is weekly. The black dotted line marks the date that the restrictions went into effect.

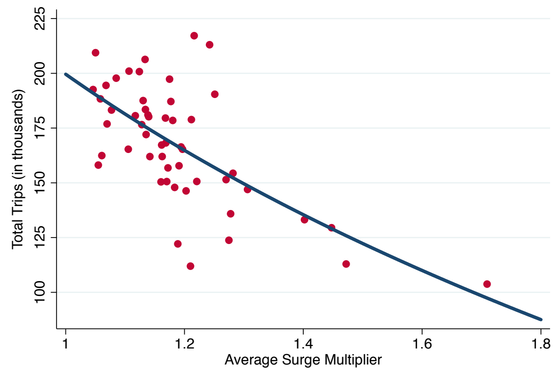
we estimate the elasticity of demand to be approximately 0.95 for all trips in Panama City. If we focus on cash-fare rides, the demand elasticity increases to about 1.00, with both elasticities evaluated at baseline prices. The share of cash-fare rides was approximately 0.4 before the driver restriction but decreased afterward, consistent with the higher elasticity of cash trips. All these trends are consistent with the trends we observe in our data from the State of Mexico.[53] The graph also shows that, even at the very high prices we could not explore in our experiments, the demand curve fits the observed patterns of total trips and prices remarkably well. Even in weeks during which prices almost double, our functional-form assumption of exponential utility fits the patterns observed in Panama well.

5.2.2 Survey Instrument: Choke Prices

We also used a survey instrument to gain further insight into how price changes might affect consumer preferences and what the choke price might be. The survey was sent to the riders

[53] Details on these estimates are provided in Section L.

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



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

in our experiments 11 months after the experiments concluded. Six different surveys were randomly given to users, with three questions each. We received more than 6,000 responses, an average of 1056 responses per survey.[54] This format allowed us to minimize response times and, at the same time, allowed us to obtain a range of responses for a given question. For example, all surveys included the following question: "If you were to receive a 20% discount for one week, how would you change the number of trips you take...". Some users were given the options to respond a) no change, b) increase less than 10%, c) increase more than 10%. A second set of users were given options to respond a) no change, b) increase less than 20%, c) increase more than 20%. And a third set of users were given options to respond a) no change, b) increase less than 30%, c) increase more than 30%.

Each survey also included two other symmetric questions, one related to a *permanent* large price decrease (e.g. "If the price of trips is permanently reduced by half, how would you change your trips...") and another related to a permanent large price increase (e.g. "If the price of trips is permanently doubled, how would you change your trips..."). Half of the surveys sent asked users to respond to permanently doubling prices or permanently reducing prices by half, while the other half of surveys asked users to respond to prices permanently tripled or cut by a third. In response to the question about a permanent price increase, the users could respond with the following options: i) no change, ii) decrease substantially, iii) stop traveling. We use the answers to the first questions to compare elasticities from

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

the survey to those obtained from our experimental design in order to validate the survey instrument and verify that the reported elasticities are informative about revealed preference elasticities. We use the last question of the survey about the permanent doubling or tripling of prices to obtain information about the distribution of choke prices and to compare it to the distribution implied by our structural framework.

To analyze users' responses, we proceed in three steps. First, we adjust the covariate distribution of survey respondents by reweighting to make the distribution more similar to the covariate distribution of the entire population that participated in our experiments based on their history of trips per week and their tenure. We accomplish this step with entropy balancing, a multivariate reweighting method described in Hainmueller (2012). Second, we use responses to the first question to validate the survey instrument and confirm that the reported elasticities are informative about the revealed-preference elasticities estimated from our experiments; the bounds implied by the survey responses align well with those in the experimental data. Lastly, we use responses to the third question to compare the reported choke prices to those implied by our model. The reminder of this section is focused on this last step, but we provide more details about the previous two steps in Section E.

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

$$\bar{P} = \exp\left(\frac{X(P)}{-k}\right) \tag{23}$$

where $X(P)$ is the number of miles a rider travels in a week and k is the semi-elasticity we estimated from experimental data. Since the survey responses provide us with a distribution of choke prices, we implement equation (23) using the data to obtain the distribution of choke prices implied by our structural assumptions. This requires taking a stance on the riders' heterogeneity. In this case, we use each user's history of average weekly fares to approximate $X(P)$ and the semi-elasticity estimated in our experiments.[55] Table 6 presents the distribution of choke prices for mixed users.

The median choke price for mixed users implied by our model is 1.82. There is considerable heterogeneity in the choke prices; the ratio between the 75$^{\text{th}}$ and the 25$^{\text{th}}$ percentiles is 2.42. Given our structural assumptions, if we doubled prices, 56% of users would leave the platform and, if we tripled prices, approximately 73% of users would stop using Uber. These figures are remarkably close to the survey responses. Approximately, 56% of respondents said they would stop traveling if prices doubled and 67% responded that they would stop traveling if prices were tripled. Next, we study pure cash users. Their choke price is defined as:

[55] To minimize measurement error in the historical average of weekly fares, we trim top and bottom 1%.

Table 6: Distribution of Choke Prices

Note: The table shows moments of the distribution of choke prices implied by framework described in Section 4 for both mixed users and pure cash users. To approximate $X(P)$, we use each user's historical average of weekly fares. To minimize the measurement error, we trim the top and bottom one percent. The semi-elasticity k is that estimated for each group of users presented in Table K1 and Table K9.

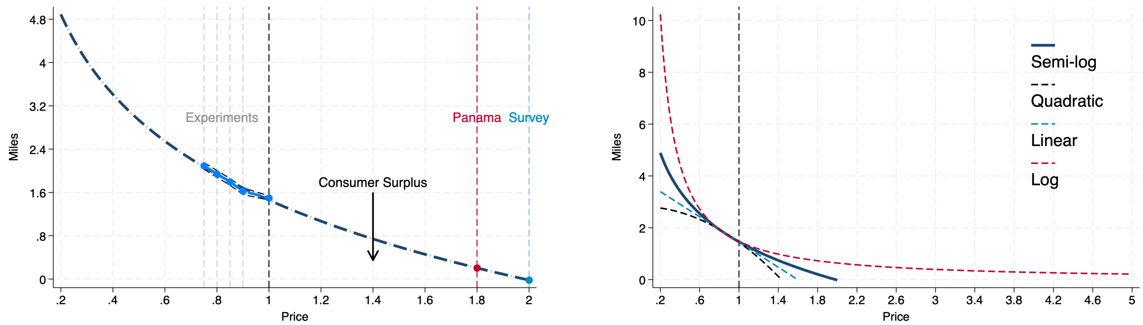
Choke Price	(1) Mean	(2) Std. Dev.	(3) 10th	(4) 25th	(5) Median	(6) 75th	(7) 90th
Mixed users	6.0	20.7	1.18	1.35	1.82	3.28	8.19
Pure cash users	4.8	12.0	1.62	1.78	2.19	3.36	7.0

$$\bar{P} = \exp\left(\frac{\tilde{a}(p_a, \infty)}{k(1-\alpha)^{\frac{1}{1-\eta}}} + \log\left((1-\alpha)^{\frac{1}{1-\eta}}\right)\right) \tag{24}$$

where $k(1-\alpha)^{\frac{1}{1-\eta}}$ is the semi-elasticity of demand for pure cash users, as estimated directly from our regressions. The median choke price in this case is 1.99 and the ratio between the 75^{th} and the 25^{th} percentiles is 1.88. Our model implies that if we doubled prices, 51% of users would leave the platform, aligning with 54% in survey responses. If prices tripled, our framework implies that 75% would leave the platform, closely matching the 69% from surveys. Given that self-reports are informative about revealed-preference elasticities, these findings about the choke prices provide additional validation to our structural assumptions.

Panel (a) Figure 8 shows the demand curve for Uber rides paid in cash. The dashed lines indicate points of the demand curve that are estimated either by experiments, observational data (Panama), or survey data. The figure shows we cover almost all the relevant range of variation in prices, from below equilibrium prices to the choke price. The chosen semi-log demand form is consistent with the observed local convexity between miles and prices, as estimated from experimental evidence, and with a finite choke price, as observed in survey data. Panel (b) of Figure 8 shows different demand curves for different functional forms. The figure illustrates that the location of the choke price significantly affects consumer surplus. In Section Q.3, we compare the reported choke prices to those implied by linear, semi-log, and log-log demand functions. We show that under a linear demand specification, too many users stop using Uber relative to the estimates from the survey. Under a semi-log demand function, as we discussed before, the estimates on the fraction of users who would stop riding Uber after a price increase are remarkably close to the survey evidence. The CES functional form (or log-log after taking logarithms) can be rejected by the survey data since this functional form does not have a finite choke price. In other words, even for very high prices, riders continue to use Uber. The survey data shows that there is a sizable share of riders who would stop using Uber if prices were to double or triple, contradicting this demand specification.

Figure 8: Demand Curve: Cash Payments Uber Rides



Note: Panel (a) displays the semi-log function. The dashed lines represent the estimated points obtained from experimental, observational, or survey data as well as the equilibrium prices. The demand curve derived from experiments is estimated using the miles traveled during the week of the experiment as the dependent variable. To calculate each point, we first demean the following observables: trips, trips squared, fares, fares squared, and tenure. We then estimate a regression of miles on all the treatment arms in logs, without including a constant. Panel (b) displays other demand functions calibrated using the same procedure. It includes a semi-log, quadratic, linear and log-log function.

5.3 Experiment 3: Net Consumer Surplus - Pure Cash Users

The estimates of the consumer surplus for pure cash users reported in Section 5.2 under our structural assumptions still need to be adjusted for the fact that, in the event of a ban on cash, riders could decide to pay the fixed cost of adopting a card and return to the application. Experiment 3 is designed to estimate the fixed cost of adopting a payment-card. The experiment is targeted to pure cash users in order to understand their card adoption patterns. We focus on users that have not registered a card with Uber.

We offered rewards if a user registered a card in the application, without imposing restrictions on the payment method used for subsequent rides. This was the first time Uber Mexico implemented an experiment of these characteristics. The treatment groups received rewards of 100, 200, or 300 pesos (5.2, 10.5 and 15.7 USD), which are approximately 3, 6, and 9 times the average weekly fares (or approximately 1, 2 and 3 average rides). The experiment is designed to obtain information about different points in the distribution of fixed costs. Given that pure cash users might or might not have a card already, the experiment had two treatments for each reward with two different time horizons. The first lasted only one week, targeting users that might already have a card, but have not registered it in the application. The second lasted 6 weeks in order to allow enough time for users to obtain a new card. These users received email reminders about the promotion every week. Overall, the experiment included six treatment groups with three incentive levels lasting one and six weeks, each made up of approximately 20,000 riders and a control group of 40,000 riders.

Table 7 shows the percent of pure cash users that adopted a payment-card (registered a

Table 7: Extensive-Margin: Adoption of a Payment-Card

Note: The table reports the percent of users that adopted a payment-card for each of the treatment groups in experiment three relative to the control group. Migration is an indicator function that equals one if the user registered a card conditional on taking trip the weeks of the experiment. The variables "Treatment" report the migration rates relative to the control group of the three treatment groups in the experiment: 3, 6, and 9 times their average weekly fares if the users register a card in the application. Column (1) reports the rates of card adoption for the experiment that lasted one week. Column (2) reports the rates of card adoption during the first week for the experiment that lasted six weeks. Column (3) reports the rates of card adoption for the experiment that lasted six weeks. Column (4) reports the rates of card adoption during the first three weeks of the experiment. Column (5) reports the rates of adoption in the last three weeks of the experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels.

	(1) 1 week	(2) 1 week	(3) 1-6 week	(4) 1-3 week	(5) 4-6 week
Treatment 1 - 1 week	0.0241***				
	(0.004)				
Treatment 2 - 1 week	0.0269***				
	(0.004)				
Treatment 3 - 1 week	0.0366***				
	(0.004)				
Treatment 1 - 6 week		0.0166***	0.0333***	0.0283***	0.0112***
		(0.004)	(0.004)	(0.004)	(0.003)
Treatment 2 - 6 week		0.0217***	0.0394***	0.0382***	0.0088***
		(0.004)	(0.004)	(0.004)	(0.003)
Treatment 3 - 6 week		0.0390***	0.0468***	0.0485***	0.0088***
		(0.004)	(0.004)	(0.004)	(0.003)
Constant	0.0272***	0.0272***	0.0711***	0.0445***	0.0372***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	20,609	20,677	46,996	36,184	46,996
R-squared	0.005	0.005	0.005	0.006	0.001

card in the application) in each of the treatment groups conditional on having taken a trip during the weeks of the experiment. Column (1) and (2) show the adoption rates during the first week, for the one-week and six-week experiments. The columns show that similar amounts of users register a card in the first week, regardless of the time horizon. In both cases, users in the treatment groups responded significantly to the incentives provided, relative to the control group. We observe more migration to card payments when larger incentives are offered. For instance, for a reward of slightly more than 15.2 USD the migration rate increases by 3.9%, which is statistically significantly larger than the migration rate with a reward of 5.2 USD, which is 1.6% –see column (2) of the table.[56]

Column (3) shows the overall migration rate over the span of 6 weeks and Column (4) and (5) examine the migration rates during weeks 1-3 and weeks 4-6 respectively. The columns show that significantly more users migrate during the first three weeks of the experiment than do in the latter three weeks. This indicates that, although our incentives were sufficiently

[56] To address concerns about potential contamination of the estimated elasticities and/or migration rates by the advertisement effect of receiving promotional emails from Uber, Table K34, Table K26, and Table K37 present results using only the variation across treatment arms. These results closely align with those reported in our baseline specifications.

enticing to encourage migration of marginal users, they were not enough to substantially incentivize users that did not own a card. Importantly, Table K35 shows that users in our treatment groups were more likely to use cards more than 6 months after our experiment ended. The table shows that, conditional on traveling 6-8 months after our experiments and having taken a trip during the weeks of our experiments, the probability of paying with a card is larger for users in our treatment groups.[57]

We next use a variety of observations to estimate the consumer surplus lost in a ban, taking into account the effect of those pure cash riders that choose to pay the fixed cost and become pure card users after the ban. To do so, we combine theoretical aspects with experimental evidence. On the theoretical side we use the specifications of preferences (described in Section 4.4), with their implications for demand (derived in Section A.5), the corresponding indirect utility functions derived in Section A.6, and the conditions that fixed cost and indirect utility have to satisfy for the optimal adoption of cards, as described in equation (13) and equation (16). On the experimental side, we use the parameters estimated in Experiment 2 for the demand of trips for pure cash users, the elasticity of substitution between cash and card payments estimated in Experiment 1 for mixed users, the migration rates under each of the incentive levels described in Section 5.3 from Experiment 3. With this information we jointly estimate the counterfactual share parameter α for pure cash users, the parameters for the utility function U for composite rides for pure cash users (k and $\bar{P}$), and the distribution of the fixed cost G. In our choice of α, we strive to be conservative by making choices that give a *lower bound* to the net consumer surplus lost. All details can be found in Section A.7.

Approximately 70% of the pure cash riders stop using Uber after the ban of cash according to the evidence from Puebla, which is a very similar city to the State of Mexico in the context of the cities served by Uber across Mexico. From Table 4 our estimated elasticities at pre-ban prices are approximately 1.38 for this group, so their consumer surplus loss is almost 47% of their yearly expenditure in Uber. For the remaining 30% of riders the losses are smaller.[58]

For the remaining 30% of riders, those who pay the fixed cost and return to the application, the losses are smaller. Pure cash users who transition to exclusively using cards significantly reduced their number of trips after the ban. Using this information, along with the excess migration rates estimated in Experiment 3, we calculate a lower bound for the net consumer surplus for pure cash users who register a card after the ban of about 44% of their

[57] Table K36 shows unconditional migration rates – users registering a card in the application regardless of whether they took trips during the weeks of the experiment. The table shows that the overall unconditional migration, over the six weeks that the experiment lasted, are similar to those presented in Table 7.

[58] In Section M we compare Puebla and the State of Mexico and we correct our estimates to take into account observable differences between Puebla and the State of Mexico, which may lower this estimate up to 29%; Puebla's residents have in average about one more year of education, and have higher financial inclusion. In the spirit of obtaining a lower bound on the consumer surplus lost, we retain the 30% figure.

yearly expenditure on Uber. The net consumer surplus lost varies significantly across the distribution of riders. The consumer surplus lost is higher for pure cash users who travel more due to the convexity of the net consumer surplus lost and the skewness of the distribution of historical trips.[59] Aggregating both groups, riders who register a card and riders who do not register a card after a ban on cash, the ban on cash results in an average loss of consumer surplus for pure cash riders, amounting to about 46% of their total Uber expenditures.

6 Consumer Surplus Estimates

6.1 Taking Stock

The consumer surplus lost after a ban on cash payments has a *lower bound* of at least 50% of total expenditures on cash-fare Uber rides, and an *upper bound* of 57%. We proceed by summarizing how we computed these estimates. For mixed users, who account for about 50% of Uber fares, we estimate a loss in consumer surplus of about 25% of what they spend on Uber rides. For pure cash users, who account for 20% of all fares collected by Uber and tend to be poorer, we estimate a loss in consumer surplus of at least 46%. Adding up the loss of consumer surplus from mixed users and pure cash users, the consumer surplus lost is about 30% of what the two groups spend on Uber rides. Considering that mixed users pay for about 37% of their Uber rides with cash, we obtain our 50% headline figure for the lower bound of the consumer surplus lost in a ban on cash.[60] An upper bound of this estimate can be found if we do not account for pure cash riders registering a card in the app after a ban on cash. The upper bound estimates are very close to the lower bound estimates, at about 57% of total expenditure on cash-fare Uber rides. The magnitudes of our estimates reflect i) the intensity with which cash is used in the application by *both* mixed users and pure cash users, ii) the convexity of the demand curve for Uber rides, iii) the high costs of registering cards, and iv) the fact that users view cash and cards as far from perfect substitutes.

6.2 Short-Run vs Long-Run

Throughout this paper, our objective has been to obtain credible consumer surplus estimates by considering price variations over several periods. First, we validate our estimates of the elasticity of demand, denoted as ϵ, using data from a four-week price experiment that more

[59] Section A.7 presents the detailed calculations for this lower bound. It also shows the net consumer surplus lost computed cell-by-cell, where the cells are percentiles of the distribution of the historical number of trips.

[60] The calculation for the consumer surplus lost is the average of the consumer surplus of pure cash users and mixed users weighted by their share of total cash expenditures: $0.46 \times \frac{0.20}{0.2+0.5\times0.37} + 0.67 \times \frac{0.5\times0.37}{0.2+0.5\times0.37} > 0.5$.

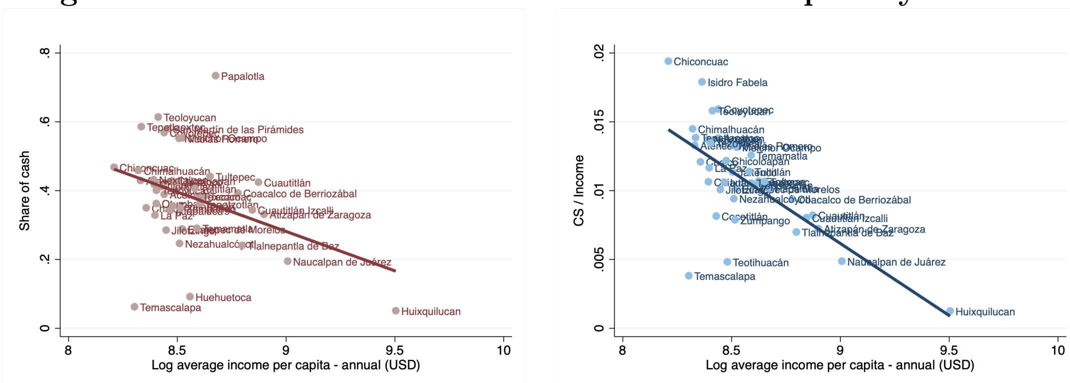
closely approximates permanent changes in prices. Furthermore, we rely on the natural experiment in Panama to gather information on large price increases lasting more than a year. Second, we estimate the distribution of fixed costs through a six-week experimental design and data from an actual ban on cash payments in Puebla (i.e., ψ_{ban}). Lastly, our survey instrument is designed to specifically elicit responses to *permanent* price increases, and the choke prices implied by our structural framework align with the responses obtained from the survey instrument.

