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Abstract

We use two quasi-natural experiments that encouraged the use of debit cards and facilitated the use of ATMs in Mexico to estimate the elasticity of crime and informality to the availability of cash as means of payment. We then construct a simple model to quantify the private costs of restricting cash-usage in the economy. Our model captures the degree of substitution between cash and other payment methods at both the intensive and the extensive margins. We estimate the welfare effects of restricting cash by means of three key inputs: i) the elasticity of substitution between cash and credit, ii) the share of expenditures in cash by type of good obtained from detailed micro data, and iii) the elasticity of crimes to the availability of cash as means of payment. The social benefits of restricting cash usage are driven by the reduction of some criminal activities. The costs arise from the distortions that the anti-cash regulation imposes on the individual choices regarding the means of payment. We find that the private costs of heavily taxing the use cash outweigh the social benefits that we identify.

JEL Classification Numbers: E4, E5
Keywords: Cash, Credit, Means of Payments

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The use of cash has received considerable attention by policymakers and academics who, many times, have expressed their negative assessment of its role. Many argue that restricting cash usage would diminish criminal activities including tax evasion, see e.g. Rogoff's (2017) book *The curse of cash*, and the ensuing debate on the costs and benefits of a "war on cash" (e.g. Bundesbank (2017)). A concrete policy that was recently carried out along these lines was the demonetization in India (see Chodorow-Reich et al. (2018); Lahiri (2020)). However, despite the relevance of the issue, the scholarly debate on the issue is scant, a situation also lamented by Sands (2017). First, data on cash usage and its relation with illegal activities have been the subject of very few scholarly analyses (e.g., Wright et al. (2017); Gandelman et al. (2019); Schneider (2017)). Second, to the best of our knowledge, there are no estimates of the social benefits of curbing cash related crimes. Finally, although a preliminary quantitative assessment of the private costs of banning cash is given in Alvarez and Lippi (2017) and Briglevics and Schuh (2020), the scope of those results is limited to households who have access to both means of payments, while in actual economies cash is the only payment instrument for many households and the adoption of alternative technology is costly. Our contribution is an attempt to tackle these issues up front, featuring three ingredients that are essential to discuss the issue rigorously: detailed micro data, an explicit identification of the causal effects of cash on illegal activities, and an explicit model of both the costs and benefits associated to cash usage.

In this paper, we present a welfare analysis of the consequences of restricting the use of cash, accounting for both social benefits and private costs. Our application considers the case of Mexico for three reasons. First, the availability of detailed data sets on the access and use of cash, by both households and firms, allows us to document cash usage in the country with high precision. Second, we take advantage of two recent policies that aimed to restrict the use of cash in the country to study the impact of cash on criminal activities and informality. Third, the availability of estimates about the cash-credit elasticity of substitution, as estimated for the case of Mexico using experimental data in Alvarez and Argente (2020a) and observational data in Alvarez and Argente (2020b). The latter point is key to analyze the consequences of cash elimination to cash-only households, who are still a non-negligible fraction of the population in several countries.

We begin by documenting several facts on the use of cash in Mexico. Using a variety of household-level surveys and firm-level surveys, we show that although more than 90% of transactions in Mexico are paid in cash, mixed users – individuals who have access and use both cash and cards – are prevalent and widespread in Mexico. More than 50% of households in Mexico are mixed users. We show that cash is the most important payment method even for mixed users; approximately 80% of their expenditures are paid in cash. The prevalence of cash among these users is relevant because policies restricting the use of cash could impact mixed users if cash and cards are not perfect substitutes.

In order to measure the social benefits of restricting the use of cash we estimate the impact of two policies that lead to a reduction in cash usage in Mexico on outcomes such as crime, informality, and tax evasion. First, we study a policy that changed the payment method of the conditional cash transfers program in Mexico (Prospera). Approximately 1.3 million beneficiaries of the program received a debit card between 2009 and 2015. The policy aimed to increase financial inclusion in the country and discourage the use of cash. Indeed, the analysis of this policy in Bachas et al. (2017) and Higgins (2019) shows that, after the rollout of cards, both the number of ATM transactions and the prevalence of POS terminals increased drastically. The fact that the implementation of this policy was staggered across randomly selected localities allows us to use an event-study design to estimate the implications of a reduction on the availability of cash on several outcomes. We find that the policy had a small significant effect on theft and on robberies. On the other hand, we do not find an impact of the rollout of debit cards on homicides, informality, or local tax revenue.

Second, we consider the impact of a policy that reduced the regulatory requirements to implement ATM-sharing agreements between banks (either commercial or development). This policy was implemented by the Bank of Mexico in October 2014 and resulted in the gradual adoption of agreements throughout the period of study (2014-2019) between different banks to share their ATM infrastructure. Each agreement reduced the fees of ATM operations, such as balance checks and withdrawals, and thus provides plausible exogenous variation for cash holdings of clients of the agreeing banks. Because agreements occur between banks at the National level, a natural empirical strategy is a shift-share design that exploits the differential exposure of municipalities to these common agreements. In particular, municipalities that have a large presence of banks in an agreement will be more exposed to it relative to municipalities with a small presence of these banks. In our preferred specification, we observe an increase in the growth rate of ATM withdrawals after an agreement in municipalities that have a higher exposure relative to those with a lower exposure. Consistent with the results of the first policy experiment, we find an impact of the policy on thefts and robberies, particularly on those where pedestrians are the victims. The policy had no impact on the homicide rate or on the total number of informal workers.

Using the observed patterns of cash usage and the estimated elasticity of crime to cash, we turn to the estimation of the effects of restricting cash usage to households, which includes a complete ban on cash. The essential ingredients of our model are a general utility function that considers goods paid in cash as a different good than those paid with credit. To analyze the welfare effect of policies restricting cash payments, we start with an initial situation where agents face the same price for goods paid in cash and goods paid in credit. Starting from this situation we consider the effect on agents' welfare under several alternative scenarios, such as a full ban on goods paid in cash as well as other intermediate policies such as limits on the value of cash payments and taxes on the goods paid in cash. We parameterize the model using observations for individuals grouped over different income groups and considering their consumption over several categories goods using the National Survey of Household Income and Expenditure (ENIGH).

We also consider the social benefits that each policy may bring by reducing the prevalence of criminal activities. Given that in the two policies we studied, a reduction in cash caused a statistically significant reduction in theft and robberies, we focus on these two crimes. We rely on victimization surveys to measure the prevalence of these crimes and calculate their direct costs, measured as the fraction of GDP that is stolen. We quantify the indirect costs, measured by the deadweight losses of the crimes, which include tangible costs (e.g. preventive police cost, judiciary costs) as well as the intangible costs (e.g. psychological costs for the victim) drawing from the economics of crime literature.[1]

The private losses of 40% tax on cash are approximately 6% of GDP or higher. A key parameter for this result is the elasticity of substitution between cash and credit, which in our baseline analysis is approximately equal to $\eta = 5$. We show that the magnitude of these welfare losses of restricting the use of cash are high for a wide range of parameter values, including a doubling of tripling of η. On the other hand, the deadweight losses of cash-related crimes gives an upper bound for the social benefits of eradicating theft and robberies, which is about 1.3% of GDP. Even if we consider the social benefits of eradicating all crime (approximately 3% of GDP using UK data) these benefits are half of the costs associated with a 40% tax on cash and less than a third of those associated with a full ban on cash, which are approximately 10% of GDP.

The remainder of this paper is organized as follows. In Section 1, we present several stylized facts of the used of cash in Mexico. Section 2 studies the impact of the Mexican government's rollout of debit cards to the beneficiaries of its conditional cash transfers program on outcomes such as criminal activities and informality. In Section Section 3, we study the impact of newly established ATM-sharing agreements between banks on the same outcomes. Section 4 develops a simple model to quantify the private costs of taxing the use of cash and calculates the social benefits of elimination cash related crimes. Section 5 concludes.

[1] Examples of these estimates can be found in Price (2000); Albertson and Fox (2008); Heeks et al. (2018) and the summary of the main estimates for the tangible and intangible indirect costs collected in the meta study by Wickramasekera et al. (2015).

1 Empirical Facts

We start our analysis by documenting cash usage in Mexico. We rely on four detailed data sources. First, the National Survey of Financial Inclusion (ENIF), which provides a detailed description of the use of payment methods at the household level. We complement this evidence with the National Survey of Household Income and Expenditure (ENIGH), which allows us to estimate the share of expenditures in cards by type of good. We then use the Financial Inclusion Databases (BDIF) collected by the National Banking and Securities Commission (CNBV) to characterize the access to payment methods in Mexico. The data set includes information of the bank branches, ATMs, point-of-sale terminals (POS), bank accounts and debit and credit cards at the municipality level. Lastly, we have use the National Survey of Firms' Financing (ENAFIN), a confidential data set provided by the Mexican Statistical Agency (INEGI) that includes information of the payment methods accepted by the firms in Mexico. The data allow us to determine the share of firms in the economy that only take cash as a payment method and their characteristics.

We then analyze the adoption of cards in the Prospera program and the implementation of ATM-sharing agreements between banks. In the analysis of the rollout of cards in Prospera, we use the administrative data of the program obtained through a freedom-of-information request to the Federal Institute for Access to Information (INAI). We obtained information of ATM-sharing agreements and the associated percent reduction in fees from the CNBV. We use data from the National Employment Survey (ENOE) and the State and Municipal Public Finances (EFIPEM) to analyze the impact of these two policies on informality and tax collection. Lastly, to analyze the impact of these policies on crime we use i) Statistics of Registered Deaths collected by INEGI, ii) Registered Crimes collected by INEGI and iii) Criminal Incidence from the Executive Secretariat of the Public Security National System (SESNSP). We provide more details of each these data sets in Section D.

Cash is the most important payment method in Mexico

Cash is the main method of payment in Mexico. According to the National Survey of Household Income and Expenditure (ENIGH), a national representative survey collecting information on households' expenditures and means of payment, around 90% of payments are conducted in cash.[2] Table 1 shows that across all income groups and type of goods, cash is the most common means of payment. The table shows that cash is most commonly used

[2] Figure A5 shows that approximately 95% of respondents of the National Survey of Financial Inclusion (ENIF) reported cash as their most frequent payment method for transactions below 20 USD and 87% for transactions above 20 USD. Figure A2 shows this fraction is similar for payments in sectors.

by households in the bottom tercile of the income distribution.

Table 1: Share of Expenditures Paid in Card by Type of Good

Note: The table reports the share of expenditures paid in card by type of good. The table also shows the share of consumption by type of goods. The source is the National Survey of Household Income and Expenditure (ENIGH), which was conducted from August 21st to November 28th, 2018. The information is based on a diary of daily expenditures collected along with the survey. Households are asked to report the payment method they use for each good as well as the total amount spent on each. The table splits households into terciles according to their reported income. Columns (1)-(3) show the share of expenditure in payment methods other than cash. Columns (4)-(6) show the share of consumption by type of good and for each income group.

	Share Card			Share Consumption		
	Bottom	Middle	Top	Bottom	Middle	Top
	(1)	(2)	(3)	(4)	(5)	(6)
Food, Alcohol, Tobacco	0.001	0.004	0.050	0.557	0.491	0.376
Housing	0.002	0.001	0.028	0.037	0.032	0.025
Utilities	0.002	0.005	0.058	0.074	0.089	0.100
Education, Culture, Recreation	0.003	0.008	0.102	0.021	0.033	0.046
Cleaning	0.004	0.013	0.052	0.055	0.049	0.059
Personal Care	0.004	0.013	0.097	0.075	0.074	0.064
Communication and Vehicle Services	0.005	0.012	0.062	0.052	0.081	0.112
Clothing	0.010	0.024	0.164	0.059	0.066	0.072
Domestic Utensils	0.021	0.043	0.201	0.005	0.005	0.007
Transport	0.031	0.028	0.162	0.016	0.027	0.066
Health	0.033	0.018	0.152	0.031	0.028	0.036
Domestic Appliances	0.052	0.067	0.130	0.015	0.019	0.027
Entertainment	0.159	0.168	0.311	0.003	0.005	0.009

The prevalence of cash can in part be explained by the lack of access to financial infrastructure. There are only 1.5 branches per 10,000 adults in Mexico, which represents a level below countries with a similar GDP per capita. The lack of financial infrastructure is more pronounced in rural municipalities where only 8% of rural municipalities have an ATM; 99% of municipalities with more than 50,000 inhabitants have an ATM.[3]

Mixed users are widespread in Mexico

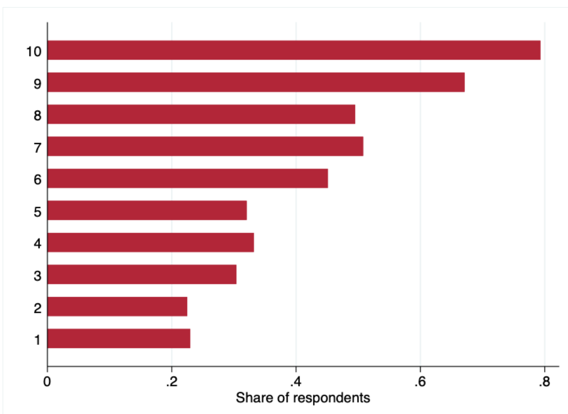
However, the lack of financial infrastructure is not the most prevalent reason for why people do not have access to bank accounts or cards.[4] In fact, the majority of the Mexican population

[3]On average, each adult withdraws cash 17.3 times per year. Figure A3 shows that the ATM and POS transactions are mainly concentrated in the cities (darker colors) whereas rural populations have less than one ATM on average.

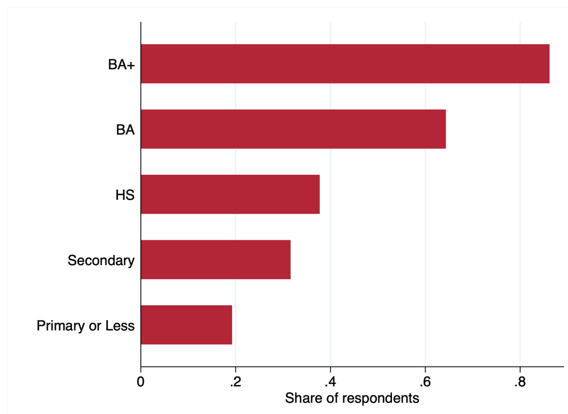
[4]When those who do not have a bank account were asked in the National Survey of Financial Inclusion (ENIF), "what is the reason you do not have a bank account?" 33% respond that they do not have enough earnings, 27% respond that they do not need it, 11% respond that they do not meet the requirements. Less

(70 %) have access to at least one financial product (i.e. a bank account, some form of formal credit, retirement savings, etc.) and half have at least one debit or credit card. This means that the majority of the Mexicans are *mixed users*, individuals who have access and use both cash and cards. Panel (a) in Figure 1 shows the fraction of people that have access to either a debit or a credit card by income decile. Not surprisingly, as the level of income or the level of education increases, the likelihood of having access to debit or credit cards also increases. Panels (c) and (d) show a similar pattern for bank accounts.

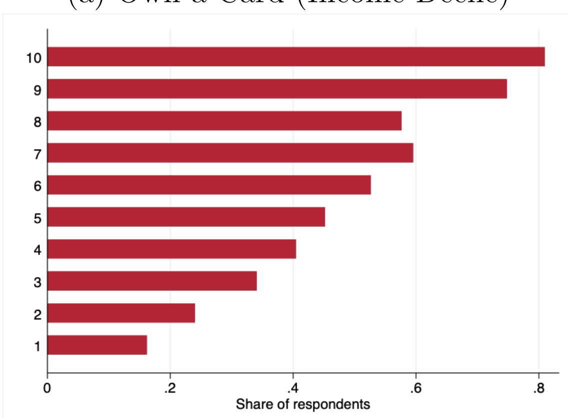
Figure 1: Access to Cards and Bank Accounts



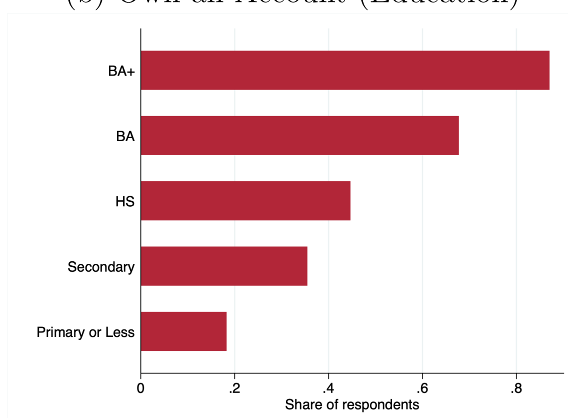
(a) Own a Card (Income Decile)



(b) Own an Account (Education)



(c) Own an Account (Income Decile)



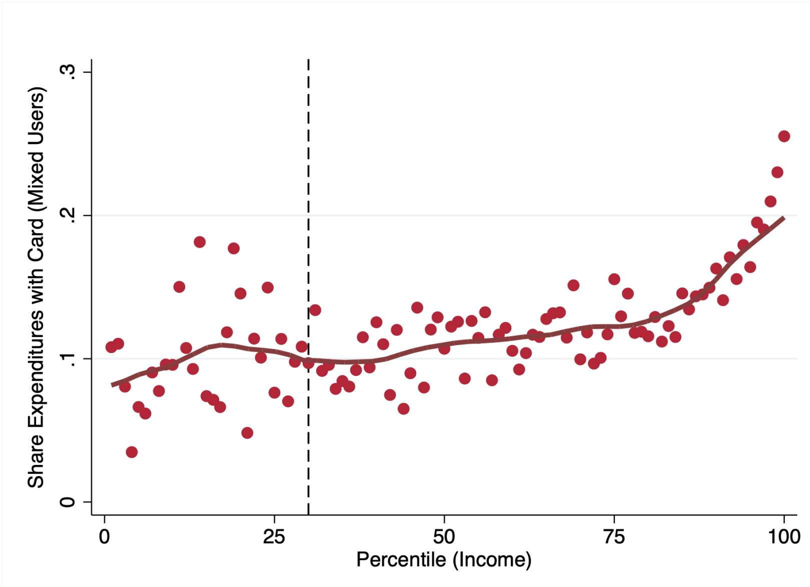
(d) Own an Account (Education)

Note: The figure shows the share of households in Mexico who have used a debit card in the last three months (from the time they were surveyed). Panels (a) and (b) shows the share of households by income deciles and education respectively. Panels (c) and (d) show the share of households who have a bank account by income and education. The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

than 3% respond that they do not have an account because the bank is far. Similarly, when those who do not have a card were asked in the National Survey of Financial Inclusion (ENIF), "what is the reason you do not have a card" 32% respond that they do not like debt, 26% respond that they do not need it, 23% respond that they do not meet the requirements. Less than 2% respond that they do not have a card because the bank is far. We present these statistics in Figure A4.

Cash is the most important payment method for mixed users

Figure 2: Share of Payments with Card - Mixed Users



Note: The figure shows the share of expenditures paid with payment methods other than cash for each percentile of the income distribution of Mexico. The sample of households include only those who reported making at least one payment with a method other than cash. Payment methods other than cash include debit cards, credit cards, transfers, and mobile payments. The source is the National Survey of Household Income and Expenditure (ENIGH), which was conducted from August 21st to November 28th, 2018. The information is based on a diary of daily expenditures collected along with the survey. Households are asked to report the payment method they use for each good as well as the total amount spent on each.

Despite the prevalence of mixed users, cash accounts for the majority of payments in Mexico. Among mixed users, cash is also the most used method of payment. Figure 2 shows the share of payments with card for those with either a debit or a credit card. The figure is calculated using ENIGH and shows that mixed users pay approximately 21% of their total expenditures in card. Table 2 shows that, among mixed users, goods such as food and housing are more likely to be paid in cash. On the other hand, mixed users are more likely to pay with cards for goods used for entertainment (e.g. TV, DVD players, radios, video games, musical instruments). Panel (a) of Figure A5 shows that approximately 90% of respondents of the National Survey of Financial Inclusion (ENIF) reported cash as their most frequent payment method for transactions below 20 USD and 70% for transactions above 20 USD. Figure A6 shows that approximately 85% of people respond that cash is the most frequent payment method when paying for their taxes, services, and transportation.

Table 2: Share of Expenditures Paid in Card by Type of Good: Mixed Users

Note: The table reports the share of expenditures paid in card by mixed users and by type of good. The table also shows the share of consumption of mixed users by type of goods. The source is the National Survey of Household Income and Expenditure (ENIGH), which was conducted from August 21st to November 28th, 2018. The information is based on a diary of daily expenditures collected along with the survey. Households are asked to report the payment method they use for each good as well as the total amount spent on each.

