Reporte de Estabilidad Financiera

Septiembre de 2010

Bank Provisioning and Microcredit

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Working Paper

January 2011

Abstract

In this paper we develop a banking model to study the traditional credit and the microcredit markets. We suppose a monopolistic traditional bank that specializes in screening potential debtors based on their risk profile and a microcredit bank that focus on monitoring the riskier profile customers. The model is calibrated with Colombian financial data. The results show that when banking provisioning depend only on the screening level, a significant portion of the risky debtors are left out of the financial system and the microcredit bank would not operate in certain market conditions. Nonetheless, when we consider provisions that include monitoring considerations, the microcredit bank would be profitable for the different debtor risk profiles, and its optimal monitoring level is higher in comparison with the one chosen by the traditional bank.

JEL Classification:D20, D23, D42, G21 and G28.

Key words: Bank Provisioning, Microcredit banking model, Regulation and risk profiles, debtor screening, debtor monitoring.

*We thank Agustín Saade for his useful ideas in the inception of this paper, his contributions are used throughout. We thank the people from the Financial Stability Department of Banco de la República for their useful comments and valuable recommendations. We are particulary in debt with Estaban Gómez and Nancy Zamudio. The opinions expressed in this article are those from the authors and do not necessarily represent those of Banco de la República or its Board of Directors. Any remaining mistakes and omissions are solely our responsibility. All comments are welcome.

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1 Introduction

Microcredit and micro finance have increasingly gained importance in the financial systems around the world. The first experiments in this direction, carried out by countries like Bangladesh, India and Brazil during the seventies, successfully showed the viability of financial institution that focus on low income population and exhibited positive results in terms of profitability and high repayment rates on the loans (Navaja and Tejerina (2007)). Initially, providing credit to the portion of the population that was shed out of the traditional banking system seemed as a government, multilateral agents and non-governmental organizations responsibility. Nonetheless, as the microcredit business became profitable, the private sector started showing interest in investing in these type of banking system.

The microcredit business differs significantly from the intermediation activities carried out by traditional banks. These differences are closely related with the idiosyncratic characteristics of its objective population. In general terms, microcredit is defined as the set of small value loans issued to low income population that usually would not have access to the traditional banking system due to their lack of collateral.

The Basel Committee recognizes that credit risk of the microcredit loans has different determinants than traditional ones, and suggests that a distinct provision and capital requirement scheme should be impose (Basel Banking Supervision Committee (2010)). In particular, the Committee identifies a set of characteristics such as the short term and small value of the loans, the lack of guarantees, the accelerated deterioration of the credit rating and the risk of geographical contagion, as some of the main features that influence the repayment level of the microcredit loans. Micro finance technology instruments are meant to mitigate this risk by making a close follow up of the debtors and their financial conditions. It is therefore desirable to consider some measure of this monitoring effort in the development of a regulatory framework for microcredits.

In Colombia, microcredit was introduced formally quite recently. It was defined and regulated by the Financial Superintendency (Superintendencia Financiera de Colombia) on 2000[1]. Although currently microcredit only represents 2.5% of the total loans (Banco de la Republica (2010)), its has gained importance as it has been growing quicker than the other types of credit. Moreover, there is general consensus about the socioeconomically benefits of fomenting this type of credit and broadening its access (Dermiguç-Kunt (2007))[2].

Due to its intrinsic characteristics, microcredit is considered more risky than the other types of credits. The uncertainty about the future net flows of the microcredit customers and the lack of collateral, increase the loans' repayment risk. To ameliorate the effects

[1] Ley 590 de 2000 and modified by Ley 905 de 2004.

[2] For a more thorough analysis of the current situation of microcredit and micro finance in Colombia we highly recommend (Banco de la República *et al* (2010)).

of the large information uncertainty and asymmetry, microcredit institutions have to divert a big portion of their resources towards monitoring the evolution of their customers (Banco de la República *et al* (2010)). In contrast, traditional banks usually focus on screening their potential clients in such a way that only future debtors with ideal guarantees and good credit history, are accepted.