However, a caveat arises due to the short-term nature of the price variations used to estimate the elasticity of substitution, η. This could introduce a bias toward finding a lower estimate for the elasticity than the long-run elasticity, potentially leading to an overestimation of consumer surplus loss.

To ameliorate this concern, we draw upon the quasi-natural experiments documented in Alvarez and Argente (2022), which provide information on the long-run elasticity of substitution across payment methods, *given an estimate of the elasticity of demand and the combination of CES and semi-log assumptions*. Thus, the estimates in this paper for the elasticity of demand ϵ allow us to recover η from observational data in Puebla, following an actual ban on cash payments.[61] We believe this estimate for η complements the estimates using experimental data presented in this paper. While the estimate in this paper comes from short-run variation, it is cleanly identified using exogenous changes in relative prices. On the other hand, the estimate that can be obtained using data in Alvarez and Argente (2022) is indirect, as it relies on assumed functional forms, given that prices change from zero to infinity. It may also be contaminated by confounding factors occurring after the ban on cash in Puebla, such as changes in crime. However, it offers a long-run estimate of the elasticity of substitution, which is relevant for the evaluation of a permanent ban on cash. Our short-run estimates (i.e., $\eta \approx 3$) are close but smaller than the long-run estimates (i.e., $\eta \approx 5$). This ordering is reassuring since it is consistent with the Samuelson/Le Chatelier principle. Using the *long-run* elasticity, the consumer surplus loss for mixed users is 11% of what mixed users spend on Uber. Considering both pure cash and mixed users, we obtain a long-run estimate of 38% of total cash expenditures. Figure 4 and Figure 5 show the sensitivity of the consumer surplus estimates to a wider range of demand elasticities.

[61] More specifically, to estimate η from observational data, we rely on equation (28) to formulate an expression for the change in total trips before and after the ban on cash: $\Delta T = \alpha^{\frac{1}{1-\eta}} \left(1 - \frac{\epsilon}{1-\eta} \ln \alpha\right)$. Since the change in trips is observed in the data, we can use our estimates for ϵ and data for α to infer η.

Figure 9: Share of Cash Fares and Consumer Surplus by Income



(a) Share of Cash Fares (b) Consumer Surplus

Note: Panel (a) shows the share of cash fares and the average income per capita per year in USD. Panel (b) shows the consumer surplus from paying Uber in cash in each municipality of the State of Mexico as a fraction of the average income per capita per year. The consumer surplus lost at the municipality-level is the average of the consumer surplus of pure cash users and mixed users weighted by their share of total expenditures. We multiply income times 1.24 to account for the fact that individuals with access to a smartphones earn higher income. The income data comes from individuals that report labor income surveyed in the Intercensal Survey of 2015. The data on smartphone usage comes from the 2015 National Survey of Financial Inclusion (ENIF). The data of Uber rides are from August of 2018 in the State of Mexico.

6.3 Distributional Consequences

To determine the *distributional* consequences of a ban in the cash payment option, we estimate the consumer surplus at the municipality-level, the finest level of aggregation at which per capita income is available. To do so, we use geolocalized information about every trip taken in the State of Mexico during the month of August 2018. We assign each user to the municipality where most of his or her trips originated.[62] After classifying riders into pure cash users and mixed users, we calculate the consumer surplus for both groups in USD, considering that pure cash users spend approximately 80 USD per year in Uber rides while mixed riders spend 200 USD per year.[63] The consumer surplus lost at the municipality-level is the average of the consumer surplus of pure cash users and mixed users, weighted by their share of total expenditures in Uber in the municipality.

Panel (b) of Figure 9 displays the consumer surplus loss as a share of the average annual income of Uber riders at the municipality-level. A rider who uses cash either sometimes or exclusively suffers an average loss in consumer surplus of approximately 0.8% of her annual income.[64] The figure also shows that cash ban losses fall mostly on households who reside

[62] Section G shows that income per capita is correlated with financial access, commuting times, transportation modes, public infrastructure, and the use of cash in Uber.

[63] Table D1 reports the weekly expenditures by pure cash users and mixed users. In order to accurately classify riders across user types, we consider riders with at least 4 trips in August 2018. We also use the share of payments made with card at the municipality-level to reduce potential measurement error.

[64] The average annual income of Uber users in the State of Mexico is approximately 6,400 USD. This

in low-income municipalities. These households rely more heavily on the cash option. Panel (a) of Figure 9 indeed shows that the share of cash fares declines with income per capita.[65] These findings imply that, in the case of Uber rides, restrictions on the use of cash have important distributional consequences that mainly affect the least-advantaged households.

6.4 Applications: The Cases of Panama and Argentina

Our results can be used to estimate the welfare effects of similar policies promulgated elsewhere. We have estimated price elasticities for riders of different types in Panama that are similar to those in the State of Mexico—see Section 5.2.1 and Section L. Thus, keeping other parameters at the values estimated for the State of Mexico, the ban on cash fares in Panama caused a consumer surplus loss of approximately 50% of total expenditures paid in cash.

Our estimates are also relevant for policies applied in the southern cone. In Argentina, the municipal government of the city of Buenos Aires, as a way to curtail the use of Uber, issued a prohibition on the processing of card payments in the Uber app, which had the implication that cards were not accepted in the entire country. Hence, for a while, Argentina's riders could only pay with cash. Motivated by this, we estimate the consumer surplus losses from a *ban on card payments*, assuming that all the parameters are as in the state of Mexico –see Section N for details. We found that the consumer surplus loss from a ban on card payments is approximately 80% of the yearly expenditure on Uber paid by card before the ban. This loss exceeds the loss from a ban on cash. Throughout our analysis, we assume there is no fixed cost associated with using cash.[66] Consequently, according to our model, it implies that pure card riders have very strong preferences for card payments (i.e., $\alpha \approx 1$) because the cash option has always been available to pure card riders at no cost, yet they consistently opt not to pay with cash.[67] This indicates that, in the event of a ban on card payments, pure card riders would cease using Uber altogether, resulting in the complete loss of their consumer surplus. These users tend to spend more on rides, and their demand for rides is less elastic. Furthermore, mixed users are more affected by a ban on card payments than by a ban on cash payments, given that they pay for approximately 63% of rides with a card.

estimate is calculated by averaging the per capita income across municipalities weighted by the total number of Uber users in each municipality. We multiply this number by 1.24 to account for the fact that individuals with access to a smartphone earn higher income. The income data comes from Intercensal Survey of 2015 and the data on smartphone usage comes from the 2015 National Survey of Financial Inclusion (ENIF).

[65] Figure G1 shows a similar pattern for the share of pure cash users at the municipality-level.

[66] Consistent with our assumption that the cash option has no fixed costs, Figure J1 shows that mixed users are more likely to start as pure card users rather than pure cash users before switching.

[67] Alternatively, viewed through the lens of the discrete choice model developed in Section B, their preference shocks always lead them to choose card over cash.

7 Conclusion

Policies restricting means of payment have recently received great interest, and their possibility has been debated both by policymakers and academics. There are very few attempts to quantify the welfare effects of such policies, mainly because opportunities for accurate estimations of the relevant elasticities for this calculation for a given good or service are rare. In this paper, we combine a theoretical model with three large field experiments in Mexico to estimate the consumer surplus of using cash as a payment method in Uber. The total consumer surplus lost after a ban on cash payments is large, equivalent to 40-50% of total expenditure on cash-fare Uber rides. Given that the majority of trips paid in cash originate in low-income municipalities, these losses fall mostly on the least-advantaged households, who rely heavily on the cash payment option.

We have several other findings of interest for the literature on money demand and for the analysis of policies attempting to encourage or discourage payment methods. We found a statistically significant but small elasticity of the adoption/registration of cards when riders are given incentives. A reward of 15 USD increases the adoption rate by less than 4%, which is largely explained by the registration of existing cards. Nevertheless, users who registered a card after receiving a reward were more likely to use it to pay for rides in the future. This finding is relevant for the analysis of policies that encourage access to financial services, particularly in developing countries where pure cash users are widespread.

We also provide a well-estimated elasticity of substitution across payment methods using experimental data, an important input to models that incorporate a choice between means of payment. The low substitutability across payment methods implies that the optimal response of shifting away from cash payments (e.g. during the COVID-19 pandemic) is not without cost, even if people have access to other means of payment. This elasticity of substitution can be used to parameterize models designed to analyze counterfactuals in which means of payment are subject to a tax or a subsidy. For example, Alvarez et al. (2021) use our estimates to quantify the private costs of heavily taxing the use of cash to pay for all goods in Mexico and found that the private losses that follow a 40% tax on cash are approximately 6% of GDP. The extension of our analysis of Uber trips to the analysis of different goods and services, as well as our estimated elasticities, are important areas for future research.

References

Allen, R., Rehbeck, J., 2018. Assessing Misspecification and Aggregation for Structured Preferences. Manuscript. Working Paper.

Alvarez, F., Argente, D., 2021. Cash-management in times of covid-19. The BE Journal of Macroeconomics .

Alvarez, F., Argente, D., 2022. On the effects of the availability of means of payments: The case of uber. The Quarterly Journal of Economics .

Alvarez, F., Argente, D., Jimenez, R., Lippi, F., 2021. Cash: A blessing or a curse? Journal of Monetary Economics .

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

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

Anderson, S.P., De Palma, A., Thisse, J.F., 1987. The ces is a discrete choice model? Economics Letters 24, 139–140.

Angrist, J.D., Caldwell, S., Hall, J.V., 2021. Uber versus taxi: A driver's eye view. American Economic Journal: Applied Economics 13, 272–308.

Borzekowski, R., Kiser, E.K., Shaista, A., 2008. Consumers' use of debit cards: patterns, preferences, and price response. Journal of money, credit and banking 40, 149–172.

Briglevics, T., Schuh, S., 2020. This is"what's in your wallet"... and here's how you use it .

Buera, F.J., Kaboski, J.P., Shin, Y., 2021a. The macroeconomics of microfinance. The Review of Economic Studies 88, 126–161.

Buera, F.J., Kaboski, J.P., Townsend, R.M., 2021b. From micro to macro development .

Ching, A.T., Hayashi, F., 2010. Payment card rewards programs and consumer payment choice. Journal of Banking & Finance 34, 1773–1787.

Chodorow-Reich, G., Gopinath, G., Mishra, P., Narayanan, A., 2020. Cash and the economy: Evidence from india's demonetization. The Quarterly Journal of Economics 135, 57–103.

Cohen, P., Hahn, R., Hall, J., Levitt, S., Metcalfe, R., 2016. Using Big Data to Estimate Consumer Surplus: The Case of Uber. Working Paper 22627. National Bureau of Economic Research.

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

Dubé, J.P.H., Joo, J., Kim, K., 2022. Discrete-Choice Models and Representative Consumer Theory. NBER Working Papers 30130. National Bureau of Economic Research, Inc.

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

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

Hainmueller, J., Hangartner, D., Yamamoto, T., 2015. Validating vignette and conjoint survey experiments against real-world behavior. Proceedings of the National Academy of Sciences 112, 2395–2400.

Hall, J.V., Horton, J.J., Knoepfle, D.T., 2023. Ride-sharing markets re-equilibrate. Technical Report. National Bureau of Economic Research.

Hansen, L., 2007. Generalized method of moments estimation. the new palgrave dictionary of economics, ed. by stephen durlauf, and lawrence blume.

Hausman, J.A., 1981. Exact consumer's surplus and deadweight loss. The American Economic Review 71, 662–676.

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

Kaboski, J.P., Townsend, R.M., 2011. A structural evaluation of a large-scale quasi-experimental microfinance initiative. Econometrica 79, 1357–1406.

Karlan, D., Osman, A., Zinman, J., 2016. Follow the money not the cash: Comparing methods for identifying consumption and investment responses to a liquidity shock. Journal of Development Economics 121, 11–23.

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

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

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

Koulayev, S., Rysman, M., Schuh, S., Stavins, J., 2016. Explaining adoption and use of payment instruments by us consumers. The RAND Journal of Economics 47, 293–325.

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

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

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

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

Méndez, E., Van Patten, D., 2021. Voting on a trade agreement: Firm networks and attitudes towards openness .

Parker, J.A., Souleles, N.S., 2019. Reported effects versus revealed-preference estimates: Evidence from the propensity to spend tax rebates. American Economic Review: Insights 1, 273–90.

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

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

Stokey, N., 2019. Means of Payment. Working Paper. University of Chicago.

Townsend, R.M., 2020. Distributed Ledgers: Design and Regulation of Financial Infrastructure and Payment Systems. MIT Press.

Vives, X., 1987. Small income effects: A marshallian theory of consumer surplus and downward sloping demand. The review of economic studies 54, 87–103.

Wang, L., Wright, R., Qian, L., 2019. Money and Credit: Theory and Applications. forthcoming. International Economic Review.

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

Yang, B., Ching, A.T., 2014. Dynamics of consumer adoption of financial innovation: The case of atm cards. Management Science 60, 903–922.

ONLINE APPENDIX

A Model: Details

A.1 Proofs

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

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

Thus, using the envelope theorem:

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

Hence, using the fundamental theorem of calculus:

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

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

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

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

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

where the last term uses the derivative of the indirect utility function.

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

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

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

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

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

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

and using the derivative of the indirect utility function:

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

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

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

Putting the two parts together we have:

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

where we use that $p_2,...,p_n$ are held fixed, as the empirical evidence suggest. Notice that if this is the case, the calculation above does not require cross-price elasticities or information on the quantity demanded of goods $2,...,n$. This is a general property of demand theory, not unique to our setup.[68] Using the definition we can verify that $\mathcal{CS}(1,1)=0$. Thus

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

A.2 Random Quasi-linear Utility Test

In this section, we test all restrictions implied by our experimental data on the aggregate quasi-linear utility function. The null hypothesis for the test is that the data set given by the experiments was generated by some quasi-linear utility function at the aggregate level. This test consists on checking several inequalities as explained below. We assume that the rider's i utility function of cash and card rides (a_i,c_i) is given by the composition of version H and $\tilde{U}$. We fix the type ϕ and allow for unobservable idiosyncratic shocks ω to $\tilde{U}$, so the utility function of the rider (ϕ,ω) is:

$$\tilde{U}\left(H\left(a_i,c_i;\phi\right);\phi,\omega\right)\tag{25}$$

[68]See Section C.1 for more details.

where $\tilde{U}(\cdot;\phi,\omega)$ has been described in equation (7). The function $H(\cdot;\phi)$ is the cash-card sub-utility function, which can depend on the observable type ϕ, but cannot depend on the idiosyncratic shock ω.

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

$$U(a,c;\phi) \equiv \max_{a_i,c_i} \int \tilde{U}\left(H\left(a_i(\omega),c_i(\omega);\phi\right);\phi,\omega\right)\,\mu(d\omega|\phi) \tag{26}$$
$$\text{subject to: } a = \int a_i(\omega)\,\mu(d\omega|\phi) \text{ and } c = \int c_i(\omega)\,\mu(d\omega|\phi)\,.$$

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

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

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

This, in turn, is equivalent to a test of $J \equiv \sum_{\ell=2}^K K!/((K-\ell)!\ell)$ inequalities on partial sums of $p_a^r a^s + p_c^r c^s$ for different values of s and r. To be concrete, in one of our experiments we have one control and six treatment effects, so that the test consists on checking up to $J = 2,365$ inequalities. Note that this notation includes the case where there are only changes on the price of cash, as it is the case in the experiments to pure cash users. In this case, with one control and four treatments, the test is equivalent to test up to $J = 84$ inequalities. We implement this test using the linear programming problem suggested by Allen and Rehbeck (2018). The summary statistics of the necessary data to conduct this test are reported in Table A1 and Table A2 in Section A.2. We found that all restrictions are satisfied for the two price experiments we conducted.

Table A1: Random Quasi-linear Utility Test: Experiment 1 (Mixed Users)

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

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

Table A2: Random Quasi-linear Utility Test: Experiment 2 (Pure Cash Users)

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

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

A.3 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 card 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 card 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 and

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

where the ideal price index is: $\mathbb{P}(p_a,p_c) = [\alpha p_c^{1-\eta} + (1-\alpha)p_a^{1-\eta}]^{\frac{1}{1-\eta}}$.

A.4 Exponential Utility for Composite Rides

Let denote the aggregate composite trips by x and assume that $U(x) = -k\exp\left(-\left(x+\bar{x}\right)/k\right)$. We are interested in $U'(x) = P$ (i.e. $\exp\left(-\left(x+\bar{x}\right)/k\right) = P$) or $x = -k\log P - \bar{x}$. In general $X(P) = -k\log P - \bar{x}$ and the choke point is $X(\bar{P}) = 0 = -k\log\bar{P} - \bar{x}$ or $\log\bar{P} = -\bar{x}/k$.

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

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

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

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

We can define the elasticity $\epsilon(P) \equiv -\frac{P}{X(P)}\frac{\partial X(P)}{\partial P}$ as:

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

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

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

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

$$\begin{aligned}
C(P_0) &= \int_{P_0}^{\bar{P}} X(p)dp = -k\int_{P_0}^{\bar{P}} \log p dp + [-\bar{x}]\left(\bar{P}-P_0\right) \\
&= k(\bar{P}-P_0) - P_0X(P_0)
\end{aligned}$$

which are observables, since we can estimate k and $\bar{p}$. The consumer surplus is positive:

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

where the inequality follows from the concavity of log. Also 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 expenditures:

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

where $\epsilon(P_0)$ is the elasticity evaluated at p_0. Expanding the exponential 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, which follows because the remaining terms in the MacLaurin expansion are all positive. As $\epsilon(P_0) \to \infty$, the two expressions converge.

A.5 Demand Functions for Different Users Types

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

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

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

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

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

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

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

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

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

5. Pure card users (card demand for arbitrary p_c) but infinite cash price $p_a = \infty$.

$$\tilde{c}(\infty, p_c) = \begin{cases} k\alpha^{\frac{1}{1-\eta}}\left[\log\left(\frac{\bar{P}}{\alpha^{\frac{1}{1-\eta}}}\right)\right] - k\alpha^{\frac{1}{1-\eta}} \log p_c & \text{if } \alpha^{\frac{1}{1-\eta}} p_c < \bar{P} \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

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

A.6 Indirect Utility

Let $U(x) = -\exp\left(-(x+\bar{x})/k\right)/k$ (i.e. exponential) and $H(a,c) = \left[\alpha c^{1-\frac{1}{\eta}} + (1-\alpha)a^{1-\frac{1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$ (i.e. CES). The indirect utility $v(p_a, p_c)$ is thus

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

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

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

Thus the indirect utility, in terms of the numeraire:

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

Indirect Utilities for selected cases

1. Mixed user

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

2. Pure cash user

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

3. Pure card user

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

4. Non-Uber user

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

Indirect Utility Comparisons:

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

$$\frac{v(1,1) - v(\infty,1)}{(c^*(1,1) + a^*(1,1)))} = \begin{cases} \frac{1}{\log \bar{P}}\left[-\log(\bar{P}) - 1 + \bar{P}\right] & \text{if } \alpha^{\frac{1}{1-\eta}} \geq \bar{P} \\ \frac{1}{\log \bar{P}}\left[-\log(\bar{P}) - 1 - \alpha^{\frac{1}{1-\eta}}\left(\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right)\right] & \text{otherwise} \end{cases} \tag{29}$$

2. Pure cash users vs. non Uber-users

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

and

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

3. Pure card users vs. non Uber-users

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

and

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

4. Mixed Users vs Pure cash Users

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

and

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

A.7 Net Consumer Surplus Lost: Pure Cash Users

In this section, we compute the adjustment to the consumer surplus of pure cash users in the case of a ban due to the option of becoming pure card users. Riders are heterogeneous with respect to the cost of registering/obtaining a card. In particular, we obtain an interval for the counterfactual value of α for these riders, and for each value of α we describe the corresponding values of k and $\bar{P}$. We assume that the elasticity of substitution η is the same as the one we estimate from mixed users. For each feasible value of α, the corresponding values of $(k,\bar{P})$, and distribution $g(\cdot)$ for ψ we compute the consumer surplus lost in the ban:

$$\begin{aligned} CS_{ban,a}(\phi) &\equiv v(1,\infty;\phi) - \int \max\left\{v(\infty,1;\phi)-\psi, v(\infty,\infty;\phi)\right\} g(\psi|\phi)d\psi \\ &= v(1,\infty;\phi)-v(\infty,\infty;\phi)-\left[v(\infty,1;\phi)-v(\infty,\infty;\phi)\right]\int_{\underline{\psi}}^{\max\{\underline{\psi},\psi_{ban}\}} g(\psi|\phi)d\psi \\ &+ \int_{\underline{\psi}}^{\max\{\underline{\psi},\psi_{ban}\}} \psi g(\psi|\phi)d\psi \end{aligned} \tag{30}$$

where g is the distribution of fixed cost among the pure cash users before the ban conditional on ϕ, $\underline{\psi}$ is the lower bound of the support of g, and ψ_{ban} is the highest fixed cost for which a rider will migrate from being pure cash to pure card in the case of a ban. Note that a lower bound of equation (30) is

$$\begin{aligned} CS_{ban,a}(\phi) \geq \underline{CS}_{ban,a}(\phi) \equiv v(1,\infty;\phi) - v(\infty,\infty;\phi) \\ - \left[v(\infty,1;\phi) - \underline{\psi} - v(\infty,\infty;\phi)\right] \int_{\underline{\psi}}^{\max\{\underline{\psi},\psi_{ban}\}} g(\psi|\phi)d\psi \end{aligned} \tag{31}$$

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

1. We obtain a set of values of $\phi = (\eta, \alpha, k, \bar{P})$, which can be represented as an interval for α. These parameters have to satisfy the following conditions/assumptions, which are discussed at the end of Section 4.4.

