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Why Do Formal Credit, Informal Credit, and both Types of Credits Coexist as Consumer Choices?

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Abstract

We analyze why formal credit, informal credit, and both types of credits coexist as consumer choices. We construct a model in which the households pay a fixed cost to access each type of market and face a market particular interest rate. The model induces a cost curve that defines an optimal, systematic sorting into credit types. The cost curve establishes that it is optimal to have informal credit when credits are small and formal credit when credits are relatively large. When using an intermediate amount of credit, the household finds it optimal to have both types of credits. After presenting the model, we use data from a pseudo-experimental, exogenous price variation spanned by a governmental intervention in Mexico to test the parametrization of the model and quantify comparative statics exercises arising from it.

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1 Introduction

Mexico has a banking system that provides financial services to a relatively reduced number of big firms and high-income individuals, while there is a relatively high number of medium to small firms and millions of low-income individuals without access to basic financial services (Castañeda et al., 2011). The Mexican government has undertaken several initiatives to ensure access to financial services for low-income individuals, such as the Program to Strengthen the Popular Credit and Savings Sector (PCSS). However, the success of such programs depends on the individuals' effective transition from informal to formal financial markets. In this paper, we investigate how people have transitioned from informal to formal credit markets after the aforementioned intervention by the Mexican government.

Our research question is straightforward: which hypothesis, costs or preferences, has a higher contribution in explaining consumer behavior regarding the choice of formal versus informal credit? To answer this question, we consider in our analysis the types of credit portfolios that agents choose: only formal credit, only informal credit, and both types. First, we define formal credit as one granted by a tax-filing institution that complies with financial sector regulations.This category includes credit granted by the full range of institutions in terms of size, from the smallest credit unions to the biggest banks.

The rest of the credit that exists in the sample is labeled informal credit and is granted by institutions that do not comply with the aforementioned regulation; that is, money lenders, friends, family, etc. Second, we construct a simple representative household model in which there is a fixed cost to access each type of market. Once the household pays this cost, it has access to a particular credit market, in which the household faces a given interest rate. This particular interest rate is the parameter that characterizes the variable cost for credit granted by this market.[1]

As a rational decision maker, the household is a cost minimizer. Our simple household model induces an optimal cost curve that defines the regions in which each credit type is optimal; i.e., the optimal sorting into the different credit options. We parameterize this model in a way such that each credit type is optimal in a specific interval. This cost curve establishes that it is optimal for a representative household to have informal credit when credits are relatively small and formal credit when credits are relatively large. When the amount of credit is of intermediate value, a representative household finds it optimal to have both types of credits. This induces a systematic, optimal sorting of the households in the credit market. Since both types of credits are optimal in this intermediate interval, some households will choose the informal credit while others will choose the formal one, explaining their empirical behavior.

After presenting our model, we use data from a four year longitudinal survey carried on by the Mexican government to study the impact of PCSS with two purposes: (1) to test the parametrization of the model; and, (2) to exploit its pseudo-experimental design on price variations to quantify comparative statics exercises. We find that the model parametrization adequately fits the data. Then, we use pseudo-experimental price variations to calculate difference in differences (diff-in-diff) estimates of the price elasticities in each credit market.

[1] One way to interpret the credit choice in this context is as a *bundled decision*. Ehrlich and Becker (1972) is a classical paper on bundled choices, in which individuals simultaneously decide to have *self-insurance* and *self-protection*.

This enables us to quantify the comparative statics that arise from the model.

The rest of the paper is structured as follows: Section 2 presents the model, Section 3 describes the data, Section 4 discusses the estimations and the results. Finally, in Section 5 we offer our concluding remarks.

