Financial Services and Household Inequality in Mexico

Villarreal, Francisco G.

UN Economic Commission for Latin America and the Caribbean

24 April 2014

Financial Services and Household Inequality in Mexico

Francisco G. Villarreal *

Subregional Headquarters in Mexico
Economic Commission for Latin America and the Caribbean
United Nations

April 24, 2014

Abstract

The Mexican government has recently launched several initiatives aimed at increasing the use of formal financial services, under the implicit assumption that they allow households to smooth consumption and finance investment in human capital. This study seeks to determine what is the impact of the use of formal financial services, proxied by the use of credit cards, on the level and distribution of household consumption in Mexico. Using data from the 2010 household income and expenditure survey, an instrumental variables approach is used in the context of quantile regressions, to correct for the bias that stems from households' self–selection in the decision to use formal financial services. The results indicate that financial services increase consumption of those households that use them, and that this effect is strongest for households in the lowest quantiles, thus reducing inequality of consumption across households.

Keywords: Financial Access, Household Inequality, Quantile Regression

JEL Codes: C21, D39, O16

Contents

*francisco.villarreal@cepal.org

1 Introduction

The modeling of consumer choice under uncertainty habitually invokes one of two polar cases: that of the representative agent where, under the assumption of complete markets, consumers can buy insurance against the occurrence of idiosyncratic shocks in all states of nature; or the permanent income hypothesis, where consumers must self–insure. In both cases the demand for insurance stems from the assumption that consumers are risk–averse and thus wish to smooth consumption across time. However, as reviewed by Guvenen (2011), the empirical evidence rejects both polar cases in favour of a partial insurance model, where access to insurance markets in particular, and formal financial services in general, is segmented according to household characteristics.

The recently published Financial Inclusion Survey (INEGI and CNBV, 2012) confirms the segmentation in the market for formal financial services in Mexico. According to the survey, only 35.5% of the adult population save at formal financial institutions, while 43.7% use informal savings mechanisms. Considering that 17.5% of adults use both formal and informal saving services, the results imply that 38.3% of adults in Mexico do not save.

This relatively low level of utilisation of formal financial services is also observed in the credit market, where only 27.5% of adults rely on credit from formal financial service providers; as well as in the insurance market, where less than a quarter of adults report having bought insurance. This explains why, according to the survey results, in the case of emergencies the main source of funds is borrowing amongst individuals.

The Mexican government, through its banking supervision authority recently launched a financial inclusion initiative (CNBV, 2012) whose objective is to encourage the provision of financial services to those segments of the population which are currently unbanked. This has been complemented by the recently approved financial reform which, among other things, aims at lowering the cost of wholesale financial services. Despite the importance assigned to the increased use of formal financial services, to date we are not aware of any study of the impact of access and use of formal financial services on household consumption and inequality.

The objective of this paper is to fill this gap, by exploring the impact of the use of formal financial services on the distribution of household consumption in Mexico. Given the restrictions of the data from the 2010 edition of the household income and expenditure survey (INEGI, 2011), use of formal financial services are proxied by the use of credit cards by households in the month preceding the survey. Since in principle we are interested in access to the use of financial services, but the data only reflects it usage, and considering that that use of credit card is an endogenous household decision, in order to estimate its impact on the inequality of household consumption, we adopt an instrumental variable identification strategy in the context of quantile regressions. In particular we use the estimator proposed by Abadie et al. (2002) to estimate the impact of credit card use on household consumption across its distribution, where we use the exogenous variation in the level of margination across households, and the years of education of its head to account for selection bias.

While the identification strategy does not allow us to estimate the impact of credit card use for the population at large, it allows us to estimate its effect on the consumption, and its distribution, of the households which use credit cards. In the language of potential outcomes the identification strategy allows us to recover the treatment effect on the treated. The evidence found indicates that the use of credit cards increases household monetary expenditures across the distribution. However, the relative increase is highest for those households in the lowest quantiles, and its effect decreases monotonically with the level household consumption until it is impossible to distinguish its effect from zero from around the 65th quantile onwards. Thus we conclude that the use of formal financial services not only has a positive effect on the level of monetary expenditure of households across the distribution, but it also reduces the inequality of households' consumption. This effect is in line with the effect of financial development and inequality found by Demirguc-Kunt and Levine (2009) using cross–country data.

The rest of the document is organised as follows. Section 2 briefly reviews the literature on the relationship between financial services and household inequality, where it is stressed that although the theoretical evidence is ambiguous with respect to the sign of the relationship, the empirical evidence in general supports the notion that financial services can reduce inequality. Next, section 3 discusses the details of the empirical identification strategy. Section 4 discusses the main features of the data, with particular emphasis of the differences in characteristics of those households which use credit cards and those which do not. The results are discussed in section 5, and finally section 6 concludes with a discussion of possible extensions of the analysis.

2 Financial Services and Inequality

A useful way to organise the literature on the channels through which access to formal financial services affect household consumption inequality, is to follow the approach of Coibion et al. (2012) and focus on the channels through which monetary policy shocks are transmitted to households.

In an environment of segmented access to formal financial services, households from the lower quantiles will hold a higher proportion of their financial assets in cash as in Algan and Ragot (2010). Thus, expansionary policy shocks that result in higher inflation will affect the poor disproportionately, increasing inequality as in Albanesi (2007) and Erosa and Ventura (2002). This effect will be further accentuated to the extent that richer households benefit from expansionary policy shocks, through their access to financial intermediation services, as in the models of Ledoit (2011) and Williamson (2008).

On the other hand, if as in the model of Doepke and Schneider (2006), higher inflation results in transfers from savers, which generally exhibit higher levels of income and consumption, to debtors, expansionary policy shocks could in principle reduce inequality. However, considering that debtor households tend to be found in the middle of the distribution, while poorer households have limited access to formal financial services (Figueroa, 2011), it is not clear what would be the aggregate effect of this channel on inequality.

From an intergenerational perspective, Becker and Tomes (1979, 1986) and Galor and Zeira (1993), among others, argue that reductions in the financial system imperfections, such as improved access, reduce inequality by enabling household investment in human capital. This effect is further reinforced when, as in the model of Jacoby and Skoufias (1997), access to formal financial services expand the opportunity set available to face adverse shocks. In contrast, if improved access to and quality of formal financial services increases the intensity of use of those who already have access to it, as in the model of Greenwood and Jovanovic (1990), its benefits would be enjoyed mainly by richer households, accentuating inequality.

In their review of the empirical literature, Demirguc-Kunt and Levine (2009) conclude that financial development benefits households from lower quantiles disproportionately, reducing both the level and persistence of inequality. Moreover, they find that most of the effect operates indirectly, such as through the impact of better financial services of the creation of employment opportunities as in Beck et al. (2008).

Considering the priority assigned to increased financial access and use by the Mexican government CNBV (2012), the study of its impact on the level of household consumption and its distribution is relevant for the design and evaluation of public policy.

3 Identification Strategy

In principle, if access to and use of formal financial services was randomly assigned, its impact on the level of consumption could be measured by comparing the difference in the means of household expenditures between the group that was assigned access C_i^1, and the group that was not C_i^0.