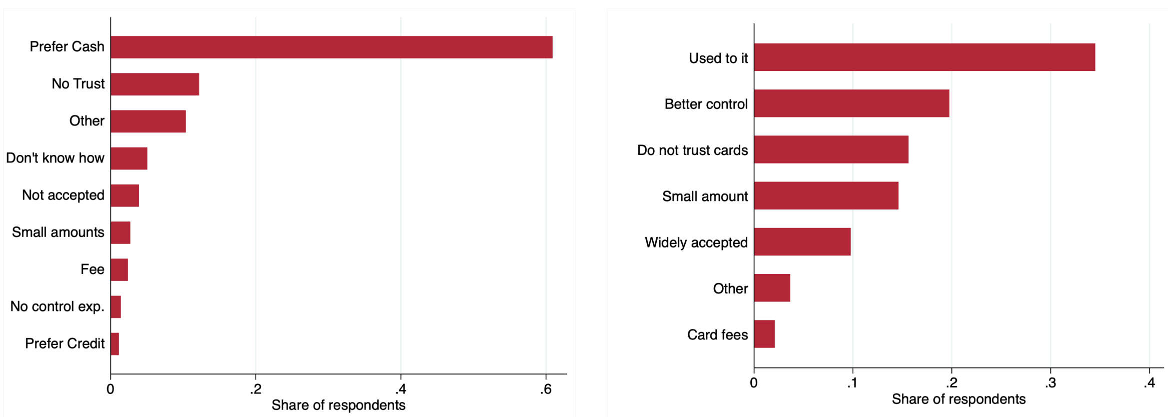
	Share Card Mixed	Share Consumption Mixed
Food, Alcohol, Tobacco	0.159	0.337
Housing	0.083	0.025
Utilities	0.178	0.093
Education, Culture, Recreation	0.246	0.054
Cleaning	0.136	0.069
Personal Care	0.326	0.056
Communication and Vehicle Services	0.198	0.103
Clothing	0.455	0.076
Domestic Utensils	0.466	0.034
Transport	0.352	0.086
Health	0.372	0.044
Domestic Appliances	0.344	0.034
Entertainment	0.653	0.014

Mixed users might prefer cash if they are likely to be victims of credit card related crimes. Panel (a) Figure A7 shows this is not the case; very few have been victims of identity theft, card cloning or fraud. Alternatively, it is possible that most people receive their wages in cash, thus, increasing the likelihood they spend their earnings in cash. Panel (b) shows that those who report owning a card are also more likely to receive their payments directly into their bank accounts and, as a result, are less likely to use cash in order to evade taxes.

Another alternative is the size of the informal sector. There are approximately 4 million firms in Mexico, 99.8% are small and medium enterprises (52% of GDP and 72% of total employment). Only 43.3% are formal and account for 77.48% of GDP. Given that informal firms can be found by tax authorities if they accept means of payments other than cash, it is unlikely that they accept another payment method. However, according to the National Survey of Enterprise Financing (ENAFIN), even among formal firms, cash is the most important payment method. Figure A8 shows the share of firms that accept credit or debit cards in the formal sector according to their size and sector. The figure shows that, even among registered firms that pay taxes, most firms take only cash. This is true across sectors and for large (more than 100 employees) and micro firms (6-10 employees). The figure also shows that, consistent with the share of payments in card by mixed users obtained for household survey data (ENIGH), the share of payments received in debit and credit cards among formal firms is approximately 25%.[5]

However, few mixed users report the fact businesses do not accept cards as the primary reason why they do not use a card. In fact, when those who own a card were asked in the National Survey of Financial Inclusion (ENIF), "why don't you use your card?',' more than 60% respond they prefer cash. Panel (b) of Figure 3 shows that when the same people were asked, "why do you prefer cash?", 35% respond that they are used to it, 20% respond that it allows them to have better control of their finances, 15% respond that they only make payments in small amounts, 15% respond that they do not trust cards, 10% respond that they use cash because it is widely accepted, 2% respond that they want to avoid card fees, and the rest had other reasons.

Figure 3: Mixed Users: Why Do You Prefer Cash



(a) Why Don't You Use It? (b) Why Do You Prefer Cash?

Note: Panel (a) shows the responses of households to the question "why don't you use your debit card?". Panel (b) shows the responses of households to the question "Why do you prefer cash?." The sample of households report owning a debit or a credit card. The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

[5]When firms are asked, "what are the reasons you do not accept cards as payment method?" The most common answer for large firms is that they prefer transfers since they receive large payments. Micro firms, on the other hand, respond that they prefer cash. For micro firms, 17% respond they prefer cash since they receive payments of small amounts and 16% respond that it is too costly for them to accept cards as a payment method. Across sectors, the reasons firms do not accept card are consistent. For large amounts, firms prefer transfers. For small amounts, firms prefer cash. Across all sectors, an important share of firms state their preference for cash. These results can be found in Figure A10 and Figure A9. Interestingly, cash is also a very important payment method use by firms to cover their inputs and payrolls. Figure A11 shows that almost 40% of large firms pay for their inputs in cash. More than 35% of micro firms pay for their payroll in cash. Figure A12 shows that a large share of manufacturing and construction firms in the formal sector pay for their payrolls in cash. In the commerce and services sector, more than 30% of firms pay for their inputs in cash.

2 Prospera: Card Adoption

To study the impact of a reduction of the use of cash on crime, informality, and tax evasion, we take advantage of a large shock to consumers' adoption of debit cards in Mexico. Between 2009 and 2012, the Mexican government disbursed more than one million debit cards as the new payment method for its conditional cash transfer program, Prospera. By 2015, the program had distributed approximately 1.3 million debit cards. The program, previously known as Progresa (1997-2002) and Oportunidades (2002-2014), was a conditional cash transfer program targeting poor households with an estimated income per capita lower than the minimum necessary to acquire the basic food basket and whose social-economic conditions hinder the development of their members in terms of nutrition, health and education.[6]

The program provided cash transfers every two months. These transfers were conditional on attendance to a scheduled appointment with health services and enrolling children in school as well as encouraging them to attend school on a regular basis. The size of the payment depended on the compliance of these co-responsibilities and on the characteristics of the family; it averaged US$150 per two-month payment period during the years of the card rollout.

Before the card rollout, each beneficiary had a savings account at National Savings and Financial Services Bank (Bansefi), a government bank created to promote savings and financial inclusion. Benefits were deposited in this account and beneficiaries could choose to withdraw any amount at any point in time. Nonetheless, Bachas et al. (2017) report that, prior to the debit card rollout, 90% of beneficiaries made one trip to the bank per payment period, withdrawing their entire transfer. This is because the benefits could only be withdrawn at a Bansefi branch which are on average 5 kilometers away from an urban beneficiary household. The debit card rollout allowed beneficiaries to withdraw their benefits from any ATM and to pay using their Visa debit card at any business accepting cards as payment method. Thus, the program considerably reduced the travel costs of beneficiaries increasing the number of ATM withdrawals (Bachas, Gertler, Higgins and Seira, 2017) and the number of times they pay in POS terminals using their cards (Higgins, 2019).

The rollout of debit cards was implemented at the locality level, a geographical unit smaller than a municipality. On average, there are approximately 60 localities in each municipality (median 30). At each treated locality (those chosen for the debit card rollout), all beneficiaries obtained a debit card during the same payment period. Because the payments were disbursed every two months, the administrative data from Prospera identifies at this

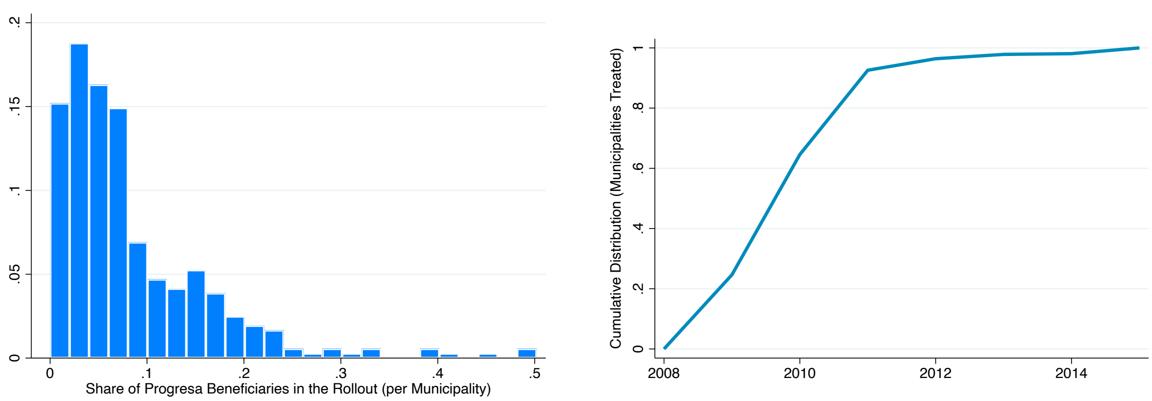
[6] By 2008 the size of the program stabilized after reaching one-fourth of Mexican households and covering virtually all municipalities. In 2015, the last year of our sample, the program represented approximately 1.6% of Mexico's national budget (equivalent of 0.4% of GDP) (Dávila Lárraga, 2016).

frequency the timing of the rollout and the number of beneficiaries in each locality.

Since the initial selection of localities is correlated with locality characteristics, our identifying assumption relies on the work by Higgins (2019) and is the following: conditional on being included in the rollout, the timing of when a locality received the card shock is uncorrelated with locality-level observables or other trends. Higgins (2019) explains that Prospera officials wanted the localities that received cards at each stage of the rollout to be similar so that they could test their administrative procedures for the rollout with a quasi-representative sample. Indeed Bachas et al. (2017) show that the timing of the treatment is uncorrelated with pre-treatment wages, prices, POS terminals, bank branches, ATMs, debit cards, credit cards, beneficiary savings, number of ATM withdrawals, program beneficiaries, or whether the party in power at the municipal level corresponds with the party in power at the national level.

Panel (a) in Figure 4 shows that within a treated municipality, approximately 8% of Prospera beneficiaries received a card. In contrast to Higgins (2019), who only focuses on urban localities, we include all treated localities with at least one thousand inhabitants, a total of 966 localities and 418 municipalities. On average, 41% of localities in treated municipalities were included in the rollout. Panel (b) shows that the majority of cards were distributed before 2012. Nonetheless, we extend our analysis to 2015 since we observe in the data that some municipalities are included until that year.[7]

Figure 4: Prospera Beneficiaries



(a) Beneficiaries Within Municipalities

(b) Municipalities Across Time

Note: Panel (a) shows the share of beneficiaries of the Prospera program that were part of the rollout of debit cards in each of the treated municipalities. Panel (b) shows the cumulative distribution of municipalities treated. The source for both panels is the administrative data of the Prospera program from 2007 to 2015.

[7]Figure A13 shows the geographic coverage of the rollout. It shows that beneficiaries receiving cards through Prospera are distributed over the entire country.

2.1 Event Study

We begin our analysis by studying how the rollout affected cash-related outcomes in several localities and municipalities in Mexico. We use a fully dynamic event-study specification to compare several outcome variables before and after the rollout of debit cards. Let Y_{lmt} be an outcome variable for locality (or municipality when locality level data is not available) m at time t (e.g. informal workers, local taxes, number of homicides, etc). The specification for our event study is as follows:

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

where θ_m are locality-fixed effects and λ_t are time effects. K_{lt} denotes the number of periods relative to the rollout of debit cards so that γ_k for $k < 0$ corresponds to pre-trends and $k \geq 0$ corresponds to dynamic effects k periods after the rollout. X_{mt} represent a set of locality-specific time-varying controls such as the number of families in Prospera in locality i at time t. Since all the localities are treated, we require an additional restriction on the pre-trends in order to estimate the time fixed effects. Moreover, since different locations become treated at different times, heterogeneous treatment effects across time could be relevant. For this reason, we follow the methodology developed by Borusyak et al. (2020) to estimate a robust and efficient estimator that allows the implementation of two-way fixed effects in staggered designs.[8] This methodology is also robust to using locations that have not been treated yet as controls.[9]

Alternatively, in Section B we implement a semi-dynamic event study design for several specifications:

$$\ln Y_{mt} = \alpha + \beta \ln \text{CardShock}_{mt} + \theta_m + \lambda_t + \zeta X_{mt} + \epsilon_{mt} \tag{2}$$

where CardShock_{mt} is an indicator that equals to one when the municipality is treated. This specification does not have identification issues if the timing of the treatment is random, as described by the Prospera authorities, conditional on the fixed effects and controls. It estimates the average treatment effect, assumed to be homogeneous, for all periods following the event.[10] Since the error term might be both serially and cross-sectionally correlated, we

[8] We thank our discussant Gabriel Chodorow-Reich for suggesting this implementation.

[9] Our results are also robust to using the methodology developed by De Chaisemartin and D'Haultfœuille (2020b).

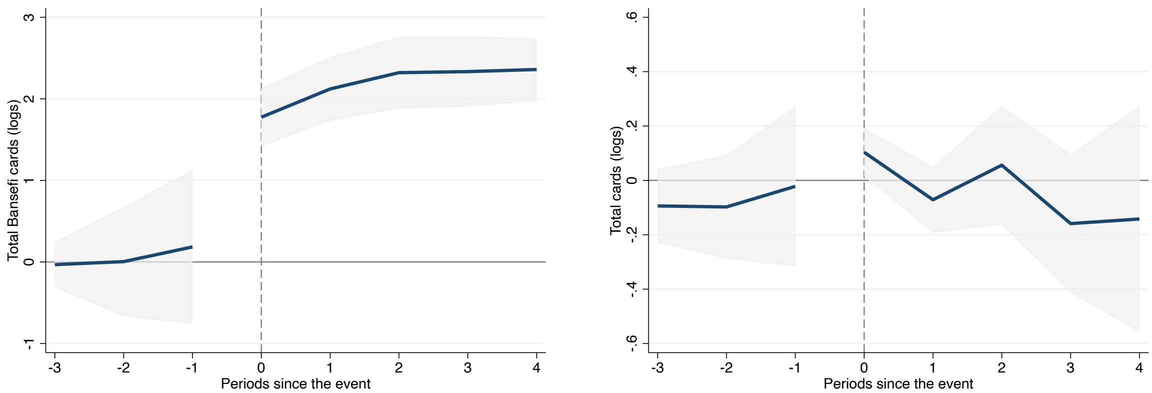
[10] Section B.1 also presents results where we use, instead of a dummy variable equal to one after the

use Driscoll and Kraay standard errors in the semi-dynamic specifications. For some of the outcomes we study, there is no data available at the locality level and bi-monthly frequency. In such cases, data availability determines both the aggregation of the outcome variables and the time frequency we consider, we provide details for each outcome variable below.

We begin by presenting evidence on the adoption of debit and credit cards. We use data from the Mexico's National Banking and Securities Commission (CNBV). Since the data is quarterly and at the municipality level, and the administrative data from Prospera is bi-monthly and at the locality level, we implement equation (1) at the municipality and bi-annual level since both data sets coincide at this frequency. We first verify that, at this frequency and level of aggregation, our specification is informative of an increase in debit cards provided by Bansefi. Panels (a) of Figure 5 shows a substantial increase in Bansefi debit cards after the start of the rollout. Higgins (2019) studies the same specification for non-Bansefi debit cards and documents their prevalence increases after the shock. He argues that this increase is due to indirect network externalities, where other consumers benefit from the increase of debit card users from the Prospera program. Here, we estimate the same specification but including all municipalities treated, instead of only urban municipalities, and extending the administrative data from Prospera to 2015. The graphs show that, conditional on municipality- and time-fixed effects, no pre-trends appear before the shock. This pattern is consistent with the timing of the introduction of cash being randomly assigned conditional on the municipality- and time-fixed effects. The identification assumption of this exercise is precisely that the rollout in these municipalities was not anticipated. Panel (b) shows a smaller and more transient response of total cards, which include all debit cards and credit cards, after the rollout. Columns (1)-(3) of Table 3 show the results of the semi-dynamic event study and Table B1 show other robustness checks. Column (3) shows that in this specification, the total number of cards increased at least 15% after including controls such as the income per capita of the municipality, total employment, number of progresa families, and total population of the municipality. This evidence, as well as the evidence in Higgins (2019) and Bachas et al. (2017) on the increase in ATM transactions after the rollout, indicate that the prevalence of cash decreased in the treated municipalities.

treatment, the share of households in a municipality that are both part of Prospera and the were included in the rollout.

Figure 5: Event Study: Bansefi Cards and Total Cards



(a) Debit (Prospera Cards)

(b) Total Cards

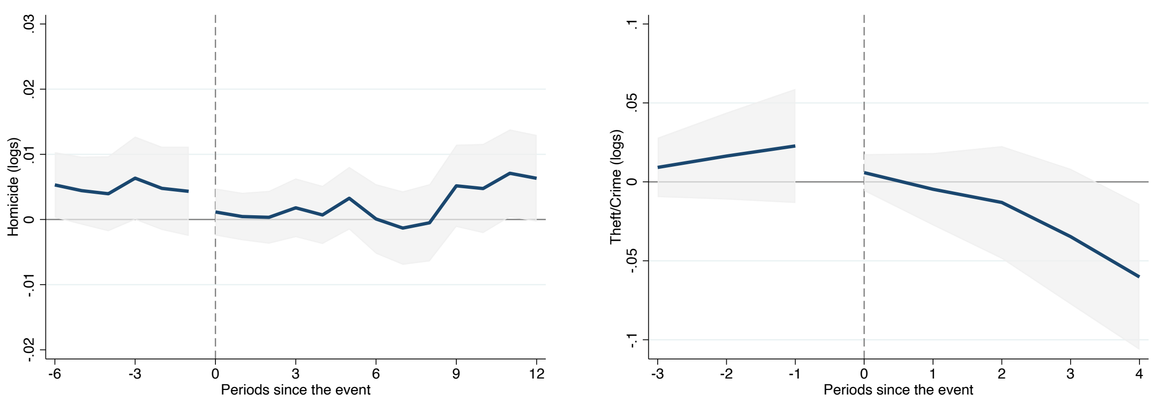
Note: The graph shows the evolution of Bansefi debit cards and total cards before and after the rollout of cards. The figures plot the coefficients of γ_k after estimating equation (1). The dashed line marks the period that cards were rollout in the municipality. Each period is a 6-months interval. The gray area depicts the 95% confidence interval.

Next, we study the impact of the shock on homicides. We use data of homicide victims based on the vital statics published by the INEGI. The data is collected from public health records filed by coroner's offices and it is based on death certificates identifying the cause of death. The data include the date and place of the homicide; thus the information is available at the locality and monthly level. Since the administrative data of Prospera is at the bi-monthly level, in this case we estimate equation (1) at this frequency and include municipality $\times$ period effects to further control for trends. Panel (a) of Figure 6 shows our results. We do not find evidence that the debit card shock decreased homicides. Table B2 presents the results under the semi-dynamic specification. Consistent with the dynamic specification of the event-study, homicides do not decrease after the shock. If anything, in this specification, we find a small increase in homicides that is statistically significant but very small in economic magnitude.

An alternative way to study the patterns of homicides is to combine two different data sets. From 2005-2010, INEGI collected crime statistics for each municipality and made it available at the State and Municipal Databases (SIMBAD). The data set is at the annual level and has information on robberies, damages, injuries, sex crimes, kidnapping, and homicides. Starting in 2011, the main source for information of criminal activity at the municipality level is reported by the Executive Secretariat of the Public Security National System (SESNSP). The data set is based on police investigations and includes the number of victims contained in those investigations.[11] Importantly, since the data is based on cases handled by law enforcement investigations, it often overestimates the number of homicides relative to the vital statistics. Nonetheless, Column (4) of Table 3 shows that we do not find any effect on homicides and Table B3 shows that we find similar patterns when we use data based on death certificates or data from law enforcement cases.

Using the combined data set we are able to study other crimes, in particular theft, which includes burglary and robbery; our crime data before 2011 do not distinguish among them. Panel (b) of Figure 6 shows a small decrease in theft after the rollout of cards by approximately a 5% on average. Importantly, in this case, the dependent variable is the logarithm of total thefts divided by total crimes in municipality i and period t. We use this dependent variable in order to further control for potential trends on criminal activity. Column (5) of Table 3 shows a negative, but not significant, decline in thefts. Nonetheless, Table B4 shows that in the semi-dynamic specification the decline in theft is significant in the unweighted specifications, particularly when we use either total thefts over population or total thefts over total crimes as dependent variables. Column (6) of Table 3 and Table B5 show our findings for total crimes at the municipality level. In this case, we do not find a significant decline. Overall, we find a small decline in theft after the rollout of debit cards but we do not find statistically significant evidence that total crime declined at the municipality level after the shock.

Figure 6: Event Study: Homicides and Thefts



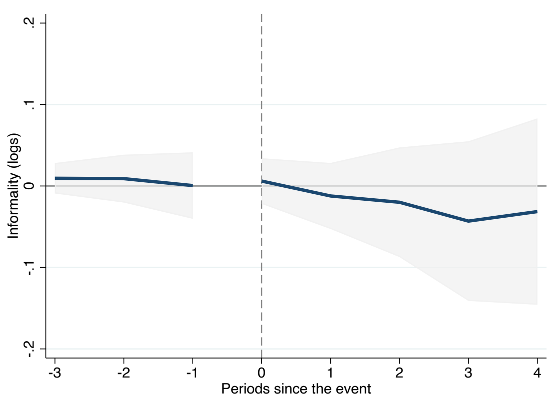
(a) Homicides (b) Theft

Note: The graph shows the evolution of homicides and thefts before and after the rollout of cards. The figures plot the coefficients of γ_k after estimating equation (1). The dashed line marks the period that cards were rollout in the municipality. In Panel (a) each period is a 2-months interval and in Panel (b) each period is a year. The gray area depicts the 95% confidence interval.