2 Model

We develop a representative household model of credit choice. As a rational decision maker, the household minimizes costs when making its choice of credit type. The cost that the household pays for a credit has two components: one fixed and one variable. We think of the fixed cost as the monetary amount that the lender requires from the household as collateral in order to get a credit.[2]

The household accesses a credit type and faces a particular interest rate related to its choice, which implies a different variable cost function for each credit type. Let f, i, and b index, respectively, the three types of credits we consider: only formal credit, only informal credit, or a mix of both formal and informal credits; c denotes the credit units the household gets.[3] The credit type j has a fixed cost κ_j and a variable cost ζ_j. Hence, in order to access the j^{th} market, the household has to pay a fixed cost κ_j and a price ζ_j for each unit of credit it acquires; i.e., it faces a fixed interest rate per credit unit: if it obtains c units of credit it has to pay back to the lender $\zeta_i c$. The total cost function of credit j is, thus, $C_j(c) = \kappa_j + \zeta_j c$.

We order the parameters of the model according to Condition (1). With this ordering, informal money lenders require a lower fixed cost to grant a credit. We assume that the formal credit institutions require the highest fixed cost. When the household accesses both types of credits, it pays a cost that is in between these two fixed costs. The order of the interest rates follows from the discussion above and is also stated in Condition (1). Figure 1 displays the optimal cost curve, which is the envelope of the cost curves for each credit type.

$$\kappa_i < \kappa_b < \kappa_f, \ \zeta_i < \zeta_b < \zeta_f \tag{1}$$

$$\frac{\kappa_i}{\zeta_i} > \frac{\kappa_b - \kappa_i}{\zeta_i - \zeta_b} > \frac{\kappa_f - \kappa_b}{\zeta_b - \zeta_f} \tag{2}$$

The model induces a cost curve that defines an optimal, systematic sorting into the credit types. For a credit of less than ρ_i units it is optimal to have an informal credit. As the credit amount increases, it pays a higher fixed cost but a lower variable cost. This process has two stages: having both credit types and having only formal credit. It could be the case, as in the segment $[\rho_i, \rho_f]$, that it pays a medium fixed cost, κ_b, and obtains a medium

[2]For simplicity, we assume that the agent has only one asset. Put differently, we think of the asset as the sum of all the assets that the household has. This assumption can be dropped without affecting the conclusions of the model.

[3]Along with the type of credit used, an important dimension to consider is the length of use of each type of credit, which may affect variable costs and even the household's choice of credit. However, a dearth of information on the length of loans combined with short-term follow-up prevent us from considering this dimension.

variable cost per credit unit, ζ_b. Finally, there is a threshold that defines when it is optimal to start having only formal credits, i.e., credits higher than ρ_f.[4]

3 Data

Since 2004, the Mexican government has run the PCSS through two agencies: Bansefi and Sagarpa. This program has three main objectives: (i) to stimulate formal credit and savings among all the individuals in the population; (ii) to provide financial education as an instrument for financial inclusion; and, (iii) strengthen the provision and distribution of non-banking governmental services. Through this program, the Mexican government provides support in two ways: (i) the clients that have a non-banking account with Bansefi are supported with subsidies during the first year; and,(ii) the government completely covers a diagnosis of non-banking institutions in order to evaluate their profitability. Appendix A.1 provides details on the sample, attrition, and sampling method.[5]

In the context of the model explained in Section 2, what the "pseudo-experimental" intervention tries to do is to lower the cost of formal credit. Roughly, its aim is to widen the households' access to formal credit by expanding supply and by subsidizing demand. This causes a drop either in κ_f and κ_b, the required fixed cost to access the formal market through only formal or through both types of credits, or in the interest rates paid in the markets that involve formal credit, ζ_f and ζ_b. In both cases, the total cost that the household pays for a credit drops.

4 Empirical Strategy

Had households in the treatment group in 2004 been statistically equal in mean observable characteristics to the ones in the control group, we would have been able to use mean-based estimators to assess the average treatment effect of the intervention, interpreting the intervention as described above (i.e., considering the "pseudo-experimental" design of our data). However, Tables A.2 and A.3 show that the two samples differ in observable characteristics. Then, we make use of a basic matching estimator to control for the initial differences between the treatment and control groups.

We think of the intervention as a "pseudo-experimental", exogenous price variation: the treatment lowers the price of formal credit in both of its iterations (only formal, formal and informal) in order to affect the credit status of the control group. This design allows us to quantify the comparative static exercises found below. Moreover, we evaluate the parametrization of the model using the same econometric framework.[6] We estimate the model in (3) through a matching, diff-in-diff approach. We need a matching technique because the intervention fails to be random, as stated above. In particular, we use an inverse

[4] Note that the model does not characterize a utility maximizing framework in which the agent chooses a kind of credit. It defines the ranges in which each kind of credit is optimal in a cost minimization framework.