However, in practice, neither the access nor the use of formal financial services is distributed randomly. Instead it depends on household characteristics. Moreover, access is only observed through the use of financial services. The main challenge for the identification of the impact of formal financial services on households' consumption, and its distribution, is the fact that the utilisation of financial services is the result of an endogenous household decision. This self–selection problem has been widely studied in the literature (Vella, 1998). Before discussing the identification strategy, it is useful to analyse the following model, in order to understand the origin of the bias caused by self–selection:

$$C_i = X_i'\beta + \delta D_i + \varepsilon_i \tag{1}$$

$$D_i = \begin{cases} 1, & \text{if } D_i^* > 0; \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$D_i^* = W_i'\gamma + \nu_i \tag{3}$$

where (1) is the output equation, where observed expenditures are determined as a function of the observable characteristics' vector X, with coefficients β, and the binary indicator D_i, which takes the value of one when the household decides to make use of formal financial services, and zero otherwise. The coefficient of interest is δ, which measures the impact of formal financial services use on consumption.

As detailed in equations (2) and (3), the utilisation of financial services depends on the value of an unobserved variable D_i^*, which is in turn assumed to be determined by the observable variable vector W_i with coefficients γ.

The selection bias occurs when the innovations ε_i and ν_i are not orthogonal, which imply that D_i is endogenous. This can happen when, for example, the households with a more prosperous outlook are more likely to use credit cards. Since the evaluation of the households' outlook is necessarily subjective, and thus unobservable, the errors ε_i and ν_i will not be independent.

As stressed by Puhani (2000), the most common approach in the empirical literature to solve for selection bias, is to use a variant of Heckman's two–step estimator (Heckman, 1976, 1979). However, as discussed by Angrist (2001), in order to recover the causal effect of a given treatment, such as use of financial services, on the distribution of an outcome variable such as household expenditures, it is not necessary to impose all the restrictions needed to identify the parameters of Heckman's two–step estimator and its variants. Instead, he proposes the adoption of an instrumental variables approach to solve for the endogeneity of the regressor D_i.

In view of the above, and considering that the primary objective is to estimate the impact of the use of formal financial services on the distribution of household consumption, the quantile treatment effect (QTE henceforth) estimator proposed by Abadie et al. (2002) is used. The QTE estimator generalises the traditional quantile regression estimator of Koenker and Bassett (1978), under the assumption that there exists a binary variable Z_i, that is a valid instrument for the endogenous regressor D_i.

The QTE estimator is given by:

$$(\hat{\beta}^q, \hat{\delta}^q) = \arg\min_{\beta,\delta} E[\kappa_i \rho_q (C_i - X_i\beta' - \delta D_i)] \tag{4}$$

where the function $\rho_q(e) = (q - \iota[e < 0])e$ determines the asymmetric absolute loss function, while the weights k_i are given by:

$$\kappa_i = 1 - \frac{D_i(1 - Z_i)}{1 - P(Z_i = 1|X_i)} - \frac{(1 - D_i)Z_i}{P(Z_i = 1|X_i)} \tag{5}$$

It is readily verified that traditional quantile regression estimator is a special case of the QTE when $D_i = Z_i$. In this sense, the relationship between both quantile estimators is analogous to that between least squares and instrumental variables.

Up to this point, the interest of the discussion has been the contrast between the consumption of households that use formal financial services, and those who do not use them. However, there are households that have access to formal financial services but decide not to make use of them, as well as households that would make use of them but do not have access. The relationship between the regressor D_i, and its instrument Z_i in the QTE regressor allows us to identify these different households separately.

As discussed, D_i reflects the decision by households to use formal financial services. As is well known, a valid instrument must be relevant, in the case of interest it must be related to the decision to use financial services, but otherwise must be independent of the outcome variable. That is it must be unrelated to household expenditures, except through its effect on the decision to use financial services. Thus, the instrument Z_i can be interpreted, precisely, as a binary variable that determines whether a household has access to formal financial services.

With this notation, it is possible to separately identify households that have access and make use of formal financial services ($D_i = 1, Z_i = 1$), from those that have access to financial services but decide not to use them ($D_i = 0, Z_i = 1$), and those that do not have access to the formal financial system and thus can not make use of its services ($D_i = 0, Z_i = 0$)[1].

Without going into their details, its important to note that the function of the weights k_i is to identify, on average, those households that have access to formal financial services and decide to make use of them. In the language of treatment effects, the QTE estimator allows us to identify the average impact of the treatment on the treated. That is it measures the impact of using financial services on the population that has access to the formal financial system, and decides to use its services.

In order to use the estimator, it is necessary to estimate the weights k_i. The problem is that when $D_i \neq Z_i$, the value of some of the weights can be negative, which makes the minimisation problem posed in (4) non–convex. In practice, the expectation of k_i is computed, conditional on the matrix of observed regressors, which is equivalent to computing the following probability:

$$Pr[D_i^1 > D_i^0|C_i, D_i, X] = 1 - \frac{D_i(1 - E[Z_i|Y_i, D_i = 1, X_i])}{1 - P(Z_i = 1|X_i)} - \frac{(1 - D_i)E[Z_i|Y_i, D_i = 0, X_i])}{P(Z_i = 1|X_i)} \tag{6}$$

4 Data

The analysis uses data drawn from the 2010 wave of the Mexican Household Income and Expenditure Survey (ENIGH as it is known in Spanish). In particular, the sample studied focuses on monetary income

[1]Given the institutional restrictions, in this context it is not possible to observe households that despite not having access to formal financial services, make use of them ($D_i = 1, Z_i = 0$).

and expenditure of households headed by individuals aged between 25 and 65 years.

While the recently published data from the Financial Inclusion Survey, contain a rich characterisation of the use of different financial services by Mexican households, the survey does not include data on expenditures. Thus we proxy the use of financial services by the use of credit cards in the month preceding the household income and expenditure survey. Once the data for the 2012 wave of the Household Income and Expenditure Survey are made available a more nuanced analysis of both access and use of different financial services will be possible.

Table 1[2] presents summary statistics at the national, urban and rural level[3]. The first four columns summarize the socioeconomic characteristics of households at the national level. There it can be seen that the median household is headed by a married male aged 44, who does not identify himself as belonging to an indigenous group, and who with 12 years of formal schooling –including preschool– just finished middle school. He is employed full-time in the private sector and does not receive social security benefits, which implies he works in the informal sector. The median household is composed of a single family group with four members, owns its house, is located in an urban[4] municipality classified by the National Population Council (CONAPO), as having a very low margination index[5], and does not receive government transfers.

Median monetary income in 2010 was 18,752.52 Mexican Pesos, which is equivalent to 1,488.3 US dollars, while monetary expenditures amount to 17,264.16 pesos –approximately 1,370 dollars–, which implies that the median household save 6.4% of their monetary income. Discounting rent the median household savings rise to 9.3% of monetary income, and further discounting education and health expenditures, its savings are equivalent to 17.6% of monetary income. Moreover, only 21% of households are situated in locations with less than 2,500 inhabitants, and at the national level only 11.3% used a credit card on the month preceding the survey.