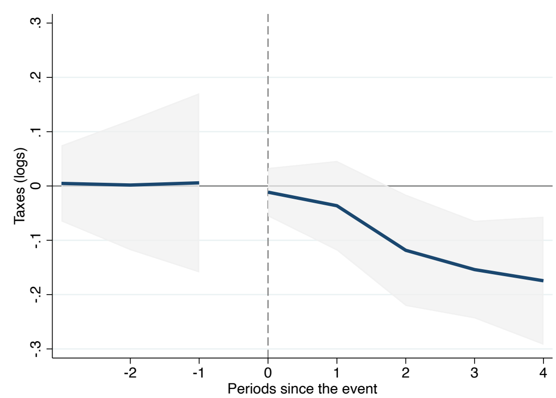
[11] Although there are differences in methodology across these data sets, Figure A14 shows that there is a smooth transition in the aggregate series for several crimes including homicides.

Next, we study the impact of the shock on informality and tax collection. In Mexico, almost 60% of workers are informal. We use the National Employment Survey (ENOE), the main source of labor market statistics in Mexico. ENOE provides quarterly level representative samples of the national labor market.[12] Since the data from Progresa is bi-monthly, we aggregate the data at the bi-annual level. Our measure of informality is constructed using the definitions provided by INEGI. A worker employed in the informal sector is one that is employed, works for a non-agricultural economic unit that operates from the resources of the household, but without forming itself a company, so that the income, materials and equipment used for the business are not independent and/or distinguishable from those of the household. Informal workers are employed with no benefits, health benefits only (universally provided to all workers by the government). Our definition of informal worker includes both workers in the informal sector and those outside the informal sector working without benefits.[13] Panel (a) of Figure 7 shows our results in the fully dynamic specification of the event study. We do not find an effect of the shock on the logarithm of informal workers in a municipality. Column (7) of Table 3 and Table B6 show similar findings when we use the semi-dynamic specification. We find similar results when we consider the total number of self-employed workers as a dependent variable.

Figure 7: Event Study: Informality and Taxes



(a) Informality



(b) Taxes

Note: The graph shows the evolution of informal workers and local taxes before and after the rollout of cards. The figures plot the coefficients of γ_k after estimating equation (1). The dashed line marks the period that cards were rollout in the municipality. In Panel (a) each period is a 6-months interval and in Panel (b) each period is a year. The gray area depicts the 95% confidence interval.

[12]The data is a rotating panel (households are interviewed for five consecutive quarters and then replaced) and has 120,260 households and 420,000 individuals per quarter on average.

[13]Our conclusions do not change if we use either of these measures separately.

To further check the impact of the shock on tax evasion, we use information of local tax collection from the State and Municipal Public Finances (EFIPEM) collected by INEGI. This database is the most detailed available account of public finances for both federal, state-level and local spending at the municipality-level and at annual frequency. The information is obtained from the Ministry of Finance of each state and from the Treasury of each municipality. It includes local tax collection of payroll taxes and real-estate taxes, among others.[14] We use the total taxes collected by each municipality in a calendar year as dependent variable. Panel (b) of Figure 7 shows our results. We find that the increase in the prevalence of cards in a municipality decreases the amount of taxes collected by the municipality. Column (8) of Table 3 and Table B7 show similar but not significant results.

Table 3: Effect of Card Shock

Note: The table reports the results for the coefficient of β after estimating equation (2). The dependent variable in Column (1) is the logarithm of debit cards. Column (2) use debit cards excluding those given as part of the Prospera program through Bansefi and Column (3) use the sum of debit cards and credit cards as dependent variable. The dependent variable in Column (4) is the logarithm of homicides using data from SESNSP based on criminal cases, in Column (5) the logarithm of total thefts and in Column (6) the logarithm of theft divided by total crimes. The dependent variable in Column (7) is the logarithm of informal workers and Column (8) is the logarithm of local taxes. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1) Debit	(2) Debit Not Prospera	(3) Total Cards	(4) Homicides	(5) Theft	(6) Crimes	(7) Informality	(8) Taxes
Card Shock	0.1673***	0.3057***	0.1276***	0.0923	-0.0238	0.0164	0.0089	-0.0060
	(0.040)	(0.075)	(0.032)	(0.062)	(0.013)	(0.014)	(0.010)	(0.016)
Observations	5,212	5,212	5,212	3,149	3,027	3,027	6,224	2,895
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

[14] At the local level, municipalities have their own treasuries and enforce their local tax law, which determines the structure of each tax. Local taxes account for approximately 21.5% of the total income of the municipalities. Our measure of local taxes do not include federal taxes collected by the Tax Administration Service (SAT), part of the Ministry of Finance. The main federal taxes are value added taxes (IVA), income taxes (ISR), and excise taxes (IEPS).

2.2 Discussion

Overall, we find evidence that the rollout of Prospera cards, which distributed debit cards to more than 2% of households in Mexico, increased the number of households owning either a debit card or a credit card. Despite the size of the shock, we do not find evidence that the shock decreased the total number of homicides, which we can study at the finest level of geographic aggregation and at the highest possible time frequency. If anything, under some specifications, there is a statistically significant increase in homicides although it is of small magnitude. We find a decline in thefts of approximately 2-5%; under some specifications, particularly those weighted by population, the estimates are not very precise. Overall, our results are consistent with Wright et al. (2017) and Gandelman et al. (2019) who show an impact of cash on property crimes but not on violent crimes.

The number of informal and self-employed workers are not statistically different before or after the rollout of cards. We find that the shock decreases tax collection, but a limitation of our analysis is that our measures of local taxes do not include federal taxes, including value added taxes. To the best of our knowledge, this information is not available at the municipality level. Hondroyiannis and Papaoikonomou (2017) show evidence that restrictions on the use of cash could increase VAT revenue. The impact of the card shock on VAT revenue in Mexico is not clear given the evidence presented by Higgins (2019). He shows that, although corner stores were more likely to adopt POS terminals after the shock, the change in consumption at corner stores was driven mostly by customers who already had cards. Furthermore, Bachas et al. (2017) show that Prospera beneficiaries responded to receiving a debit card by decreasing total consumption to finance an increase in overall savings.

3 ATM-Sharing Agreements

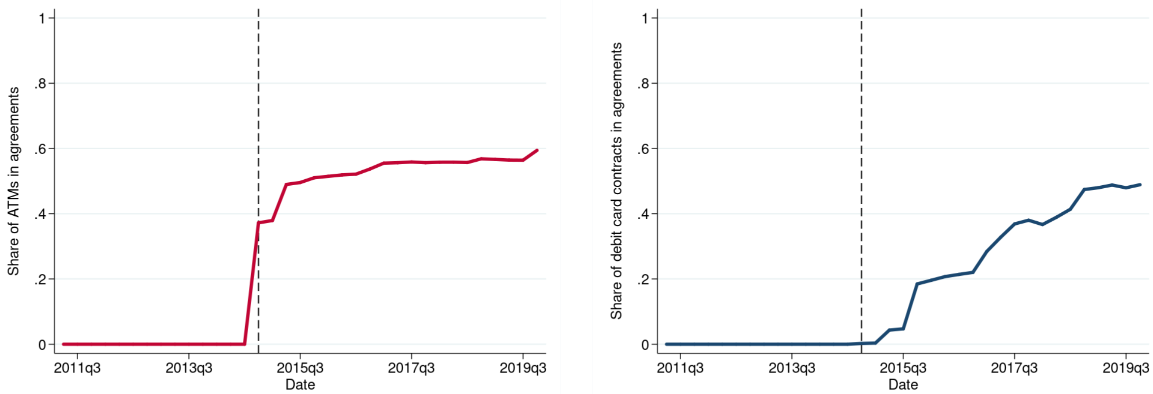
Next, we consider a policy change that triggered 24 ATM-sharing agreements between banks throughout 2014-2019 (see the list of agreements in Table C1).[15] When two banks agree to share their ATM infrastructure, customers of one bank can use the ATMs of the other at a reduced fee.[16] The Financial Reform of 2014 effectively allowed banks to celebrate these agreements—since the regulatory requirements were too restrictive before. The law was put in place in October 2014, when the Bank of Mexico issued the new requirements for

[15] The 24 agreements happened between 29 different pairs of banks. There are approximately 64 banks in our sample (4,032 pairs of different banks).

[16] Agreements are not necessarily symmetrical (i.e., they could benefit only the customers of one of the two banks).

the agreements.[17] The first agreement was implemented one month after the law and more agreements have been implemented every year since then. The reduction in ATM fees ranged from 7.2% to 100%. Figure 8 shows the share of ATMs and debit cards that were part of an agreement after the Financial Reform of 2014; more than 50% of ATMs and 50% of cards entered into some agreement between 2014 and 2019.

Figure 8: Share of ATMs and Debit Cards in Agreements



(a) ATMs (b) Debit Cards

Note: The figure show the quarterly fraction of ATMSs and the fraction of debit card contracts that belong to banks in agreements. The vertical dashed line indicates when the Bank of Mexico instituted the ATM-sharing agreements policy (October 2014). Note that an ATM or a card might enter in an agreement multiple times; in the figure, we consider the first time each entered in an agreement. The data comes from the CNBV.

3.1 Shift-Share Design

Because agreements occur between banks at the national level, a natural empirical strategy is a shift-share design—or "Bartik" instrument—that exploits the differential exposure of municipalities to these common agreements. In particular, municipalities that have a large presence of banks in an agreement will be more exposed relative to municipalities with a small presence of these banks.

Let w_{ijmt} denote the number of withdrawals using the card from bank i on ATM j in municipaliy m in period t (which corresponds to quarters in our data). Let w_{mt} be the total

[17] The Financial Reform of 2014 modified the Law of Transparency and Financial Services Ordering (LTOSF) to allow banks to enter in agreements to charge lower fees to customers of other banks (for financial services in general). Before the reform, banks were only allowed to charge lower fees to their own customers. Circular 15/2014 of the Bank of Mexico eliminated the requirement of constituting a third party to be able to enter into an ATM-sharing agreement.

withdrawals in municipality m, so $w_{mt} = \sum_i \sum_j w_{ijmt}$. Start with the "accounting" equality:

$$d \ln w_{mt} = \sum_i \sum_j d \ln w_{ijmt} s^w_{ijmt} \tag{3}$$

where $s^w_{ijmt} \equiv w_{ijmt}/w_{mt}$ is the share of withdrawals on bank pair ij. As usual in this type of design, we fix the shares to an initial time period, s^w_{ijm0}. Given that the CNBV financial data set only has ATM withdrawal information at the bank-level and not at the bank-pair level, we replace the share of withdrawals from card i on ATM j with the inner product of the card share of i and the ATM withdrawal share of j. In other words, we approximate s^w_{ijm0} with $z_{ijm0} \equiv s^{card}_{im0} \times s^w_{jm0}$ where $s^{card}_{im0} = cards_{im0}/cards_{m0}$ and $s^w_{jm0} = w_{jm0}/w_{m0}$.[18]

The next step in a shift-share design is to decompose the bank-pair-location-period growth rate into a bank-pair-period growth rate (g_{ijt}) and an idiosyncratic bank-pair-location-period term ($\widetilde{g}_{ijmt}$):

$$d \ln w_{ijmt} = \underbrace{d \ln w_{ijt}}_{\equiv g_{ijt}} + \widetilde{g}_{ijmt}$$

We further instrument the bank-pair-period growth rate with agreement dummies E_{ijt}, that indicate whether there was an agreement in place between banks i, j in the previous period. We weight this variable by the percentage change in fee ($d \ln p_{ijt}$) associated with the agreement (i.e., the "size" of the agreement):[19]

$$d \ln w_{ijt} = \beta E_{ijt} d \ln p_{ijt} + \psi_{ijt}$$

Plugging back in Equation (3) we get the "first-stage" Bartik-type equation:

$$d \ln w_{mt} = \gamma^w \underbrace{\sum_i \sum_j E_{ijt} d \ln p_{ijt} z_{ijm0}}_{\text{Bartik instrument} \equiv B_{mt}} + \theta^w_m + \lambda^w_t + \zeta^w X_{mt} + \epsilon^w_{mt} \tag{4}$$

The Bartik instrument is the inner product of the agreement shocks, $E_{ijt} d \ln p_{ijt}$, and the exposure to these shocks, z_{ijm0}. θ^w_m and λ^w_t are municipality and time fixed-effects, respectively, and X_{mt} represents a set of municipality-specific time-varying controls.[20] We

[18] The variable $cards_{im0}$ denotes the number of card contracts issued by bank i in municipality m on period t.

[19] See the change in fees for each agreement in Table C1. We only observe the change in fees for banks that enter into agreements. Results remain very similar if we do not weight agreements by the fee reductions. To help with interpretability, we use the absolute value of the percentage change in fees; i.e., an agreement with a 50% fee reduction will have $d \ln p_{ijt} = 0.5$.

[20] Figure C1 shows that there is no evidence of pretrends in the first stage. The Bartik instrument does not seem to have an effect on the growth rate of ATM withdrawals on periods before the agreements take place.

also estimate reduced-form regressions analogous to Equation (4) considering different outcomes y_{mt} such as crime, informality and taxation:

$$d \ln y_{mt} = \gamma B_{mt} + \theta_m + \lambda_t + \zeta X_{mt} + \epsilon_{mt} \tag{5}$$

where the coefficient of interest is γ in Equation (5) interpreted as the differential change in the growth rate of the outcome variable y_{mt} in municipalities with a higher exposure to the shock, relative to municipalities with a lower exposure. Identification, as in Goldsmith-Pinkham et al. (2020), relies in the exogeneity of the shares z_{ijm0} with respect to the error terms ϵ_{mt} after adding the controls and fixed effects. Because we exploit differential exposure of municipalities to national-level agreements, identification in terms of shares is a more adequate assumption than identification coming from exogenous shocks (see, for instance, Borusyak et al., 2018).[21]

Table C9 and Figure C2 contain the diagnostics suggested by Goldsmith-Pinkham et al. (2020). They show that the Bartik estimator can be decomposed as a weighted sum of the coefficients of just-identified IV regressions, where each agreement share is used as an instrument.[22] Intuitively, agreements with larger weights (called "Rotemberg" weights) tend to drive the estimates. The top 5 agreements concentrate 34% of the positive weight in the estimator—slightly less than in other applications. Panel D shows that the overidentification test does not reject the null of exogenous instruments or no misspecification. Hence, the assumption of constant effects (across time and municipalities) is reasonable. Nevertheless, Figure C2 shows substantial heterogeneity in the 2SLS estimates across agreements. As Goldsmith-Pinkham et al. (2020) point out in the context of heterogeneous effects, this suggests that some of the underlying effects could potentially receive negative weight. This affects the LATE-like interpretation of our estimate, suggesting that it need not be robust to heterogeneous effects.[23]

Our implementation considers only those municipalities where there are at least two different banks with ATMs and debit cards (such that they are potential candidates to be exposed to an ATM-sharing agreement). The data of ATM withdrawals is available since

[21] In particular, note from Table C1 that the agreements occur between a small subset of banks and no more than 45% of Banks signed an agreement.

[22] We can decompose the Bartik instrument as a sum over ATM agreements (rather than bank pairs), $B_{mt} = \sum_k E_{kt} d \ln p_{kt} z_{km0}$, where k denotes one of the 56 national-level agreements. We can do this because the shocks E_{kt} are always zero for banks that do not enter into an agreement.

[23] We thank our discussant Gabriel Chodorow-Reich for pointing this out. To the best of our knowledge, the literature has not yet developed an estimator robust to unrestricted heterogeneity in this context. The closest related work is de Chaisemartin and Lei (2021), who develop an estimator that is robust to location-specific effects in the context of random shocks, as opposed to the random shares approach that we adopt.

March 2011, so we use March, 2011, to December, 2012, as baseline period.[24]

Table 4 presents the results from our preferred specification, which includes municipality and quarter fixed effects as well as controls for income per capita, total employment, and total population. These regressions are weighted by population and standard errors are clustered at the municipality level. Column (1) shows the effect of the Bartik instrument on the number of ATM withdrawals. It shows that the growth rate of ATM withdrawals is positive and strongly significant. The reduction in ATM-fees resulted in more ATM transactions in municipalities more exposed to the shock. This estimate implies that bank-sharing agreements dropping ATM fees completely in a municipality more than doubles withdrawals. One standard deviation increase in the Bartik instrument, conditional on an agreement taking place in a municipality (mean 0.001, std. 0.007), changes ATM transactions positively by 1.2 percent. Column (2) shows the results when we use the number of debit card contracts as a dependent variable. We observe a positive response of debit cards to the shock, but the coefficient is not statistically significant.

In Columns (3)-(6) we use homicides, thefts/robberies, pedestrian theft, and total crime as dependent variables. We find that pedestrian theft, a street crime where the victim is a pedestrian and the offender attempts the theft of cash or other property, is negative and statistically significant. We do not find the effect of ATM agreements on homicides, total thefts/robberies, or total crime statistically significant. These results are consistent with an interpretation of ATM sharing agreements as arrangements that reduced the average cash holdings per individual, thus decreasing the possibility that cash related crimes take place. The last two columns show results using the total number of informal workers and the local tax collection as dependent variables. Consistent with the evidence presented in Section 2, we do not find that the shock affected informality and we find evidence that local tax collection decreased.

3.2 Discussion

We interpret the implementation of ATM sharing agreements as a shock that dropped the price of ATM withdrawals and thus is likely to decrease the average cash holdings of customers. This shock provides exogenous variation to the use of cash similar to the rollout of debit cards explored in Section 2. Indeed, we find similar results in these two quasi-natural experiments. First, in both experiments there is an increase in the number of ATM transactions. The number of debit cards increased in both cases. None of the experiments have a significant effect on the number of informal workers or on the total

[24]Note that we are using the lagged agreement dummies, E_{ijt}, to construct the agreement shocks in Equation (4). We consider alternative leads and lags in Figure C1 in Section C as a robustness check.

Table 4: Effects of ATM-Sharing Agreements

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-quarterly level. The dependent variable in Columns (1) is the quarterly change in the logarithm of the total ATM withdrawal count. Column (2) uses the quarterly change in the logarithm of debit card contracts. Column (3) is the quarterly change in the logarithm of homicides (using data from INEGI based on death certificates). Column (4) is the quarterly change in the logarithm of total thefts/robberies. Column (5) is the quarterly change in the logarithm of total thefts to pedestrians. Column (6) is the quarterly change in the logarithm of total crimes. Column (7) is the quarterly change in the logarithm of informal workers. Column (8) is the quarterly change in the logarithm of local taxes. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. Regressions are weighted by the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level.

	(1) ATM Trans.	(2) Debit	(3) Homicides	(4) Thefts	(5) Ped. Theft	(6) Crimes	(7) Informality	(8) Taxes
Bartik	1.6770***	0.6504	-2.9215	-3.7118	-6.1498*	-3.8172	-1.6562	-2.8440**
	(0.600)	(1.093)	(3.138)	(3.426)	(3.454)	(2.497)	(1.268)	(1.385)
Obs.	20,695	20,695	20,710	20,710	20,710	20,710	20,710	3,822
Mun.	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

number of homicides. Both experiments have an effect on cash-related crimes such as theft. Importantly, the fact that after 2011 the Mexican Criminal Incidence data report counts of theft across different categories allows us to explore the impact of ATM sharing agreements on different types of theft. Consistent with a reduction of cash in circulation, we find that pedestrian thefts decline in response to agreement shocks. In both quasi-natural experiments, we estimate a negative effect on local tax collection, which could imply additional costs of policies restricting the use of cash. In Section 4.4, in order to present conservative estimates of the social benefits of precluding the use of cash, we focus only on quantifying the benefits of reducing the prevalence of cash-related criminal activities.

4 Simple Cash-Credit Model for Welfare Analysis

In this section we present a simple model where utility comes from differentiated goods, which themselves are aggregates of the same good/service paid in cash or by other means of payment, which we denote by card. This is a reduced form, or indirect utility, which should capture how agents' choice of means of payment depend on the relative price. We first present a representative agent version of the model, and then a version with both "banked" and "unbanked" households, which is important for matching the intensive/extensive margins decisions observed in the data. Finally, we return to the evidence on cash and credit usage described above to calibrate the model and to quantify the costs of either a large tax on cash or an outright ban.

Our choice of a cash-credit model, along the lines of Lucas and Stokey (1987), provides a tractable framework that allows for a simple welfare analysis of the restrictions on cash usage. Related efforts to give an explicit account of the fundamental transactions choices, and hence of the fundamental nature of the welfare costs, such as Gomis-Porqueras et al. (2014); Alvarez and Lippi (2017); Wang et al. (2020); Deviatov and Wallace (2014), provide an interesting avenue for future research towards a deeper understanding of the costs and benefits of cash usage.

4.1 A Representative Household Model of Cash-Credit Choice

We assume an agent's utility over a set of $\mathcal{A}$ varieties of goods, indexed by α is given by

$$u \equiv \left(\sum_{\alpha \in \mathcal{A}} \phi_\alpha^{\frac{1}{\sigma}} x_\alpha^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{6}$$

where ϕ_α is a preference weight parameter and σ is the constant substitution elasticity between goods.

Following Lucas and Stokey (1987) we assume that each good variety α can be purchased using either cash or an alternative means of payment, which we refer to as credit. The quantity of the goods are denoted by a if paid by cash and c if paid by credit. Thus the quantity x_α is itself a composite of cash and credit purchases for that variety according to

$$x_\alpha = \left(\alpha^{\frac{1}{\eta}} c_\alpha^{\frac{\eta-1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} a_\alpha^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{7}$$

where η is the substitution elasticity between cash and credit goods and α is the name of the good, and also the preference weight parameter for the "good" with credit share α.