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

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

   $$\beta_0 = k(1-\alpha)^{\frac{1}{1-\eta}} \left[\log\left(\frac{\bar{P}}{(1-\alpha)^{\frac{1}{1-\eta}}}\right)\right] \tag{32}$$

   $$\beta_1 = -k(1-\alpha)^{\frac{1}{1-\eta}} \tag{33}$$

   (c) Pure cash users that become pure card users take fewer rides after the ban. This means that $\tilde{a}(1, \infty; \phi) > \tilde{c}(\infty, 1; \phi) > 0$. This was shown in the analysis of Puebla by Alvarez and Argente (2022). Using the expression in Section A.5 we have:

   $$\alpha \leq 1/2 \tag{34}$$

   (d) The demand of a pure cash rider that becomes a pure card rider after the ban must be strictly positive, or $\tilde{a}(\infty, 1; \phi)$. The estimated parameters β_0, β_1 and equation (32) and equation (33) enforce that the demand of pure cash users is positive. Using the expressions in Section A.5 we have:

   $$\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}} \leq 1 \tag{35}$$

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

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

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

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

   $$\underline{\psi} \equiv v(1,1;\phi) - v(1,\infty;\phi) = -k(1+\log \bar{P}) - k(1-\alpha)^{\frac{1}{1-\eta}} \left[\log\left(\frac{(1-\alpha)^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] \tag{36}$$

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

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

   $$\psi_{ban} = v(\infty,1;\phi) - v(\infty,\infty;\phi) \equiv k\alpha^{\frac{1}{1-\eta}} \left[\log\left(\frac{\alpha^{\frac{1}{1-\eta}}}{\bar{P}}\right) - 1\right] + k\bar{P} \tag{37}$$

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

   (d) The shape of g in the interval $[\underline{\psi},\ \psi_{ban}]$ is obtained by using the information of the Experiment 3, given the parameters (α, k, $\bar{P}$, η). For a given discount rate ρ, these experiments give three values of the CDF for g inside the interval $[\underline{\psi},\ \psi_{ban}]$. See equation (16) for the relevant expressions. We interpolate these values so that they are consistent with the experiments and, among them, we choose the one with the highest cost (in a first order stochastic dominance sense). Furthermore, we use $\rho = 0.25$ so the expected duration of the fixed cost is four years.

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

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

Using the definitions of β_0 and β_1 and Proposition 2 we can write

$$\widehat{CS}_{ban,a}(\beta_0, \beta_1) = -\beta_0 + \beta_1 - \beta_1 \exp\left(-\beta_0/\beta_1\right) \tag{38}$$

On the other hand, the consumer surplus of pure cash users who switch to card payments can be written as a function of α given β_0, β_1, and η. Using Proposition 2 and the definitions of β_0 and β_1 and substituting into equations equation (36) and equation (37) we find

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

and

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

The consumer surplus lost for switchers can be written as

$$\widehat{CS}_{ban,a}(\alpha; \beta_0, \beta_1, \eta) = \left[-\beta_0 + \beta_1 - \beta_1 \exp\left(-\beta_0/\beta_1\right)\right] - \int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}}, \widehat{\psi}_{ban}\}} \left[\psi - \underline{\widehat{\psi}}\right] \widehat{g}(\psi) d\psi \tag{39}$$

with lower bound

$$\underline{\widehat{CS}}_{ban,a}(\alpha; \beta_0, \beta_1, \eta) \equiv \left[-\beta_0 + \beta_1 - \beta_1 \exp\left(-\beta_0/\beta_1\right)\right] - \tilde{\psi} \int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}}, \widehat{\psi}_{ban}\}} \widehat{g}(\psi) d\psi \tag{40}$$

where $\tilde{\psi} \equiv \widehat{\psi}_{ban} - \underline{\widehat{\psi}}$ and $\widehat{g}$, $\underline{\widehat{\psi}}$, $\widehat{\psi}_{ban}$, and $\tilde{\psi}$ are evaluated at $(\alpha; \beta_0, \beta_1, \eta)$.[69] Given that $\tilde{\psi}$ only affects the consumer surplus of the users that switch to card payments, we can obtain the lower bound of the net consumer surplus by evaluating $\tilde{\psi}$ for all values of $\alpha \in [\underline{\alpha}, \alpha = 1/2]$. In practice $\tilde{\psi}$ is a single-peaked function with maximum either at $\alpha = \underline{\alpha}$ or at $\alpha = 1/2$.

A.7.1 Case with No Heterogeneity

In this case, all users have the same ϕ. From Table K1 we obtain the following point estimates $\beta_1 = -2.044$ and $\beta_0 = 1.48$ for the miles specification. We use the mile specification because the price of a trip has been normalized to one, as in the theory. This corresponds to an elasticity of 1.38. Aiming to be conservative, this is the largest elasticity, which gives the lowest consumer surplus. Using the values β_0 and β_1 we obtain a consumer surplus lost by

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

the pure cash users that do *not* migrate after the ban, estimated using equation (38), of approximately 36 USD per year, or about 0.47 of the yearly expenditure on rides paid in cash. Moreover, with this values of β_0, β_1 and our benchmark estimates of η, the difference $\tilde{\psi}$ is increasing in α ranging between $\tilde{\psi} = 0$ and and $\tilde{\psi} = 10.8$ USD per year at $\alpha = 0.5$. Thus we can use the lower bound on the consumer surplus lost is given by selecting $\alpha = 0.5$ and using the formula for the lower bound we obtain $\underline{\widehat{CS}}_{ban,a} \geq 33.4$ USD per year or about 0.43 of the yearly expenditure of cash rides in Uber. For this lower bound we have used $\int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}},\widehat{\psi}_{ban}\}} \hat{g}(\psi)d\psi = 0.3$, based on Puebla.

We can use the results of Experiment 3 to obtain a better estimate of $\int_{\underline{\widehat{\psi}}}^{\max\{\underline{\widehat{\psi}},\widehat{\psi}_{ban}\}} \psi\hat{g}(\psi)d\psi$. We use that for one time rewards of 5.3, 10.5 and 15.7 USD the excess migration rate in six weeks have been 3.3%, 3.9% and 4.7% respectively –see Table 7, column (3). Since these are one time rewards, we need to convert them into flows, by using a rate of discount, which should take into account the duration of the cards. To be conservative we use $\rho = 0.2$, so the average duration is 5 years, i.e. the rewards are about 1, 2.1, and 3.6 USD dollars per year. We can use these figures to obtain a tighter upper bound as follows:

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

In this case we obtain $\widehat{CS}_{ban,a} \approx 36 - 1.9 = 34.1$ USD per year or about 0.44 of the yearly expenditure on Uber paid in cash by pure cash riders. This calculation is our headline number for pure cash users who switch to cards in a ban. The results are similar if, instead of using $\eta = 3$, we use a higher value (i.e. η=5). In this case, the net consumer surplus lost is 31.2 USD per year or about 0.40 of the yearly expenditure on Uber paid in cash.

A.7.2 Case with Heterogeneity

Next, we allow consumer to have different β_0. For each percentile of the distribution of β_0 reported in Columns (1)-(2) of Table A3, we compute the consumer surplus lost of both pure cash users that do not switch to card payments and those that do. Columns (3) reports the percentiles that migrate to card after a ban on cash consistent to our model (i.e. $\tilde{\psi} > 0$). We aim to provide a lower bound for the consumer surplus lost. First, in order to be consistent with the evidence from Puebla, we allow 30% of the users to migrate. We use the percentiles of the distribution with migration consistent with our model and with a lower consumer

Table A3: Net Consumer Surplus Lost in a Ban on Cash for Pure Cash Users

Note: The table reports the net consumer surplus lost of pure cash users after a ban on cash for several percentiles of miles per week, β_0. The net consumer surplus lost is the adjustment to the consumer surplus of pure cash users in the case of a ban due to the option of becoming pure card users. Column (3) shows the percentiles of the distribution of β_0 that switch to card payments (i.e. $\tilde{\psi} > 0$) according to our model. Column (4) shows the percentiles that percentiles of the distribution of β_0 that we elect to migrate to card payments in order to be consistent with the data of Puebla (30% of the population) and also to provide a lower bound of the consumer surplus lost. Column (5) reports the lower bound of the net consumer surplus lost by the pure cash users, those that migrate are adjusted by the costs paid to migrate. All calculations use β_1 = -2.044, η=3, and α=1/2 since for that α the consumer surplus lower bound is attained. The average β_0 in our sample is 1.48.

(1) Percentile	(2) β_0	(3) Consistent	(4) Migrate	(5) Net Consumer Surplus Lost (USD)
5	0.16	0	0	0.3471
10	0.23	0	0	0.7359
15	0.30	0	0	1.2043
20	0.36	0	0	1.7879
25	0.42	0	0	2.5156
30	0.49	0	0	3.4231
35	0.57	0	0	4.5722
40	0.65	0	0	6.0297
45	0.74	0	0	7.9076
50	0.84	0	0	10.356
55	0.95	0	0	13.582
60	1.08	0	0	18.011
65	1.23	1	1	24.091
70	1.42	1	1	31.143
75	1.65	1	1	41.493
80	1.96	1	1	57.841
85	2.38	1	1	86.165
90	3.01	1	1	144.09
95	4.11	1	0	307.85
100	8.24	1	0	2952.1

surplus lost. These percentiles are reported in Column (4). Second, we evaluate $\underline{\widehat{CS}}_{ban,a}$ at $\alpha = 1/2$ since, for all percentiles that switched to card payments, it provides a maximum value for $\tilde{\psi}$ and hence a lower bound for the net consumer surplus. The last column reports the lower bound of the net consumer surplus lost for each percentile. Notice that the net consumer surplus lost is convex in β_0 as shown in equation (38). The consumer surplus lost is higher for pure cash users that travel more because of the convexity of the net consumer surplus lost and the skewness of the distribution of historical trips. The median net consumer surplus lost is 10.3 USD (mean 185 USD). If we use η=5, results are similar, the median is 10.6 USD (mean 181 USD).

B Discrete Choice Model

In this section, we provide an explicit microfoundation for our modeling choices while keeping the model amenable for estimation using our experimental evidence. The microfoundation takes into account: i) agents' decisions on whether, in each period, they take a trip with Uber or not, and ii) Uber riders' decision on the means of payment they use (i.e., cash or card). More specifically, we develop an intensive discrete choice model of Uber ridership and the choice of means of payment that gives rise to our demand system. This version of the model is specific about: i) the probability distribution of costs that gives the utility value of taking a ride with Uber and a constant semi-elasticity specification, and ii) the distribution of shocks that give rise to our CES specification and the parameters of these distributions that map to the elasticity of substitution η. This version of the model shows that our estimated elasticity of demand ϵ captures substitutions from other available riding options. Changes in Uber prices do influence the decision to take an Uber ride. Therefore, the estimation of the elasticity of demand for composite Uber trips is conducted in the first stage. Intuitively, the estimated elasticity of demand for Uber rides measures how substitutable Uber rides are for alternative transportation options. The discrete model also shows why it is consistent to estimate η in the second stage e.g., conditional on riders having chosen to take a trip.

Model summary. The decision for a rider has two steps, consistent with the weak separability assumed between (a, c) and the rest of the goods/services $x_2, \ldots, x_n$. In the first stage, the rider decides whether to take a trip with Uber in each period or not. In the second stage, the rider decides on the means of payment, either cash or card. Each step is modeled as a discrete choice decision. This gives rise to a probability for an Uber trip, and conditional on the Uber trip, a probability that the trip is paid in cash or, as its complement, paid in card.

1. We start from the second stage, where the rider has already decided to take an Uber trip. At this time, the rider will use E dollars to pay for a trip. The rider draws a preference shock for the value of each means of payment $m = a, c$. We denote this vector of shocks as $\epsilon = (\epsilon_a, \epsilon_c)$, which are drawn from the CDF denoted by F_ϵ. The value of an Uber ride with payment m is $\psi_m(\epsilon_m; \phi)q_m$, where q_m is the length of the trip, so the expenditure on the trip is $E = q_m p_m$ if means m is chosen. Note that we assume the expenditure E has already been decided. After the preference shocks are realized, the rider solves:

$$\tilde{v}(p_a, p_c, \epsilon, \phi) = \max \left\{ \psi_a(\epsilon_a; \phi) \frac{E}{p_a} \, , \, \psi_c(\epsilon_c; \phi) \frac{E}{p_c} \right\} \tag{41}$$

   We will specify ψ so that the marginal value per mile $\psi_m(\epsilon_m) \geq 0$ for all ϵ_m and $m = a, c$. Before the shocks ϵ are realized, but after the rider has committed to an Uber ride, the value for an agent to take a trip is given by:

$$\tilde{H}(p_a, p_c; \phi) \equiv \int \int \log \tilde{v}(p_a, p_c, \epsilon, \phi) \, dF_\epsilon(\epsilon_a, \epsilon_c) \tag{42}$$

We specify

$$\psi_m(\epsilon_m) = e^{\tilde{\alpha}_m + \epsilon_m} \text{ for } m = a, c.$$

Dubé et al. (2022) show this is the only specification giving rise to expected choices consistent with a demand system. We note that α_a, α_c and E are part of the vector ϕ. The vector ϕ also includes the parameters of the CDF F_ϵ.

2. In the first stage, the rider draws a preference shock ω, which represents the value of using an alternative to Uber. The rider also observes the prices p_a and p_c, but does not yet know the values of the vector ϵ. The shock ω is drawn from a CDF denoted by F_ω. We assume that ω and ϵ are independent random variables. With the realization of ω at hand, the rider chooses an Uber ride only if $\tilde{H}(p_a, p_c; \phi) \geq \omega$. Thus, ex-ante, the indirect utility of the rider is:

$$v(p_a, p_c; \phi) = \int \max\left\{\tilde{H}(p_a, p_c; \phi)\ ,\ \omega\right\} dF_\omega(\omega)$$

Now, we provide more details on the solution of each of the two stages, on the properties of their indirect utility functions, and the corresponding demands. We also specify the distributions of F_ϵ and F_ω, which give rise to the CES, and constant semi-elasticity of demand case that we use.

Second stage: means of payments We use known results from discrete choice to describe the choice of means of payments. In particular, we follow Dubé et al. (2022) and define

$$\delta_m(p_m) \equiv \tilde{\alpha}_m - \log p_m \text{ for } m = a, c$$

where $\delta = (\delta_a, \delta_c)$. Thus, the choice of means of payment solves:

$$\mathcal{G}(\delta) = \int\int \max\left\{\delta_a + \epsilon_a\ ,\ \delta_c + \epsilon_c\right\} dF_\epsilon(\epsilon_a, \epsilon_c).$$

Define

$$H(p, \phi) \equiv \exp\left(\mathcal{G}\left(\delta\left(p_a, p_m\right)\right)\right))$$

Note that:

$$\tilde{H}(p_a, p_c, \phi) = \log E + \mathcal{G}\left(\delta\left(p_a, p_c\right)\right)) = \log E + \log H(p_a, p_c, \phi)$$

Assuming the F_ϵ is absolutely continuous, the function $\mathcal{G}$ is differentiable. In this case:

$$s_m(\delta) \equiv \Pr\left[\epsilon_m + \delta_m \geq \epsilon_{m'} + \delta_{m'}\right] = \frac{\partial \mathcal{G}(\delta)}{\partial \delta_m} = \frac{\frac{\partial H(\delta)}{\partial \delta_m}}{\frac{\partial H(\delta)}{\partial \delta_c} + \frac{\partial H(\delta)}{\partial \delta_a}} \text{ and}$$

$$p_m\, q_m(p_a, p_c) = s_m\left(\delta(p_a, p_c)\right)\, E$$

The quantity $s_m(\delta)$ is the expected expenditure paid with means of payment $m = a, c$ given δ. Since, given the prices (p_a, p_c) the expenditure is fixed, it is also the expected value that the means of payment m is used. Notice that we can define $H(p_a, p_c, \phi)\, E$ as the indirect utility function corresponding to an homogenous of degree one utility index for the choice of means of payment.[70] Associated with this utility there is an ideal price index:

$$\mathbb{P}(p_a, p_c, \phi) = \frac{1}{H(p_a, p_c, \phi)} = \exp\left(-\mathcal{G}\left(\delta(p_a, p_c)\right)\right)$$

CES case: Here we follow Anderson et al. (1987) as a special case of what was presented. As their abstract states "The CES demand function is a special case of a nested logit model whose second state is deterministic." Consider the case where F_ϵ is the product of two Gumbel distribution each with CDF:

$$\tilde{F}(\epsilon_m) = \exp\left[-\exp\left(-\frac{\epsilon_m + \mu\, \eta_E}{\mu}\right)\right] \text{ and } F_\epsilon(\epsilon_a, \epsilon_c) = \tilde{F}(\epsilon_a)\tilde{F}(\epsilon_c)$$

where η_E is the Euler's constant. In this case, ϵ_m has mean zero and variance $\mu^2\, \pi^2/6$. It is also the case that:

$$H(\delta) = \left(\sum_{m=a,c} e^{\delta_m/\mu}\right)^{\mu}$$

thus

$$\frac{\partial H(\delta)}{\partial \delta_m} = \left(\sum_{m=a,c} e^{\delta_m/\mu}\right)^{\mu-1} e^{\delta_m/\mu}.$$

Moreover,

$$s_m\left((\delta(p_a, p_c)\right) = \frac{e^{\tilde{\alpha}_m/\mu}\, p_m^{-1/\mu}}{e^{\tilde{\alpha}_c/\mu}\, p_c^{-1/\mu} + e^{\tilde{\alpha}_a/\mu}\, p_a^{-1/\mu}} \text{ for } m = a, c$$

[70] Since $H(p_a, p_c, \phi)\, E$ is a monotone transformation of $\tilde{H}$, they give the same choices.

and

$$\mathbb{P}(p_a, p_c) = H(\delta(p_a, p_c))^{-1} = \left(\sum_{m=a,c} e^{\tilde{\alpha}_m/\mu} p_m^{-1/\mu} \right)^{-\mu}$$

which together give a CES demand system for the quantities $E_\epsilon q_m^*(p_a, p_c)$, with its corresponding CES ideal price index $\mathbb{P}(p_a, p_c)$. To get a CES with elasticity of substitution η and with share of expenditures paid in cards α, we set $\mu = \frac{1}{\eta-1}$, $\tilde{\alpha}_c = \mu \log \alpha$ and $\tilde{\alpha}_a = \mu \log(1-\alpha)$. We then obtain:

$$s_a\left((\delta(p_a, p_c)\right) = \frac{\alpha\, p_a^{1-\eta}}{\alpha p_a^{1-\eta} + (1-\alpha) p_c^{1-\eta}} \text{ and } \mathbb{P}(p_a, p_c) = \left(\alpha p_a^{1-\eta} + (1-\alpha) p_c^{1-\eta}\right)^{1/(1-\eta)} \tag{43}$$

First stage: choice of Uber ride. In this section, we provide more details on the model of the choice of taking an Uber ride. The rider draws shock ω from a distribution with CDF F_ω that gives the utility value of taking a ride different from Uber. If, instead, the rider takes a ride with Uber, she obtains a utility $\tilde{H}(p_a, p_c, \phi) = \log E + \log H(p_a, p_c, \phi)$. Recall that we can write the ideal price $\mathbb{P}(p_a, p_c) = 1/H(p_a, p_c)$. Thus, the rider uses Uber if and only if

$$\omega \leq \log E + \log H(p_a, p_c; \phi) = \log E - \log \mathbb{P}(p_a, p_c)$$

Thus, the probability of a trip per unit of time is: $F_\omega\left(\log E - \log \mathbb{P}(p_a, p_c)\right)$. We let $P = \mathbb{P}(p_a, p_c)$ and assume that the demand $X(P)$ correspond to $N \geq 1$ periods, where the shocks ω, ϵ are i.i.d. through time. So the expected number of trips as function of the price P is:

$$X(P) \equiv N\, F_\omega\left(\log E - \log P\right) .$$

Constant semi-elasticity of demand case. Consider a demand with constant semi-elasticity of demand as

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

where $k > 0$ and $\bar{P}$ are two parameters. The semi-elasticity is k and $\bar{P}$ is the choke price. This demand corresponds to a uniform distribution of shocks ω. To see why set:

$$-k\left(\log P - \log \bar{P}\right) = N\, F_\omega\left(\log E - \log P\right) \text{ or } F_\omega\left(\log E - \log P\right) = \frac{k}{N}\left(\log \bar{P} - \log P\right)$$

so setting:

$$F_\omega(\omega) = \frac{k}{N}\omega \text{ for } \omega \in [0, \frac{N}{k}] \text{ and } E = \bar{P}$$

we obtain the desired system. Note that since the maximum that the demand can take is N, then this demand has constant semi-elasticity for $P \in [\underline{P}, \bar{P}]$, where $\underline{P}$ is defined as $N = k(\log \bar{P} - \log \underline{P})$ or $\underline{P} = \bar{P}e^{-N/k}$. For prices lower than $\underline{P}$, the demand is constant, i.e. the agent is satiated at this price. Two comments are in order. First, as $N \to \infty$, then $\underline{P} \to 0$. That is, fixing a time interval and decreasing the length of time in which a trip can take place, removes the limitation of the demand. Second, this restriction has no effect on the calculation of the consumer surplus for any price $P \geq \underline{P}$.