Based on the above discussion, we develop a simple Monti-Klein microeconomic model (Klein (1971) and Monti (1971)) that reflects the traditional and the microcredit banking systems, to study the role played by different bank provisioning regulatory frameworks. The model is calibrated using Colombian financial data. The results show that if bank provisioning only considers the risk profiles of the debtors based on its screening activities, most of the risky debtors are left out of the financial system and the microcredit bank would not operate under some market conditions. In contrast, if provisioning takes into account both screening and monitoring, the microcredit bank is profitable for any risk profile debtors and therefore an otherwise unprovided population, would have access to the financial system.

The remaining of this paper is organized as follows: in section 2 we present the model, in section 3 we describe the main calibration strategies, in section 4 we present the results and in section 5 we draw some conclusions and recommendations.

2 Model

In this section we describe the model that represents both the traditional and the microcredit bank optimization problem. The main objective is to show that both banking systems are profitable under some market conditions and that provisioning regulation should not be the same for them due to the distinct nature of their businesses.

In general, a traditional bank focuses on screening and scoring the creditrisk profiles of their clients before issuing loans. They spend more resources on identifying low risk customers, than the ones used in monitoring the credit after it has been issued. In contrast, a microcredit bank usually accepts clients that are rejected by a traditional bank, and focus its efforts closely monitoring them to assure the repayment of the credits issued.

In the model we denote the traditional bank with T and the microcredit bank with M. The model is a modification of the Monti-Klein model of a monopolistic bank[3]. Let s denote the screening level and m the monitoring level chosen by a given bank. Suppose that the microcredit bank has a fixed minimum level of screening $\underline{s}$ and the traditional bank has a minimum level of monitoring $\underline{m}$. We suppose that screening level s is a continuous linear map that associates traditional credit rating $\Omega := \{A, B, C, D, E, F\}$ with the set of real

[3]See Freixas and Rochet (1998)

numbers $\mathbb{S} \in [0,5]$ such that $s(F)=0$, $s(E)=1$, $s(D)=2$, $s(C)=3$, $s(B)=4$ y $s(A)=5$ [4].

We model the loans repayment proportion as a function that has the following properties,

$$
\begin{aligned}
\lim_{m\to\infty} p(m,s) &= 1, \qquad \forall s \in \mathbb{S} \\
\lim_{s\to\infty} p(m,s) &= 1, \qquad \forall m \in \mathbb{M} \\
p(0,0) &= 0 \geq 0
\end{aligned}
$$

In particular from the above assumptions, the repayment function for the traditional banks is given by $p(\underline{m},s) \geq 0$,$\forall s \in \mathbb{S}$ and for the microcredit bank $p(m,\underline{s}) \geq 0$, $\forall m \in \mathbb{M}$ [5]. Furthermore, we suppose the repayment function is,

$$p(m,s) = 1 - e^{-(m+s)},$$

Note that since there is freedom in measuring the monitoring level, we scale it in a way that it replicates the risk profiles of debtors when considering its effect over the repayment function. Therefore a monitoring level of $m=5$ would have the same effect on the repayment function as a screening level of $s=5$, the mapping of an A credit rating debtors.

2.1 Credit Demand and Deposit Supply

Following the Monti-Klein model, the monopolistic banks confront a demand function for loans $L(r^b)$ and supply function for deposits $D(r^D)$, where $b \in \{T,M\}$ denotes de bank's type.To simplify the model, we assume that credit demand and deposit supply functions are linear. Hence, we can compute the inverse credit demand and deposit supply functions a

$$r^b(L) = \overline{r}^b + \gamma^b L_b \tag{1}$$

$$r^D = \underline{r} + \gamma^D D, \tag{2}$$

[4]Credit rating F would reflect debtors with a risk profile such that they are not able to access the financial system because of their idiosyncratic conditions.

[5]Note that function $p(m,s)$ is not the joint distribution of m and s. It is a function that maps these decision variables onto the space $[0,1]$ such that it represents the repayment proportion of the credits issued.

2.2 Traditional Banks

In the maximization problem for traditional banks we impose the restriction $s \in \mathbb{S}$. We suppose that screening acts as a filter, in such a way that the debtors accepted by banks resemble the final composition of the bank's portfolio[6]. This means that if a traditional bank chooses a screening level of $s = 5$, all of its loan portfolio would have a credit scoring A [7].

The traditional bank solves the following maximization problem by optimally choosing the net credit supply $L \geq 0$, the deposits' demand $D \geq 0$ and the screening level $s \in \mathbb{S}$.