We view as a reasonable hypothesis to consider parameter values such that the substitution elasticity between physically goods/services is smaller than the substitution elasticity between cash and credit, i.e. $\sigma \leq \eta$, but of course the model could use any parameter. For instance, below we discuss a simple expression for a lower bound on the cost of a ban of using cash as a means of payment that holds when $\eta = \sigma$.

We select the units of the goods/services so that we can normalize each good's price in terms of the numeraire and consider the agent's budget constraint in the baseline prices as:

$$\sum_{\alpha \in \mathcal{A}} \Big(c_\alpha + a_\alpha (1+\tau) \Big) = y + \varrho \tag{8}$$

where y is the agent's income, τ represents a tax on cash purchases, and ϱ a transfer, that is used to rebate the taxes levied on cash purchases.

The ideal price index p_α for the cash-credit bundle of type α given the tax rate on cash purchases τ is the usual one implied by CES utility.[25] This is the minimum cost, in units of the numeraire (goods paid with credit), which yields a utility $x_\alpha = 1$. It is given by

$$p(\alpha;\tau) = \Big(\alpha + (1-\alpha)(1+\tau)^{1-\eta} \Big)^{\frac{1}{1-\eta}} \tag{9}$$

Aggregating across all goods varieties α yields the ideal price index $\mathcal{P}(\tau)$ for the agent's aggregate consumption as a function of τ:

$$\mathcal{P}(\tau) = \left(\sum_{\alpha \in \mathcal{A}} \phi_\alpha \, p(\alpha;\tau)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} = \left(\sum_{\alpha \in \mathcal{A}} \phi_\alpha \left(\alpha + (1-\alpha)(1+\tau)^{1-\eta} \right)^{\frac{1-\sigma}{1-\eta}} \right)^{\frac{1}{1-\sigma}} \tag{10}$$

Let A denote the quantity of cash goods bought per unit of income, i.e. $A = \sum_{\alpha \in \mathcal{A}} a_\alpha/(y+\varrho)$. We can use A to compute the rebate to the agent of the taxes levied on cash payments as $\varrho = \tau(y+\varrho)A$, so that $\varrho = y\tau A/(1-\tau A)$. The quantity $A(1+\tau)$ is the share of expenditure paid with cash of the total income $y+\varrho$. Of course in equilibrium A is itself a function of τ, so that when useful we will write $A(\tau)$.

The parameters ϕ_α have the interpretation of the expenditure share on the goods with credit share α at baseline prices, i.e. when $\tau = 0$. Recall that in this baseline case units are chosen so that $p(\alpha;0) = 1$ for all goods. Note that in this case the share of goods paid with cash is $A(0) = \sum_{\alpha \in \mathcal{A}} \phi_\alpha (1-\alpha)$. We can, in principle, measure ϕ_α and α for different categories of goods and services using expenditure surveys, such as in Table 1.

[25] To see this just solve the dual problem of choosing a_α and c_α optimally to minimize the cost yielding one unit of utility.

We assume the tax on cash goods is rebated to the agents, so that the welfare cost of a tax on cash is measured by

$$W(\tau) \equiv \frac{y+\varrho}{\mathcal{P}(\tau)} = \frac{y}{\mathcal{P}(\tau)} \frac{1}{(1-\tau A(\tau))} \tag{11}$$

where we use expression for ϱ derived above. The term $y + \varrho$ denotes the sources of income, given by income y and transfers $\varrho = y\tau A/(1-\tau A)$. These resources are used by the agent to buy goods and pay taxes. If $\tau = 0$ then $\mathcal{P} = 1$ and $W(0)/y = 1$, which is the baseline level of welfare absent a tax on cash. If cash is taxed $\tau > 0$ then $\mathcal{P} > 1$, so that any given level of welfare is more expensive, and welfare decreases. The welfare cost must take into account the fact that the tax on cash is rebated to the households, an effect measured by the $A\tau$ term in the numerator of equation (11). Taxing cash gives rise to a welfare cost as it distorts the agent's optimal choices. We will use equation (11) to assess the cost of restrictions to cash usage, or a finite tax on cash ($\tau < \infty$), as well as a ban on cash modelled as an infinite tax on cash goods ($\tau \to \infty$).

To compute A we use the following equations that are readily derived from the agent's first order conditions for a CES utility function:

$$\frac{a_\alpha}{x_\alpha} = (1-\alpha)\left(\frac{1+\tau}{p_\alpha}\right)^{-\eta} \quad \text{and} \quad \frac{x_\alpha}{(y+\varrho)/\mathcal{P}} = \phi_\alpha \left(\frac{p_\alpha}{\mathcal{P}}\right)^{-\sigma} \tag{12}$$

where above we omit that the ideal price $\mathcal{P}$ and p depend on τ. We can then write the *share* of expenditures paid in cash:

$$(1+\tau)A(\tau) = (1+\tau)\frac{\sum_{\alpha\in\mathcal{A}} a_\alpha}{y+\varrho} = \left(\frac{1+\tau}{\mathcal{P}(\tau)}\right)^{1-\eta} \sum_{\alpha\in\mathcal{A}} (1-\alpha)\phi_\alpha \left(\frac{p_\alpha(\tau)}{\mathcal{P}(\tau)}\right)^{\eta-\sigma} \tag{13}$$

so that welfare as a function of τ is given by

$$W(\tau) \equiv \frac{y}{\mathcal{P}(\tau)} \left(\frac{1}{1 - \frac{\tau}{1+\tau}\left(\frac{1+\tau}{\mathcal{P}(\tau)}\right)^{1-\eta} \sum_{\alpha\in\mathcal{A}} (1-\alpha)\phi_\alpha \left(\frac{p_\alpha(\tau)}{\mathcal{P}(\tau)}\right)^{\eta-\sigma}} \right) \tag{14}$$

We refer to $-\log W(\tau)$ as the (private) welfare cost of taxing cash, expressed in log points. We call it private because it abstract from external effects such as crime, tax avoidance, etc. A few special cases yield analytic insights into the cost of taxing cash.

A ban on cash. We can obtain the private welfare cost of a ban on cash, by letting $\tau \to \infty$. Assume that $\eta > 1$ so that $A \to 0$ and hence cash is not used, then we have

$$\lim_{\tau \to \infty} W(\tau) = \lim_{\tau \to \infty} \frac{y}{\mathcal{P}(\tau)} = \frac{y}{\left(\sum_{\alpha \in \mathcal{A}} \phi_\alpha \alpha^{\frac{1-\sigma}{1-\eta}}\right)^{\frac{1}{1-\sigma}}}$$

Three remarks are in order.

1. If all goods have the same credit share, i.e. if $\phi_{\bar{\alpha}} = 1$, then we have

$$\mathcal{P}(\infty, \sigma, \eta) \equiv \lim_{\tau \to \infty} \mathcal{P}(\tau, \sigma, \eta) = \bar{\alpha}^{\frac{1}{1-\eta}}$$

which is, trivially, independent of σ.

2. If $\sigma = \eta$ then,

$$\mathcal{P}(\infty, \sigma, \eta) = \bar{\alpha}^{\frac{1}{1-\eta}}$$

where $\bar{\alpha} = \sum_{\alpha \in \mathcal{A}} \phi_\alpha \alpha$, which is the aggregate share of expenditure on credit at baseline prices.

3. The cost of a ban is decreasing in the elasticity of substitution between goods, i.e.

$$\mathcal{P}(\infty, \sigma', \eta) < \mathcal{P}(\infty, \sigma, \eta) \text{ for any two } \sigma' > \sigma \geq 1 \quad .$$

This is quite intuitive, as higher elasticity σ makes it easier for the agent to substitute to goods with smaller cash share. To see why this must hold, note that $\mathcal{P}(\infty)$ solves the same equation as the consumption equivalent for an agent with risky consumption $x = \alpha^{1/(1-\eta)}$, and a CRRA utility function i.e. $\mathcal{P}(\infty)^{1-\sigma}/(1-\sigma) = E[\frac{x^{1-\sigma}}{1-\sigma}]$. Thus, using the Arrow-Pratt Theorem, we obtain the desired results.

Under the assumption that $\sigma \leq \eta$ we can obtain a simple lower bound for the cost of a ban, namely

$$\mathcal{P}(\infty, \sigma, \eta) \geq \mathcal{P}(\infty, \eta, \eta) = \bar{\alpha}^{1/(1-\eta)}$$

where again $\bar{\alpha} = \sum_{\alpha \in \mathcal{A}} \phi_\alpha \alpha$ is the aggregate share of expenditure on credit at baseline prices. Note that in this case we have that the welfare cost gives:

$$-\log W(\infty) \equiv \log \mathcal{P}(\infty, \eta, \eta) = \frac{1}{1-\eta} \log \bar{\alpha}$$

This shows that the cost of the ban of cash is inversely proportional to the elasticity η, and that it is decreasing and convex in the share of credit $\bar{\alpha}$.

Large elasticity, i.e $\eta = \sigma$. Under the assumption that the substitution elasticity across varieties equals the elasticity across means of payments the formulas simplify and we can write:

$$\mathcal{P}(\tau) = \left(\sum_{\alpha \in \mathcal{A}} \phi_\alpha \left(\alpha_\alpha + (1-\alpha_\alpha)(1+\tau)^{1-\eta} \right) \right)^{\frac{1}{1-\eta}} = \left(\bar{\alpha} + (1-\bar{\alpha})(1+\tau)^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

where $\bar{\alpha} = \sum_{\alpha \in \mathcal{A}} \phi_\alpha \alpha$ is the baseline aggregate share of payments in credit. Computing welfare gives

$$W(\tau) = \frac{y}{\mathcal{P}(\tau)} \frac{1}{1 - \tau A(\tau)} = \frac{y}{(\bar{\alpha} + (1-\bar{\alpha})(1+\tau)^{1-\eta})^{\frac{1}{1-\eta}}} \left(\frac{1}{1 - \frac{\tau}{1+\tau} \frac{(1+\tau)^{1-\eta}(1-\bar{\alpha})}{(\bar{\alpha}+(1-\bar{\alpha})(1+\tau)^{1-\eta})}} \right)$$

A few remarks are in order:

1. By the same argument used above, for any fixed tax τ, the ideal price index $\mathcal{P}(\tau)$ decreases with η.

2. It is clear from the expression above, that for $\bar{\alpha} < 1$ and a fixed $0 < \tau < \infty$, the share of cash $(1+\tau)A$ decreases with η. Hence $1/(1-\tau A) = 1/(1 - \frac{\tau}{1+\tau}(1+\tau)A)$ also decreases with η.

3. For small τ the welfare cost is increasing in η for $0 < \bar{\alpha} < 1$, i.e. a second order approximation around $\tau = 0$ gives the Harberger's triangle type expression:

$$-\log W(\tau) = \frac{1}{2}(1-\bar{\alpha})\, \bar{\alpha}\, \eta\, \tau^2 + o(\tau^2) \tag{15}$$

Hence, for a fixed $0 < \tau < \infty$ the welfare cost defined as $-\log W(\tau)$, is a non-monotone function of the elasticity of substitution η. Instead, as shown above, as $\tau \to \infty$ we have that the welfare cost is $-\log W(\infty) = \frac{-\log(\bar{\alpha})}{\eta - 1}$, and thus at very large τ the welfare cost is decreasing in η. This is to be compared with the second order approximation derived in equation (15) which shows that for small τ, the welfare cost is increasing in η.

4.2 Intensive-Extensive Choice of Cash-Credit

Next we modify the representative agent setup described above to model the agent's choice to be unbanked, and thus be a cash only user, or to pay a fixed cost and access both cash and credit services. The extension is motivated by the empirical observations that several households are unbanked and thus do not have a cash-credit choice at the moment. We derive a lower bound for the cost of a ban on cash, or a large tax, that has an expression identical to the ones derived for the representative agent model above. The key difference is in the interpretation, and hence calibration. We show that in this case one should use the fraction of credit purchases $\bar{\alpha}$ that corresponds to the currently banked households, i.e. what we identify as the mixed users in Mexico. This has the effect of reducing substantially the cost of a ban (or a large tax) on cash.

The outline of the model is as follows. We assume that in the baseline case there is a fraction $\beta \in [0, 1]$ of the population that have access to both payment methods (the "banked" population), and the remaining fraction $1 - \beta$, which we refer to as the "unbanked", whose only means of payment is cash. We assume that the utility function of both types is the same, and given by equation (6) and equation (7). The problem of the "banked" households is the one described above in the representative agent version. Instead, for the unbanked households we assume that if they pay a fixed cost $\psi > 0$, measured in the same units as utility w, then they gain access to both means of payment, and hence will face the same problem as the currently banked households. Below we describe in more detail the problem of the unbanked households. Finally, we give a formula for a lower bound on the cost of a (large) tax on cash τ that applies to the case where there is a fraction β of banked and $1 - \beta$ of unbanked households. The expressions for this lower bound are identical to the ones derived in the representative agent model. The difference, as mentioned above, is in the interpretation. Since, in the baseline situation, only the banked households use both means of payments, then we need to calibrate the model to their share of credit payments $\bar{\alpha}$, which is larger –inversely proportional to their share of expenditure in the population. This larger share of payments in credit, by using the expressions derived above, reduces the cost of a ban on cash since everyone is more predisposed to use credit.

We let $U(\tau)$ be the utility for the unbanked facing a tax on cash τ.

$$U(\tau) = \max\left\{\hat{W}(\tau), W(\tau) - \psi\right\} \tag{16}$$

where $\hat{W}(\tau)$ is the utility for the unbanked conditional on not adopting credit, while $W(\tau)$ is the utility of the household conditional on adopting credit analyzed in the previous section. We use ψ for the flow equivalent of the fixed cost that an unbanked agent has to pay to become banked and have access to credit as a means of payment. The utility $\hat{W}(\tau)$ solves

$$\hat{W}(\tau) = \max_{a_\alpha} \sum_{\alpha \in \mathcal{A}} \left[\hat{\phi}_\alpha^{1/\sigma}\, a_\alpha^{1-1/\sigma}\right]^{\frac{\sigma}{\sigma-1}} \text{ s. t. : } \sum_{\alpha \in \mathcal{A}} a_\alpha (1+\tau) = y + \varrho \tag{17}$$

$$\text{and where } \hat{\phi}_\alpha \equiv \phi_\alpha\, (1-\alpha)^{\frac{\sigma-1}{\eta-1}} \tag{18}$$

since the unbanked household problem is equivalent to one where we set $c_\alpha = 0$ for all α and hence

$$\hat{p}(\alpha;\tau) = (1+\tau)\,(1-\alpha)^{\frac{1}{1-\eta}} \text{ and } \hat{x}_\alpha = a_\alpha\,(1-\alpha)^{\frac{1}{\eta-1}} \tag{19}$$

In this section we assume that the banked households have already paid the cost of using credit, so we ignore these scost since they are sank. For future reference we make two remarks.

1. For $\tau = \infty$ the unbanked households will choose to pay the cost ψ and have access to both means of payments. Likewise, for τ large, but finite, the unbanked households will still pay the cost.

2. Since in the baseline case with zero tax on cash and no rebate (i.e. $\tau = \varrho = 0$), the unbanked have chosen not to pay the fixed cost ψ, so that $U(0) = \hat{W}(0)$, then we can obtain the following lower bound for its value:

   $$\psi \geq \underline{\psi} \equiv W(0) - \hat{W}(0) \tag{20}$$

   In words, $\underline{\psi}$ is the minimum fixed cost that will make the unbanked indifferent between using both means of payments or just cash at baseline prices (when $\tau = 0$).

Let's assume that τ is large enough so that the unbanked agents will pay the cost ψ and use both means of payments when facing the tax on cash τ. The difference in utility after and before the tax on cash $U(\tau) - U(0)$ for the unbanked is:

$$U(\tau) - U(0) = W(\tau) - \psi - U(0) \leq W(\tau) - \underline{\psi} - U(0) = W(\tau) - W(0) \tag{21}$$

where the first equality follows from the assumption on τ, the second inequality follows from $\psi \geq \underline{\psi}$, and the last equality from the definition of $\underline{\psi}$. Importantly, the last difference is exactly the welfare cost of a tax τ for the banked households, i.e for large enough τ we have:

$$\text{Welfare cost for unbanked} \equiv U(0) - U(\tau) \geq W(0) - W(\tau) \equiv \text{Welfare cost for banked} \tag{22}$$

We briefly discuss the hypothesis we use to derive the inequality in equation (22). To accomplish this analytically, consider the simple model where either α has a degenerate distribution, or where $\sigma = \eta$. Under these assumptions one can verify that for each $\eta > 1$, $\bar{\alpha} \in (0,1)$ and $\tau > 0$ there is a non-empty interval of values of ψ for which simultaneously: (i) it is optimal for the (unbanked) not to pay the fixed cost and remains using only cash when $\tau = 0$, and (ii) it is optimal to pay the fixed cost and used both means of payments for

$\tau > 0$. This is equivalent to verify the following inequality:

$$W(0) - \hat{W}(0) \leq \psi \leq W(\tau) - \hat{W}(\tau)$$

Verifying this inequality is simplified by using that the rebate ϱ for the case of $\tau > 0$ cancels in the right hand side, so, one can compare the (the reciprocal) of the corresponding ideal prices. Define $D(\tau) \equiv W(\tau) - \hat{W}(\tau)$. Then, under the stated assumptions, this simplifies to the following inequality:

$$D(0) = \frac{y}{1} - \frac{y}{(1-\bar{\alpha})^{\frac{1}{1-\eta}}} \leq D(\tau) = \frac{y}{\left[\bar{\alpha} + (1-\bar{\alpha})(1+\tau)^{1-\eta}\right]^{\frac{1}{1-\eta}}} - \frac{y}{(1-\bar{\alpha})^{\frac{1}{1-\eta}}(1+\tau)}$$

That $D(0) \leq D(\tau)$ is immediate from the fact that $W(\tau) \geq \hat{W}(\tau)$ since the latter is welfare obtained under the constraint that $c = 0$, an outcome that can always be replicated by the unconstrained agent. We note moreover that differentiating $D(\tau)$ with respect to τ, and using that $\bar{\alpha} \in (0, t)$, shows that the function $D(\tau)$ is increasing in τ provided $\eta > 2$, a reasonable assumption in our data. It follows that a higher tax rate on cash τ implies larger incentives to adopt the banking technology.[26]

4.3 Quantifying the Cost of Taxing Cash

Next we use the model sketched in Section 4.1 and Section 4.2 to gauge the welfare cost of taxing cash. The quantification is based on the equation (14), where welfare is measured as a function of the tax on cash goods, τ, the distribution of credit shares $\{\phi_\alpha\}$, and the elasticities σ and η. We used the results of Section 4.2 to obtain a lower bound for the cost in the case of having both banked and unbanked agents. Our preferred estimate of a 40% tax on cash is a cost of approximately 6% of GDP or higher. We remark that the welfare cost is expressed in units of GDP, which makes it convenient to quantify the magnitude of the costs in terms of a compensating variation of GDP itself. Thus, the metric does not imply that taxing cash will lead to a *change* in the GDP level. As a matter of fact, conventionally measured GDP in our simple model is constant.[27]

[26] Differentiating $D(\tau)$ gives, after simple algebra,

$$\frac{\partial\, D(\tau)}{\partial\, \tau} = y(1-\alpha)^{\frac{1}{\eta-1}}(1+\tau)^{-2}\left[1 - \left(1 + \frac{\alpha}{1-\alpha}(1+\tau)^{\eta-1}\right)^{\frac{2-\eta}{\eta-1}}\right]$$

Inspecting the expression reveals that the derivative is positive for every τ provided that $\eta > 2$.

[27] We thank our discussant Gabriel Chodorow-Reich for suggesting to us to clarify this potentially confusing point. Equation (14) gives the welfare-equivalent output reduction in the absence of any distortion in relative prices.

The objective is to parameterize the model to replicate behavior observed in Mexico circa 2016, and use an elasticity of substitution between cash and credit expenditures, η, estimated in Alvarez and Argente (2020a) and Alvarez and Argente (2020b), to analyze several counterfactuals where cash expenditures are subject to a tax τ per unit of cash expenditure. Alvarez and Argente (2020a) estimates $\eta = 3$ using a large field experiment where riders where faced with different prices for Uber trips depending on whether the trips were paid with cash of with cards. Importantly, they find that a CES function summarizes well preferences between paying in cash or cards for price variation in the range of 40%. For this reason, below we consider a tax on cash $\tau = 0.40$ besides an outright ban of cash. Alvarez and Argente (2020b) study the ban on cash for Uber payments in the city of Puebla, Mexico. The changes in trips after the ban on cash for riders that before the ban have used cash and card with different intensity imply a long-run elasticity of substitution between 3 and 5. Thus, in this paper, we use the latter as our benchmark value and apply it to all the goods in the economy. Several alternative parameterizations will be used to discuss the robustness of the findings.