[5] The link for the data appendix is `http://www.jorgeluisgarcia.com/research/`.

[6] Before deciding which credit to have, households decide whether they have credit or not. Thus, any estimation presented henceforth includes a polynomial function on the empirical propensity score of having credit (by year) to avoid selection bias. For details on this correction see Heckman (1990).

probability weighting scheme (IPW) to match the control and the treatment groups when estimating the parameters of the following equation.[7]

$$c_{it} = \beta_1 + \tau_i + \beta_2 r_{2,it} + \beta_3 r_{3,it} + \beta_4 r_{4,it} + \Delta_2 r_{2,it} \cdot T_i + \Delta_3 r_{3,it} \cdot T_i + \Delta_4 r_{4,it} \cdot T_i + z_{it}\delta + \varepsilon_{it} \quad (3)$$

where τ_i is a household fixed effect; $r_{k,it}$ is a time dummy variable for the surveyed periods 2005, 2006, and 2007 and indexed by 2, 3, 4, with baseline as 1; T_i is a dummy variable indicating if the household is in the treatment group; z_{it} is a vector of household observable characteristics; and ε_{it} is a random term. Finally, c_{it} takes the values 1, 2, 3 for only informal credit, both types of credit, and only formal credit, respectively.[8] This order is induced by the model in Section 2. The subindices of the variables are as usual: i indexes household and t indexes time.

4.1 Parametrization Test

Before going forward into the analysis of the model, we evaluate its parametrization by testing the order it induces. Section 2 presents a model that rationalizes one of the possible six orders that only informal credit, both types of credit, and only formal credit could have. Then, in order to evaluate how well the model explains the data, we compare the model's fit to the fit of the other five possible models. Table 1 presents the three most popular measures of fit for a linear model, R^2, $Adjusted\ R^2$, and $Pseudo - R^2$.

Table 1: Model's Fit

Model	R^2	$Adjusted\ R^2$	$Pseudo - R^2$
1	0.083	0.080	0.183
2	0.052	0.048	0.087
3	0.076	0.073	0.045
4	0.076	0.073	0.045
5	0.052	0.048	0.087
6	0.083	0.080	0.183
N	5,809	Number of Clusters	2,932

Note: the labels are the following: Model 1 (=1, informal credit; =2, both types of credits; =3, formal credit); Model 2 (=1, informal credit; =2 formal credit; =3 both types of credits); Model 3 (=1 both types of credit; =2 informal credit; =3 formal credit); Model 4 (=1 formal credit; =2 informal credit; =3 both types of credit); Model 5 (=1 both types of credit; =2 formal credit; =3 informal credit); Model 6 (=1 formal credit; =2 both types of credit; =3 informal credit). Note, however, that Model 1 and Model 6 should have an identical fit because the dependant variable in Model 6 is a linear transformation of the dependent variable in Model 1. The same happens with Model 2 and Model 5, and Model 3 and Model 4, respectively.

Table 1 shows that Model 1, which respects the order induced by the theoretical Model developed in Section 2, adequately fits the data. Table 2 considers a 200-fold cross validation procedure: we evaluate the fit of each model 200 times through a "leave k^{th} out procedure", using mean absolute errors (MAE) as the measure and compute a mean difference t-test. The results point in the same direction: Model 1 correctly fits the data.

[7] We calculate the proportion of households that would be in the treatment group based on the regressors listed in Table A.3 except for interest rate. We ignore the latter because we observe it for less than 3,000 observations out of the 17, 233. The IPW estimation should not be affected to a great extent by doing this because we have a considerable set of covariates (see Wooldridge, 2007).

[8] This model is a non-parametric (or linear) version of the ordered non-linear models in the literature such as the ordered probit or ordered logit.