The next set of columns presents summary statistics for urban and rural households. While the households in these two groups differ in several dimensions, most notably in the level of income and consumption, for the purposes of this investigation, the salient difference is the use of credit cards. Whereas credit card use amongst urban households reach 14%, above the national mean of 11%, among rural households only 2% of households use credit cards.

As discussed below, since credit card use is based on an endogenous decision by the household, it is not possible to identify the impact of its use on household consumption and its distribution for the whole population. Instead it is only possible to estimate its impact for households which use credit cards. In other words the counterfactual studies is what would happen to the consumption level and distribution of households which use credit cards, if they did not use them. Considering the very low level of use of credit cards among rural households, in the rest of the document we restrict our attention to urban households.

Table 2 summarises the socioeconomic characteristics of urban households depending on whether they use credit cards or not. In terms of the characteristics of the head of the household, the most prominent difference is that, on average, those who use credit cards are more educated, more likely to work in the formal sector (as proxied by whether they receive social security benefits), and less likely to work in family owned enterprises. In terms of the characteristics of the household, those who use credit cards tend to be

[2]Tables and figures are presented in annex A.

[3]Unless otherwise noted all summary statistics and results were computed taking into account the survey's complex design.

[4]Following the convention adopted by the Mexican statistical institute (INEGI), a household is considered urban if its location has at least 2,500 inhabitants.

[5]CONAPO's margination index classifies municipalities based on the incidence of illiteracy, the level of access to improved sanitation facilities, the overcrowding of living areas, the proportion of households with dirt floors, the percentage of the population living in locations with less than 5,000 inhabitans, and the proportion of the population that earns up to twice the minimum wage. For further reference see (CONAPO, 2011, Annex C.)

located in municipalities with lower margination indices, and are less likely to receive government transfers. Finally, concerning households finances, both income and consumption of households which use credit cards are significantly greater than those who do not, although in both groups there is a wide dispersion of income and expenditure.

With respect to inequality of consumption between households, whereas the Gini index of (log) monetary expenditures of households who use credit cards is 0.30, the corresponding Gini index of households who do not use credit cards is 0.34. Moreover the difference of 0.04 is statistically significant. This finding is confirmed in figure 1, which shows the difference in Lorenz curves for both groups, there it can be seen that the Lorenz curve of the households which use credit cards dominates the curve of those that do not. That is the inequality of consumption is greater for households who do not use credit cards across all quantiles, although it seems to be more acute for the highest quantiles.

If this difference could be attributed to the use of credit cards, then it would be evidence that their use enables households to smooth consumption. The next section explores whether this is the case.

5 Results

Although the primary interest is to study the impact of credit card use on the distribution of household consumption, it is relevant to study the impact on mean consumption as it completes the picture of the role of the use of credit cards in the determination of consumption. Moreover, it allows us to explore which of the variables listed in table 1 are relevant for the subsequent analysis.

This section begins exploring how much of the difference in consumption, and its distribution, between the two groups of households is explained by the difference in their characteristics, next we explore the impact of the use of credit cards on mean household consumption, and then we proceed to study its effect on consumption inequality.

5.1 Decompositions

5.1.1 Oaxaca–Blinder Decomposition

As was discussed in section 4 the characteristics of urban households that use and do not use credit cards are very different. To examine how much of the observed difference in mean consumption reflects observable household characteristics we use the decomposition proposed by Blinder (1973) and Oaxaca (1973).

The basic idea is to decompose the observed difference in expenditures into differences in the household characteristics, and differences of the impact of those characteristics on expenditures. In a regression framework this translates into differences of the matrix of observable regressors, and differences in its coefficients.

If we were confident that household expenditures are completely determined by the matrix of observable regressors, we could conclude that the difference not explained by the difference of observable characteristics across groups, is due to difference in its coefficients. However as is well know, if a relevant regressor is omitted, then the coefficients will be biased, so that the unexplained difference will be due to differences in coefficients as well as differences between the error terms. Despite this, if the unexplained difference is statistically significant, the evidence can be interpreted as indicating a role for the use of credit cards in accounting for the difference in household consumption across groups.

In order to identify the relevant explanatory variables from the list of variables summarised in table 1, as well as the squares of continuous variables, we used a general to specific approach based on the algorithm proposed by Hendry and Krolzig (2001)[6].

Table 3 shows the results of the Oaxaca–Blinder decompositions. The top panel summarises the mean of (log) monetary expenditure for both groups, and its difference; while the bottom panel provides details of the difference decomposition. The difference between the columns stems from the coefficients that are used form reference. In the first column the reference coefficients are those from a pooled regression of observations from both groups, whereas in the second and third column, respectively, the reference coefficients are those of the group which uses credit cards, and those who do not.

The first feature to note is the magnitude of the difference, which amounts to almost 0.7 log points. Irrespective of the coefficients used as reference a sizeable proportion of this difference is attributable to differences in observable characteristics, with the most relevant one being the (log) of household income. Nevertheless, we can see that when the pooled coefficients and the coefficients for the households who do not use credit cards are used as reference, the unexplained difference is statistically significant. That is even accounting for observable differences, the evidence suggests that the use of credit cards does have a positive impact on mean (log) household consumption.

5.1.2 DiNardo, Fortin and Lemieux Decomposition

To explore whether the use of credit cards also impinge on the distribution of household consumption, in this subsection we use the decomposition proposed by DiNardo et al. (1996) (DFL henceforth). The intuition behind the DFL decomposition is to compare the observed distribution of (log) monetary expenditure of households which use credit cards with the distribution of an appropriate counterfactual.

The simplest counterfactual would be the distribution of the same group of households if they did not use credit cards. Of course this is not observed, so DFL suggest estimating the propensity of using credit cards by the different households based on observable characteristics. In particular, the DFL decomposition is implemented by first estimating a probit regression[7], and then using the predicted probability of not using a credit card to build the counterfactual.

Figure 2 shows the results of the DFL decomposition. The left panel contrasts the density of the distribution of (log) monetary expenditures for households which use credit cards (solid line), with the density of consumption of household which do not use credit cards (dashed line). In addition it plots the density of the counterfactual (dotted line). We can see that when the households which use credit cards are weighted by the relative probability of not using credit cards, the density shifts left and perhaps counterintuitively it seems to become more concentrated.

The panel on the right shows the difference between the density of households which use credit cards and its counterfactual. We can see that at least for (log) expenditures larger than 10 –or roughly the median expenditure of urban households– the difference in densities is statistically significant. That is, even after controlling for observable differences, the evidence implies that credit card use also affects the distribution of household consumption.

[6] The basic idea behind the procedure is to progressively eliminate all variables that are not statistically significant, while not rejecting a standard set of regression diagnostics.

[7] As was the case in the choice of explanatory variables for the Oaxaca–Blinder decomposition, the choice of explanatory variables in the probit regression followed a general to specific reduction procedure based on the algorithm proposed by Hendry and Krolzig (2001)

5.2 Impact on mean household expenditures

As discussed in section 3 least square coefficients are likely to be contaminated by selection bias. Nevertheless they serve as a useful benchmark to compare the results of instrumental variable regression.

The first column of table 4 shows the least squares estimates for the preferred specification. The F statistic, in the bottom panel, indicates that the regression is statistically significant with a coefficient of determination of 95.5%. With the exception of the coefficients for household size, and the indicator of whether the household is composed of a nuclear family, the rest of the coefficients are significant at the conventional levels.