We start with a discussion of the distribution of the share of payments made in cash vs those made with other methods, which we refer to as credit. As mentioned in Section 1 cash is used extensively in Mexico. In Table 1 we use a consumption survey and for each tercile of the entire population ordered by expenditure we display the fraction of expenditure for each broad category of goods, and for each category the fraction that is paid with card. Overall this gives a fraction of expenditures paid with card, denoted by $\bar{\alpha}$ in the model, just above 5%. In that section we also discussed that half of the population own a credit or debit card, which will correspond to our banked population in the model. Finally, in Figure 2 and Table 2, we display the share of consumption paid in card for those that have completed at least one purchase using cards during the survey. The expenditure of those households amount to about 21% of the total expenditure, which will correspond to $\beta = 0.21$ in the model of Section 4.2. The fraction of consumption paid in card for these mixed users is approximately $\bar{\alpha} \approx 0.25$. Based upon the results in Section 4.2, we can estimate a lower bound on the cost of a tax on cash τ for the entire population by using the expression in equation (14) for the distribution with $\bar{\alpha} = 0.25$ or higher. We include results for larger values of $\bar{\alpha}$ since in the National Survey of Firms' Financing (ENAFIN) (Figure A8) the fraction of revenues paid with card is as high as 18.5% – obtained as a weighted average of 25% for formal firms (75% of GDP) and assumed to be zero for informal firms. Some of the payments for firms are intra-firm transactions, hence this is an upper bound for households. To understand the robustness of the estimates, we report results using values of $\bar{\alpha}$ as high as 0.50, and to be conservative we use $\bar{\alpha} = 0.40$ as our benchmark.

Figure 9: The private welfare cost as a function of the tax τ

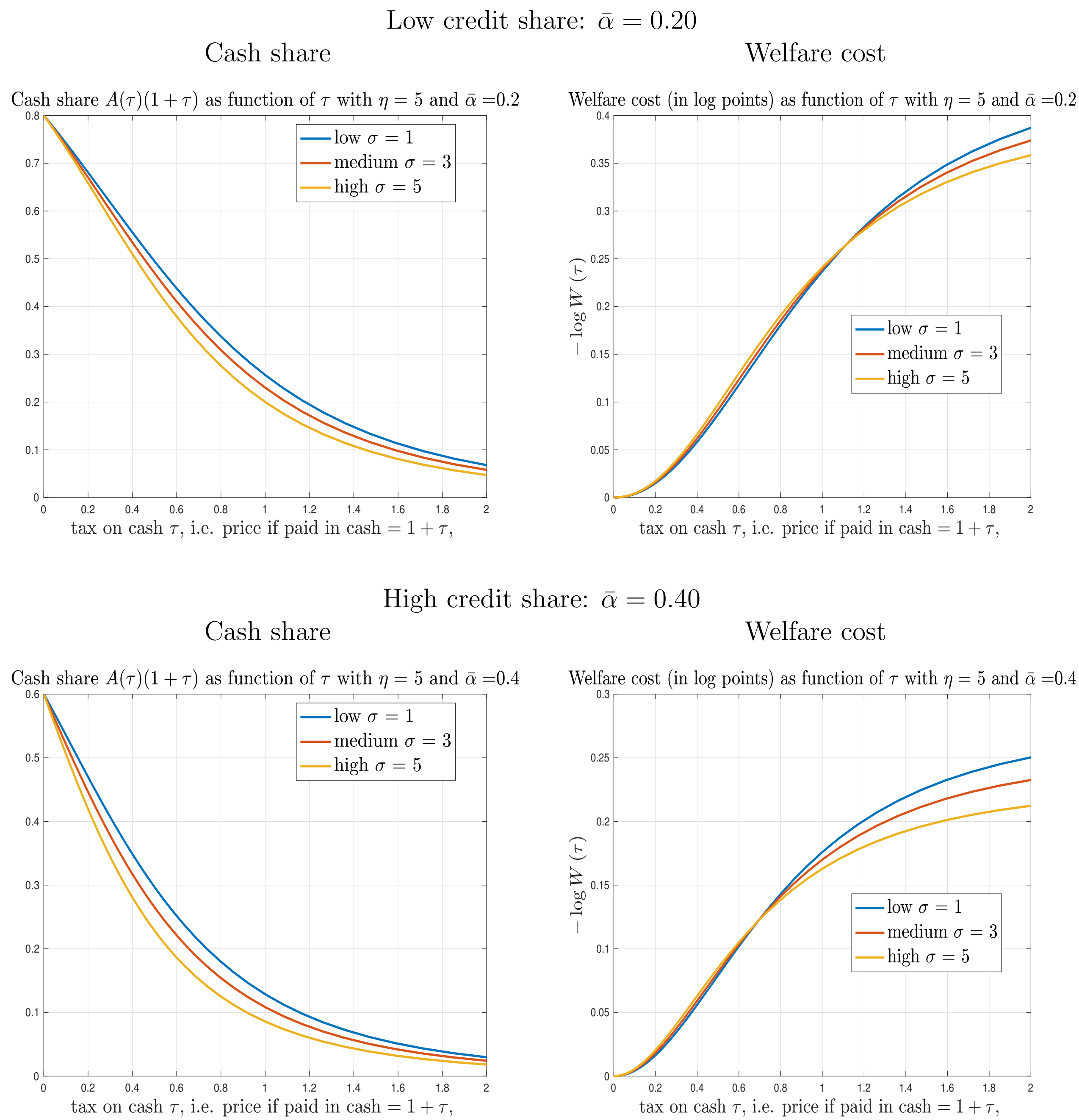
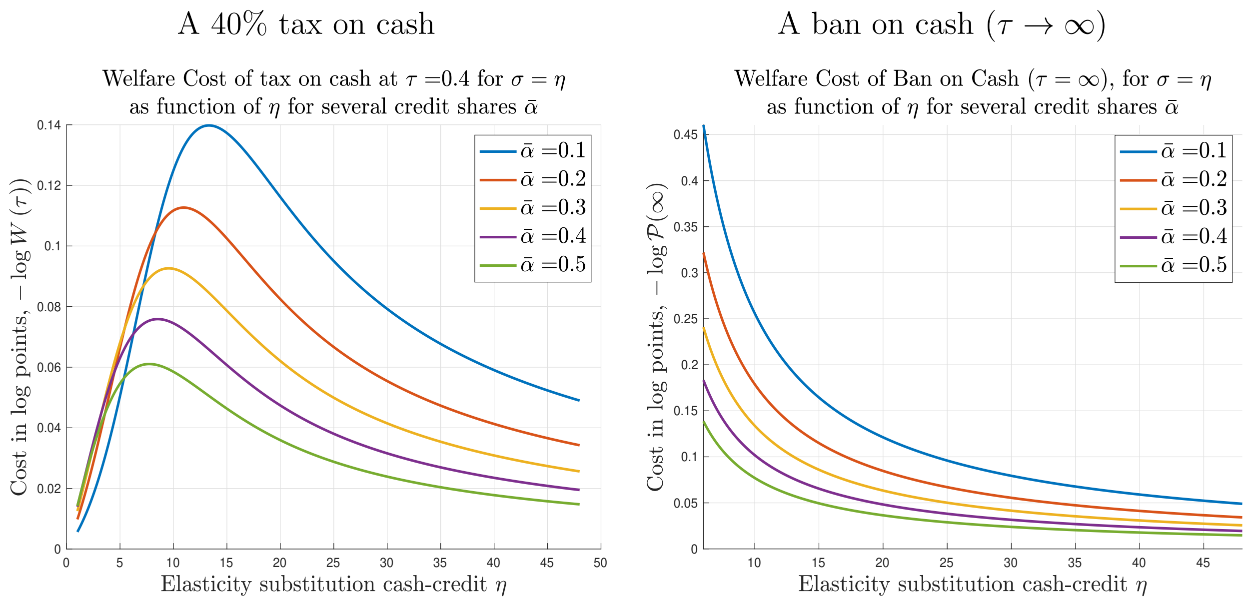


Figure 9 plots the cash share of expenditures $A(\tau)\,(1+\tau)$ and the welfare cost $-\log W(\tau)$ both as function of the tax on cash τ. In all the plots on this figure we use the distribution of the share of cash purchases for mixed users scaled up so that the average credit share $\bar{\alpha}$ is either 20% in the top panel or 40% in the bottom panel. In each plot we include three lines,

Figure 10: The private welfare cost as a function of the elasticity η



corresponding to three values of σ. In each plot we let the tax on cash vary between 0 and 200%, or $\tau \in [0, 2]$. Figure 9 uses $\eta = 5$ in all plots. The welfare costs are quite insensitive to σ compared with the effect of other parameters. As explained in Section 4.1, the welfare costs are decreasing in the average credit share $\bar{\alpha}$, but they are still very high for $\bar{\alpha} = 0.4$. In view of the insensitivity with respect to σ, in Figure 10 we consider the case of $\sigma = \eta$, which gives a lower bound for the cost, and vary η over a large range of values. Figure 10 has two panels, one corresponding to $\tau = 0.4$, which is in the upper range of the experimental evidence, and the other panel for $\tau = \infty$, i.e. a ban on cash. In each case we plot the welfare cost for five different values of $\bar{\alpha}$. As explained in Section 4.1, we expect the welfare cost to be non-monotone for small τ. The non-monotonicity is clearly present in the left panel of Figure 10. For instance, for $\tau = 0.40$ and $\bar{\alpha} = 0.40$ the welfare cost for $\eta = 5$ is similar to the one for $\eta = 12$, and in both cases about 6.5%. For $\bar{\alpha} = 0.20$ the welfare cost corresponding to $\eta = 5$ is similar to the one for $\eta = 20$, and both of them are close to 8%. Instead the welfare cost of a ban on cash, i.e. the welfare cost of $\tau = \infty$ is about 10% for $\bar{\alpha} = 0.40$ and $\eta = 10$. Using much larger elasticities, say around $\eta = 30$ for $\bar{\alpha} = 0.40$, the welfare cost is smaller but still sizeable, say about 3% for both $\tau = 0.40$ and for $\bar{\tau} = \infty$. Summarizing, our preferred estimate of a 40% tax on cash is a cost of approximately 6% of GDP or higher.

4.4 Social Benefits of Curbing Cash Related Crimes

This section discusses some evidence on the social cost of crime with the goal to quantify the benefits that follow a reduction, or even the eradication, of criminal activities related to cash. As reported in Section 2 and Section 3, a reduction in the use of cash caused a statistically significant reduction in theft and robberies, while no significant change was detected in other categories such as violent crime or tax avoidance. For this reason, we focus on theft and robberies to quantify the benefits associated to a reduction in the use of cash. Furthermore, in order to provide an upper bound of the social benefits of policies restricting the use of cash, in what follows, we assume that all thefts and robberies related to cash are *eradicated* as a result of these policies. Measuring the incidence of these two crimes in Mexico between 2014 and 2016, and assessing the deadweight losses of such crimes, give an upper bound for the social benefits of eradicating both crimes between 0.48% and 1.28% of GDP.

Next, we illustrate the details of this computation, that is made of two steps. First we use aggregate statistics from National Survey on Victimization and Perception of Public Safety (ENVIPE) to measure the prevalence of cash-related theft and robberies in Mexico and quantify their magnitude.[28] This step yields an estimate of the direct cost of cash crimes, measured as the fraction of GDP that is stolen. We refer to this magnitude as the *direct* cost, because such a measure does not include the *indirect* costs triggered by crime, such as the preventive police cost, the judiciary costs, as well as the intangible costs associated to the crimes (psychological costs for the victims and other costs). Second, we quantify the *indirect* costs, i.e. the deadweight losses caused by theft and robberies, drawing from estimates of the cost of crime developed in economics of crime literature, such as Price (2000); Albertson and Fox (2008); Heeks et al. (2018), and the summary of the main estimates for the tangible and intangible indirect costs of crime collected in the meta study by Wickramasekera et al. (2015). According to the Beckerian logic, the welfare loss of cash crimes is measured by the deadweight losses of such crimes, since the direct cost represents a *transfer* from one individual to another. We assume that the deadweight losses are proportional to the direct cost, therefore, both steps are needed to quantify the benefits of eradicating cash crimes.

Quantifying the direct cost of cash theft and robberies in Mexico. We quantify the direct cost due to robbery and theft associated with incidents where cash is stolen. Alternative measures can make this figure as high as 0.8% of GDP, or as low as 0.29% of GDP. This range informs us on the order of magnitude of the direct costs of crime. In short, using the number of incidents of cash related theft and robbery (about 13% per year) times

[28] The years are ENVIPE 2017, ENVIPE 2016, and ENVIPE 2015, all from INEGI. Each survey reports data for the year before the one indicated in the title.

the currency in circulation per person (about 6% of GDP) yields a loss of 0.8% of GDP per year. Alternatively, using the reported direct economic cost from the victimization survey, we get 0.29% of GDP per year.

We estimate these values in two different ways. The number of incidents comes from the ENVIPE victimization surveys (various years).[29] In particular, the first figure comes from averaging the rates from 2014 to 2016 of all crimes reported which are $(42{+}35{+}37)/3 = 38$ per 100 inhabitants. We take the fraction of those events that correspond to theft and robbery in the street or public transportation, plus robbery in other forms, plus other crimes, which include "express kidnapping". Note that we are excluding robbery at home, while in other categories we include crimes that may not be cash related. For 2016 these fractions are $25.9{+}5.1{+}3.4 = 34.4\%$ (ENVIPE 2017), for 2015 they are $28.2{+}3.7{+}2.9{=}34.8\%$ and for 2014 they are $28.6{+}3.5{+}3.0{=}35.1$, so that the average fraction of incidents where cash is taken is about 35%. The product of the total crime incidence (38%) and the fraction of cash related crimes (35%) yields an average probability of cash theft of 13% per year. We apply this crime incidence to the stock of currency in the hands of the public between 2014 and 2016, which is about 6% of GDP, yielding a total cost of $0.13 \times 0.06 = 0.0079$ of GDP per person per year, or 0.8% of GDP per person per year.

The second estimate uses the victimization survey, which reports for all crimes an average loss of 1.27% of GDP for 2014, 1.25% for 2015 and 1.10% for 2016, or an average loss of 1.20% of GDP overall. Of these costs, the following fraction corresponds to the "economic losses as a consequences of these crimes" 68.3% for 2014, 62.9% for 2015 and 60.6% for 2016 or 63.9% on average. Multiplying these two averages and using that 38% of the crimes are thefts and robberies, which we associate with cash being stolen, we get $1.20 \times 0.639 \times 0.38$ or 0.29% of GDP per year in direct economic losses.

Quantifying the deadweight loss of cash related crimes. Most crimes involve tangible and intangible indirect costs. We rely on estimates of these deadweight losses developed in the economics of crime literature, such as the contributions surveyed in Wickramasekera et al. (2015). A synopsis of the various costs estimated by 14 different studies on the issue is given in Table 3 by Wickramasekera et al. (2015).[30] Several studies estimate the direct cost of the crime, and of the associated indirect tangible (police, medical assistance and judiciary) as well as of the indirect intangible costs (reflecting the fear, pain, suffering, and lost quality of life).[31]

[29] http://en.www.inegi.org.mx/programas/envipe/2019/

[30] These estimates are available mostly for developed countries (Australia, New Zealand, UK, USA).

[31] As the authors explain *"Indirect costs refer to the economic value of consequences of crime that do not involve a direct monetary exchange. These include lost productivity of both offenders and/or victims, and the*

There are 7 studies reporting the costs of *robberies* in the survey. These allow us to compute the deadweight loss per dollar stolen, measured by the ratio of the total social cost of the crime (including both tangible and intangible indirect costs) relative to the direct cost of the crime. For robberies, the average value of the deadweight loss per dollar stolen is 3.1, suggesting that every dollar robbed causes an additional 3.1 dollars of deadweight loss.[32]

There are also 7 studies concerning the cost of *theft* in the survey. For theft, the average value of the deadweight loss per dollar stolen is 1.1, suggesting that every dollar stolen causes an additional 1.1 dollars of deadweight loss. The deadweight loss is much smaller than the one for robberies because the lack of violence in thefts significantly reduces the indirect costs.[33]

We discussed above, in reporting the ENVIPE results, that the relative frequency of theft is about 25% while the frequency of robbery is about 8.5% of all crimes, so that their relative weight is 75% and 25% respectively. Using these weigths to combine the deadweight losses for theft (1.1 per dollar) and robbery (3.1 per dollar) with their relative frequency we obtain an average deadweight loss of about $0.75 \times 1.1 + 0.25 \times 3.1 = 1.6$ per dollar crime committed. Multiplying this average deadweight loss with the average cost of crime discussed above gives a lower bound of $1.6 \times 0.29 = 0.48\%$ of GDP and an upper bound of $1.6 \times 0.8 = 1.28\%$ of GDP.

5 Conclusion

Policies restricting the use of cash have recently received great interest and their possibility has been debated both by policymakers and academics. However, there are almost no attempts to quantify the welfare consequences of such policies accounting for both social

value of volunteer time. Often lost productivity is estimated by calculating the forgone productivity as a result of the offence. For example, lost productivity can be determined by multiplying hourly average income with the number of hours a victim has spent out of work as a consequence of a crime. Intangible costs are costs incurred by victims, potential victims and society which include fear, pain, suffering, and lost quality of life. These costs are the most difficult to quantify as there is no market value or monetary exchange. As a result, intangible costs are usually inferred by revealed or stated preference-based methods such as willingness-to-pay or contingent valuation."

[32] A recent report of the UK Home Office indicates substantively larger costs associated to robberies, with a deadweight loss close to a factor of 10 (of which 3.6 is due to physical and emotional harm and another 3.6 is due to judiciary costs), see Table 1 in Heeks et al. (2018). Including this study raises the average deadweight loss of robberies to a value of about 4 times the dollars stolen.

[33] ENVIPE also includes a measure of the indirect costs of crime. They include health costs and the costs of preventive activities such as (e.g. changing doors and windows, changing doors' locks, installing fences, organizing joint activities with neighbors, acquiring a guard dog). The total of these indirect costs is in the order of 64% of the direct costs, much lower than our benchmark estimates. These estimates, however, do not include utility enhancing activities that were prevented by crime (such as going out at night, wearing personal valuable items, etc). Indeed, in ENVIPE, a large fraction of households report making adjustments to their daily activities because of crime. Unfortunately, we do not have an estimate of the monetary value of these costs.

benefits and private losses. In this paper, we attempt such a calculation for the case of Mexico. The social benefits of restricting the use of cash rely on estimates of the elasticity of crime and informality obtained from two quasi-natural experiments in Mexico that encouraged the use of debit cards. The private costs are estimated using a reduced form model and expenditure shares obtained from the Mexican expenditure survey. We find that the private costs of restricting the use of cash are at least twice as large as the social benefits.

Our calculation naturally relies on several assumptions that are necessary to make progress on the matter. We see the exploration of the robustness of these assumptions as a fertile ground for future research. First, our estimates for the private costs of restricting the use of cash heavily rely on the available estimates of the elasticity of substitution between cash and cards available in the literature. These estimates are calculated using experimental and observational data for Uber services in Mexico. More work is needed to compute an elasticity applicable to the entire economy.

Second, we do not consider the effect of the policy on tax evasion given that we do not find significant effects of the two policies we study on informality. Interestingly, no major effects on tax compliance are visible even in Lahiri (2020) analysis of the great demonetization that occurred in India in 2016.[34] It is possible, however, that there is an impact of cash on tax evasion and other crimes, especially if the size of the intervention is larger. A full ban on cash, for instance, could have an impact on crimes such as extortion.

Lastly, our calculation does not consider the general equilibrium effects of the policy. One is the restriction that the storability of cash has on the level of nominal interest rates, i.e. the zero lower bound. Another is the supply side response of alternative payment methods. These calculations could change the welfare effects of the policy estimated in this paper and are an important area for future research.

[34] Cite from page 64 "The general picture that emerges from Figure 2 is that there has been some improvement in public finances in India since 2016, but it is difficult to attribute this to demonetization because the changes appear to be consistent with a prior trend. Hence, the indirect effect of demonetization on seizing undeclared income seems muted at best."