Table 2: 200-Fold Cross-Validation, MAE

Test	Mean MAE, Model 1	Mean MAE, Alt. Model	t	$p-value$
Model 1 vs. Model 2	0.493	0.504	-3.493	0.001
Model 1 vs. Model 3	0.493	0.954	-125.865	0.000
Model 1 vs. Model 4	0.493	0.954	-121.327	0.000
Model 1 vs. Model 5	0.493	0.504	-3.470	0.001
Model 1 vs. Model 6	0.493	0.492	0.002	0.978

4.2 Comparative Statics

The intervention generates an exogenous price variation. As discussed before, this price variation could imply perturbations either in the fixed cost parameters or in the variable cost parameters that involve formal credit. We consider the case of variations in the variable cost parameters.[9] Table 3 shows how the relevant parameters of the variable cost change from 2004 to 2007.

Table 3: Estimated Parameters of the Model

Parameter/Credit Type	2004	2007
ζ_f	0.297	0.262
	(0.182)	(0.183)
ζ_b	0.367	0.2974
	(0.235)	(0.183)

Note: estimates are sample means across control and treatment samples. Standard errors are in parenthesis.

We are not able to state that the changes in the parameters are exclusively a consequence of the intervention. However, we can say that some of the variation does respond to the program and proceed with quantifying the comparative statics exercises. For both groups the interest rates in the formal credit market drop, either when they have only formal credit or when they have formal and informal credits. In terms of the model, the intervention reduces the slopes of the credit cost functions c_f and c_b, respectively. Graphically,

The dashed lines represent the new cost functions. Under Condition (1) and (2), the new optimal cost curve implies lower values for both ρ_i and ρ_f. Hence, after the policy was implemented, formal credit is optimal in a wider interval of the total credit amount. It is so because the intervals for only informal credit and both formal and informal credits decrease. The model predicts that, after the intervention, having informal credit is still optimal, although in a smaller interval.

A test for this prediction is a transition matrix between credit types from 2004 to 2007.[10] Table 4 shows that matrix for the whole sample.[11] The households that have formal credit in 2004 transition, mostly, to formal credit in 2007. We are able to say that there is persistence in the formal credit market, up to a proportion of .735. This is consistent with the fact that only formal credit is optimal in a wider interval in 2007 compared to 2004.

[9] The conclusions from the comparative statics on the fixed costs are identical.

[10] There is a relevant market variable that is also affected by the intervention: the number of suppliers. Unfortunately, we do not have dynamic data on the number of suppliers.

[11] Table 4 also shows the transition matrices for the treatment and control groups. The only irregularity that we find here is that the proportion that of transition from only formal to both types of credit is relatively high for the control group. The next subsection analyzes whether this effect is significant through by the price elasticities after the intervention.

Figure 1: Comparative Static Exercise

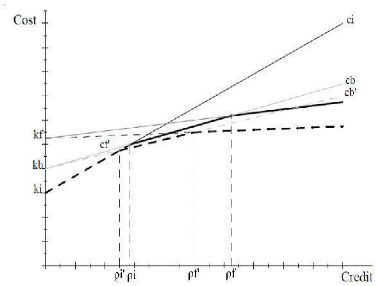

Table 4: Transition Matrix 2004-2007

		2007											
		Full Sample				Control				Treatment			
2004		Formal	Both	Informal	Total	Formal	Both	Informal	Total	Formal	Both	Informal	Total
	Formal	0.735	0.263	0.002	1	0.578	0.407	0.015	1	0.753	0.247	0.000	1
	Both	0.392	0.592	0.016	1	0.264	0.714	0.023	1	0.495	0.495	0.011	1
	Informal	0.212	0.731	0.058	1	0.171	0.771	0.057	1	0.294	0.647	0.059	1

The households that used both types of credits do not often transition to only informal credit. The proportion of transition to only formal credit is relatively higher, which is consistent with the model because, as ρ_f changes to ρ'_f, people who used to use both types of credit change to using only formal. This happens because the interest rate (or the fixed cost, or both) in the only formal credit market is low enough to make this decision optimal. There is a relatively high proportion having both credits in 2007, compared to the households that had formal credit in 2004. In the model, this can be interpreted as a straightforward consequence of ρ_i being lower than ρ_i. Moreover, there is a higher proportion of those directly jumping to only formal credit, which is also consistent with the model's predictions.