In Section R, we discuss how to estimate the parameters of the model using GMM for the data generated in Experiment 1.

C Othe Means of Transportation

C.1 Demand Theory

Suppose that the prices of taxis and other substitutes, such as the prices of other ride-hailing companies, are kept constant after a ban of cash as the empirical evidence suggests (we will provide detailed evidence that this is a reasonable assumption below). This finding is key to be able to evaluate the consumer surplus of Uber cash *without* measuring the impact on quantities of other goods or cross elasticities. It is convenient to have a specific notation for the price of Uber rides paid in cash, for which we use p_a, and Uber rides paid with credit, for which we use p_c as in the main paper. We let $p_2, ..., p_n$ the price of the rest of the goods (including taxis) and θ index the preferences of different riders. Suppose also that there is an outside good with quasi-linear demand; a simplification that is tested and validated for the Uber case in Section A.2. Then, using the envelope theorem on the indirect utility function we find:

$$\frac{\partial}{\partial p_a} v(p_a, p_c, p_2, \ldots, p_n; \theta) = -\tilde{a}\left(p_a, p_c, p_2, \ldots, p_n; \theta\right) \tag{44}$$

where $\tilde{a}\left(p_a, p_c, p_2, \ldots, p_n; \theta\right)$ denotes the optimal choices for Uber rides paid in cash. Notice that equation (44) holds independently of the utility function specification that relates transportation methods. Using the fundamental theorem of calculus:

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

For simplicity, let $p_a = p_c = 1$. Following demand theory, the consumer surplus lost after a cash payment ban can be computed as the area below the aggregate demand for cash-fare

Uber rides. We define the aggregate demand, where the cash price unexpectedly increases to $p_a \geq 1$ as:

$$A(p_a, 1, , p_2, \ldots, p_n) = \int \tilde{a}(p_a, 1, , p_2, \ldots, p_n; \theta) dF(\theta)$$

Then, if $p_2, ..., p_n$ are held fixed, as the empirical evidence suggests, we have:

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

Thus, consumer surplus is:

$$\mathcal{CS}(p_a, 1) = \int_1^{p_a} A(p, 1) dp \, . \tag{45}$$

Importantly, if another price were to increase in response to increases in p_a, then the consumer surplus estimated in equation (45) will have to be adjusted to account for this change in prices. If this is the case, the estimates provided in the paper are a lower bound of the true consumer surplus as you correctly suggested. Another thing to notice is that if $p_2, ..., p_n$ are held fixed, the calculation above does not require cross-price elasticities or information on the quantity demanded of goods $2, ..., n$. We illustrate this property of demand systems combined with the envelope theorem with the following example.

C.2 An Example of Consumer Surplus Calculations: Fixed Prices

In this example, we show that the consumer surplus calculation after an increase in prices of a certain good 1 can be computed without information on the quantity demanded of other goods $2, .., n-1$ or information about cross elasticities, as long as the prices of goods $2, .., n-1$ remain constant. This is a general property of demand systems and does not rely on the functional forms assumed in the paper or the dimensionality of the vector of prices. The advantage of this example is that is simple enough to compute the indirect utility functions in closed-form, while ilustrating the main properties that we want to show. The utility function in this example is, for simplicity, the following:

$$u(x) = -\frac{1}{2} x' \Theta x + a' x$$

where $a \in \mathbb{R}_+^{n-1}$, $\Theta \in \mathbb{R}^{n-1 \times n-1}$. As it will be shown below, the main takeaways of this example do not depend on the specifics of the utility function. The consumer maximizes

$$\max -\frac{1}{2} x' \Theta x + a' x - p' x + I$$

where $p \in \mathbb{R}^{n-1}$. After taking first order conditions we find

$$x^\star = \Theta^{-1}(a-p)$$

The indirect utility function can be written as:

$$v(p) = \frac{1}{2}(a'-p')\Theta^{-1}(a-p).$$

Using the envelope theorem we find:

$$\frac{\partial v}{\partial p} = -(a'-p')\Theta^{-1} = -x^\star$$

which mirrors equation (44). We develop two cases. In Case 1, we specify demand functions that are related across goods so that the demand for other goods depend on the price of good 1 and vice versa. In Case 2, we specify demand functions that are not related across goods, so that the demand for each good depends only on its own price. We then compare the cases and show that, when the prices of other goods remain constant, welfare calculations for good 1 are identical under the two cases.

Case 1: To simplify the calculations, we focus on the 2×2 case. As it will be clear, the dimensionality of the problem does not affect our main findings. Suppose that Θ and a are defined as follows:

$$\Theta = \begin{pmatrix} 1 & \theta \\ \theta & 1 \end{pmatrix} \qquad \text{and} \qquad a = \begin{pmatrix} \alpha \\ \alpha \end{pmatrix}$$

This is, we assume that the elasticity across goods 1 and 2, θ, is not zero. The optimal demands for the two goods are:

$$x^\star = \frac{1}{1-\theta^2}\begin{pmatrix} 1 & -\theta \\ -\theta & 1 \end{pmatrix}\begin{pmatrix} \alpha - p_1 \\ \alpha - 1 \end{pmatrix}$$

where we assumed that the price for good 2 is constant and equal to 1. The demand for each good can be written as:

$$x_1^\star = \frac{1}{1-\theta^2}\left(\alpha - p_1 - \theta(\alpha-1)\right) \qquad \text{and} \qquad x_2^\star = \frac{1}{1-\theta^2}\left(-\theta(\alpha-p_1)+\alpha-1\right).$$

Importantly, notice that the demand for good 2, $x_2^\star$, depends on the price for good 1 given that $\theta \neq 0$.

Case 2: We assume that the elasticity across goods 1 and 2 is zero. Namely,

$$\Theta = \begin{pmatrix} \beta & 0 \\ 0 & \beta \end{pmatrix} \qquad \text{and} \qquad a = \begin{pmatrix} \mu \\ \mu \end{pmatrix}$$

Optimal demand can be written as

$$x^\star = \begin{pmatrix} 1/\beta & 0 \\ 0 & 1/\beta \end{pmatrix} \begin{pmatrix} \mu - p_1 \\ \mu - 1 \end{pmatrix}$$

where we again assumed that the price for good 2 is constant and equal to 1. Notice that in this case the demand for good 2, $x_2^\star$, does not depend on the price of good 1.

$$x_1^\star = \frac{1}{\beta}(\mu - p_1) \qquad \text{and} \qquad x_2^\star = \frac{1}{\beta}(\mu - 1)$$

Comparing Case 1 and Case 2: We now compare the two cases. Notice that $x_1^\star$ is the same in both examples under the appropiate parameterization. To see this, note

$$\frac{1}{1-\theta^2}(\alpha - p_1 - \theta(\alpha - 1)) = \frac{1}{\beta}(\mu - p_1)$$

where the left-hand side is $x_1^\star$ in Case 1 and the right-hand side is $x_1^\star$ in Case 2. Both sides are equal if we set $\beta = 1 - \theta^2$ and $\mu = \alpha(1-\theta) + \theta$. So that

Case 1	**Case 2**
$\Theta = \begin{pmatrix} 1 & \theta \\ \theta & 1 \end{pmatrix}$	$\Theta = \begin{pmatrix} 1-\theta^2 & 0 \\ 0 & 1-\theta^2 \end{pmatrix}$
$a = \begin{pmatrix} \alpha \\ \alpha \end{pmatrix}$	$a = \begin{pmatrix} \alpha(1-\theta)+\theta \\ \alpha(1-\theta)+\theta \end{pmatrix}$

For Case 1 the indirect utility function is:

$$\begin{aligned} v(p,1) &= \frac{1}{2(1-\theta^2)} \begin{pmatrix} \alpha - p_1 \\ \alpha - 1 \end{pmatrix}' \begin{pmatrix} 1 & -\theta \\ -\theta & 1 \end{pmatrix} \begin{pmatrix} \alpha - p_1 \\ \alpha - 1 \end{pmatrix} \\ &= \frac{1}{2(1-\theta^2)} \left((\alpha - p_1)^2 - 2\theta(\alpha - p_1)(\alpha - 1) \right) + \text{constant} \end{aligned}$$

For Case 2 the indirect utility function is:

$$v(p,1) = \frac{1}{2(1-\theta^2)}\begin{pmatrix}\alpha(1-\theta)+\theta-p_1\\ \alpha(1-\theta)+\theta-1\end{pmatrix}'\begin{pmatrix}\frac{1}{1-\theta^2} & 0\\ 0 & \frac{1}{1-\theta^2}\end{pmatrix}\begin{pmatrix}\alpha(1-\theta)+\theta-p_1\\ \alpha(1-\theta)+\theta-1\end{pmatrix}$$
$$= \frac{1}{2(1-\theta^2)}\left((\alpha-p_1)^2 - 2\theta(\alpha-p_1)(\alpha-1)\right) + \text{constant}$$

The indirect utility functions *are the same* in both cases and, thus, changes in welfare after an increase in p_1 are the same. In contrast to Case 2, in Case 1, $x_2^\star$ changes as p_1 increases, yet changes in welfare are the same. As long as the price for good 2 is held constant, we do not need information of cross-elasticities or demand changes in $x_2^\star$ to compute the welfare changes after an increase in p_1. In fact, the availability of this information does not affect or improve the consumer surplus calculations for good 1.

D Experiments: Details

D.1 Descriptive Statistics

D.2 Implied Elasticities Mixed Users' Demand for Cash Trips

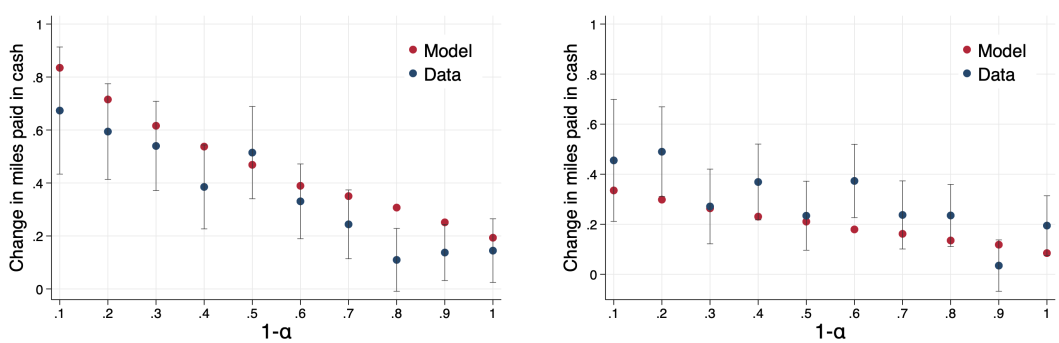
In this Appendix, we compute the price elasticities of mixed users' demand for cash trips using our structural model – evaluated at the estimated parameters – and compare them with the observed elasticities from the experimental data. In particular, we compare the two elasticities obtained after giving riders discounts on cash trips in Experiment 1; recall that, while there are six treatment groups, only two of them, treatment (i) and treatment (iv), involved discounts conditional on paying only with cash. Figure D1 compares the observed percent change in miles paid in cash with those predicted by our model for each decile of the riders' historical cash share. In the data, the riders' elasticities are estimated as the difference between the average number of miles of riders in the treatment and control groups for each of the two discounts. In the model, we use our preferred parameter estimates (i.e. $\eta = 3$ and $\epsilon = 1.1$) to compute the elasticities implied by mixed users' cash demand described in Section A.5 together with a choice of $\bar{P}$ to match the historical cash fares of each rider. Note that η and ϵ are estimated using different price changes; they are estimated using either all six treatment groups in Experiment 1 or using only the treatment groups where Uber prices are the same for rides paid in cash and paid with cards. Figure D1 shows that the model predictions are roughly in line with the observed elasticities for both 20% and 10% discounts on trips paid with cash.

Table D1: Summary Statistics: Experiments

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

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

Figure D1: Elasticity of Demand: Trips Paid in Cash (Model vs Data)



(a) 20% off trips paid with cash (b) 10% off trips paid with cash

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

E Survey

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

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

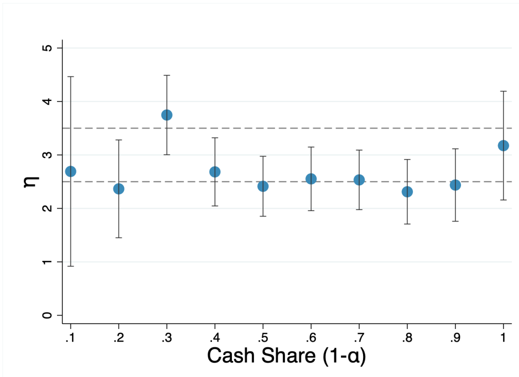
To analyze the responses, we adjust the covariate distribution of the survey respondents by reweighting such that it becomes more similar to the covariate distribution of the entire population that participated in our experiments. We implement entropy balancing, a multivariate reweighting method described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

In order to provide external validity to our survey-based evidence, we compare the bounds in the elasticity of demand implied by the survey to those implied by the field experiments. We use the first question of the survey, where users are asked to describe their behavior if they were to receive a 20% discount for one week. Recall that equation (27) shows the relationship between the demand, the choke price, and the elasticity of demand implied by our model. The equation can be used to recover the response of users to a change in prices P that is consistent with both our experimental evidence and our structural framework. We implement equation (27) using the semi-elasticity k estimated in our field experiments and the choke prices $\bar{P}$ of users recovered (when they face prices equal to 1) from the average of their weekly historical fares.[71] In this case, when we decrease prices by 20%, given that in our model users always change their trips if prices change, we find that 11% of users would increase their trips less than 10%, 32% of users would increase their trips less than 20%, and 49% of users would increase their trips less than 30%. The responses of the survey are remarkably similar. They show that, conditional on users changing their trips, 14.75% of the users would increase their trips less than 10%, 39.7% would increase their trips less than 20%, and 46% of users would increase their trips less than 30%. Overall, we find that the estimated bounds of the elasticity of demand in the survey are informative of the revealed bounds obtained using our experimental data. More details on the survey results can be found in Section Q.1 and Section Q.2.

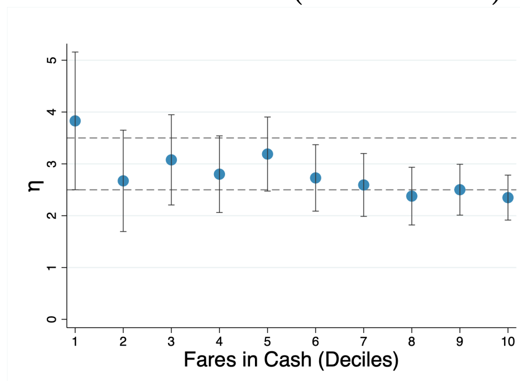
[71] To minimize the measurement error in the average of weekly historical fares, we trim the top and bottom one percent.

F Experiments: Riders's Heterogeneity

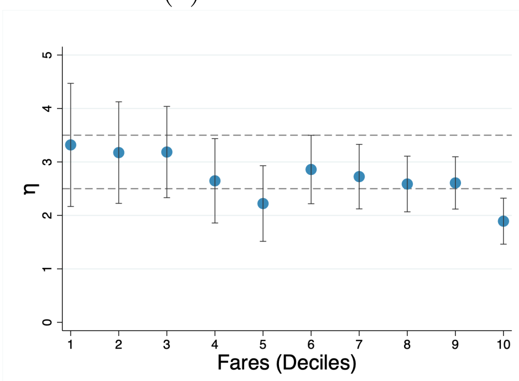
Figure F1: Elasticity of Substitution: Mixed Users (Observables)



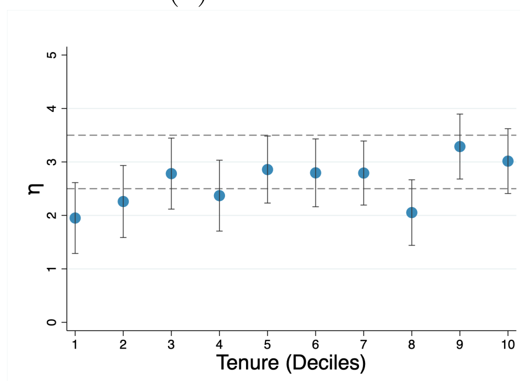
(a) Cash Share



(b) Cash Fares



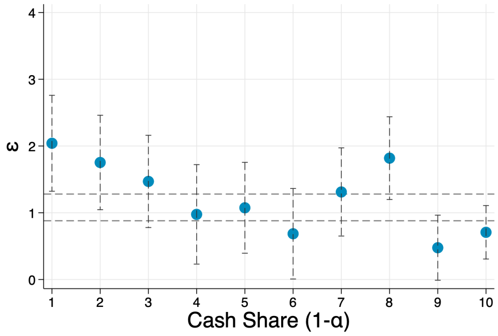
(c) Fares



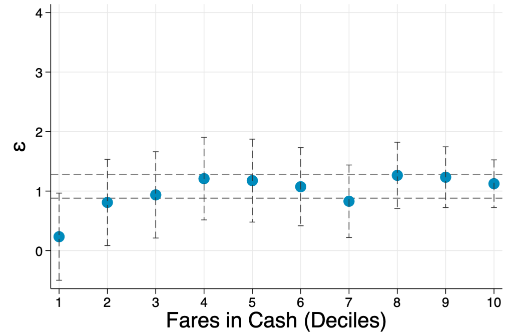
(d) Tenure

Note: The figure reports estimates of the elasticity of substitution between cash and card payments for mixed users for different deciles of the riders' cash share, cash fares, fares, and tenure. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. Each dot in the figure was estimated using the CES second order approximation in equation (19). The estimates include mixed users with more than 1% of their fares paid in cash and less than 99%. The confidence intervals represent statistical significance at the 5% level.