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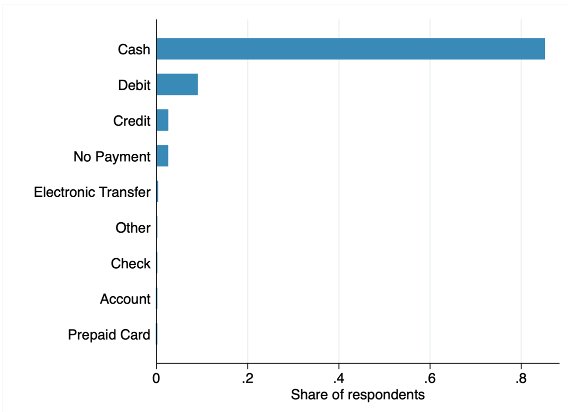
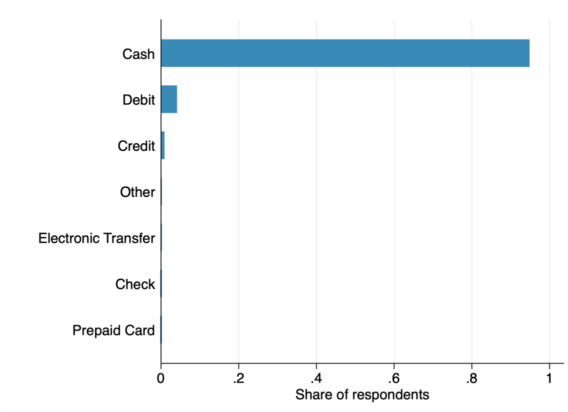
APPENDIX

A Figures and Tables

Figure A1: Payment method by Amount



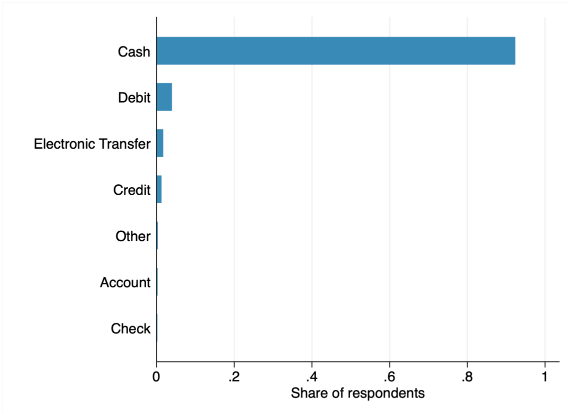
(a) 20 USD or More



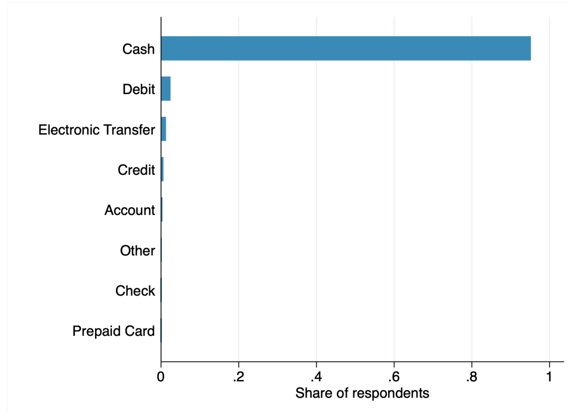
(b) 20 USD or Less

Note: The figure shows the most frequent payment methods reported by households for payments 20 USD or more and for 20 USD or less. The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

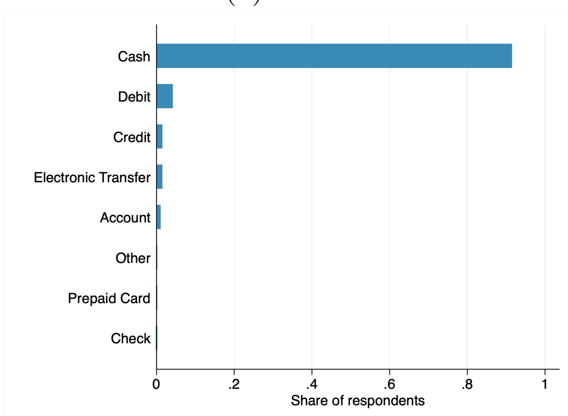
Figure A2: Payment Method by Sector



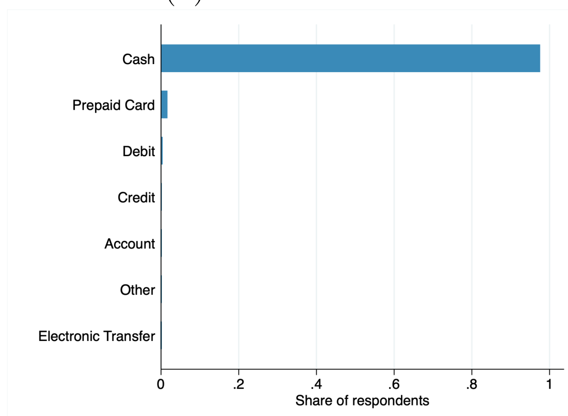
(a) Taxes



(b) Public Services



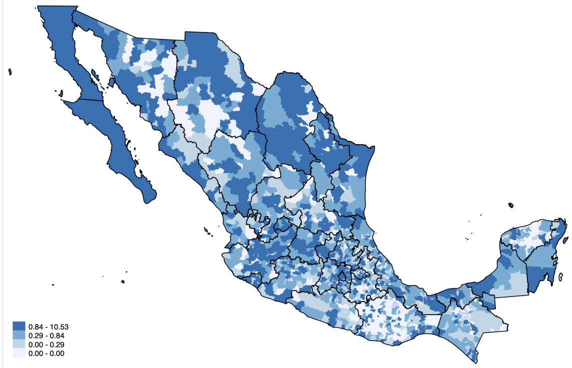
(c) Private Services



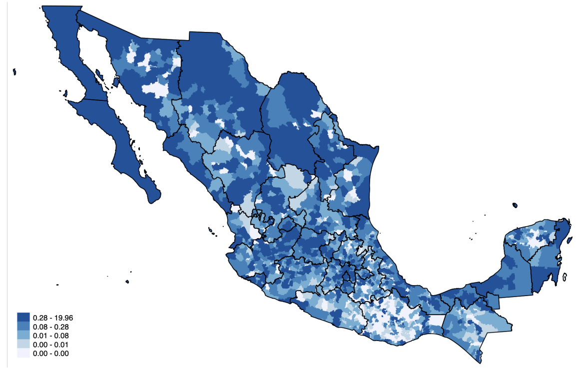
(d) Transportation

Note: The figure shows the most frequent payment methods reported by households for different types of expenditures. The panels report expenditures on taxes, expenditures on public services (e.g. water, electricity), private services (e.g. cable, phone, internet), and transportation (e.g. taxi, bus). The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

Figure A3: Access to Financial Infrastructure



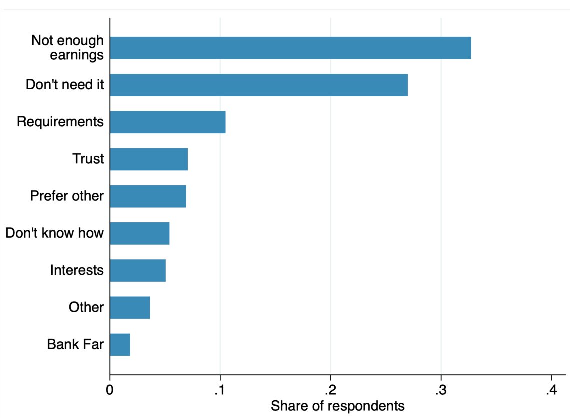
(a) ATM Transactions per Capita



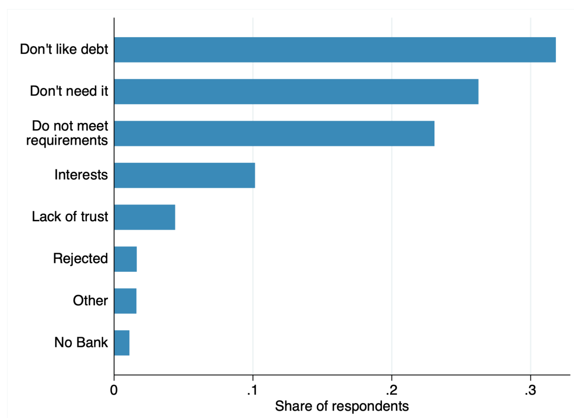
(b) POS Transactions per Capita

Note: Figure maps the number of ATM transactions per inhabitant and the number of POS transaction per inhabitant by municipality. Darker colors represent a higher numbers per capita. Data come from the Financial Inclusion Databases from the National Banking and Securities Commission (BDIF).

Figure A4: Cash Users That Do Not Own an Account or a Card



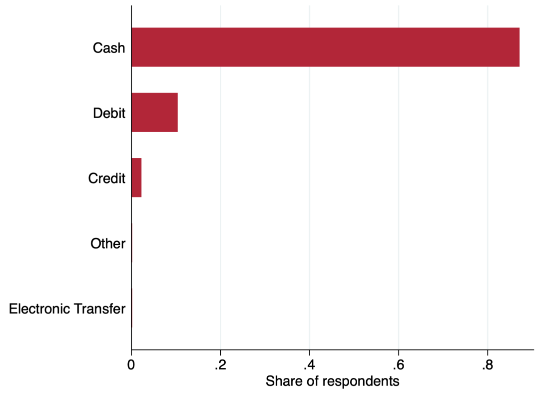
(a) Reason Not to Have an Account



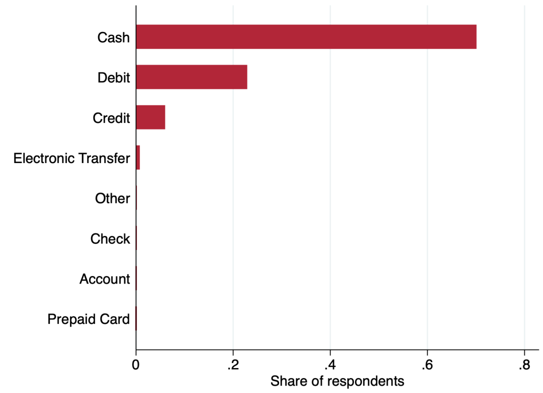
(b) Reason Not to Have a Card

Note: Panel (a) shows the most frequent reasons mentioned by households for not having an bank account. Panel (b) shows the most frequent reasons mentioned by households for not having a card. The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

Figure A5: Payment method by Amount - Mixed Users



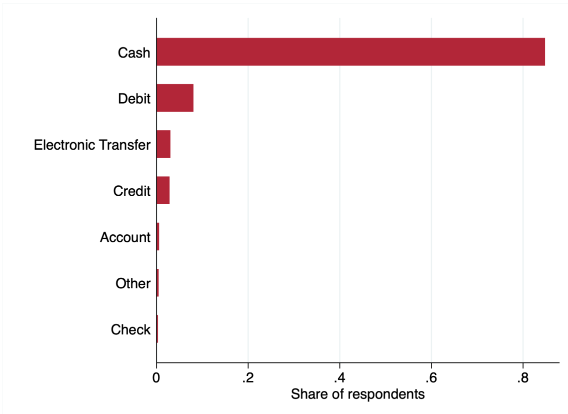
(a) 20 USD or Less



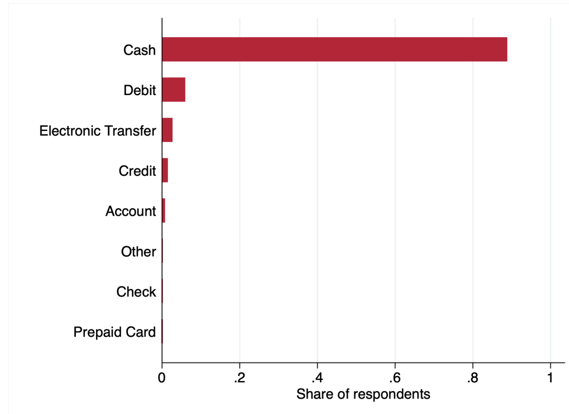
(b) 20 USD or More

Note: The figure shows the most frequent payment methods reported by households for payments 20 USD or more and for 20 USD or less. The sample of households report owning a debit or a credit card. The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

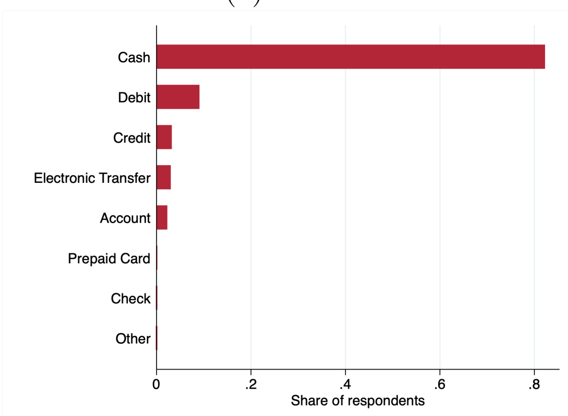
Figure A6: Payment method - Mixed Users



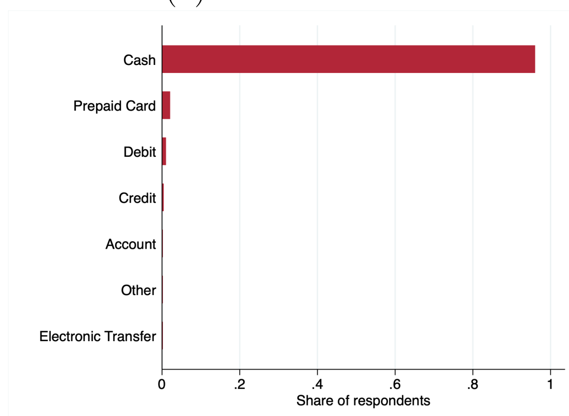
(a) Taxes



(b) Public Services



(c) Private Services



(d) Transportation

Note: The figure shows the most frequent payment methods reported by households for different types of expenditures. The panels report expenditures on taxes, expenditures on public services (e.g. water, electricity), private services (e.g. cable, phone, internet), and transportation (e.g. taxi, bus). The sample of households report owning a debit or a credit card. The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

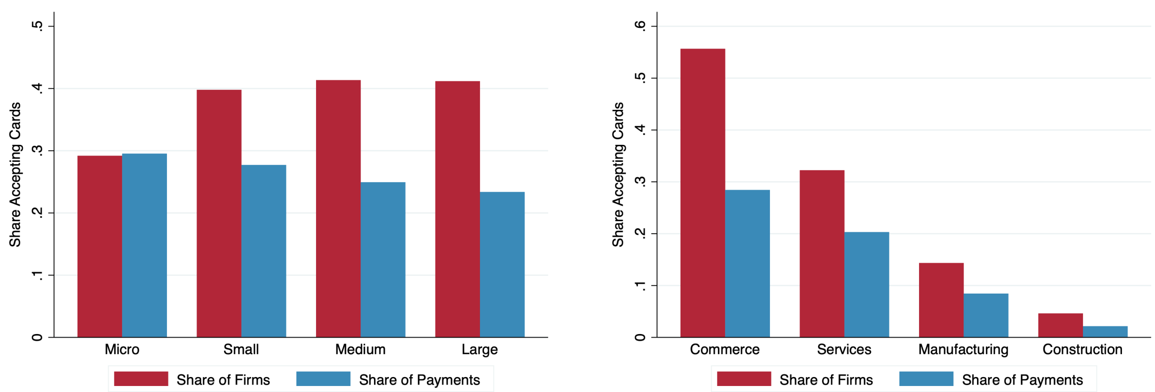
Figure A7: Mixed Users: Crime and Wages

(a) Victim of a card related crime?

(b) Method you get paid?

Note: Panel (a) shows the responses of households to the question "have you been victim of a credit card related crime?." Panel (b) shows the responses of households to the question "What payment method do you get paid in?." The sample of households report owning a debit or a credit card. The data comes from the 2018 National Survey of Financial Inclusion (ENIF).

Figure A8: Share of Firms Accepting Card

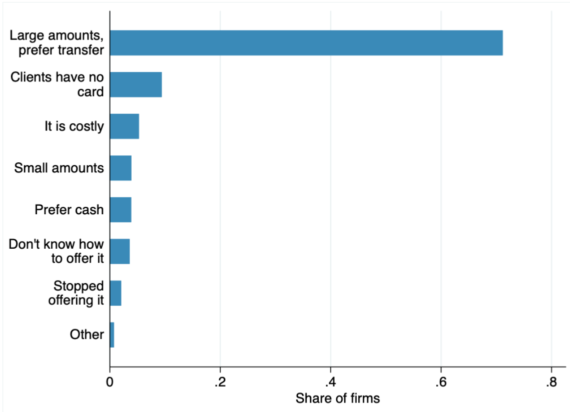


(a) Size

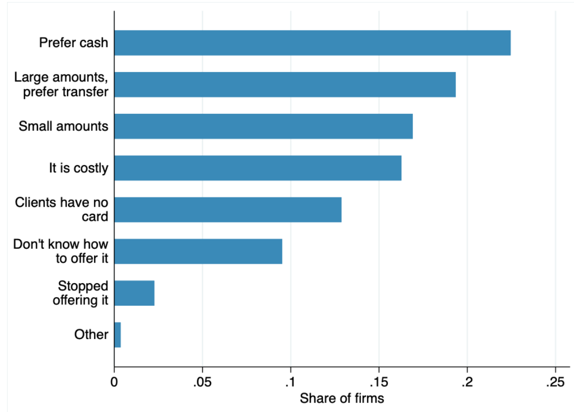
(b) Sector

Note: The figure reports the share of firms that accept credit or debit cards and the share of total payments by size and by sector. The size bins are defined by the total number of employees: Micro (6-10), small (11-30), medium (30-100), large (100+). The data comes from the 2018 National Survey of Enterprise Financing (ENAFIN).

Figure A9: Reasons For Not Accepting Card As Payment Method by Size



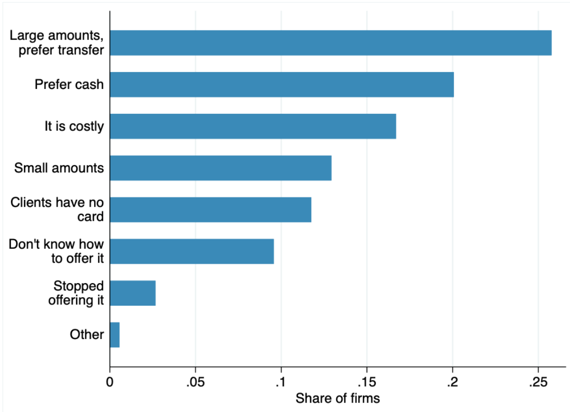
(a) Large Firm



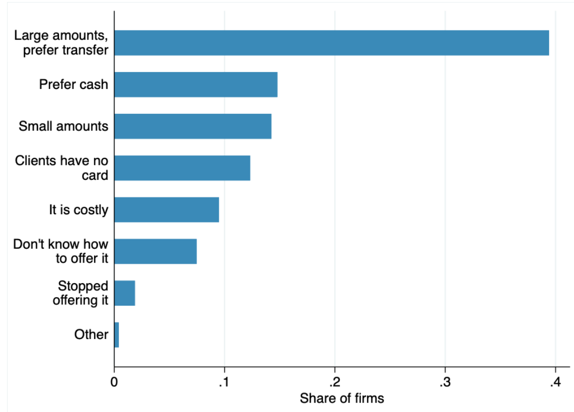
(b) Micro Firm

Note: The figure reports the most frequent reason stated by large and micro firms for not accepting cards as payment method. The data comes from the 2018 National Survey of Enterprise Financing (ENAFIN).

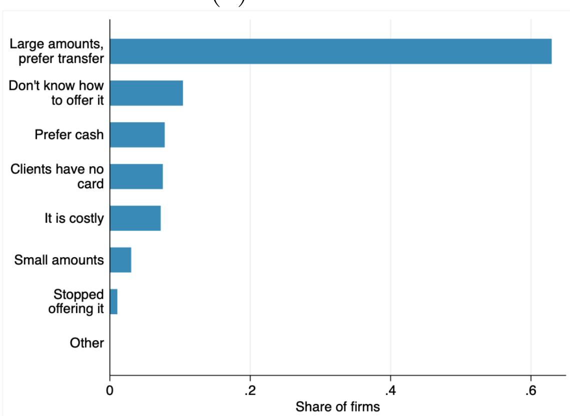
Figure A10: Reasons For Not Accepting Card As Payment Method by Sector



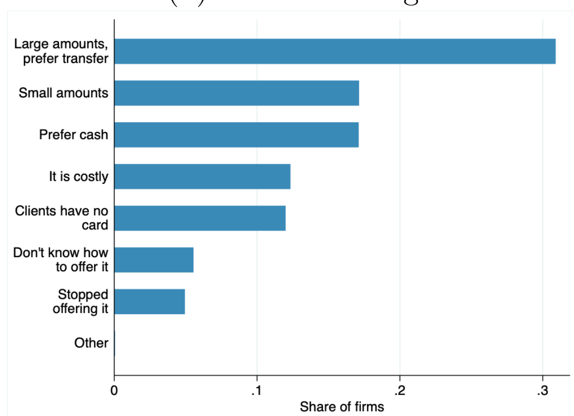
(a) Services



(b) Manufacturing



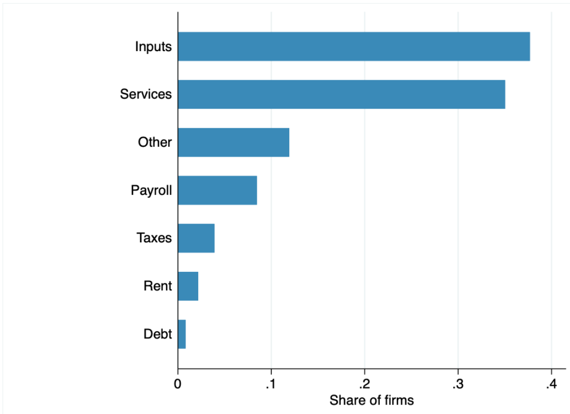
(c) Construction



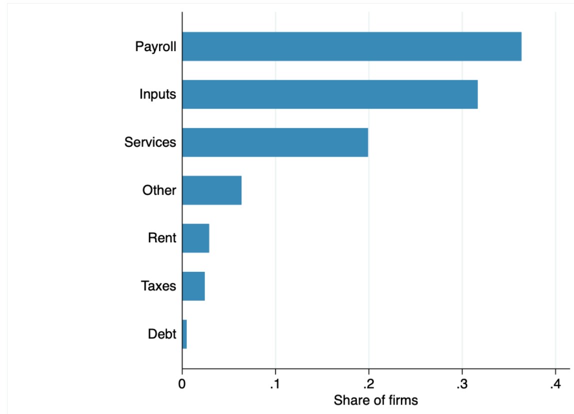
(d) Commerce

Note: The figure reports the most frequent reason stated by firms of different sectors for not accepting cards as payment method. The data comes from the 2018 National Survey of Enterprise Financing (ENAFIN).