According to least square estimates, the most important determinant of household expenditures is its income level, which as expected has a positive sign, followed by household savings, which have a positive impact on consumption but at a marginally decreasing rate, as evidenced by the negative sign in the square of household savings. The negative sign of the proportion of business income as a proportion of household monetary income, is most likely due to the fact that most family or independently owned businesses in Mexico are very small, very likely to be located in the informal sector, and characterised by relatively low productivity levels OECD and ECLAC (2012). However, this is at odds with the negative sign of the indicator of whether the household head is an employee, as opposed to working independently or being an employer.

Although, not statistically significant in this specification, the coefficient of household size, which indicate that larger households have higher expenditures but at a marginally decreasing rate, seem to point towards the existence of economies of scale within households. The positive coefficient for the indicator of whether the household is composed of a nuclear family, seems to support this hypothesis. The negative sign on the indicator of whether households own their home reflects the fact that the implicit reference household under this specification, has to pay monthly rent thus incurring in higher expenditures. Finally, the use of credit card apparently enable households to increase their expenditure level by 3,4%.

The next four columns in table 4 show the estimates using instrumental variables. Before discussing the coefficients it is important to discuss the rationale for the choice of the instruments for the use of credit cards. As discussed previously a valid instrument must be related to the use of credit cards, but must affect household expenditures only through it relationship with credit card use. Since what is observed is credit card use and not access to their use, a natural instrument would be to look for differences in household characteristics which are related to access to financial services. To do so we started with a list of variables which are statistically significant in a probit regression of credit card use, but redundant in a least squares regression of household expenditures, such as the one just described.

This set of variables includes whether the household head receives social security benefits, which is a proxy for whether the head works in the formal sector; the set of binary variables for levels of margination which, considering that we control for household income level, are interpreted as being proxies for ease of access to financial services providers; and years of schooling. In the case of the first few variables, both anecdotal evidence as well as the results from the financial inclusion survey (INEGI and CNBV, 2012) indicate that both the ability to show proof of income, hindered by working in the informal sector, as well as physical access to financial service providers, hindered by margination, are important obstacles to financial service access. With respect to years of schooling, as discussed by Dick and Jaroszek (2013) financial literacy is found to be a significant covariate in the rational use of financial services[8], thus it is likely that households whose heads are more financially literate, have a better financial history and thus are more likely to have

[8] In particular, Dick and Jaroszek (2013) find that households in Germany whose head has more schooling are less likely to use current account loans, which are more expensive than other types of credit.

access to formal financial services than those household whose head is less financially literate.

The second column shows the estimates of two stage least squares, when the full set of instruments just discussed is used to account for the endogeneity of the use of credit cards, whereas the results in column three correspond to the case where redundant instruments are dropped from the specification. From column three, we can see that while the main coefficients (income and saving) remain relatively unchanged, the coefficient of credit card use jumps to over 38%, signalling a significant selection bias in the least square estimation. In the bottom panel, we can see that while both the Kleinbergen and Paap (2006) test for underidentification, and the Hansen–Sargan test for overidentifying restrictions reject the hypothesis that instruments are irrelevant, according to the Stock and Yogo (2005) critical values, the instruments used in column 2 are only weakly correlated with the use of credit cards. Although when redundant instruments are dropped, as in column three, the weakness of the instruments is attenuated, the diagnostics suggest that an estimator that is robust to weak identification would be preferred.

Columns four and five of table 4 show the results using a Limited Information Maximum Likelihood Estimator, where in contrast to the two stage least squares just described, we fail to reject the hypothesis of irrelevance of the instruments, and we reject the hypothesis of instrument weakness. As before, column four uses the full set of instruments, while column five only uses non redundant instruments. The results in column five are our preferred specification, where importantly for our analysis the use of credit cards have a positive and significant impact on the level of household expenditures. In fact the evidence suggests that credit card use increases household consumption by roughly 40%. In the next section we explore how is this impact distributed across households with different consumption levels.

5.3 Impact on the distribution of household expenditures

One of the limitations of the QTE estimator is that the instrument Z_i must be a binary variable, thus we need to combine the chosen instruments – household's head years of schooling, and a binary indicator of whether the household is located in a municipality with a moderate level of margination – into a single binary variable.

The first step is to transform years of schooling into a binary indicator of whether the household head finished high school or not. Since years of schooling have a positive impact on the probability of using a credit card, but the level of margination has a negative sign, the binary instrument is defined as the product of the indicator for high school and the indicator of whether the household is located in a municipality with a very low margination index.

Using this binary instrument we use the QTE estimator to find estimates for each quantile of the distribution of household expenditures, using the specification detailed in table 5 where the results are summarised by decile. We can see that once we estimate the results using quantile regressions, the only variables that are significant across the distribution are household monetary income, savings, the square of savings and credit card use.

The first relevant finding is that the impact of household income on consumption is declining in the level of household expenditures. This is easily explained by the fact that richer households tend to save more as a proportion of their income, than poorer households.

In line with the previous result, the coefficients on savings and credit card use are also declining with household income. This is consistent with the idea the households from the lower quantiles are more prone to idiosyncratic shocks, so that the availability of savings and credit allow them to increase their expenditures given their monetary income.

Figure 3 shows the coefficient for credit card use, as well as its 95% confidence interval across the distribution. We can see that its impact is positive for all households up to about the 65th quantile, where according to the estimates it becomes statistically indistinguishable from zero. Moreover, its impact is highest for households from the lowest quantiles, reaching almost 70% in the first deciles, and declining to approximately 13% for the median household. The fact that the effect is monotonically decreasing is interpreted as supporting the notion that access and use of formal financial services can reduce the inequality of consumption across households.

6 Conclusions

While the results indicate that credit card use can account for the lower Gini index of consumption of those households that use credit cards, the results must be interpreted with caution. On the first hand, the estimates measure the impact on expenditure of those household which use credit cards, in other word they measure how much lower would the expenditure of households who use credit cards would be if they did not use credit cards, so the results are relevant to this subset of the population and not to the population at large.

Secondly, the use of credit cards is a relatively narrow proxy for the use of formal financial services in general. For example for households from the lowest quantiles of the sample, a more relevant question would be to ask what is the effect of being able to save at a formal financial institution instead of using informal services or keeping cash at home. Considering this, a natural extension of this study would be to use data from the Financial Inclusion Survey, with data from the 2012 wave of the Household Income and Expenditure Survey, which at the time of writing is not available to the public.

Moreover, it is necessary to explore the robustness of the results presented to different specifications. In particular robustness needs to be verified along three particular lines.

The first is to the choice of sample used, in particular for the results across the distribution, whose standard errors where obtained asymptotically. A semiparametric procedure could be used to explore the sensitivity of the functional forms used to estimate the weights of the QTE estimator. Additionally, instead of reporting standard errors derived from asymptotic theory, it would be useful to check the significance of estimates under bootstrapped errors.