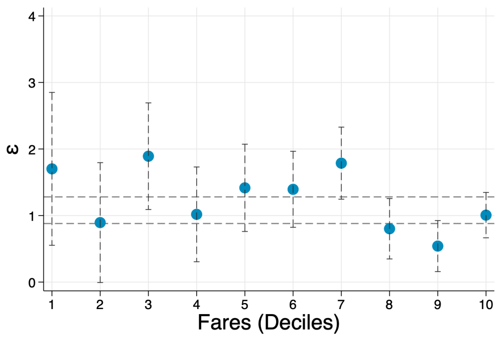
Figure F2: Elasticity of Demand: Mixed Users (Observables)



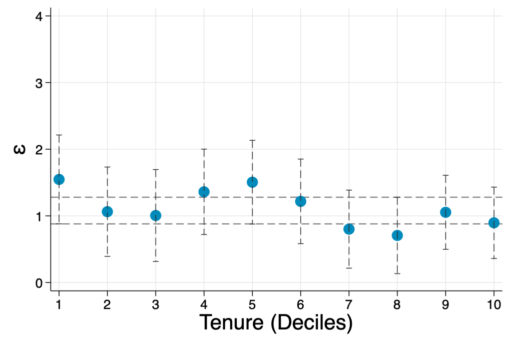
(a) Cash Share



(b) Cash Fares



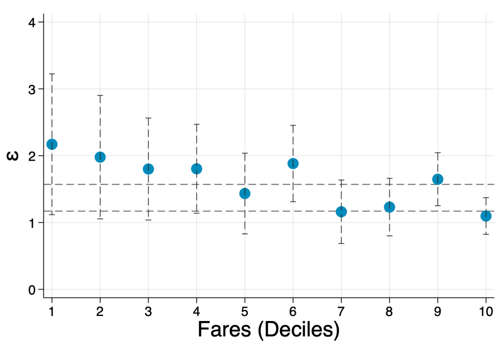
(c) Fares



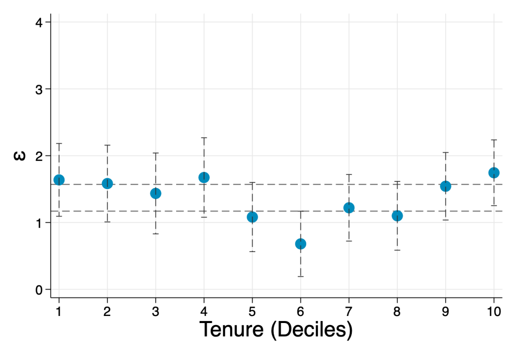
(d) Tenure

Note: The table reports the elasticity of demand for mixed users estimated using equation (27) using miles as the dependent variable for each decile of the distribution of cash share, cash fares, fares, and tenure. The confidence intervals represent statistical significance at the 5% level from our baseline estimate.

Figure F3: Elasticity of Demand: Pure Cash Users (Observables)



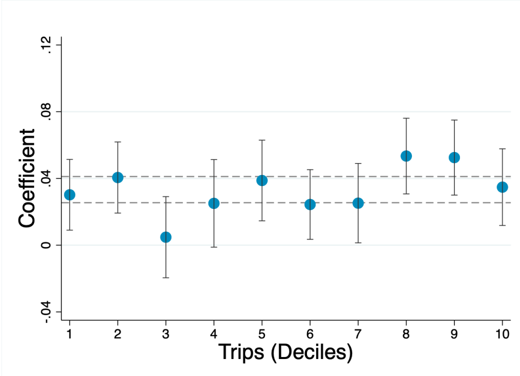
(c) Fares



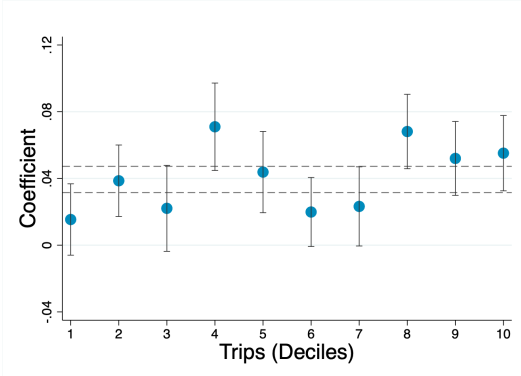
(d) Tenure

Note: The table reports the elasticity of demand of pure cash users estimated from equation (27) using miles as dependent variable for each decile of the distribution of fares, and tenure. The confidence intervals represent statistical significance at the 5% level from our baseline estimate.

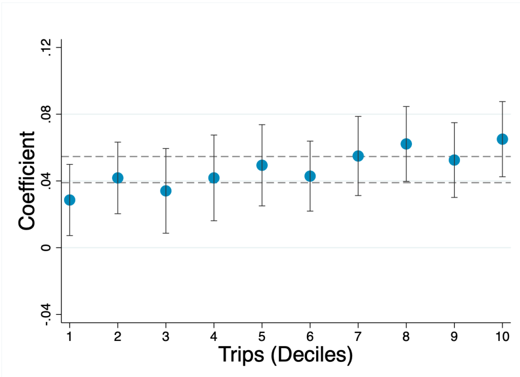
Figure F4: Extensive-Margin: Adoption of a Payment-Card (Historical Trips)



(a) Treatment 1 - 6 weeks



(b) Treatment 2 - 6 weeks



(c) Treatment 3 - 6 weeks

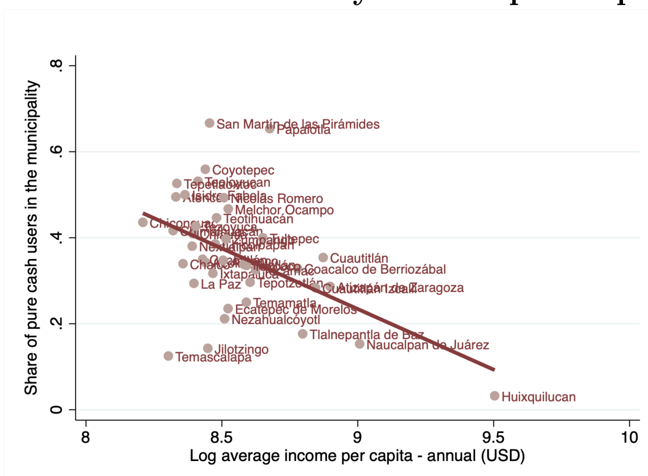
Note: The figure reports the percent of users that adopted a payment-card for each of the treatment groups in Experiment 3 relative to the control group for different deciles of riders' historical trips. The figure reports estimates for the experiment that lasted six weeks. In the regression, the dependent variable is an indicator that equals one if the user registered a card conditional on taking trip the weeks of the experiment. The independent variable reports migration rates relative to the control group. Panel (a) reports migration rates in the treatment group 1: reward of 3 times their average weekly fares if the users register a card in the application. Panel (b) migration rates in the treatment group 2: reward of 6 times their average weekly fares if the users register a card in the application. Panel (c) migration rates in the treatment group 3: reward of 9 times their average weekly fares if the users register a card in the application. The dashed lines are confidence intervals representing statistical significance at the 5% level of the coefficients reported in Column (3) of Table 7.

ONLINE APPENDIX
(NOT FOR PUBLICATION)

G Demographics

G.1 Income

Figure G1: Share of Pure Cash Users by Income per Capita (Municipality)



Note: The figure shows the share of pure cash users (riders that do not register a payment card in the app) in each municipality. We multiply income times 1.24 to account for the fact that individuals with access to a smartphones earn higher income. The income data comes from individuals that report labor income surveyed in the Intercensal Survey of 2015. The data on smartphone usage comes from the 2015 National Survey of Financial Inclusion (ENIF). The data of Uber rides are from August of 2018 in the State of Mexico.

We use geolocalized information about every trip taken in the State of Mexico during the month of August 2018. The data include the date, time, and the pick-up and drop off locations (i.e. latitude and longitude) of every trip during this period as well as the total fare paid and an indicator for whether the trip was paid for in cash. Our sample of users are those whose most-frequent city of origin for an Uber request is Greater Mexico City. The latitude and longitude coordinates allow us to assign each user to the municipality where most of his or her trips originated. The Mexican Census provides shape files containing the coordinates of the polygons surrounding each census block in the country. We use the longitude and latitude of the centroid of each census block as its location. Then, we match each Uber trip to the closest census block by minimizing the Euclidean distance between the two. In case of ties we assigned users to the municipality where the majority of her trips started in the morning (before noon) and where the majority of her trips ended at night (after 5 pm).[72] This step allows us to use income data from the Inter-censal Survey to determine the average income of groups of Uber users, while identifying users that are more likely to use cash for payment. Figure G1 shows the share of pure cash users (riders that do not register a payment card in the app) in each municipality. It shows that the share of pure cash users declines with income per capita.

Table G1: Demographics and Income (Census Block)

Note: The table shows the relationship between the share of cash paid by Uber riders (quintiles) and several demographic variables from the Mexican Census reported at the census block level. The demographic variables included are the average years of schooling, the share of homes with internet, the share of homes with cell phone, and the share of homes with a car. The last row reports the relationship between the share of cash paid by Uber riders and the first principal component of the rest of the variables reported in the table.

	Share of Fares in Cash (Quintiles)				
	1	2	3	4	5
Years of Education	10.75	10.11	9.73	9.33	8.83
Share of Homes with Cell Phone	0.65	0.62	0.60	0.59	0.57
Share of Homes with Internet	0.36	0.27	0.22	0.19	0.16
Share of Homes with Car	0.46	0.39	0.34	0.32	0.29
First Principal Component	0.96	0.13	-0.34	-0.66	-0.99

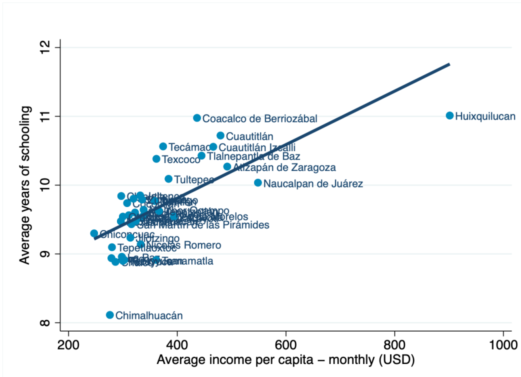
Income at the local level is strongly correlated with factors that influence the use of cash (as shown in Figure 9) and the choice of transportation modes. Income measures are also highly correlated with the availability of public infrastructure for households, including public transport. Furthermore, we find that income measures are strongly correlated with commuting times. Finally, we show that income is closely related to variables that assess access to financial services, such as debit cards and ATM transactions.

We begin by showing that variables at the census block level that are correlated with income, such as years of education and the share of homes that own a car, also decrease as the share of fares paid in cash increases. This can be seen in Table G1.

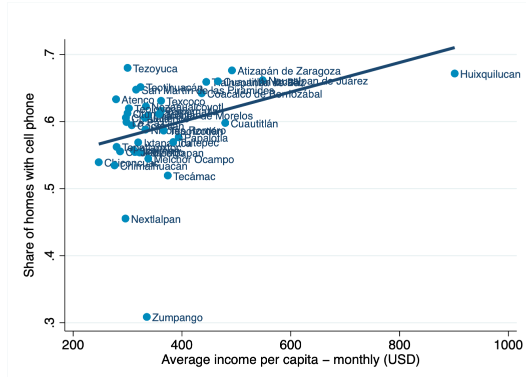
[72]Our results are not sensitive to switching the order of these criteria.

Figure G2: Demographics by Income per Capita (Municipality)

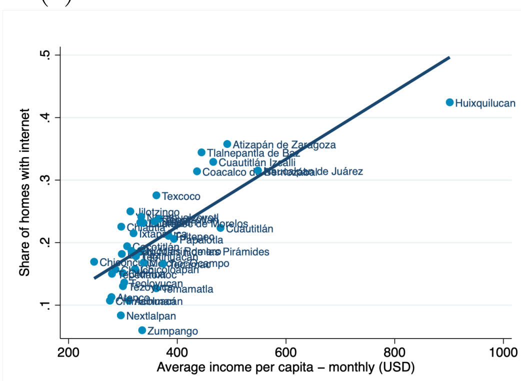
(a) Schooling



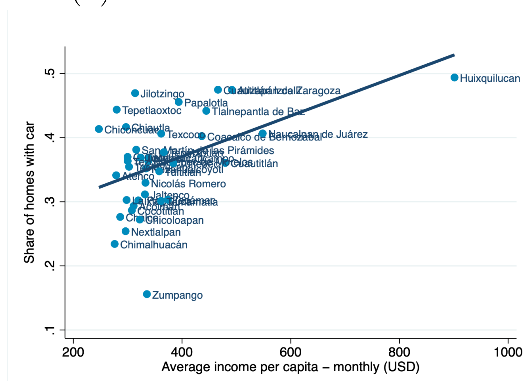
(b) Share of Homes with Cell Phone



(c) Share of Homes with Internet



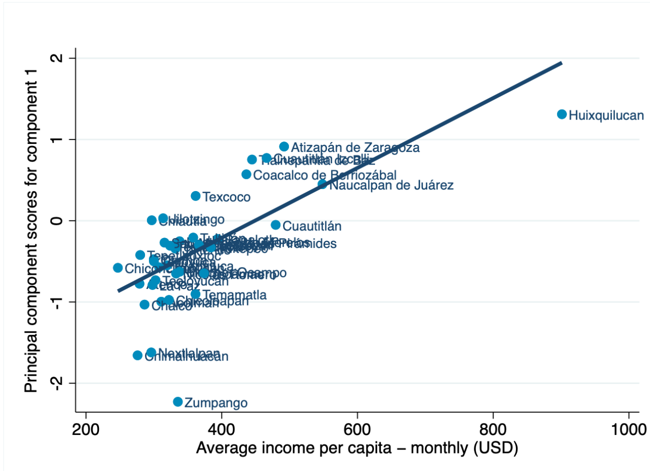
(d) Share of Homes with Car



Note: The figure shows the relationship several demographic variables from the Mexican Census and income per capita at the municipality level. The demographic variables included are the average years of schooling, the share of homes with internet, the share of homes with cell phone, and the share of homes with a car. The income data comes from individuals that report labor income surveyed in the Intercensal Survey of 2015.

Since income per capita is only available at the municipality level, next we show that each of the variables presented in Table G1 are strongly correlated with income measures at the municipality level. This is shown in Figure G2. Indeed, the first principal component of these variables strongly predicts the income per capita at the municipality level. This is shown in Figure G3. As a result, we believe that using income summarizes other relevant variables available in the Mexican census.

Figure G3: First Principal Component



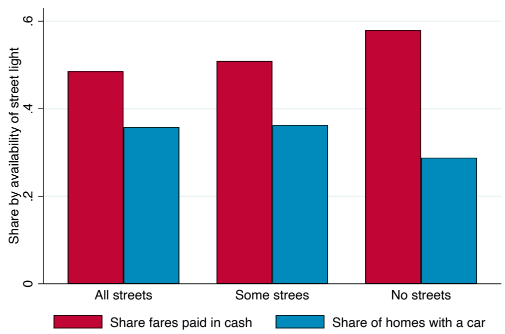
Note: The figure shows the relationship between income and the first principal component of the following demographic variables: average years of schooling, share of homes with internet, share of homes with cell phone, and share of homes with a car. The source of the demographic variables is the Mexican Census. The income data comes from individuals that report labor income surveyed in the Intercensal Survey of 2015.

Next, we show that measures of the availability of public transportation and infrastructure also correlate with income. Figure G4 illustrates that the percentage of trips paid in cash is higher in suburban regions of the State of Mexico and in census blocks with less-developed infrastructure. This is measured by factors such as the availability of street lights, pavement, or whether the census block has access to public transport. The figure also indicates that the percentage of households owning a car, a variable that is a proxy for income, is positively correlated with infrastructure development.

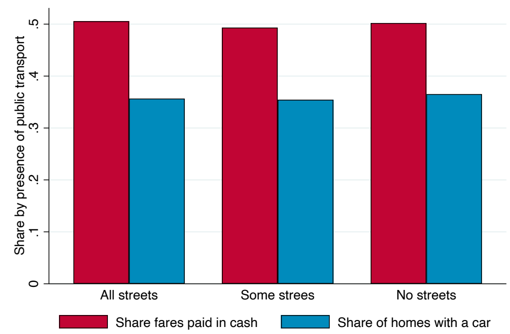
We now show that average income per capita is also positively correlated with commuting time, as measure by the average time it takes a person to go to school or work. This is shown in Panels (a) and (b) of Figure G5. These figures use data from the Intercensal Surveys, which are carried to update some socio-demographic information at the midpoint between censuses. Furthermore, Figure G5 shows that income also correlates with household choices of transportation modes. Panels (c) and (d) show a positive relationship between income and the share of households that drive their own vehicle to go to school or to go to work.

Figure G4: Share of Cash by Availability of Public Infrastructure

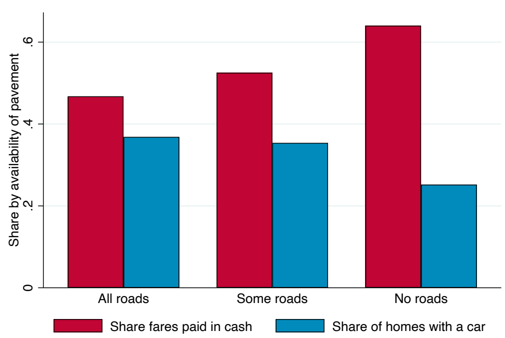
(a) Street Light



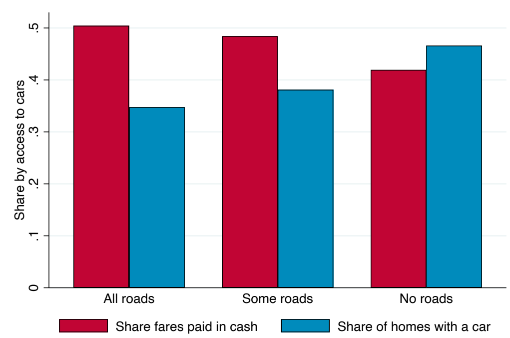
(b) Public Transport



(c) Pavement

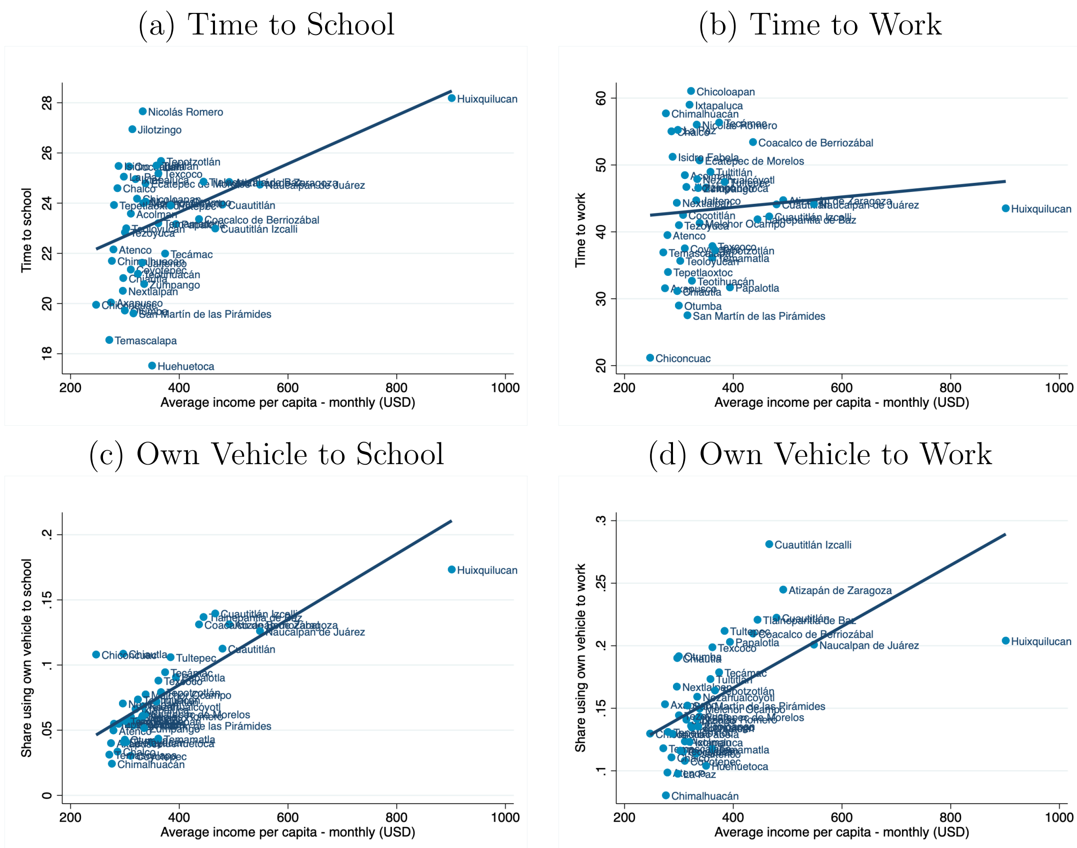


(d) Access to Cars



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

Figure G5: Commuting time and Transportation Mode



Note: Panel (a) shows the relationship between income and the average time (in minutes) households report it takes them to go to school. Panel (b) shows the relationship between income and the average time (in minutes) households report it takes them to go to work. Panel (c) shows the relationship between income and the share of households that drive their own vehicle to go to school. Panel (d) shows the relationship between income and the share of households that drive their own vehicle to go to work. The income data comes from individuals that report labor income surveyed in the Intercensal Survey of 2015.