Figure A11: Share of Payments Made in Cash by Size



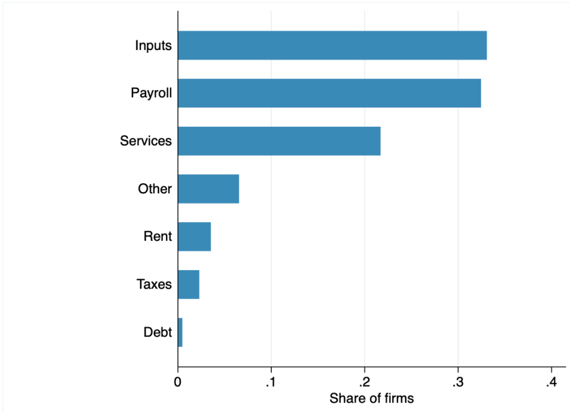
(a) Large



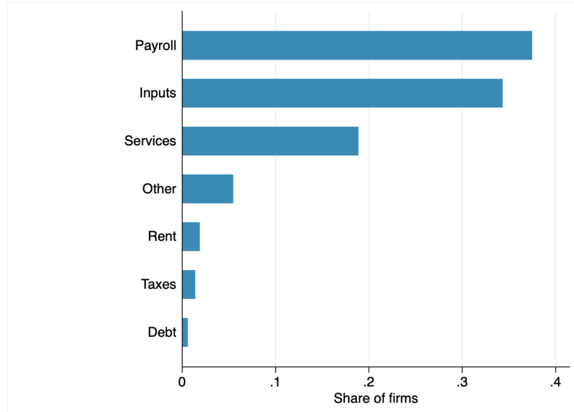
(b) Micro

Note: The figure reports the share of payments made by firms in cash by type of payment. Panel (a) shows firms with more than 100 employees and Panel (b) firms with 6-10 employees. The data comes from the 2018 National Survey of Enterprise Financing (ENAFIN).

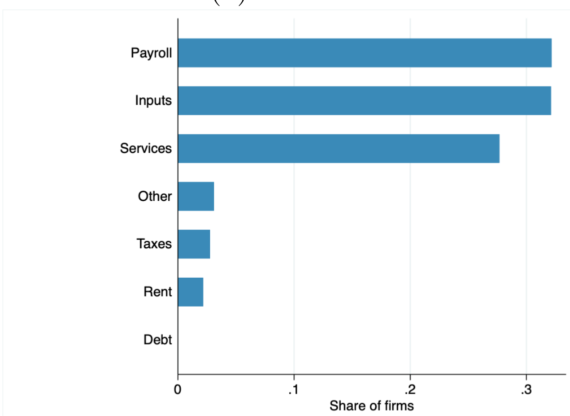
Figure A12: Share of Payments Made in Cash by Sector



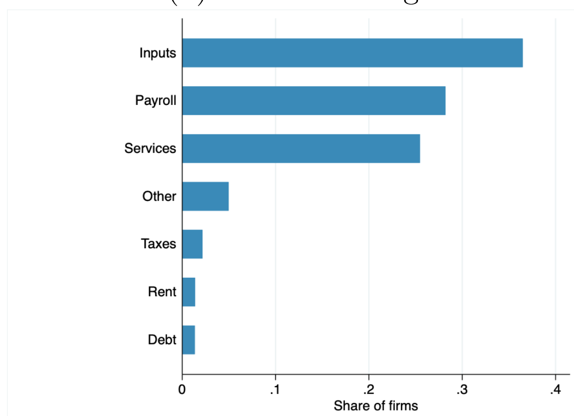
(a) Services



(b) Manufacturing



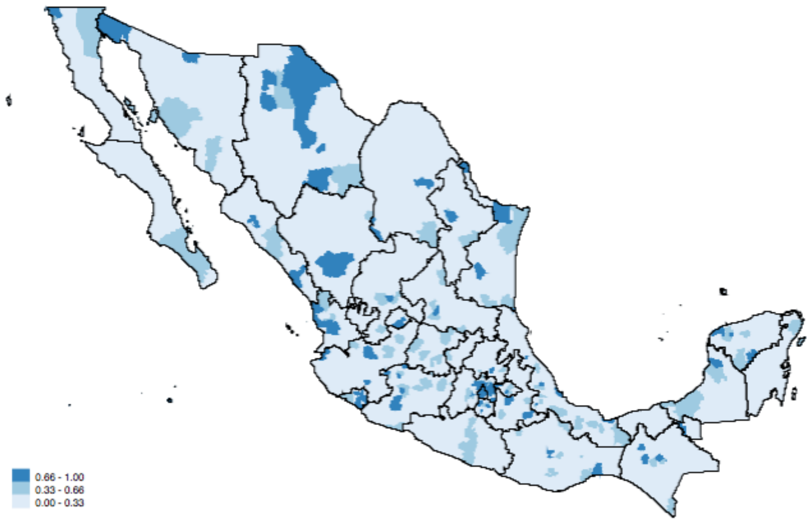
(c) Construction



(d) Commerce

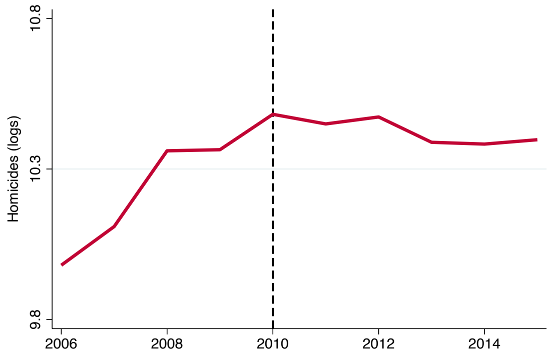
Note: The figure reports the share of payments made by firms in cash by type of payment. Panels (a)-(c) show the responses of firms in services, manufacturing, construction, and commerce respectively. The data comes from the 2018 National Survey of Enterprise Financing (ENAFIN).

Figure A13: Share of Beneficiaries in the Rollout by Municipality (2012)

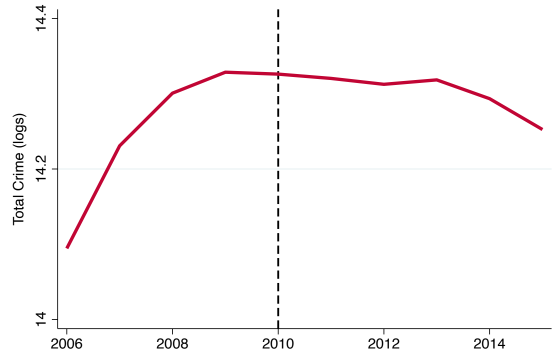


Note: The map shows the share of beneficiaries that were part of the rollout of debit cards by municipality. The shares are calculated for 2012. The data comes from the administrative data of the Prospera program.

Figure A14: Crime



(a) Homicides



(b) Theft

(c) Thefts

(d) Other Crimes

Note: The figure shows the evolution of the total number crimes, homicides, thefts, and other crimes from 2006 to 2015. From 2006-2010, the figures use information from the State and Municipal Databases (SIMBAD). From 2011 onward, the figures use data from the Executive Secretariat of the Public Security National System (SESNSP). The dashed line indicates the transitions across data sets.

Table AI: Share of Firms that Accept Debit Cards as Payment Method

Note: The table shows the share of firms that accept debit cards as payment method. Each cell indicates the share of firms within that cell that accept debit cards. The size bins are defined by the total number of employees: Micro (6-10), small (11-30), medium (30-100), large (100+). The data comes from the 2018 National Survey of Enterprise Financing (ENAFIN).

	Large	Medium	Small	Micro
Commerce	0.715	0.724	0.677	0.451
Construction	0.203	0.028	0.020	0.061
Manufacturing	0.055	0.156	0.134	0.142
Services	0.379	0.381	0.397	0.252

Table AII: Share of Firms that Accept Credit Cards as Payment Method

Note: The table shows the share of firms that accept credit cards as payment method. Each cell indicates the share of firms within that cell that accept credit cards. The size bins are defined by the total number of employees: Micro (6-10), small (11-30), medium (30-100), large (100+). The data comes from the 2018 National Survey of Enterprise Financing (ENAFIN).

	Large	Medium	Small	Micro
Commerce	0.733	0.746	0.672	0.445
Construction	0.173	0.065	0.020	0.075
Manufacturing	0.068	0.165	0.137	0.151
Services	0.393	0.389	0.403	0.254

B Card Shock: Semi-Dynamic Event Study

Table B1: Effect of Card Shock on Debit and Credit Cards

Note: The table reports the results for the coefficient of β after estimating equation (2). The dependent variable in Columns (1), (2), (9) and (10) is the logarithm of debit cards. Columns (3), (4), (11) and (12) use debit cards excluding those given as part of the Prospera program through Bansefi. Columns (5), (6), (13) and (14) use credit cards and Columns (7), (8), (15) and (16) us the sum of debit cards and credit cards as dependent variable. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Debit		Debit Not Prospera		Credit		Total Cards	
Card Shock	0.4932***	0.4873***	0.5376*	0.5603**	0.1846*	0.1966***	0.2932**	0.2920***
	(0.153)	(0.120)	(0.251)	(0.189)	(0.086)	(0.066)	(0.104)	(0.074)
Observations	6,181	5,212	6,181	5,212	6,181	5,212	6,181	5,212
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N	N	N
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Debit		Debit Not Prospera		Credit		Total Cards	
Card Shock	0.2051***	0.1673***	0.3609***	0.3057***	0.1396**	0.1154**	0.1513***	0.1276***
	(0.047)	(0.040)	(0.105)	(0.075)	(0.058)	(0.050)	(0.039)	(0.032)
Observations	6,181	5,212	6,181	5,212	6,181	5,212	6,181	5,212
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table B2: Effect of Card Shock on Homicides (Locality)

Note: The table reports the results for the coefficient of β after estimating equation (2) at the locality level and at bi-monthly frequency. The dependent variable is the logarithm of the total number of homicides. We use the inverse hyperbolic sine transformation in all cases. We control for the total number of families in the Prospera program in each locality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
Card Shock	0.0073***	0.0053*	0.0092**	0.0064**	0.0047*	0.0084**
	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Observations	540,594	540,594	529,653	540,594	540,594	529,653
Municipality	Y	Y	Y	Y	Y	Y
Controls	N	N	N	Y	Y	Y
Period	Y	N	N	Y	N	N
State $\times$ Period	N	Y	N	N	Y	N
Municipality $\times$ Period	N	N	Y	N	N	Y

Table B3: Effect of Card Shock on Homicides (Municipality)

Note: The table reports the results for the coefficient of β after estimating equation (2). The dependent variable in Columns (1), (2), (9) and (10) is the logarithm of homicides using data from INEGI based on death certificates. Columns (5), (6), (13) and (14) use the logarithm of homicides using data from SESNSP based on criminal cases. We use the inverse hyperbolic sine transformation in all cases. Columns (3), (4), (11) and (12) use homicide rate per 10,000 persons from INEGI as dependent variable. Columns (7), (8), (15) and (16) use homicide rate per 10,000 persons from SESNSP as dependent variable. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	INEGI Homicides		SESNSP Homicides		INEGI Homicide Rate		SESNSP Homicide Rate	
Card Shock	-0.0156	-0.0144	0.1712	0.1533	0.0810**	0.0763*	0.3208	0.3039
	(0.053)	(0.052)	(0.118)	(0.147)	(0.033)	(0.034)	(0.185)	(0.234)
Observations	3,672	3,149	3,149	3,149	3,517	3,028	3,028	3,028
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	N
Weights	N	N	N	N	N	N	N	N
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	INEGI Homicides		SESNSP Homicides		INEGI Homicide Rate		SESNSP Homicide Rate	
Card Shock	0.0911	0.0923	0.2849*	0.3153**	0.0427	0.0393	0.2394**	0.3203***
	(0.065)	(0.062)	(0.138)	(0.116)	(0.030)	(0.029)	(0.093)	(0.090)
Observations	3,149	3,149	3,149	3,149	3,028	3,028	3,028	3,028
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table B4: Effect of Card Shock on Theft

Note: The table reports the results for the coefficient of β after estimating equation (2). The dependent variable in Columns (1), (2), (7) and (8) is the logarithm of total thefts. We use the inverse hyperbolic sine transformation in all cases. Columns (3), (4), (9) and (10) use theft rate per 10,000 persons. Columns (5), (6), (11) and (12) use the logarithm of theft divided by total crimes. We again use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
	Thefts		Theft Rate		Theft/Crime	
Card Shock	-0.0478	-0.0088	-0.9098*	-0.7936*	-0.0123**	-0.0065
	(0.035)	(0.049)	(0.446)	(0.395)	(0.004)	(0.004)
Observations	3,505	3,027	3,505	3,027	3,452	2,989
Municipality	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N
	(7)	(8)	(9)	(10)	(11)	(12)
	Thefts		Theft Rate		Theft/Crime	
Card Shock	-0.0405	-0.0238	-0.8949	-0.3181	-0.0099	-0.0065
	(0.024)	(0.013)	(0.753)	(0.940)	(0.006)	(0.005)
Observations	3,505	3,027	3,505	3,027	3,452	2,989
Municipality	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y

Table B5: Effect of Card Shock on Total Crime

Note: The table reports the results for the coefficient of β after estimating equation (2). The dependent variable in Columns (1)-(4) is the logarithm of total crimes. We use the inverse hyperbolic sine transformation in all cases. Columns (5)-(8) use crime rate per 10,000 persons. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crimes				Crime Rate			
Card Shock	0.0182	0.0377	0.0100	0.0164	-0.8181	-1.1457	-1.8768	-1.3784
	(0.027)	(0.036)	(0.020)	(0.014)	(1.153)	(1.087)	(1.337)	(1.426)
Observations	3,505	3,027	3,505	3,027	3,505	3,027	3,505	3,027
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N	Y	Y

Table B6: Effect of Card Shock on Informality

Note: The table reports the results for the coefficient of β after estimating equation (2). The dependent variable in Columns (1), (2), (9), and (10) is the logarithm of informal workers. The dependent variable in Columns (5), (6), (13), and (14) is the logarithm of self-employed workers. We use the inverse hyperbolic sine transformation in all cases. The dependent variable in Columns (3), (4), (11), and (12) is the ratio of informal workers and the total population of the municipality. The dependent variable in Columns (7), (8), (15), and (16) is the ratio of informal workers and the total population of the municipality. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Informality		Informality Rate		Self-Employed		Self-Employed Rate	
Card Shock	-0.0118	-0.0013	0.0004	-0.0009	-0.0129	-0.0026	0.0002	-0.0004
	(0.033)	(0.009)	(0.003)	(0.002)	(0.037)	(0.025)	(0.002)	(0.002)
Observations	6,225	6,224	6,225	6,224	6,225	6,224	6,225	6,224
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N	N	N

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Informality		Informality Rate		Self-Employed		Self-Employed Rate	
Card Shock	0.0108	0.0089	0.0012	0.0017	0.0020	-0.0005	-0.0002	-0.0000
	(0.020)	(0.010)	(0.002)	(0.002)	(0.024)	(0.017)	(0.001)	(0.001)
Observations	6,225	6,224	6,225	6,224	6,225	6,224	6,225	6,224
R-squared	0.949	0.993	0.814	0.896	0.928	0.965	0.657	0.704
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table B7: Effect of Card Shock on Local Taxes

Note: The table reports the results for the coefficient of β after estimating equation (2). The dependent variable in Columns (1)-(4) is the logarithm of local taxes. The dependent variable in Columns (5)-(8) is the ratio of taxes and the total population of the municipality. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Taxes				Taxes/Population			
Card Shock	-0.0125	-0.0086	-0.0084	-0.0060	3.0979	3.9631	7.5085	6.1952
	(0.013)	(0.019)	(0.015)	(0.016)	(3.184)	(3.252)	(5.607)	(5.545)
Observations	3,382	2,895	2,895	2,895	3,382	2,895	2,895	2,895
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N	Y	Y

B.1 Card Shock: Share of Prospera Beneficiaries and in the Rollout

In this section we use the same specification used in Section B but we consider the intensity of the treatment in the dependent variable. Specifically, we estimate the following equaiton:

$$\ln Y_{mt} = \alpha + \beta \ln \text{ShareProgresaRollout}_{mt} + \theta_m + \lambda_t + \zeta X_{mt} + \epsilon_{mt} \tag{23}$$

where $\text{ShareProsperaRollout}_{mt}$ is the ratio of the households participating in Prospera and in the rollout divided by the total number of households in the municipality.

Table B8: Effect of Card Shock on Debit and Credit Cards

Note: The table reports the results for the coefficient of β after estimating equation (23). The dependent variable in Columns (1), (2), (9) and (10) is the logarithm of debit cards. Columns (3), (4), (11) and (12) use debit cards excluding those given as part of the Prospera program through Bansefi. Columns (5), (6), (13) and (14) use credit cards and Columns (7), (8), (15) and (16) us the sum of debit cards and credit cards as dependent variable. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Debit		Debit Not Prospera		Credit		Total Cards	
Share Progresa	2.8126**	2.5897***	-1.7814	-2.8945	2.0676***	2.3487***	2.0258***	2.0191***
× Rollout	(0.951)	(0.612)	(2.201)	(1.704)	(0.450)	(0.391)	(0.529)	(0.333)
Observations	6,181	5,212	6,181	5,212	6,181	5,212	6,181	5,212
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N	N	N
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Debit		Debit Not Prospera		Credit		Total Cards	
Share Progresa	1.2932**	1.3495**	-1.5966*	-1.1192	2.5350***	2.6644***	1.2415***	1.3074***
× Rollout	(0.479)	(0.516)	(0.905)	(1.057)	(0.508)	(0.496)	(0.354)	(0.377)
Observations	5,213	5,212	5,213	5,212	5,213	5,212	5,213	5,212
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table B9: Effect of Card Shock on Homicides (Municipality)

Note: The table reports the results for the coefficient of β after estimating equation (23). The dependent variable in Columns (1), (2), (9) and (10) is the logarithm of homicides using data from INEGI based on death certificates. Columns (5), (6), (13) and (14) use the logarithm of homicides using data from SESNSP based on criminal cases. We use the inverse hyperbolic sine transformation in all cases. Columns (3), (4), (11) and (12) use homicide rate per 10,000 persons from INEGI as dependent variable. Columns (7), (8), (15) and (16) use homicide rate per 10,000 persons from SESNSP as dependent variable. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	INEGI Homicides		SESNSP Homicides		INEGI Homicide Rate		SESNSP Homicide Rate	
Share Progresa	-0.0875	-0.4188	-0.2699	-0.4325	0.3537	0.2915	-2.1235	-2.4744
$\times$ Rollout	(0.226)	(0.237)	(0.638)	(0.666)	(0.347)	(0.367)	(1.585)	(1.536)
Observations	3,672	3,149	3,149	3,149	3,517	3,028	3,028	3,028
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	N
Weights	N	N	N	N	N	N	N	N

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	INEGI Homicides		SESNSP Homicides		INEGI Homicide Rate		SESNSP Homicide Rate	
Share Progresa	0.2176	0.2932	3.2159**	3.3644***	0.8094*	0.8576**	4.2859**	3.7177**
$\times$ Rollout	(0.454)	(0.425)	(0.979)	(0.991)	(0.378)	(0.372)	(1.303)	(1.389)
Observations	3,149	3,149	3,149	3,149	3,028	3,028	3,028	3,028
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table B10: Effect of Card Shock on Theft

Note: The table reports the results for the coefficient of β after estimating equation (23). The dependent variable in Columns (1), (2), (7) and (8) is the logarithm of total thefts. We use the inverse hyperbolic sine transformation in all cases. Columns (3), (4), (9) and (10) use the theft rate per 10,000 persons. Columns (5), (6), (11) and (12) use the logarithm of theft divided by total crimes. We again use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
	Thefts		Theft Rate		Theft/Crime	
Share Progresa	-0.6041	-0.3237	0.6341	0.4615	0.0551	0.1106
× Rollout	(0.370)	(0.399)	(4.573)	(5.089)	(0.048)	(0.070)
Observations	3,505	3,027	3,505	3,027	3,452	2,989
Municipality	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N
	(7)	(8)	(9)	(10)	(11)	(12)
	Thefts		Theft Rate		Theft/Crime	
Share Progresa	0.2872	0.4112	28.5657	34.6705**	0.2176	0.2678
× Rollout	(0.435)	(0.396)	(16.700)	(14.559)	(0.147)	(0.147)
Observations	3,505	3,027	3,505	3,027	3,452	2,989
Municipality	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y

Table B11: Effect of Card Shock on Total Crime

Note: The table reports the results for the coefficient of β after estimating equation (23). The dependent variable in Columns (1)-(4) is the logarithm of total crimes. We use the inverse hyperbolic sine transformation in all cases. Columns (5)-(8) use the crime rate per 10,000 persons. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Crimes				Crime Rate		
Share Progresa	-0.6388**	-0.4620	-0.2425	-0.2503	-7.3589	-16.5165**	26.7512*	27.4000**
$\times$ Rollout	(0.234)	(0.260)	(0.170)	(0.151)	(8.126)	(6.829)	(13.091)	(10.839)
Observations	3,505	3,027	3,505	3,027	3,505	3,027	3,505	3,027
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N	Y	Y