4.3 Price Elasticities

We interpret the average treatment effect (ATE) of the intervention as a price elasticity with respect to each credit type. In a longitudinal design, the diff-in-diff estimator $\triangle_k$ is the ATE. It subtracts the difference in year k dependent variable's mean from the baseline year dependent variable's mean of the treatment group from the same difference for the control group. If the outcome of interest is dichotomous, theis diff-in-diff estimates the change in the proportion of households having a certain type of credit equal to 1.

There is a price elasticity for each credit type. To obtain them, we create 3 different outcome dummies and estimate the parameters of (4).[12] The structure of the RHS of this equation is identical to the one of (3) and, in the LHS, c^l_{it} is an indicator of credit type l=only informal, both types of credit, only informal.

$$c^l_{it} = \beta_1 + \tau_i + \beta_2 r_{2,it} + \beta_3 r_{3,it} + \beta_4 r_{4,it} + \Delta_2 r_{2,it} \cdot t_i + \Delta_3 r_{3,it} \cdot t_i + \Delta_4 r_{4,it} \cdot t_i + z_{it}\delta + \varepsilon_{it} \quad (4)$$

[12]This approach is analogous to the one used when estimating (3) using a parametric ordered model: it captures the marginal effect on the proportion of households holding each type of credit. In that case, as in this, there are as many marginal effects per covariate as categories.

By the construction of the dependent variables, $\hat{\Delta}_k$ is an estimate of the change across groups in the proportion of households having a certain type of credit from the baseline to year k.[13] Thus, $\hat{\Delta}_k$ is negative.

Table 5: IPW ATE Diff-in-Diff Estimations

Dependent Variable	Formal Credit	Both Credits	Informal Credit
Baseline Mean: Control/Treatment	.171/.565	.795/.429	.034/.007
Round 2005*Treatment	-0.015	-0.027	0.042***
$\hat{\Delta}_2$	(0.031)	(0.034)	(0.012)
Round 2006*Treatment	-0.080**	0.057	0.023
$\hat{\Delta}_3$	(0.039)	(0.041)	(0.016)
Round 2007*Treatment	-0.170***	0.163***	0.006
$\hat{\Delta}_4$	(0.037)	(0.040)	(0.016)
R^2	0.081	0.069	0.015
Adjusted R^2	0.078	0.065	0.012
N	5,809	5,809	5,809
Number of Clusters	2,932	2,932	2,932

Note: Robust Standard Errors in Parenthesis (clustered by households). *** p<.01, ** p<.05, * p<.1

The estimation results in Table 5 point in the same direction as the comparative static exercises. There is a positive, significant effect of providing non-banking governmental institutional credit infrastructure in the choice of households between the formal and the informal credit markets. The price elasticities with respect to the intervention indicate that households transition to the formal market in different ways: either exiting the only informal credit category or exiting the both types of credit category. This induces significant increases in the proportion having only formal credit. In the model, this is summarized by the changes in ρ_i and ρ_f induced by the price variation.

5 Conclusions

Our analysis helps us to understand the systematic, efficient sorting of the agents in the credit market, which is theoretically helpful in the understanding of discrimination, information asymmetries, and other market failures that are continuous targets of public policy.

The quantification of the comparative static exercises arising from the model indicates that when households are granted access to the formal credit market: (i) the proportion having only formal credit considerably increases through the years that we study; (ii) the proportion acquiring informal credit decreases, through a smaller proportion of households having only informal credit or both formal and informal credits. We have shown that the cost hypothesis explains transition between formal and informal credit markets, although we cannot ignore the preference hypothesis since some consumers stay in the informal market by choosing only informal credits or both types of credits.

In order to provide a better answer to this research question, data from a better experimental design are needed. Also, building a theoretical model of how agents transition from the informal to the formal credit markets and do some calibration exercises to contrast them with our current findings could be another avenue worth exploring.

[13] This follows from the fact that the dependent variable is a dummy.

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