Lastly, Table G2 shows that more trips are paid for in cash in municipalities that have less access to banking services, as measured by debit cards per capita, credit cards per capita, ATM transactions per capita, ATMs per capita, POS transactions per capita, POS terminals per capita, mobile banking per capita, and correspondents per capita. Access to financial services is also strongly correlated with income per capita.

Table G2: Banking Services

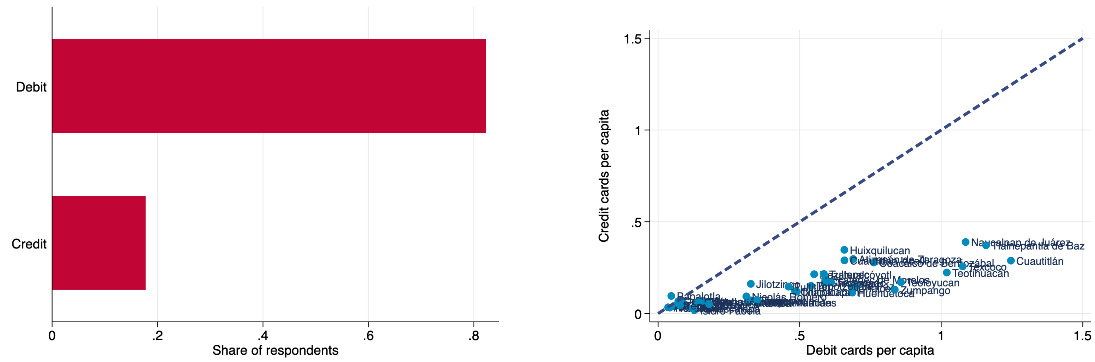
Note: The table displays various measures of the availability of banking services for municipalities in the State of Mexico, categorized into two groups: those with less than or equal to 50% of their fares paid in cash and those with more than 50% of their fares paid in cash. The income data is sourced from individuals who reported labor income in the Intercensal Survey of 2015. Data regarding debit cards, credit cards, ATM transactions, ATMs, POS transactions, POS terminals, mobile banking, and correspondents is obtained from the Financial Inclusion Database (BDIF).

	Share of Fares in Cash	
	$< 50\%$	$\geq 50\%$
Average Income per Capita	401.06	307.99
Debit Cards per Capita	0.71	0.36
Credit Cards per Capita	0.24	0.09
ATM Transactions per Capita	1.23	0.48
ATM per Capita	0.29	0.10
POS Transactions per Capita	1.00	0.21
POS per Capita	5.37	1.29
Mobile Banking per Capita	0.08	0.04
Correspondents per Capita	0.22	0.14

Overall, we find that income per capita is correlated with financial access, commuting times, transportation modes, public infrastructure, and the use of cash in Uber. For that reason, we decided to use this variable to determine the distributional consequences of a ban in the cash payment option.

G.2 Other Demographics

Figure G6: Debit and Credit Card Usage



(a) Cards: Most Frequent Payment Method (b) Debit vs Credit Cards Per Capita

Note: Panel (a) shows the most frequent payment method of households for transactions below 20 USD, conditional on households choosing cards as their most frequent payment method. The data comes from the National Survey of Financial Inclusion (ENIF). Panel (b) shows debit and credit cards per capita in each municipality of the State of Mexico. The dashed line is 45 degree line. The data comes from the Financial Inclusion Database (BDIF).

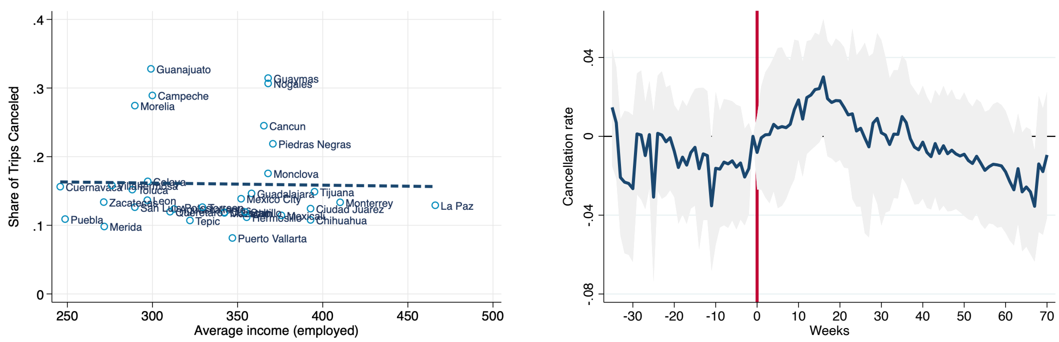
H Cancellations

In this section, we address the potential impact of cancellations on consumer surplus calculations and argue that they are unlikely to significantly affect our results. Our analysis reveals three key patterns in the data concerning cancellations. First, a minimal percentage of trips, only 2.4%, are canceled by drivers, with the majority of cancellations originating from riders. The ratio of trips canceled by riders over total trips is approximately 13.5%. In Mexico City, these rates are very similiar 3% and 10.8%.

Second, both rider and driver cancellation rates do not show any dependence on the average income of the city. Panel (a) of Figure H1 shows that the share of trips canceled is not correlated with the average income of the city. Panels (a) and (b) of Figure H2 shows the same patterns if we divide the cancelation rates for riders and drivers. This pattern indicates that cancellations are not significantly influenced by socioeconomic factors.

Lastly, the introduction of cash as a payment option did not result in a notable change in cancellation rates by riders or drivers. Panel (b) of Figure H1 shows how the introduction of cash payments affected cancelation rates in Mexico. We use an event study approach to compare the cancelation rate before and after the introduction of cash payments following the methodology developed by Alvarez and Argente (2022). The graph show that conditional on city and time fixed effects, no pretrends appear at least 20 weeks before the introduction of cash. This pattern is consistent with the timing of the introduction of cash being randomly assigned conditional on the city and time fixed effects. The graphs also show that the cancelation rate did not change after the introduction of cash payments. Panels (c) and (d) of Figure H2 show similar patterns for the cancelation rate of drivers and riders; both remain fairly constant after the introduction of cash. Taken together, these findings strongly suggest that cancellations are unlikely to substantially affect the accuracy of our consumer surplus calculations.

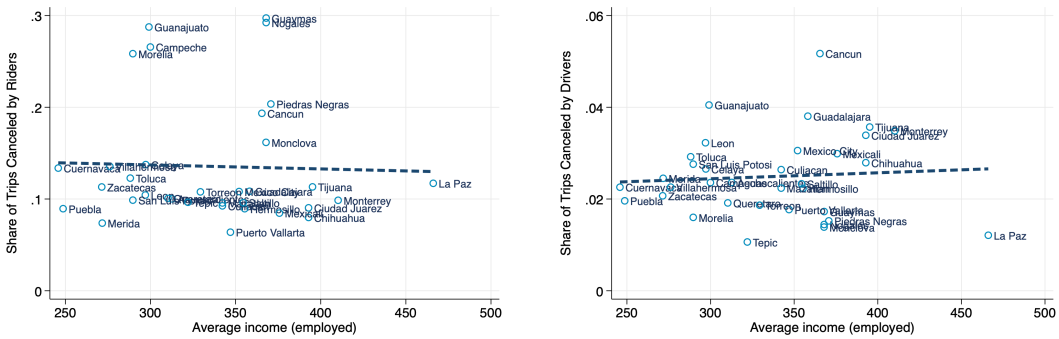
Figure H1: Cancellation Rate: All Trips



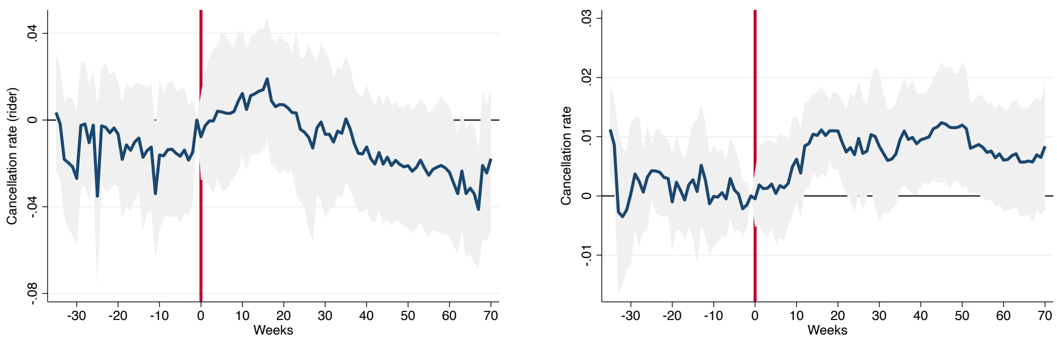
(a) Cancelation Rate and Income (b) Event Study: Cancelation Rate

Note: Panel (a) shows the relationship between the average cancelation rate and the avarage income of employed workers in each city where Uber is active. Income estimates are obtained from the National Employment Survey (ENOE). Panel (b) shows the evolution of the cancelation rate before and after the introduction of cash. The vertical line marks the week that cash payments were introduced. The gray area depicts the 95% confidence interval computed using Driscoll and Kraay standard errors.

Figure H2: Cancellation Rate: Riders and Drivers



(a) Cancelation Rider and Income (b) Cancelation Driver and Income



(a) Event Study: Cancelation Rider (b) Event Study: Cancelation Driver

Note: Panel (a)-(b) shows the relationship between the average cancelation rate of riders (drivers) and the average income of employed workers in each city where Uber is active. Income estimates are obtained from the National Employment Survey (ENOE). Panel (c)-(d) shows the evolution of the cancelation rate of riders (drivers) before and after the introduction of cash. The vertical line marks the week that cash payments were introduced. The gray area depicts the 95% confidence interval computed using Driscoll and Kraay standard errors.

I Price Response of Uber and Other Means of Transportation: A Summary of the Empirical Evidence

In this section, we review the available evidence on the price response of several transportation modes to the entry or ban of cash in Uber. For all the details regarding the implementation of the empirical analysis, please refer to Alvarez and Argente (2021), as all the references below are based on this work.

- No change in Uber prices: Figure 3 plots the response of several outcome variables before and after the introduction of cash payments. The graphs show that, conditional on city- and time-fixed effects, no pre-trends appear at least 20 weeks before the introduction of cash. This pattern is consistent with the timing of the introduction of cash being randomly assigned conditional on the city- and time-fixed effects. Panels (d) and (e) of Figure 3 show that neither the average price per mile nor the average surge multiplier increased after the introduction of cash. We also exploit the fact that cash was introduced only in the State of Mexico to compare census blocks that did and did not have the option to pay for Uber rides in cash. To do so, we use coarsened exact matching (CEM) to identify the appropriate counterfactual for each census block where cash was introduced. Table 1 reports the average treatment effect of the introduction fo cash. Column (7) shows no significant change in prices after the introduction of cash. Lastly, we use an RD design to estimate the effect of the introduction of cash on each side of the border of Mexico City and test whether the introduction of cash caused discontinuous changes in the number of trips near the border. Table C5 shows that, consistent with the event study and with the coarsened exact matching evidence, the regression discontinuity approach reveals no significant effect on prices. To study the effect of Puebla's ban on cash payments on prices, we use the synthetic control method. We do not find significant changes in ride prices, as shown in Panels (c) and (d) in Figure 8.

- No change in estimated time of arrival (ETA) of Uber rides: Panel (f) of Figure 3 shows that drivers' estimated time of arrivel after a ride is hailed remains unchanged after the introduction of cash payments.

- No change in the price of taxis: Figure A2 shows that in an event study the introduction of cash payments also did not lead to any increase in average taxicab prices. Figure D2 shows using a synthetic control method that the ban on cash did not affect the prices of taxis either.

- No change in ETA of taxis: Taxi prices might be regulated and, and thus unlikely to be responsive to changes in demand in the short run. If taxi prices were fixed, other non- pecuniary costs like wait times may have responded to the change in demand. We analyze data from the application EC Taximeter to address this concern. EC Taximeter lets users verify that they are being charged fairly for a regular taxi ride. Our data set contains information about the trips taken by regular taxicabs, including those that can be called on the phone, those circulating in the street, and those queued up at taxicab stands. Table 5 shows that despite the large increase in demand for Uber rides that followed the introduction of cash payments, the entry of cash payments had no significant effect on ETAs of taxis. We find similar results for the ban on cash in Puebla. This evidence is presented in Panel (a) of Figure D2.

- No change in the price of other ride-hailing companies: We use data from Google Maps to study the changes in prices that took place before, during, and after the ban on cash that took place in Panama City between September 30, 2019 and February 6th, 2020. During this period, we collected prices and ETAs from Uber along with those of public transport and other ride-hailing services for several origin addresses evenly distributed across Panama City. Panel (a) in Figure 11 shows the patterns of prices for Uber and Cabify before and after the ban on cash payments after controlling for origin-address-fixed effects. The prices for Uber or Cabify did not change around the implementation of the ban. Panel (b) Figure 11 shows that the prices of ride-hailing companies remained constant when cash was reintroduced a few months later.

- No change in ETA other ride-hailing companies: Panel (c) and (d) in Figure 11 show that the ETA of ride-hailing companies such as Cabify did not change after ban/entry of cash payments in Uber rides.

- No change in the time to location of public transport: The prices of public trasport regulated and, and thus unlikely to be responsive to changes in demand in the short run. For that reason, collect data for time to location. Panel (e) and (f) show that the estimated times to location of ride-hailing companies or public transport did not change after the introduction or ban on cash payments in Uber.

Overall, these evidence shows that despite the large demand changes in the number of trips and fares observed when cash payments are either introduced or banned, we do not observe changes in the prices of Uber or its close substitutes, whether those costs were pecuniary or not.

J Mixed Users

J.1 Heterogeneity

Index riders by i and assume that $\bar{P}_i$ is rider specific. Assume that the demands of total trips by mixed riders facing $P = p_a = p_c$ can be written as: $x_i = k \log \bar{P}_i - k \log P = \beta_{0i} + \beta_1 \log P$. We assume that k, and hence the slope of the regression, is common across riders. We can then write:

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

The rider specific elasticity is $\log \bar{P}_i / \log P = 1/\epsilon_i(P)$ 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. 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 control group's fares. Given the randomization, the control group has the same average fares, pre-experiment, as the treatment groups. We let:

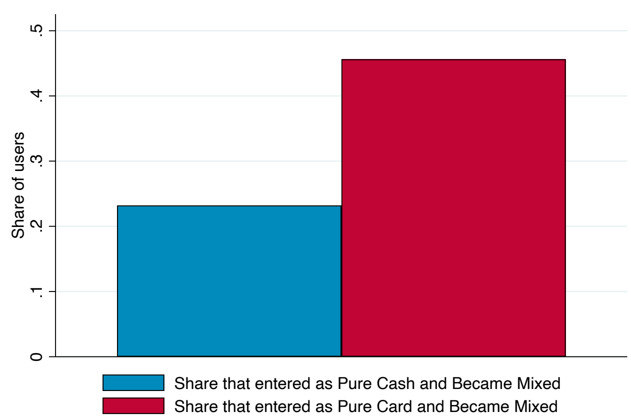
$$\epsilon(1) = \beta_1/\beta_0$$

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

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

J.2 Switchers

Figure J1: Share of Switchers by Type of Rider at Entry

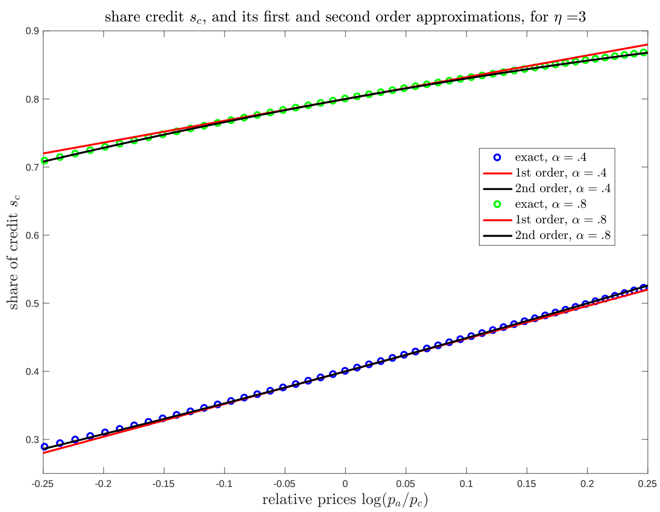


Note: The figure shows the share of pure card riders and the share of pure credit riders that become mixed riders in the State of Mexico from 2017 to November 2018. Riders are classified as pure cash and pure credit riders according the the payment method chosen in their first trip.

K Experiments: Additional Robustness Checks

K.1 CES

Figure K1: Quality of the approximations



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

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

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

using the identity

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

thus

$$s_c = \frac{1}{1 + \left(\frac{1-\alpha}{\alpha}\right)\left(\frac{p_a}{p_c}\right)^{1-\eta}} \tag{46}$$

A first order approximation of s_c around $\log(p_a/p_c) = 0$ gives equation (18). A second order approximation of s_c around $\log(p_a/p_c) = 0$ gives equation (19). Note that the second order approximation can be convex or concave depending on whether $\alpha \geq 1/2$ or not. Figure K1 plots the exact expression given by equation (46) and its first and second order approximation given by equation (18) and equation (19) respectively. The range of the x-axis coincides with the range on variability on the relative prices the experiment for mixed users. The value $\eta = 3$ used for the elasticity of substitution in the figure is our preferred estimate. We plot the exact expression for s_c and its two approximations for two values of α, one above 1/2 and one below. From Figure K1 we conclude that for this range of parameters the first order approximation is very accurate and the second order approximation is almost exact.