The second is to the measure of income and expenditure. In this sense a natural check would be to verify the robustness of results to the use of current income and expenditure. Finally, the third line would be to use different specifications, in particular the inclusion of information on the financial assets of the household to check whether the increase in consumption is sustainable, or it is merely deteriorating the sustainability of household finances by indebting them beyond their means.

Finally, once the robustness of results has been ascertained, it would be interesting to explore whether the coefficients have changed over time, and if they have whether these changes correspond to changes in public policy or to market developments.

References

Abadie, A., Angrist, J., and Imbens, G. (2002). Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. *Econometrica*, 70(1):91–117.

Albanesi, S. (2007). Inflation and inequality. *Journal of Monetary Economics*, 54(4):1088–1114.

Algan, Y. and Ragot, X. (2010). Monetary policy with heterogeneous agents and borrowing constraints. *Review of Economic Dynamics*, 13(2):295–316.

Angrist, J. D. (2001). Estimation of limited dependent variable models with dummy endogenous regressors. *Journal of Business & Economic Statistics*, 19(1):2–28.

Araar, A. and Duclos, J.-Y. (2007). *DASP: Distributive Analysis Stata Package*. PEP; World Bank; UNDP and Université Laval.

Beck, T., Büyükkarabacak, B., Rioja, F., and Valev, N. (2008). Who gets de credit? and does it matter? household vs. firm lending across countries. Policy Research Working Paper 4661, The World Bank, Washington D.C.

Becker, G. S. and Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy*, 87(6):1153–89.

Becker, G. S. and Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of Labor Economics*, 4(3):S1–39.

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *The Journal of Human Resources*, 8(4):436.

CNBV (2012). *Libro Blanco Inclusión Financiera*. Comisión Nacional Bancaria y de Valores, México D.F.

Coibion, O., Gorodnichenko, Y., Kueng, L., and Silvia, J. (2012). Innocent bystanders? monetary policy and inequality in the U.S. Working Paper 18170, National Bureau of Economic Research.

CONAPO (2011). *Índice de Marginación por Entidad Federativa y Municipio 2010*. Consejo Nacional de Población, México D.F.

Demirguc-Kunt, A. and Levine, R. (2009). Finance and inequality: Theory and evidence. Working Paper 15275, National Bureau of Economic Research.

Dick, C. D. and Jaroszek, L. M. (2013). Knowing what not to do: Financial literacy and consumer credit choices. ZEW Discussion Paper 13-027, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research.

DiNardo, J. E., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973–1992: A semiparametric approach. *Econometrica*, 64(5):1001–1044.

Doepke, M. and Schneider, M. (2006). Inflation and the redistribution of nominal wealth. *Journal of Political Economy*, 114(6):1069–1097.

Erosa, A. and Ventura, G. (2002). On inflation as a regressive consumption tax. *Journal of Monetary Economics*, 49(4):761–795.

Figueroa, A. (2011). La desigualdad del ingreso y los mercados de crédito. *Revista de la CEPAL*, 105:39–55.

Galor, O. and Zeira, J. (1993). Income distribution and macroeconomics. *The Review of Economic Studies*, 60(1):35–52.

Greenwood, J. and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *Journal of Political Economy*, 98(5):1076–1107.

Guvenen, F. (2011). Macroeconomics with heterogeneity: A practical guide. *National Bureau of Economic Research Working Paper Series*, No. 17622.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement*, 5(4):475–492.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1):153–161.

Hendry, D. and Krolzig, H.-M. (2001). *Automatic econometric model selection using PcGets 1.0.* Timberlake Consultants Press, London, 4. ed. edition.

INEGI (2011). *Encuesta Nacional de Ingresos y Gastos de los Hogares 2010. Descripción de la Base de Datos.* Instituto Nacional de Estadística, Geografía e Informática, Aguascalientes, México.

INEGI and CNBV (2012). Encuesta Nacional de Inclusión Financiera 2012. Análisis descriptivo de los resultados. Technical report, México D.F.

Jacoby, H. G. and Skoufias, E. (1997). Risk, financial markets, and human capital in a developing country. *Review of Economic Studies*, 64(3):311–35.

Jann, B. (2008). The blinder-oaxaca decomposition for linear regression models. *The Stata Journal*, 8(4):453–479.

Kleinbergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133:97–126.

Koenker, R. and Bassett, G. (1978). Regression quantiles. *Econometrica*, 46(1):33–50.

Ledoit, O. (2011). The redistributive effects of monetary policy. Working Paper Series 44, Department of Economics - University of Zurich.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, 14(3):693–709.

OECD and ECLAC (2012). *Latin American Economic Outlook 2013. SME Policies for Structural Change.* OECD Publishing.

Puhani, P. (2000). The heckman correction for sample selection and its critique. *Journal of Economic Surveys*, 14(1):53–68.

Stock, J. and Yogo, M. (2005). Testing for weak instruments in linear IV regression. In Andrews, D. and Stock, J., editors, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, pages 80–108. Cambridge University Press, Cambridge.

Vella, F. (1998). Estimating models with sample selection bias: A survey. *The Journal of Human Resources*, 33(1):127–169.

Williamson, S. D. (2008). Monetary policy and distribution. *Journal of Monetary Economics*, 55(6):1038–1053.