Table B12: Effect of Card Shock on Informality

Note: The table reports the results for the coefficient of β after estimating equation (23). The dependent variable in Columns (1), (2), (9), and (10) is the logarithm of informal workers. The dependent variable in Columns (5), (6), (13), and (14) is the logarithm of self-employed workers. We use the inverse hyperbolic sine transformation in all cases. The dependent variable in Columns (3), (4), (11), and (12) is the ratio of informal workers and the total population of the municipality. The dependent variable in Columns (7), (8), (15), and (16) is the ratio of informal workers and the total population of the municipality. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Informality		Informality Rate		Self-Employed		Self-Employed Rate	
Share Progresa	-0.0937	0.0937	0.0090	0.0228	-0.2776	-0.1225	-0.0045	-0.0014
× Rollout	(0.275)	(0.060)	(0.024)	(0.014)	(0.322)	(0.192)	(0.018)	(0.016)
Observations	6,225	6,224	6,225	6,224	6,225	6,224	6,225	6,224
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N	N	N
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Informality		Informality Rate		Self-Employed		Self-Employed Rate	
Share Progresa	-0.0831	0.1495**	0.0190	0.0349**	-0.1703	0.0203	0.0024	0.0057
× Rollout	(0.200)	(0.067)	(0.020)	(0.014)	(0.272)	(0.153)	(0.016)	(0.014)
Observations	6,225	6,224	6,225	6,224	6,225	6,224	6,225	6,224
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table B13: Effect of Card Shock on Local Taxes

Note: The table reports the results for the coefficient of β after estimating equation (23). The dependent variable in Columns (1)-(4) is the logarithm of local taxes. The dependent variable in Columns (5)-(8) is the ratio of taxes and the total population of the municipality. The controls we use include income per capita, total employment, and total population, and the total number of families in the Prospera program. The specifications that are weights use the total population in the municipality. We use Driscoll and Kraay standard errors in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Taxes				Taxes/Population			
Share Progresa	-0.1131	-0.0798	0.0990	0.1019	-136.4883**	-178.1038**	-229.3087*	-241.7092**
$\times$ Rollout	(0.134)	(0.152)	(0.189)	(0.166)	(40.994)	(55.615)	(100.090)	(92.197)
Observations	3,382	2,895	2,895	2,895	3,382	2,895	2,895	2,895
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N	Y	Y

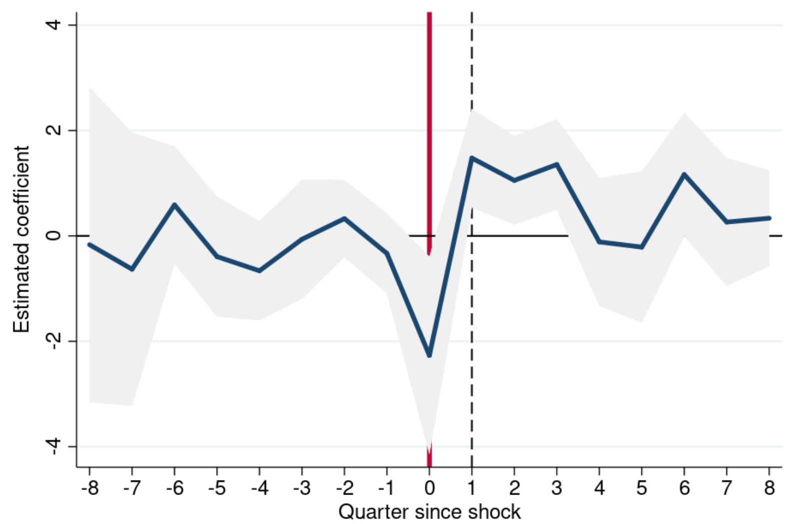
C ATM-Sharing Agreements:

Table C1: List of ATM-sharing agreements

Note: The table includes the list of 24 ATM sharing agreements approved by the Bank of Mexico between 2014 and 2019. Agreements 1 and 2 only apply to Banjército customers. Banregio joined Agreement 3 on June 27th, 2016. The CNBV has no financial data of Accendo (Agreement 18). The data comes from the 2019 *Informe Anual sobre las Infraestructuras de los Mercados Financieros* (Annual Report on Financial Market Infrastructures) of the Bank of Mexico. The reduction in fee uses the maximum fee before the agreement and the minimum fee after the agreement and it includes withdrawals and balance checks fees.

Agreement	Date	Banks	% Reduction in fee
1	November 24, 2014	Banjército, Banamex	100
2	November 24, 2014	Banjército, BBVA Bancomer	100
3	April 20, 2015	Bajío, Inbursa, Scotiabank, Banregio	60
4	June 30, 2015	Afirme, Bajío	100
5	November 24, 2015	Afirme, BanCoppel	50
6	January 20, 2016	Afirme, Scotiabank	100
7	September 19, 2016	Afirme, Inbursa	100
8	September 28, 2016	Scotiabank, Mifel	100
9	October 18, 2016	Multiva, American Express	100
10	November 15, 2016	Scotiabank, Actinver	100
11	January 24, 2017	Scotiabank, BanCoppel	50
12	January 24, 2017	Scotiabank, Intercam	60
13	March 28, 2017	Bansefi, Banjército	100
14	July 28, 2017	Scotiabank, Famsa	60
15	October 9, 2017	Bajío, Famsa	60
16	February 28, 2018	Scotiabank, Autofin	46.6
17	February 28, 2018	Scotiabank, Multiva	62.5
18	April 24, 2018	Bancoppel, Accendo	7.2
19	April 24, 2018	Actinver, Multiva	100
20	October 16, 2018	Azteca, Multiva	100
21	October 30, 3018	Bajío, Intercam	61.3
22	January 30, 2019	Azteca, Mifel	100
23	May 13, 2019	Azteca, Bajío	100
24	October 21, 2019	Afirme, Azteca	100

Figure C1: Alternative Lags and Leads for the Agreement Shock in the Bartik 1st Stage



Note: The graph shows the evolution of the growth rate ($d\ln$) of ATM transactions before and after ATM sharing agreements. The figures plot the coefficients of γ_k after estimating regressions of the form $d\ln w_{mt+k} = \gamma^w \sum_i \sum_j E_{ijt} d\ln p_{ijt} z_{ijm0} + \theta_m^w + \lambda_t^w + \epsilon_{mt}^w$, where k represent quarters after the shock. The red line marks the quarter or year in which an agreement occurred. The dashed line corresponds to $k = 0$, the lagged agreement dummies that we use in Equation (4). The gray area depicts the 95% confidence interval using standard errors clustered at the municipality level.

Table C2: Effect of ATM-Sharing Agreements on ATM Withdrawals and Debit Cards

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-quarterly level. The dependent variable in Columns (1) - (4) is the quarterly change in the logarithm of the total ATM withdrawal count. Columns (5) - (8) use the quarterly change in the logarithm of debit card contracts. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. The specifications with weights use the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level (called Report R2422).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ATM Withdrawals				Debit			
Bartik	0.0820	0.3507	1.4766***	1.6770***	0.3193	0.3253	1.0940	0.6504
	(0.519)	(0.690)	(0.476)	(0.600)	(0.502)	(0.655)	(0.981)	(1.093)
Observations	34,415	20,695	34,397	20,695	34,415	20,695	34,397	20,695
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N	Y	Y

Table C3: Effect of ATM-Sharing Agreements on Homicides

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-quarterly level. The dependent variable in Columns (1), (2), (9) and (10) is the quarterly change in the logarithm of homicides using data from INEGI based on death certificates. Columns (5), (6), (13) and (14) use the quarterly change in the logarithm of homicides using data from SESNSP based on criminal cases. Columns (3), (4), (11) and (12) use the quarterly change in the logarithm of the homicide rate per 10,000 persons from INEGI as dependent variable. Columns (7), (8), (15) and (16) use the quarterly change in the logarithm of the homicide rate per 10,000 persons from SESNSP as dependent variable. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. The specifications with weights use the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	INEGI Homicides		SESNSP Homicides		INEGI Homicide Rate		SESNP Homicide Rate	
Bartik	-2.5716	-1.6411	-2.6014	-2.3389	-1.7108*	-1.7961	-0.9848	-1.5428
	(3.023)	(4.825)	(3.484)	(2.570)	(0.926)	(1.246)	(1.717)	(1.084)
Observations	34,479	20,710	34,479	20,710	34,451	20,710	34,451	20,710
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N	N	N
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	INEGI Homicides		SESNSP Homicides		INEGI Homicide Rate		SESNP Homicide Rate	
Bartik	-0.2100	-0.1447	-2.6315	-2.9215	-1.8310*	-1.9552	-1.3776	-1.3154
	(3.9812)	(4.6458)	(3.1261)	(3.1378)	(1.0982)	(1.2745)	(1.2816)	(1.3769)
Observations	34,452	20,710	34,452	20,710	34,451	20,710	34,451	20,710
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table C4: Effect of ATM-Sharing Agreements on Theft

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-quarterly level. The dependent variable in Columns (1), (2), (7) and (8) is the quarterly change in the logarithm of total thefts. Columns (3), (4), (9) and (10) use the quarterly change in the logarithm of the theft rate per 10,000 persons. Columns (5), (6), (11) and (12) use the quarterly change in the logarithm of theft divided by total crimes. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. The specifications with weights use the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Thefts		Theft Rate		Theft/Crime	
Bartik	1.1889	0.5210	1.4190	1.0828	0.4698*	0.6397**
	(1.615)	(2.626)	(1.544)	(2.416)	(0.252)	(0.253)
Observations	34,479	20,710	34,451	20,710	31,890	19,713
Municipality	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N
	(7)	(8)	(9)	(10)	(11)	(12)
	Thefts		Theft Rate		Theft/Crime	
Bartik	-1.8427	-3.7118	-1.2211	-2.7815	0.0890	-0.0525
	(2.6112)	(3.4255)	(2.1863)	(2.8910)	(0.3958)	(0.4797)
Observations	34,452	20,710	34,451	20,710	31,875	19,713
Municipality	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y

Table C5: Effect of ATM-Sharing Agreements on Theft to Pedestrians

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-quarterly level. The dependent variable in Columns (1), (2), (7) and (8) is the quarterly change in the logarithm of total thefts to pedestrians. Columns (3), (4), (9) and (10) use the quarterly change in the logarithm of the pedestrian theft rate per 10,000 persons. Columns (5), (6), (11) and (12) use the quarterly change in the logarithm of theft divided by total crimes. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. The specifications with weights use the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pedestrian Thefts		Ped. Theft Rate		Ped. Theft/Crime		Ped. Theft/Theft	
Bartik	-4.1044*	-2.5892	-2.7902	-1.3942	-0.1043	-0.0176	-0.4934	-0.2392
	(2.446)	(2.416)	(1.806)	(1.213)	(0.090)	(0.072)	(0.314)	(0.261)
Observations	34,479	20,710	34,451	20,710	31,890	19,713	28,716	18,678
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N	N	N
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Pedestrian Thefts		Ped. Rate		Pedestrian. /Crime		Ped. Theft/Theft	
Bartik	-6.0923**	-6.1498*	-2.8432**	-2.7275	-0.0587	-0.0453	-0.1797	-0.1087
	(2.8218)	(3.4541)	(1.4173)	(1.7334)	(0.0904)	(0.1065)	(0.2775)	(0.3193)
Observations	34,452	20,710	34,451	20,710	31,875	19,713	28,701	18,678
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table C6: Effect of ATM-Sharing Agreements on Total Crime

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-quarterly level. The dependent variable in Columns (1) - (4) is the quarterly change in the logarithm of total crimes. Columns (5) - (8) use the quarterly change in the logarithm of the crime rate per 10,000 persons. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. The specifications with weights use the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crimes				Crime Rate			
Bartik	-1.0344	-2.3154	-2.5049	-3.8172	-0.9004	-2.1698	-2.2962	-3.5126
	(1.293)	(2.187)	(1.943)	(2.497)	(1.250)	(2.105)	(1.756)	(2.270)
Observations	34,479	20,710	34,452	20,710	34,451	20,710	34,451	20,710
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N	Y	Y

Table C7: Effect of ATM-Sharing Agreements on Informality

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-quarterly level. The dependent variable in Columns (1), (2), (9), and (10) is the quarterly change in the logarithm of informal workers. The dependent variable in Columns (5), (6), (13), and (14) is the quarterly change in the logarithm of self-employed workers. The dependent variable in Columns (3), (4), (11), and (12) is the quarterly change in the logarithm of the ratio of informal workers and the total population of the municipality. The dependent variable in Columns (7), (8), (15), and (16) is the quarterly change in the logarithm of the ratio of self-employed workers and the total population of the municipality. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. The specifications with weights use the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Informality		Informality Rate		Self-Employed		Self-Employed Rate	
Bartik	-6.8998*	-2.7589***	-0.3055	1.0403	-8.0917***	-3.6340	-0.1529	0.4224
	(3.536)	(0.918)	(0.192)	(0.938)	(2.457)	(2.887)	(0.146)	(0.452)
Observations	20,759	20,710	20,754	20,710	20,759	20,710	20,754	20,710
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	N	N	N	N	N	N
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Informality		Informality Rate		Self-Employed		Self-Employed Rate	
Bartik	-6.4160	-1.6562	-0.1731	1.0269	-4.7946	0.6080	-0.0224	0.4637*
	(4.2298)	(1.2684)	(0.2742)	(0.6686)	(3.8115)	(1.8885)	(0.1554)	(0.2529)
Observations	20,755	20,710	20,754	20,710	20,755	20,710	20,754	20,710
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y

Table C8: Effect of ATM-Sharing Agreements on Local Taxes

Note: The table reports the results for the coefficient γ after estimating Equation (5). Observations are at the municipality-yearly level. The dependent variable in Columns (1) - (4) is the quarterly change in the logarithm of local taxes. Columns (5) - (8) use the yearly change in the logarithm of the ratio of taxes and the total population of the municipality. We use the inverse hyperbolic sine transformation in all cases. The controls we use include income per capita, total employment, and total population. The specifications with weights use the total population in the municipality on the pre-period. Standard errors are clustered at the municipality level.

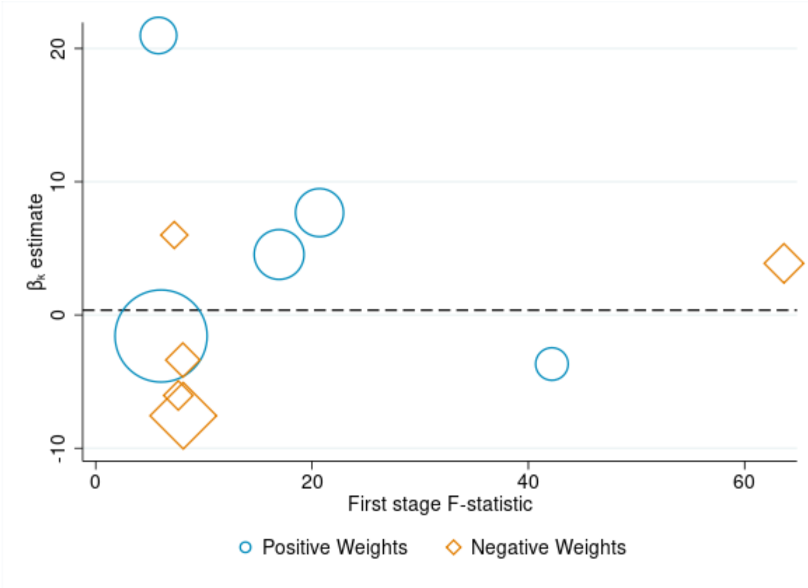
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Taxes				Taxes/Population			
Bartik	-0.8494	-0.6120	-2.5409**	-2.8440**	-0.8176	-0.5366	-2.5222**	-2.7954**
	(0.636)	(0.941)	(1.118)	(1.385)	(0.629)	(0.912)	(1.104)	(1.370)
Observations	6,031	3,822	6,028	3,822	6,028	3,822	6,028	3,822
Municipality	Y	Y	Y	Y	Y	Y	Y	Y
Period	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N	Y	Y

Table C9: Summary of Rotemberg Weights and Over Id Tests

Note The table reports statistics on the Rotemberg weights. We aggregate the weights of a given industry across years as described in Goldsmith-Pinkham et al. (2020). Panel A reports the share and sum of negative weights. Panel B reports the top 5 agreements (ATM-card) according to their Rotemberg weights $\hat{\alpha}_k$ and g_k is equal to the national-level agreement shock $E_{kt} d \ln p_{kt}$. $\hat{\beta}_k$ is the coefficient of the just-identified 2SLS regression of the growth rate of pedestrian theft on the growth rate of ATM withdrawals using as instrument the agreement shares. Agreement share is the average agreement share multiplied by 100 for legibility. Panel C reports how $\hat{\beta}_k$ varies with the positive and negative Rotemberg weights. Panel D reports estimates of the 2SLS estimates, the growth rate of pedestrian theft on the growth rate of ATM withdrawals. Column TSLS (Bartik) uses the Bartik instrument. Column TSLS uses each agreement share (times time period) separately as instruments. The overidentification test corresponds to Hansen's J statistic. Standard errors are reported in parentheses and p-values in brackets.

Panel A: Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.555	-0.035	0.263	
Positive	1.555	0.050	0.737	
Panel B: Top 5 Rotemberg weight agreements				
	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	Agreement Share
Scotiabank-Bancoppel	0.135	0.500	-1.576	0.206
Banjército-Bansefi	0.119	1.000	-0.051	0.004
Banco Azteca-Banco del Bajío	0.094	1.000	-4.691	0.000
Afirme-Scotiabank	0.092	1.000	19.352	0.003
Banco Ahorro Famsa-Scotiabank	0.090	0.600	-5.651	0.001
Panel C: Estimates of β_k for positive and negative weights				
	α-weighted Sum	Share of overall β	Mean	
Negative	-1.682	-1.969	-0.335	
Positive	2.536	2.969	4.345	
Panel D: Overidentification test				
	TSLS (Bartik)	TSLS	Over Id test	
	-3.67	0.36	1099.04	
	(2.29)	(0.18)	[0.38]	

Figure C2: Heterogeneity of β_k



Note: The graph shows the relationship between each instruments' $\hat{\beta}_k$, first-state F-statistics, and the Rotemberg weights. $\hat{\beta}_k$ is the 2SLS coefficient from the regression of pedestrian theft growth on ATM withdrawal growth rate instrumented by each share. Each point is a separate instrument's estimate (agreement share). The figure plots the estimated $\hat{\beta}_k$ for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\beta}$ reported in the TSLS column in Table C9. The figure excludes instruments with first-stage F-statistics below 5.

D Data

Financial Inclusion Database (BDIF)

The Financial Inclusion Databases (BDIF in Spanish) from the National Banking and Securities Commission (CNBV) consist of quarterly data gathered from commercial banks and other financial entities related to financial inclusion. The databases include variables such as bank branches, ATMs, point-of-sale terminals (POS), bank accounts and debit and credit cards. Data is disaggregated at the state and municipality level.[35] The data gathered for this paper is at the monthly level and corresponds to the period 2011-2019.

National Survey of Household Income and Expenditure (ENIGH)

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

National Survey of Financial Inclusion (ENIF)

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

National Survey of Enterprise Financing (ENAFIN)

The aim of the survey is to provide information related to the sources and use of financing mainly during the year 2017, as well as the needs of financial and banking services of enterprises, among other topics. Importantly for us, the survey contains information on whether the firms accept payment methods other than cash. It also has information on the payment methods firms use to conduct their own payments such as paying salaries, renting capital, or paying for services, taxes, and other financial obligations. The survey is representative at the national level and by size of locality. For the latter, there are only two ranges according to the number of inhabitants: from 50,000 to 499,999 and of 500,000 and more. Information is collected from the construction, manufacturing, trade and private non-financial services sectors including transport. The data classifies firms by their number

[35] See the instructions in the manual R24-B 2422 *Información de variables operativas.*

of employees: micro 6-10, small 10-30, medium 30-100, and large firms with more than 100 employees.

National Employment Survey (ENOE)

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

Criminal Incidence from the Executive Secretariat of the Public Security National System (SESNSP)

The criminal incidence reported by the SESNSP refers to the alleged occurrence of crimes recorded in previous investigations initiated or investigation files, reported by the Attorney General's Offices and Attorney General's offices in the case of the common law and by the Attorney General's Office in the federal jurisdiction. The data contains violent crimes (e.g. sexual assault, murder), property crimes (e.g. robery/burglary), other crimes (e.g. extortion, fraud).

Administrative data from Prospera

Prospera provided confidential data at the municipality level by two-month payment period level. The data include the number of beneficiaries in the municipality and the payment method by which they are paid. Examples of payment methods include cash, bank account without debit card, and bank account with debit card. These data, which span 2007–2015 and all 2,457 of Mexico's municipalities.

State and Municipal Public Finances (EFIPEM)

The National Institute of Statistics and Geography (INEGI) provides information on the public finances of each municipality at the annual level. The data includes the taxes collected by each municipality in a calendar year including estate taxes, property taxes, production taxes, consumption taxes, new cars and motor vehicle taxes, and gasoline taxes.

Statistics of Registered Deaths

The statistics of registered deaths are produced by the National Institute of Statistics and

Geography (INEGI). The statistics are based on death certificates. They have detailed information of the causes of death, including deaths from homicide, and the date the death occurred. They also include detailed information on the place of death at the locality level.

CONAPO Population Estimates

We use the Mexican population estimates from the National Population Council. The estimates are at the annual level and at the municipality level. The estimates are constructed using Mexican Census and Intercensal Surveys, which are carried out to update socio-demographic information at the midpoint between censuses.

Annual Crime Statistics

We use crime statistics from 2005-2010 collected from the National Institute of Statistics and Geography (INEGI) and available at the State and Municipal Databases (SIMBAD). The data is based on registered crimes collected from local criminal courts and includes information on total thefts, homicides, injuries, damages, sex crimes, and kidnaps. The rest of the crimes are classified as other crimes. The data is at the annual level and is available at the municipality level.