K.2 Estimation of Elasticities: Robustness

Table K1: Semi-Elasticity of Demand: Pure Cash Users (Miles)

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

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

Table K2: Elasticity of Demand: Pure Cash Users (Miles - at Least 5 Trips)

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

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

Table K3: Semi-Elasticity of Demand: Pure Cash Users (Miles - at Least 5 Trips)

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

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

Table K4: Elasticity of Demand: Pure Cash Users (Trips)

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

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

Table K5: Semi-Elasticity of Demand: Pure Cash Users (Trips)

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

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

Table K6: Elasticity of Demand: Pure Cash Users (Trips - Poisson)

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

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

Table K7: Elasticity of Demand: Pure Cash Users (Miles - PPML)

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

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-1.170***	-1.194***	-0.895***	-0.727*
	(0.074)	(0.068)	(0.145)	(0.377)
Observations	138,725	138,725	4,279	3,569
R-squared	0.002	0.154	0.434	0.146
Controls	No	Yes	Yes	Yes

Table K8: Elasticity of Demand: Pure Cash Users (Miles - Log)

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

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-0.530***	-0.600***	-0.834***	-0.082
	(0.042)	(0.039)	(0.135)	(0.253)
Observations	27,507	27,507	4,279	1,122
R-squared	0.006	0.153	0.346	0.135
Controls	No	Yes	Yes	Yes

Table K9: Semi-Elasticity of Demand: Mixed Users (Miles)

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

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

Table K10: Elasticity of Demand: Mixed Users (Miles - at Least 5 Trips)

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

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

Table K11: Semi-Elasticity of Demand: Mixed Users (Miles - at Least 5 Trips)

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

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

Table K12: Elasticity of Demand: Mixed Users (Trips)

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

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

Table K13: Semi-Elasticity of Demand: Mixed Users (Trips)

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

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

Table K14: Elasticity of Demand: Mixed Users (Trips - Poisson)

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

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

Table K15: Elasticity of Demand: Mixed Users (Miles - PPML)

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

	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Log Price	-0.976***	-0.977***	-1.018***	-0.911***	-1.289***
	(0.092)	(0.082)	(0.089)	(0.064)	(0.255)
Observations	109,365	109,365	98,773	11,660	4,306
R-squared	0.001	0.212	0.200	0.525	0.236
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

Table K16: Elasticity of Demand: Mixed Users (Miles - Log)

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

	(1) AA	(2) AA	(3) AA	(4) Mandin	(5) Ubernomics
Log Price	-0.465***	-0.533***	-0.584***	-0.861***	-0.739***
	(0.060)	(0.054)	(0.058)	(0.073)	(0.201)
Observations	37,890	37,890	32,486	11,659	2,107
R-squared	0.002	0.192	0.177	0.462	0.216
Controls	No	Yes	Yes	Yes	Yes
Type	1 pct	1 pct	5 pct	1 pct	1 pct

Table K17: Elasticity of Demand: Pure Card Users (Miles)

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

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

Table K18: Semi-Elasticity of Demand: Pure Card Users (Miles)

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

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

Table K19: Elasticity of Demand: Pure Card Users (Miles - at Least 5 Trips)

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

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

Table K20: Semi-Elasticity of Demand: Pure Card (Miles - at Least 5 Trips)

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

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

Table K21: Elasticity of Demand: Pure Card Users (Trips)

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

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

Table K22: Semi-Elasticity of Demand: Pure Card Users (Trips)

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

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

Table K23: Elasticity of Demand: Pure Card Users (Trips - Poisson)

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

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

Table K24: Elasticity of Demand: Pure Card Users (Miles - PPML)

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

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-0.585***	-0.588***	-0.569***	-0.341***
	(0.102)	(0.094)	(0.032)	(0.122)
Observations	88,844	88,844	47,849	26,162
R-squared	0.000	0.212	0.562	0.291
Controls	No	Yes	Yes	Yes

Table K25: Elasticity of Demand: Pure Card Users (Miles - Log)

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

	(1) AA	(2) AA	(3) Mandin	(4) Ubernomics
Log Price	-0.205***	-0.246***	-0.571***	-0.271***
	(0.066)	(0.059)	(0.036)	(0.086)
Observations	23,252	23,252	47,849	10,971
R-squared	0.000	0.198	0.480	0.239
Controls	No	Yes	Yes	Yes

Table K26: Semi-Elasticity of Demand: All Users (Miles - No Control Group)

Note: The table reports the semi-elasticity of demand of pure card users, mixed users, and pure cash users, estimated using equation (27) using miles as dependent variable and excluding the control group. Column (1) reports the estimates for pure cash users without using controls. Column (2) estimates the semi-elasticity for pure cash users using controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, and log of tenure. Column (3)-(5) report the results using for mixed users with and without controls. Column (6)-(7) reports the results for pure card users with and without controls. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) Pure Cash	(2) Pure Cash	(3) Mixed	(4) Mixed	(5) Mixed	(6) Pure Card	(7) Pure Card
Log Price	-2.517***	-2.542***	-5.554***	-5.861***	-5.473***	-2.436**	-1.911**
	(0.273)	(0.249)	(1.205)	(1.028)	(1.030)	(1.038)	(0.884)
Observations	86,645	86,645	22,364	22,364	20,191	30,202	30,202
R-squared	0.001	0.171	0.001	0.273	0.255	0.000	0.275
$\hat{y}$	1.374	1.369	4.011	3.961	3.598	3.726	3.812
Controls	No	Yes	No	Yes	Yes	No	Yes
Type			1 pct	1 pct	5 pct		

Table K27: Semi-Elasticity of Substitution: Mixed Users (Miles)

Note: The table reports estimates of the semi-elasticity of substitution between cash and card payments for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. Column (1) reports the results of estimating γ using the transformed share specification denoted in equation (20) and including mixed users with more than 1% of their fares paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Column (4) includes the constant specified in equation (20) as a regressor. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

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

Table K28: Elasticity of Substitution: Mixed Users (Miles - at Least 5 Trips)

Note: The table reports estimates of the elasticity of substitution between cash and card payments for mixed users. The dependent variable is the relative miles between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. The sample includes users with at least 5 trips during the year before the week of the experiment in the State of Mexico. Column (1) reports results after using the transformed share specification denoted in equation (20) and including mixed users with more than 1% of their fares paid in cash and less than 99%. Column (2) uses the same specification including controls including historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Column (4) includes the constant specified in equation (20) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (18). Column (6) estimates the elasticity using the CES second order approximation in equation (19). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predicted share of fares paid in card (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (18) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels.

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

Table K29: Semi-Elasticity: Mixed Users (Miles - at Least 5 Trips)

Note: The table reports estimates of the semi-elasticity of substitution between cash and card payments for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the results of estimating γ using the transformed share specification denoted in equation (20) and including mixed users with more than 1% of their fares paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Column (4) includes the constant specified in equation (20) as a regressor. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels.

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

Table K30: Elasticity of Substitution: Mixed Users (Trips)

Note: The table reports estimates of the elasticity of substitution between cash and card payments for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative trips between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. Column (1) reports the results after using the transformed share specification denoted in equation (20) and including mixed users with more than 1% of their trips paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their trips paid in cash and less than 95%. Column (4) includes the constant specified in equation (20) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (18). Column (6) estimates the elasticity using the CES second order approximation in equation (19). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predict share of trips paid in card (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (18) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels.

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

Table K31: Elasticity of Substitution: Mixed Users (Trips - at Least 5 Trips)

Note: The table reports estimates of the elasticity of substitution between cash and card payments for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative trips between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. The sample includes users with at least 5 trips during the year before the week of the experiment. Column (1) reports the results after using the transformed share specification denoted in equation (20) and including mixed users with more than 1% of their trips paid in cash and less than 99%. Column (2) reports the same specification including controls. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their trips paid in cash and less than 95%. Column (4) includes the constant specified in equation (20) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (18). Column (6) estimates the elasticity using the CES second order approximation in equation (19). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predict share of trips paid in card (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (18) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

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

Table K32: Elasticity: Mixed Users (Miles - Price Increases and Decreases)

Note: Note: The table reports estimates of the elasticity of substitution between cash and card payments for mixed users after splitting price increases and price decreases. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. Column (1)-(2) estimate the elasticity for positive price changes and negative price changes using the CES first order approximation in equation (18). Column (3)-(4) estimate the elasticity for positive price changes and negative price changes using the CES second order approximation in equation (19). The elasticity in each column is estimated including controls and mixed users with more than 1% of their fares paid in cash and less than 99%. The controls included for each users are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

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

Table K33: Elasticity of Substitution: Mixed Users (Miles) - Second Order Term

Note: The table reports estimates of the elasticity of substitution between cash and card payments for mixed users. The estimates are computed using experimental data collected in the State of Mexico. The dependent variable is the relative miles between card and cash payments for each user the week of the experiment and the independent variable is the relative price for cash and card trips. Each column estimates the elasticity using the CES second-order approximation in equation (19) and reports the elasticity estimated using the second-order term. Column (1) reports the results for mixed users with more than 1% of their fares paid in cash and less than 99% of their fares paid in cash. Column (2) includes users with more than 5% of their fares paid in cash and less than 95% of their fares paid in cash. Column (3) reports results for mixed users with more than 1% of their fares paid in cash and less than 99% of their fares paid in cash with at least 5 trips. Column (4) reports results for mixed users with more than 1% of their fares paid in cash and less than 99% of their fares paid in cash including controls. The controls included for each user are the historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (5) reports the same specification for users with at least 5 trips. The standard errors are computed using the Delta Method. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Elasticity	3.089***	2.703***	3.054***	2.935***	2.951***
	(0.324)	(0.387)	(0.332)	(0.337)	(0.341)
Observations	53,966	46,328	51,724	53,966	51,724
Controls	No	No	No	Yes	Yes
Type	1 pct	5 pct	1 pct	1 pct	1 pct
Specification	CES - Second	CES - Second	CES - Second	CES - Second	CES - Second
Term	Second Order	Second Order	Second Order	Second Order	Second Order
Trips	All	All	5 or more	All	5 or more

Table K34: Elasticity of Substitution: Mixed Users (Miles - No Control Group)

Note: The table reports estimates of the elasticity of substitution between cash and card payments for mixed users and excluding the control group in the regression. The dependent variable is the relative miles between card payments and cash for each user the week of the experiment and the independent variable are the relative prices for trips in cash and card. Column (1) reports results after using the transformed share specification denoted in equation (20) and including mixed users with more than 1% of their fares paid in cash and less than 99%. Column (2) uses the same specification including controls including historical trips, trips squared, fares, fares squared, cash fares, cash fares squared, log of tenure, cash trips, and cash trips squared. Column (3) includes users with more than 5% of their fares paid in cash and less than 95%. Column (4) includes the constant specified in equation (20) as a regressor. Column (5) estimates the elasticity using the CES first order approximation in equation (18). Column (6) estimates the elasticity using the CES second order approximation in equation (19). Column (7) reports the results of the elasticity of substitution estimated in two steps. First, we compute the predicted share of fares paid in card (i.e. $\hat{\alpha}$) using all the controls variables. Then, we estimate equation (18) using the predicted share. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elasticity	3.179***	2.910***	2.658***	3.000***	2.620***	2.618***	2.285***
	(0.357)	(0.334)	(0.178)	(0.209)	(0.102)	(0.102)	(0.080)
Observations	24,303	24,303	20,882	24,303	24,303	24,303	31,433
Controls	No	Yes	Yes	Yes	Yes	Yes	No
Type	1 pct	1 pct	5 pct	1 pct	1 pct	1 pct	1 pct
Specification	Transf.	Transf.	Transf.	Transf.	CES	CES	CES
				Cons	First	Second	First IV

K.3 Extensive-Margin: Robustness

Table K35: Extensive-Margin: Adoption of a Card (Long-Run Effects)

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

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

Table K36: Extensive-Margin: Adoption of a Card - Unconditional

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

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

Table K37: Extensive-Margin: Adoption of a Card (No Control Group)

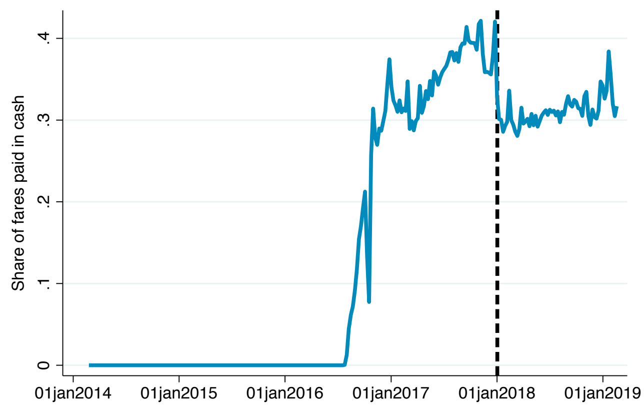
Note: The table reports the percent of users that adopted a payment-card for each of the treatment groups in experiment three relative to the first treatment group, which received 3 times their average weekly fares if the users register a card in the application. Migration is an indicator function that equals one if the user registered a card conditional on taking trip the weeks of the experiment. The variables "Treatment" report the migration rates relative to the firs treatment group in the experiment: 6 and 9 times their average weekly fares if the users register a card in the application. Column (1) reports the rates of card adoption for the experiment that lasted one week. Column (2) reports the rates of card adoption during the first week for the experiment that lasted six weeks. Column (3) reports the rates of card adoption for the experiment that lasted six weeks. Column (4) reports the rates of card adoption during the first three weeks of the experiment. Column (5) reports the rates of adoption in the last three weeks of the experiment. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels.

	(1) 1 week	(2) 1 week	(3) 1-6 weeks	(4) 1-3 weeks	(5) 4-6 weeks
Treatment 2 - 1 week	0.0029				
	(0.005)				
Treatment 3 - 1 week	0.0125**				
	(0.005)				
Treatment 2 - 6 week		0.0052	0.0061	0.0100**	0.0048
		(0.005)	(0.005)	(0.005)	(0.003)
Treatment 3 - 6 week		0.0224***	0.0135***	0.0203***	0.0055*
		(0.005)	(0.005)	(0.005)	(0.003)
Constant	0.0513***	0.0438***	0.1044***	0.0728***	0.0541***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	12,788	12,856	28,457	22,052	33,568
R-squared	0.001	0.002	0.000	0.001	0.000

L Panama

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

Figure L1: Panama: Share of Fares Paid in Cash



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

Table L1: Elasticity of Demand: Panama (Trips)

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

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

M Adapting Puebla's Evidence to State of Mexico

In this section, we adapt the evidence in Alvarez and Argente (2022) on the rate of migration of pure cash riders in Puebla after the ban, to the rate of migration of pure cash users in an hypothetical ban in the State of Mexico. In their counterfactual analysis of the ban in

Puebla using synthetic control method, they found that the State of Mexico is one of the cities with higher weights on the synthetic Puebla. Since the excess rate at which pure cash users migrated to become pure card users after the ban is an important statistic in the identification of the model, we adapt the estimates Alvarez and Argente (2022) obtained using the actual ban in Puebla to the evaluation of an hypothetical ban in the State of Mexico. They found an excess migration rate of about 30% of the pure cash users. We follow a two steps procedure to adapt this estimate to the State of Mexico. The first step is to document the difference in observable indicators for residents of Puebla and State of Mexico, where we define both locations as the municipalities covered by Uber service. The second step is to include some of these observables in their analysis of the rate of migration in Puebla, so we can take into account the difference in observables between the two cities. Overall, these difference change the estimate to the State of Mexico in less than 1%.

Table M1: Puebla vs State of Mexico: Summary Statistics at the Block Level

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

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

Table M1 displays statistics at the census block level for Puebla and the State of Mexico. Table M2 displays statistics at the municipality level for Puebla and for the State of Mexico. From these tables we conclude that, while Puebla and the State of Mexico are relatively similar in the context of the cities served by Uber across Mexico, Puebla's residents have in average about one more year of education, and have higher financial inclusion. In Table M3 we include the census block level variables we have access to in a linear probability model predicting whether a pure cash rider will take trips paid with a card in Puebla after the ban. The sample used in this regression are all the trips in three months on the year before and three months after the ban, which are geolocalized and matched with the census at the block level. [73] The presence of a bank in the geographical statistical area (AGEB) and the average years of education have the expected signs, although the values of the coefficients are

[73] This sample is smaller than the universe used in Alvarez and Argente (2022). The smaller size of the sample is due to the fact that we need to geolocalize all these trips.

small and only marginally statistically significant. Using these coefficients and the average difference between the observables in Puebla and in the State of Mexico, we obtain that the indeed the migration rate will be lower in the State of Mexico than in Puebla, but that correction is smaller than 1%, i.e. it is given by $(0.74-0.59)\times 0.0095+(9.95-8.88)\times 0.0056 = 0.0074$.

Table M2: Puebla vs State of Mexico: Financial Inclusion Statistics

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

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

Table M3: Puebla: Returning After the Ban of Cash

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

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

N Ban on the Use of Cards: Argentina

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

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

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

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

O Communication

Email Experiments 1

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

Header: Viaja más, pagando menos.

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

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

Email Experiments 2

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

Pre Header: Promoción especial sólo por esta semana.

Header: Viaja más, pagando menos.

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

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

Email Ubernomics

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

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

Email Mandin

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

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

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

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

Email Experiments 3

[Nombre],

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

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

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

P Other Experiments

P.1 Ubernomics

Table P1: Summary Statistics: Ubernomics

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

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

The experiment took place in the Greater Mexico City from May 15th to May 22nd of 2017, only a few months after the introduction of cash in the State of Mexico. The treatment groups received 10% and 20% off in all rides taken the week of the experiment. The day before the experiment started, all riders in the treatment groups were emailed and received an in-app notification informing them of the relevant price change. The promotion went live on Monday at 4 am local time and lasted through the following Monday at 4 am. Riders received a reminder of the promotion on Wednesday and Friday. To guarantee that the sample in this experiment is comparable to the one used in our experiments, we only consider riders whose most frequent city is the Greater Mexico City. Table P1 shows descriptive statistics of the users in this experiment. The sample includes 4,869 pure cash users and 4,306 mixed users. To guarantee that the estimates of the elasticity of demand are comparable across experiments, we estimate them controlling for the same observables we use to balance the treatment groups in our experiment: average of weekly historical trips, average of weekly historical fares, and log tenure (in weeks). Section K.2 shows the estimates of the elasticity of demand for pure cash users (Table 4) and mixed users (Table 3). The tables show that the estimates are close to those found using our experimental data; the null hypothesis that these elasticities are the same cannot be rejected.

P.2 Mandin Experiment

Table P2: Summary Statistics: Mandin

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

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

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

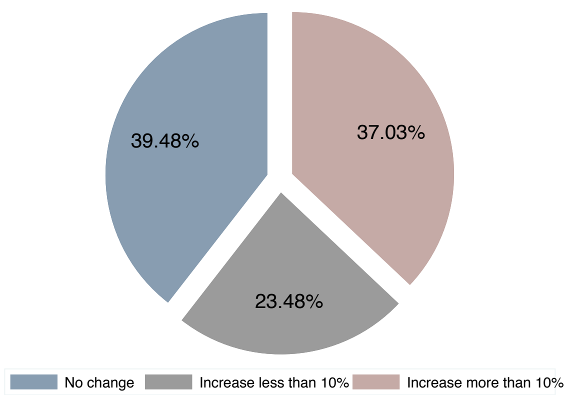
In this experiment, the control group was composed by users in the segments Remain, Regular, Mid, Power and Rockstar. The treatment groups were the following: 10% off: Remain and Regular; 20% off: Remain, Regular, Mid, Power and Rockstar; 30% off: Mid, Power and Rockstar. Discounts were offered to targeted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

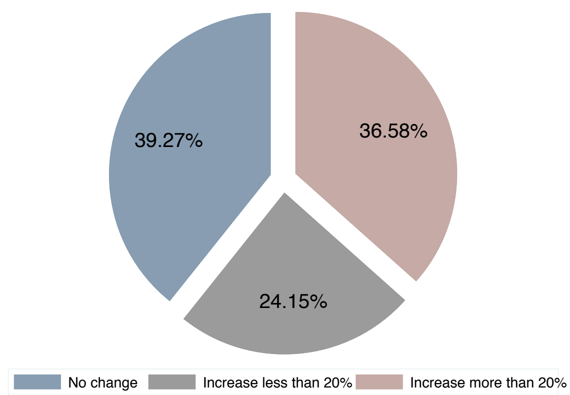
To guarantee that the sample in this experiment is comparable to the one we use we consider riders whose most frequent city is the Greater Mexico City as in our experiment. Table P2 describes the characteristics of the users that took part of the experiment. In addition, we control for the same observables we use to balance the treatment groups in our experiment: average of weekly historical trips, average of weekly historical fares, and log tenure (in weeks). Using the data of this experiment we find an elasticity of 1.1 for pure cash users and 1.2 for mixed users, which are within the range of those estimated in our experiment. Importantly, given that this experiment lasted four weeks, we consider these findings as evidence that the short-run elasticity and the medium-run elasticity of Uber rides are very similar.