A Tables and figures

A.1 Tables

	Full Sample				Urban Households				Rural Households			
	Mean	Median	Standard Deviation	Number of observations	Mean	Median	Standard Deviation	Number of observations	Mean	Median	Standard Deviation	Number of observations
Household head												
Female	0.23	0	0.42	22,192	0.25	0	0.43	17,439	0.16	0	0.37	4,753
Age	45.00	44	11.00	22,192	45.00	45	11.00	17,439	44.00	43	11.00	4,753
Years of schooling	11.41	12	5.48	22,192	12.34	12	5.34	17,439	8.00	9	4.59	4,753
Ethnicity	0.29	0	0.45	22,192	0.25	0	0.43	17,439	0.45	0	0.50	4,753
Married	0.59	1	0.49	22,192	0.58	1	0.49	17,439	0.64	1	0.48	4,753
Employer	0.14	0	0.34	19,058	0.11	0	0.31	14,888	0.23	0	0.42	4,170
Independent worker	0.15	0	0.36	19,058	0.13	0	0.34	14,888	0.23	0	0.42	4,170
Employee	0.71	1	0.46	19,058	0.75	1	0.43	14,888	0.53	1	0.50	4,170
Works full time	0.88	1	0.32	19,058	0.89	1	0.31	14,888	0.84	1	0.37	4,170
Social Security	0.44	0	0.50	22,192	0.51	1	0.50	17,439	0.18	0	0.38	4,753
Independent, personal or family owned enterprise	0.41	0	0.49	13,534	0.37	0	0.48	11,288	0.61	1	0.49	2,246
Private sector enterprise	0.38	0	0.49	13,534	0.40	0	0.49	11,288	0.26	0	0.44	2,246
Government Institution	0.19	0	0.40	13,534	0.21	0	0.41	11,288	0.12	0	0.33	2,246
Institution not managed by the government	0.02	0	0.13	13,534	0.02	0	0.13	11,288	0.01	0	0.09	2,246
Household characteristics												
Household size	4.00	4	2.00	22,192	4.00	4	2.00	17,439	5.00	4	2.00	4,753
Very high margination index	0.06	0	0.24	22,192	0.02	0	0.13	17,439	0.21	0	0.41	4,753
High margination index	0.13	0	0.33	22,192	0.07	0	0.26	17,439	0.31	0	0.46	4,753
Moderate margination	0.13	0	0.33	22,192	0.10	0	0.31	17,439	0.22	0	0.41	4,753
Low margination	0.14	0	0.35	22,192	0.14	0	0.35	17,439	0.14	0	0.35	4,753
Very low margination	0.54	1	0.50	22,192	0.66	1	0.47	17,439	0.12	0	0.32	4,753
Nuclear	0.69	1	0.46	22,192	0.68	1	0.47	17,439	0.72	1	0.45	4,753
Own house	0.72	1	0.45	21,796	0.68	1	0.47	17,097	0.87	1	0.34	4,699
Receive government transfers	0.24	0	0.43	22,192	0.14	0	0.34	17,439	0.62	1	0.48	4,753
Rural	0.21	0	0.41	22,192								
Household finances												
Monetary income	27,791.88	18,752.52	34,523.17	22,192	31,149.35	21,698.86	36,260.54	17,439	15,473.12	10,293.72	23,402.36	4,753
Monetary expenditures	24,269.27	17,264.16	26,408.48	22,192	27,224.83	19,650.44	28,428.45	17,439	13,425.14	10,487.75	11,891.14	4,753
Savings	3,522.61	1,204.57	23,116.55	22,192	3,924.52	1,618.34	24,035.47	17,439	2,047.98	238.85	19,305.94	4,753
Savings (excl. housing exp.)	4,252.18	1,741.34	23,079.85	22,192	4,842.47	2,267.77	23,971.52	17,439	2,086.37	257.98	19,309.74	4,753
Savings (excl. housing, schooling and health exp.)	7,189.39	3,295.55	24,141.31	22,192	8,211.44	4,168.08	25,111.92	17,439	3,439.44	1,021.29	19,738.23	4,753
Business income/ Monetary income	0.14	0	0.28	22,100	0.13	0	0.28	17,374	0.17	0	0.28	4,726
Use credit card	0.11	0	0.32	22,192	0.14	0	0.34	17,439	0.02	0	0.15	4,753

Table 1 – Summary Statistics of Household's Socioeconomic Characteristics
Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure

	Do not use credit card				Use credit card			
Household head	**Mean**	**Median**	**Standard Deviation**	**Number of observations**	**Mean**	**Median**	**Standard Deviation**	**Number of observations**
Female	0.25	0	0.43	15,033	0.23	0	0.42	2,406
Age	45.00	45	11.00	15,033	46.00	46	10.00	2,406
Years of schooling	11.76	12	5.22	15,033	15.94	18	4.62	2,406
Ethnicity	0.26	0	0.44	15,033	0.19	0	0.40	2,406
Married	0.57	1	0.50	15,033	0.65	1	0.48	2,406
Employer	0.11	0	0.31	12,763	0.12	0	0.33	2,125
Independent worker	0.14	0	0.35	12,763	0.09	0	0.28	2,125
Employee	0.75	1	0.43	12,763	0.78	1	0.41	2,125
Works full time	0.89	1	0.31	12,763	0.92	1	0.27	2,125
Social Security	0.47	0	0.50	15,033	0.73	1	0.45	2,406
Independent, personal or family owned enterprise	0.40	0	0.49	9,613	0.19	0	0.39	1,675
Private sector enterprise	0.40	0	0.49	9,613	0.43	0	0.49	1,675
Government Institution	0.18	0	0.39	9,613	0.35	0	0.48	1,675
Institution not managed by the government	0.01	0	0.12	9,613	0.04	0	0.20	1,675
Household characteristics								
Household size	4.00	4	2.00	15,033	4.00	4	2.00	2,406
Very high margination index	0.02	0	0.14	15,033	0.00	0	0.05	2,406
High margination index	0.08	0	0.28	15,033	0.02	0	0.14	2,406
Moderate margination	0.11	0	0.32	15,033	0.05	0	0.22	2,406
Low margination	0.15	0	0.35	15,033	0.12	0	0.32	2,406
Very low margination	0.64	1	0.48	15,033	0.81	1	0.39	2,406
Nuclear	0.67	1	0.47	15,033	0.71	1	0.45	2,406
Own house	0.67	1	0.47	14,717	0.74	1	0.44	2,380
Receive government transfers	0.15	0	0.36	15,033	0.04	0	0.20	2,406
Household finances								
Monetary income	26,527.62	19,609.49	27,884.26	15,033	60,026.56	44,110.59	60,875.88	2,406
Monetary expenditures	23,336.92	17,971.45	20,907.22	15,033	51,517.05	37,673.82	49,426.11	2,406
Savings	3,190.70	1,348.62	20,335.71	15,033	8,509.51	4,931.25	39,744.36	2,406
Savings (excl. housing exp.)	4,002.77	2,019.13	20,387.42	15,033	10,089.03	6,047.00	39,200.04	2,406
Savings (excl. housing, schooling and health exp.)	6,734.03	3,665.71	20,791.79	15,033	17,442.46	10,730.51	42,088.96	2,406
Business income/ Monetary income	0.14	0	0.29	14,973	0.10	0	0.24	2,401

Table 2 – Summary Statistics of Urban Households by Use of Credit Cards
Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure

Dependent Variable: (log) Household monetary expenditure			
	(1)	(2)	(3)
Differential			
Do not use credit card	9.829	9.829	9.829
	(1135.47)***	(1136.36)***	(1136.36)***
Use credit card	10.5194	10.5194	10.5194
	(524.98)***	(523.21)***	(523.21)***
Difference	-0.6904	-0.6904	-0.6904
	(-31.63)***	(-31.54)***	(-31.54)***
Decomposition			
Explained	-0.657	-0.6848	-0.651
	(-31.24)***	(-29.47)***	(-30.97)***
Unexplained	-0.0334	-0.0056	-0.0395
	(-5.81)***	(-0.54)	(-5.87)***
N	6704	6704	6704

z statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 3 – Oaxaca–Blinder Decomposition
Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure
Note: On the first column the pooled coefficients are used as the reference coefficients while in the second and third columns, the coefficients from households who use and do not use credit cards, respectively, are used as the reference coefficients. In the estimation the explanatory variables were (log) monetary income, (log) savings and its square, the proportion of business income to monetary income, the size of the household and its square, and indicators of whether household head is an employee, whether he works in an institution not managed by the government, whether the household is located in a very high margination municipality, whether it is a nuclear household, and whether the household owns its house. The decomposition was estimated using the Stata command developed by Jann (2008).