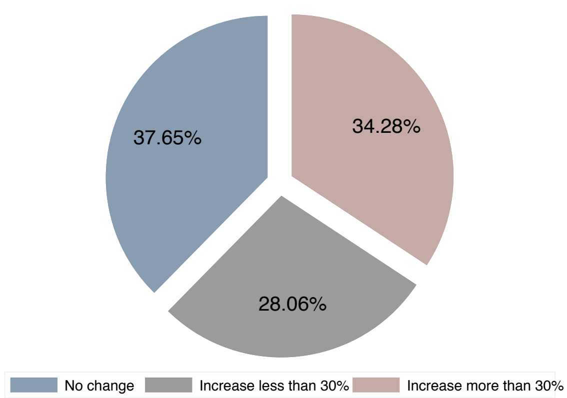
Q Survey Results

Q.1 Mixed Users

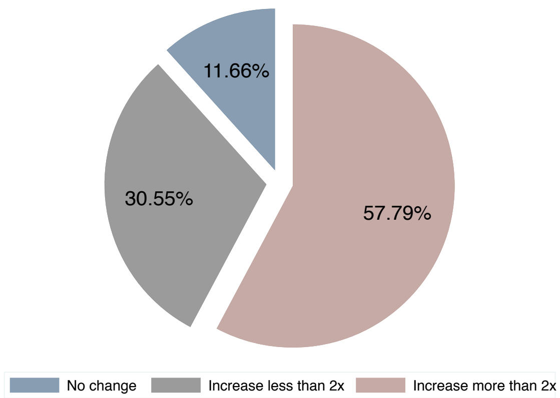
Question 1: If your receive a 20% discount for one week, how would you change your trips...



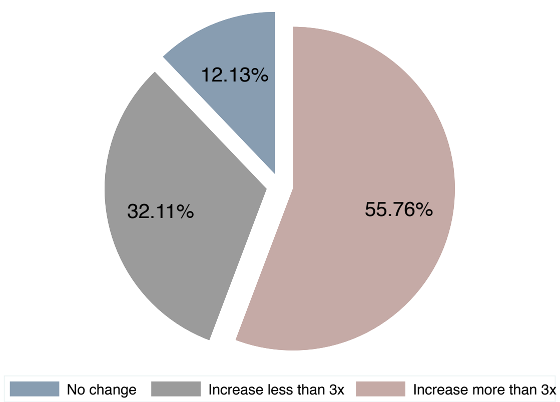




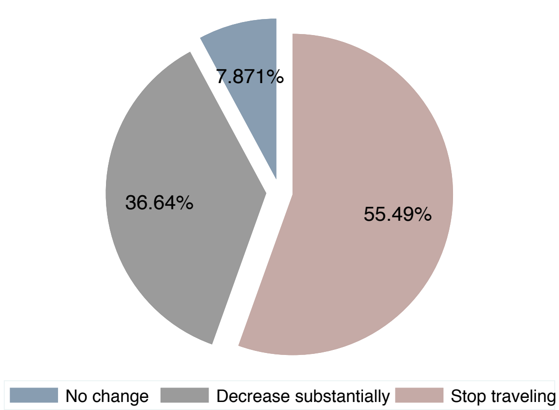
Question 2a: If the price of trips is permanently reduced by half, how would you change your trips...



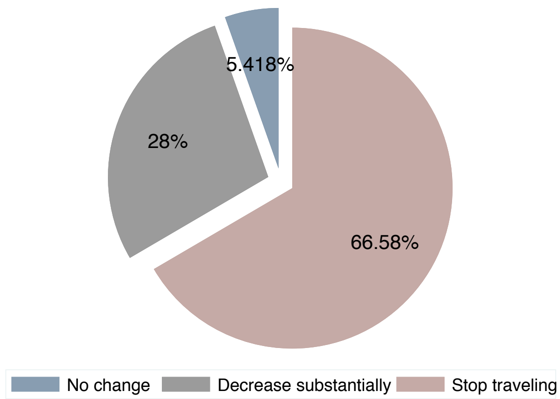
Question 2a: If the price of trips is permanently reduced to a third, how would you change your trips...



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

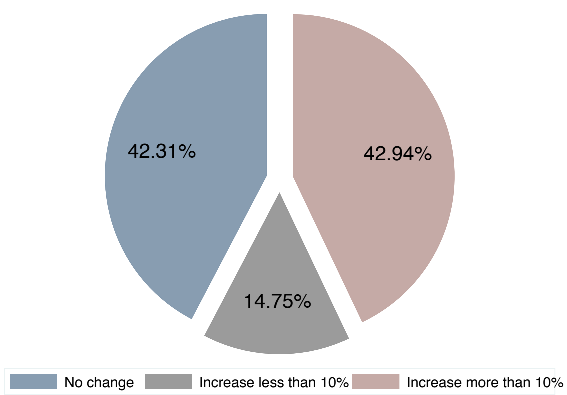


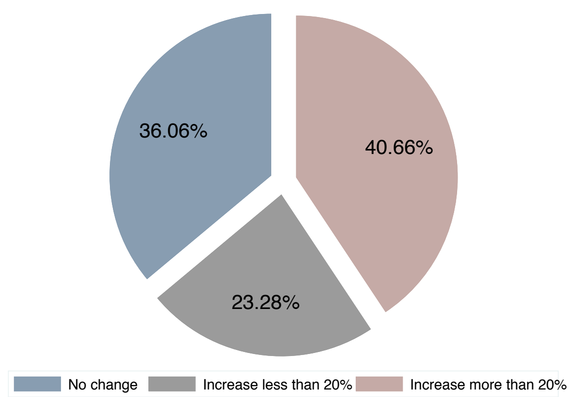
Question 3a: If the price of trips is permanently tripled, how would you change your trips...

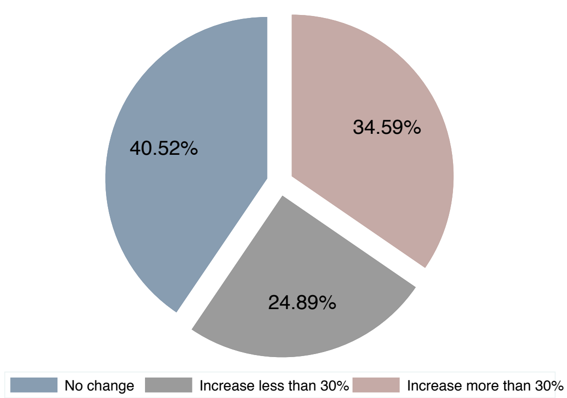


Q.2 Pure Cash Users

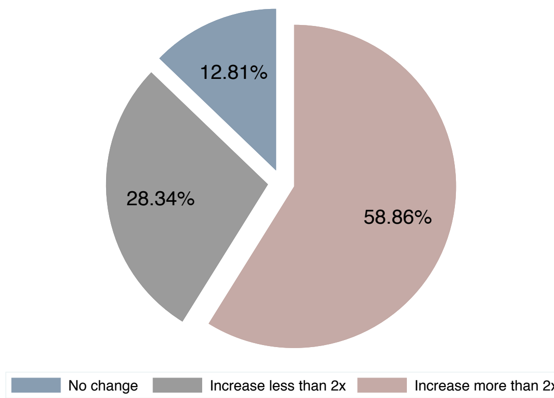
Question 1: If your receive a 20% discount for one week, how would you change your trips...



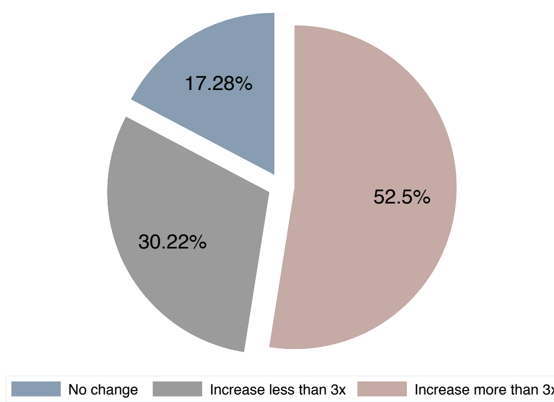




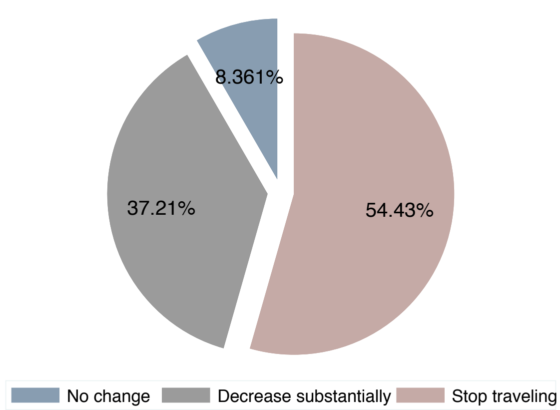
Question 2a: If the price of trips is permanently reduced by half, how would you change your trips...



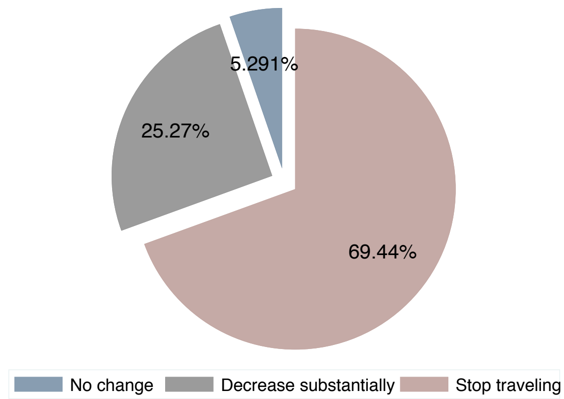
Question 2a: If the price of trips is permanently reduced to a third, how would you change your trips...



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



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



Q.3 Choke Prices - Alternative Functional Forms

Table Q1: Fraction of Users Who Would Stop Riding After Price Increase

Note: The table shows the fraction of users who responded that they would stop using Uber if prices were to permanently double or triple in our survey. It also presents the fraction of users that would stop traveling in our data under different demand specifications: linear, semi-log (baseline), and log-log.

	Survey	Semi-log (baseline)	Linear	Log-log
Pure Cash Users				
If price is permanently doubled	54%	51%	74%	0%
If price is permanently tripled	69%	75%	94%	0%
Mixed Users				
If price is permanently doubled	56%	56%	73%	0%
If price is permanently tripled	67%	73%	93%	0%

R Discrete Choice Model: GMM Estimation

Consider a data set with the following information for each rider indexed by $i = 1, 2, \ldots, I$, which corresponds to Experiment 1 in the paper. There are observations prior to the experiment, and during the experiment. We index the data prior to the experiment by w. This corresponds to the week w out of a total of W^i weeks of data. For these weeks we have:

1. T^i_w: number of trips in the week w prior to the experiment (a non-negative integer).
2. A^i_w: expenditure on cash trips in the week $w$prior to the experiment (a non-negative real).

3. C_w^i: expenditure on credit trips in the week w prior to the experiment (a non-negative real).

Prior to the experiment the prices of cash and credit trips are normalized to $(p_a, p_c) = (1, 1)$. During the experiment, which lasted a week, each rider was randomly assigned to group, which we index by $q(i) \in Q = \{0, 1, 2, 3, 4, 5, 6\}$. Each group q corresponds to different prices $p^q = (p_a^q, p_c^q)$. We have:

$$\begin{bmatrix} p_a^0 & p_c^0 \\ p_a^1 & p_c^1 \\ p_a^2 & p_c^2 \\ p_a^3 & p_c^3 \\ p_a^4 & p_c^4 \\ p_a^5 & p_c^5 \\ p_a^6 & p_c^6 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0.9 & 0.9 \\ 0.8 & 0.8 \\ 1 & 0.9 \\ 1 & 0.8 \\ 0.9 & 1 \\ 0.8 & 1 \end{bmatrix}$$

During the experiment we observed

1. T^i: number of trips during the week of the experiment (a non-negative integer).

2. A^i: expenditure on cash during the week of the experiment (a non-negative real).

3. C^i: expenditure on credit during the week of the experiment (a non-negative real).

4. $q(i)$: and indicator of the experiment the rider was assigned to (an element of Q)

We specify that each rider has two rider-specific parameters $\alpha^i, \bar{P}^i$. All the riders have the same value of the parameter k (the semi-elasticity of the demand for trips) and the parameter η (the cash-credit elasticity of substitution). We also allow a common shifter χ to all riders for the demand of trips during the experiment, i.e. a common value for all $q \in Q$.

To use GMM, we need to specify the moments that we use, all coming from the model described in Section B. The theory implies the following moment conditions:

$$0 = \mathbb{E}\left[\left(\frac{C_w^i}{A_w^i + C_w^i} - \alpha^i\right) 1_{\{T_w^i > 0\}}\right] \text{ for } i = 1, 2, \ldots, I \text{ and } w = 1, \ldots, W^i \tag{47}$$

$$0 = \mathbb{E}\left[\left(\frac{C^i}{A^i + C^i} - s_c(p_a^{q(i)}, p_c^{q(i)}); \alpha^i, \eta)\right) 1_{\{T^i > 0\}}\right] \text{ for } i \in N_q \text{ and for } q = 0, 1, \ldots, 6 \tag{48}$$

$$0 = \mathbb{E}\left[T_w^i - k \log \bar{P}_i\right] \text{ for } i = 1, 2, \ldots, I \text{ and } w = 1, \ldots, W^i \tag{49}$$

$$0 = \mathbb{E}\left[T^i - k\left(\log \bar{P}^i - \log \mathbb{P}(p_a^{q(i)}, p_c^{q(i)}; \alpha^i, \eta)\right)\right] \text{ for } i \in N_q \text{ and for } q = 0, 1, \ldots, 6 \tag{50}$$

where we let $N_q = \#\{i : q(i) = q\}$ and $M_q = \#\{i : q(i) = q \text{ and } T_i > 0\}$ for $q = 0, 1 \ldots, 6$. These are $2 \times I + 2 \times 7$ moments for $2 \times I + 2$ parameters. The functions $s_c(p_a^{q(i)}, p_c^{q(i)}; \alpha^i, \eta)$

and $\mathbb{P}(p_a^q, p_c^q; \alpha^i, \eta)$ and denote the optimal share of trips paid in card and the ideal price index defined in Section B. We are mostly interested in k and η, i.e. $\{\alpha^i, \bar{P}^i\}_{i=1}^I$ are nuisance parameters.

We propose a two step procedure following Hansen (2007); Hansen calls this procedure sequential GMM. In the first step, we estimate the nuisance parameters α^i and $K^i \equiv k \log \bar{P}^i$ using the data from the pre-experiment weeks. We use equation (47) and equation (49) to have:

$$\hat{\alpha}_i = \frac{1}{N_W^i} \sum_{w=1}^{W^i} \frac{C_w^i}{A_w^i + C_w^i} 1_{\{T_w^i > 0\}} \text{ for } i = 1, 2, \ldots, I \tag{51}$$

$$N_W^i = \#\{w : T_w^i > 0\} \text{ for } i = 1, 2, \ldots, I \tag{52}$$

$$\hat{K}^i = \frac{1}{W^i} \sum_{w=1}^{W^i} T_w^i \text{ for } i = 1, 2, \ldots, I \tag{53}$$

In the second step, we insert these estimates into the other two moment equations. The moment equations are defined by $g_q^\eta(\eta; \hat{\alpha})$ and $g_q^k(k; \hat{K})$, which are the objects for which GMM chooses the values of η and k to make their value as close to zero as possible. We use the experimental data as follows:

$$g_q^\eta(\eta; \hat{\alpha}) \equiv \frac{1}{M_q} \sum_{\{i: q(i) = q\}} \left[\left(\frac{C^i}{A^i + C^i} - s_c(p_a^{q(i)}, p_c^{q(i)}; \hat{\alpha}^i, \eta) \right) 1_{\{T^i > 0\}} \right] \text{ for } q = 0, 1, \ldots, 6 \tag{54}$$

$$g_q^k(k; \hat{K}) = \frac{1}{N_q} \sum_{\{i: q(i) = q\}} \left[T^i - \hat{K}^i + k \log \mathbb{P}(p_a^q, p_c^q; \hat{\alpha}^i, \eta) \right] \text{ for } q = 0, 1, \ldots, 6 \tag{55}$$

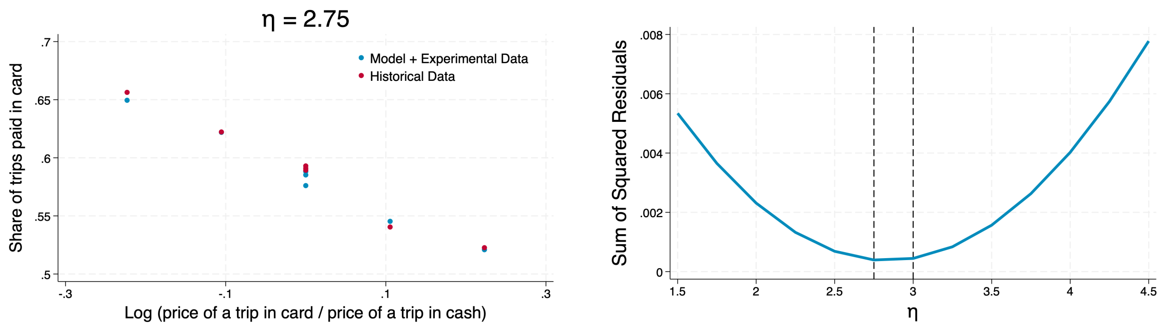
where, as described in Section 5.1, N_0 is composed of 90,000 riders, N_q is approximately 11,000 riders each for $q = 1 \ldots, 6$, and W^i is the entire rider's history of weeks in the application. The system is composed of 14 equations and 2 unknowns, namely k and η. The estimator $\hat{\eta}$ minimizes $\sum_{q=0}^6 (g_q^\eta(\cdot; \hat{\alpha}))^2$ and the estimator $\hat{k}$ minimizes $\sum_{q=0}^6 (g_q^k(\cdot; \hat{K}))^2$.

Figure R1 compares the two components of equation (54). In particular, the one labeled historical is $\frac{1}{M_q} \sum_{\{i: q(i) = q\}} \left(s_c(p_a^{q(i)}, p_c^{q(i)}) \right) 1_{\{T^i > 0\}}$ and the one based on the model and the experiments is $\frac{1}{M_q} \sum_{\{i: q(i) = q\}} \left(\frac{C^i}{A^i + C^i} \right) 1_{\{T^i > 0\}}$. The figure shows the share of payments made with cards in the historical data and compares it with the prediction by equation (43) for $\eta = 2.75$, along with the experimental variation in prices. The figure demonstrates that both align almost perfectly, indicating that for $\eta = 2.75$, there is almost no difference between the data and our model's prediction.

Panel (b) displays the sum of squared residuals for the estimator of the elasticity of substitution. To obtain this estimate, we first implement equation (54) for $q = 0, 1, 2, 3, 4, 5, 6$.

We then plot the estimator $\hat{\eta}$ on the x-axis and the sum of squared residuals, $\sum_{q=0}^{6}(g_q^{\eta}(\cdot;\hat{\alpha}))^2$, on the y-axis. The figure shows that values of $\hat{\eta}$ between 2.75 and 3 indeed minimize the sum of squared residuals between the data and our model's predictions. Importantly, this alternative method of estimating η yields the same estimate as the reduced-form estimates presented in Section 5.1.

Figure R1: GMM: Elasticity of Substitution



Note: Panel (a) compares the historical data with the model's predictions and the experimental data. It shows the share of payments made with cards in the historical data and compares it with the prediction by equation (43) for $\eta = 2.75$, along with the experimental variation in prices. Panel (b) displays the sum of squared residuals for the estimator of the elasticity of substitution. To obtain this estimate, we first implement equation (54) for $q = 0, 1, 2, 3, 4, 5, 6$. We then plot the estimator $\hat{\eta}$ on the x-axis and the sum of squared residuals, $\sum_{q=0}^{6}(g_q^{\eta}(\cdot;\hat{\alpha}))^2$, on the y-axis.