Dependent variable: (log) Monetary expenditures

	ols	tsls1	tsls2	liml1	liml2
(log) Monetary	1.3094	1.228	1.2288	0.9469	1.2238
income	(150.69)***	(54.74)***	(47.12)***	(4.16)***	(43.77)***
(log) Saving	0.4093	0.383	0.383	0.3744	0.3828
	(7.98)***	(5.09)***	(5.10)***	(4.18)***	(5.09)***
(log) Saving	-0.0419	-0.0396	-0.0396	-0.0369	-0.0395
squared	(-13.28)***	(-8.53)***	(-8.61)***	(-6.09)***	(-8.58)***
Business inc. /	-0.0627	-0.0646	-0.0646	-0.0574	-0.0645
Monetary inc.	(-2.57)*	(-2.26)*	(-2.26)*	(-0.83)	(-2.23)*
Employee	-0.0465	-0.0785	-0.0783	-0.1561	-0.0796
	(-1.59)	(-2.26)*	(-2.25)*	(-1.11)	(-2.21)*
Inst. not	0.0365	0.0099	0.0102	-0.0924	0.0084
managed by govt.	(3.25)**	-0.48	-0.48	(-0.83)	-0.38
Household	0.0034	0.0186	0.0185	0.0564	0.0192
size	-1.14	(4.29)***	(3.97)***	-1.78	(3.92)***
HH size	-0.0001	-0.0007	-0.0007	-0.0017	-0.0008
squared	(-0.46)	(-2.66)**	(-2.62)**	(-1.80)	(-2.64)**
Nuclear	0.0058	0.0018	0.0019	-0.0215	0.0015
family	-1.31	-0.3	-0.3	(-0.90)	-0.23
Own house	-0.0116	-0.0116	-0.0116	-0.0271	-0.0118
	(-2.93)**	(-2.19)*	(-2.16)*	(-1.39)	(-2.15)*
Credit card	0.0338	0.3883	0.385	1.6391	0.407
	(6.03)***	(4.84)***	(3.61)***	-1.63	(3.52)***
Constant	-3.8375	-3.0266	-3.0334	-0.4952	-2.9889
	(-14.49)***	(-6.79)***	(-7.04)***	(-0.23)	(-6.78)***
Observations	6704	6704	6704	6704	6704
R-sq	0.955	0.925	0.925	0.366	0.921
Log Likelihood	3.10E+03	1.60E+03	1.60E+03	-5.50E+03	1.50E+03
F–stat.	5.30E+03	4.50E+03	4.50E+03	641.8891	4.40E+03
Underidentification	···	60.8874	33.624	60.8874	33.624
p–value	···	0	0	0	0
Weak Id.	···	7.0519	17.0855	7.0519	17.0855
10% max IV	···	36.19	19.93	3.81	8.68
15% max IV	···	19.71	11.59	2.93	5.33
20% max IV	···	14.01	8.75	2.54	4.42
25% max IV	···	11.07	7.25	2.32	3.92
Overidentification	···	73.7712	1.7275	11.9952	1.6684
p–value	···	0	0.1887	0.1514	0.1965

z statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 4 – Impact of credit card use on mean household consumption

Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure

Note: z statistics are based on robustly estimated standard errors. The results in columns 2 and 4 were obtained using the following instruments: Binary indicator of whether household head receives social security benefits; binary indicators for household margination level (the excluded category is very low margination); household savings excluding housing, and household savings excluding housing, health and education expenditures; household´s head years of schooling and its square. The results in columns 3 and 5 were obtained using the following instruments: Binary indicator of whether the household is located in a municipality with moderate margination, and the household´s head year of schooling.

Dependent variable: (log) Monetary expenditures

	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Credit Card	0.4051	0.3132	0.2349	0.1706	0.1291	0.0987	0.0670	0.0403	0.0161
	(5.85)***	(6.22)***	(3.42)**	(2.62)**	(2.46)*	(2.3)*	(1.8)	(1.46)	(0.94)
(log) Monetary	1.4468	1.4504	1.4443	1.4264	1.4244	1.4103	1.3967	1.3787	1.3534
income	(22.89)***	(27.04)***	(20.51)***	(16.44)***	(19.73)***	(21.68)***	(24.05)***	(22.78)***	(30.42)***
(log) Savings	0.9054	0.8615	0.8230	0.7711	0.7239	0.5949	0.3565	0.2803	-0.0184
	(2.13)*	(4.8)***	(4.69)***	(4.89)***	(4.05)***	(2.73)**	(6.92)***	(1.78)	(-0.11)
(log) Savings	-0.0723	-0.0695	-0.0667	-0.0628	-0.0601	-0.0523	-0.0390	-0.0342	-0.0175
squared	(-3.09)**	(-6.86)***	(-6.1)***	(-6.69)***	(-5.88)***	(-4.4)***	(-8.31)***	(-3.45)**	(-2.14)*
Business inc. /	-0.2459	-0.0263	0.0364	0.0281	0.0060	0.0183	0.0022	-0.0169	-0.0061
Monetary inc.	(-0.06)	(-0.05)	(0.13)	(0.15)	(0.04)	(0.16)	(0.02)	(-0.17)	(-0.09)
Household	-0.0043	-0.0104	-0.0185	-0.0157	-0.0174	-0.0149	-0.0101	-0.0068	-0.0024
size	(-0.18)	(-0.45)	(-0.57)	(-0.56)	(-0.76)	(-0.7)	(-0.56)	(-0.43)	(-0.18)
HH size	0.0009	0.0013	0.0019	0.0014	0.0014	0.0011	0.0006	0.0003	0.0001
squared	(0.63)	(0.64)	(0.62)	(0.7)	(0.93)	(0.74)	(0.52)	(0.3)	(0.12)
Employee	-0.0772	-0.0544	-0.0249	-0.0220	-0.0251	-0.0211	-0.0666	-0.0515	0.0005
	(-1.37)	(-0.65)	(-0.36)	(-0.3)	(-0.38)	(-0.35)	(-1.34)	(-1.18)	(0.02)
Inst. not	0.0762	0.0743	0.0572	0.0677	0.0483	0.0214	0.0118	-0.0014	-0.0035
managed by govt.	(0.43)	(0.13)	(0.06)	(0.26)	(0.22)	(0.1)	(0.11)	(-0.02)	(-0.07)
Nuclear	-0.0445	-0.0367	-0.0292	-0.0303	-0.0357	-0.0385	-0.0309	-0.0218	-0.0058
family	(-0.8)	(-1.01)	(-0.75)	(-0.79)	(-0.87)	(-1.04)	(-0.92)	(-0.81)	(-0.35)
Own house	-0.0005	-0.0234	-0.0170	-0.0191	-0.0141	-0.0158	-0.0060	0.0003	0.0018
	(-0.01)	(-0.6)	(-0.43)	(-0.52)	(-0.42)	(-0.56)	(-0.26)	(0.01)	(0.12)
Constant	-7.5670	-7.3243	-7.0722	-6.6603	-6.3737	-5.6690	-4.4014	-3.9226	-2.3741
	(-3.55)***	(-7.22)***	(-6.69)***	(-5.68)***	(-5.67)***	(-4.39)***	(-6.68)***	(-3.87)***	(-2.85)**
N	6704	6704	6704	6704	6704	6704	6704	6704	6704

z statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 5 – Quantile Treatment Effects by Decile

Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure

A.2 Figures

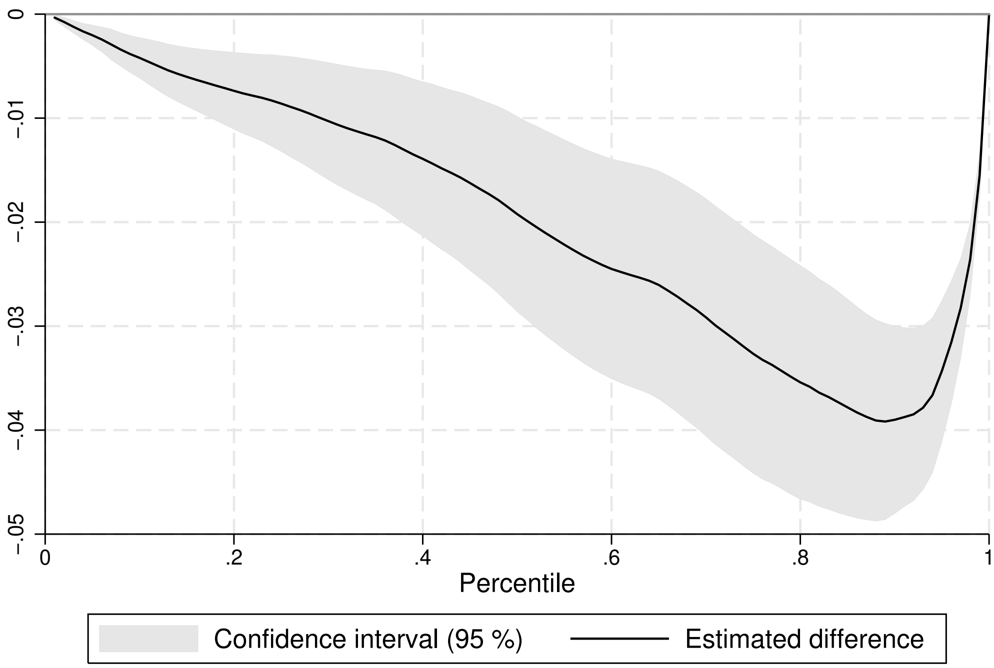

Figure 1 – Difference between the Lorenz curve of households that use credit card and those that do not use them
Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure
Note: The Lorenz curves are computed dropping the top and bottom 1% of sample observations, using the Distributive Analysis Data Package developed by Araar and Duclos (2007).

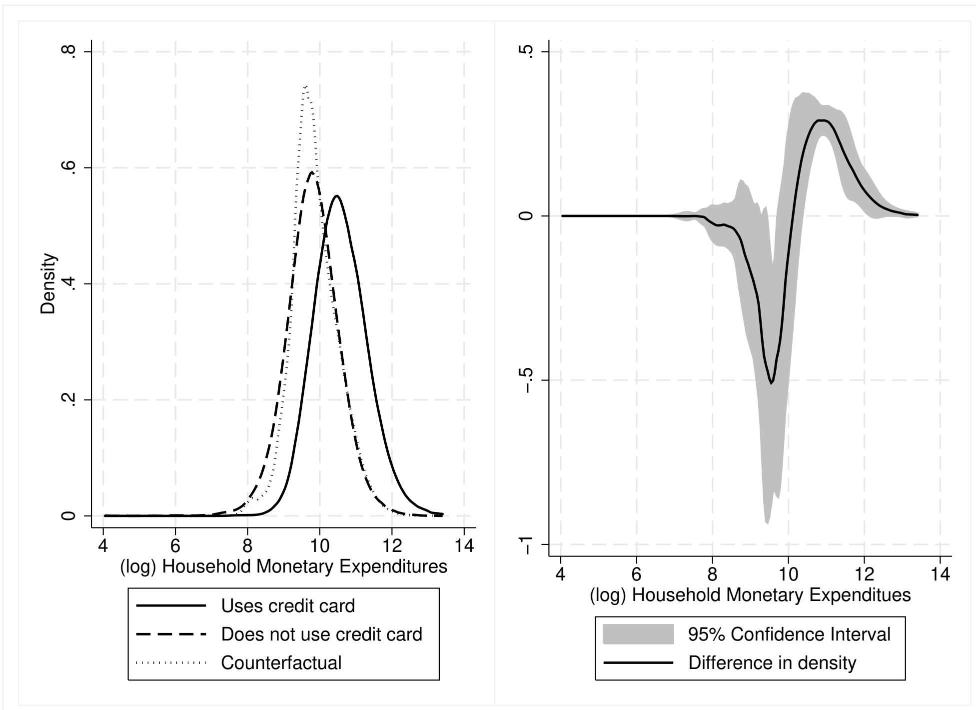

Figure 2 – DiNardo, Fortin and Lemieux Decomposition
Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure
Note: The regressors in estimation of the propensity score of using a credit card are years of schooling, household size, (log) monetary income, (log) savings excluding housing, health and education expenditures and its square, and indicators of whether the household head works is employed by an institution not managed by the government, whether the household is located in a municipality with a high or moderate margination index, and whether it receives government transfers. The confidence interval on the right panel was estimated by bootstrapping the standard errors of the density difference.

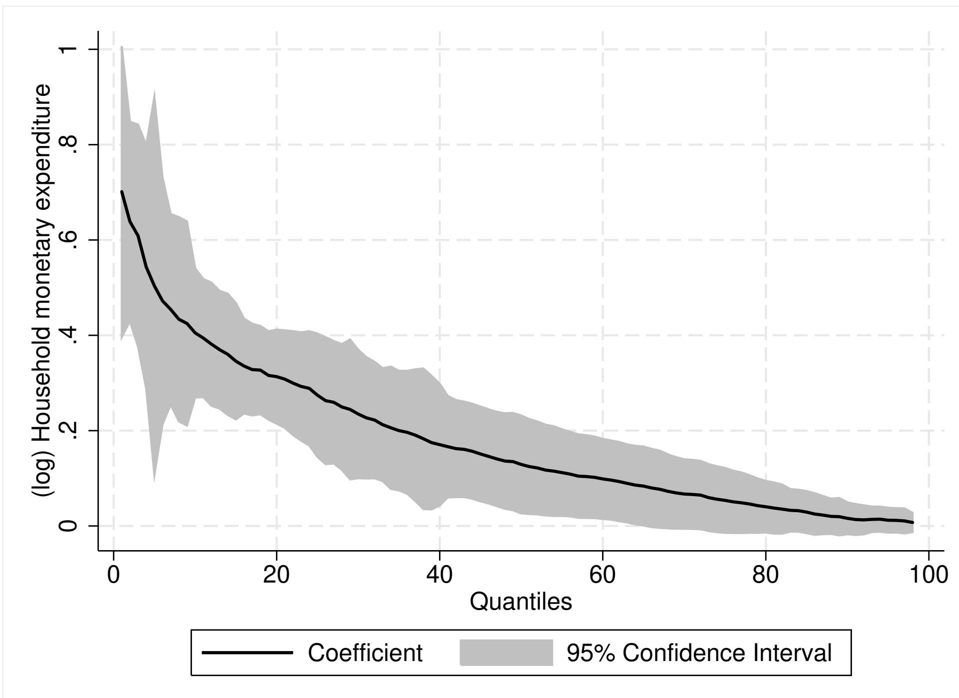

Figure 3 – Impact of use of credit card on (log) household expenditures by quantile
Source: Author's elaboration based on data from the 2010 Mexican Survey of Household's Income and Expenditure