The optimization problem of the traditional bank is[8]

$$\mathrm{Max}_{L,D,s}\Pi \quad = \quad p(\underline{m}, s)(1 + r^T(L))L - (1 + r(D))D - c(\underline{m}, s), \tag{3}$$

Subject to the budget constraint

$$(1 + \mathrm{Prov}(s, \underline{m}))L = D, \tag{4}$$

where $p(\underline{m}, s)$ is the repayment function when the monitoring level $\underline{m}$ is given, $c(\underline{m}, s)$ denote a cost function that depends both on monitoring and screening, $r^T(L)$ is the inverse of the credit demand function and $r(D)$ of the deposit supply function.

The budget constraint (4) shows that the sum of the total loans and the amount of provisions, should be equal to the deposits and the bank's equity. Notice that initially we suppose that bank provisions are dependent on both the screening level s and the monitoring level m. When we solve the model for the traditional banks we analyze two scenarios: one in which there are is no provisioning ($\mathrm{Prov}(m, s) = 0 \ \forall (m, s) \in \mathbb{M} \times \mathbb{S}$) and another in which provisioning depends only on the screening levels ($\mathrm{Prov}(m, s) = \mathrm{Prov}(\hat{m}, s) \ \forall \hat{m} \in \mathbb{M}$)[9]. In contrast, for the microcredit bank a third scenario is considered in which provisions depend on both monitoring and screening.

[6]The bank's portfolio consists of a combination of the different types of credits. More formally, we can represent this portfolio as a affine combination $\rho = \gamma_A A + \gamma_B B + \gamma_C C + \gamma_D D + \gamma_E E \in \hat{\Omega}$ such that $\sum_{i \in \Omega} \gamma_i = 1$ and $\gamma_i \in [0, 1]$

[7]Note that the function defined by s is surjective but not necessarily injective, since different affine combinations of types of credits could have the same screening level. We do not pretend to investigate how the bank chooses its portfolio (a non trivial issue) , but rather suppose that the decision variable is the screening level s.

[8]This optimization problem is solved using Kuhn-Tucker conditions.

[9]This provisions are in line with the current regulatory framework.

2.3 Microcredit Banks

The microcredit bank solves a similar maximization problem as the traditional bank, except that we suppose that its decision variable is the monitoring level m, taking screening $s = \underline{s}$ as given[10]. The monitoring level can be any positive number, $m \in \mathbb{M} = [0, \infty)$. Therefore the microcredit optimization problem is

$$\text{Max}_{L,D,m}\Pi \quad = \quad p(m, \underline{s})(1 + r^M(L))L - (1 + r(D))D - c(m, \underline{s}), \tag{5}$$

subject to the budget constraint

$$(1 + \text{Prov}(\underline{s}, m))L = D. \tag{6}$$

In this case we consider three types of budget constraints: where there is no provisioning, where provisioning depend only on screening and one in which both screening and monitoring levels are taken into account.

3 Calibration and Methodology

We calibrated the model to match some of the Colombian financial system data. Our main objective in this section is not accurately estimate the credit demand and deposit supply functions, but rather have an approximation of the parameters that might determine the linear relationship between the interest rates and equilibrium quantities. Additionally, based on the Colombia's current regulatory framework we fit a continuous provisioning function that depends on the screening s and monitoring m, and calibrate the parameters of a cost function based on the information related with the labor and administrative costs for both types of banks.

3.1 Credit Demand and Deposit Supply Functions

In order to calibrate the parameters in equation (1) and following Gattin-Turkalj (2007) we estimated a simple inverse credit demand function, assuming that the equilibrium amounts and interest rates reflect only demand factors[11]. In particular we suppose that the loan inter-

[10]Taking screening as given is supposing that the microcredit bank faces a given type of risk profile customers and decides the optimal amount of monitoring in order to increase their repayment.

[11]This is a debatable assumption since the equilibrium quantities also reflect the behavior of credit supply. Nonetheless, since we suppose debtors are price takers and banks are monopolists, it is reasonable to assume that the bank sets an interest rate based on the observed debtor's demand.

est rate depends on the amount of credit demanded L_b and other exogenous macroeconomic factors that on average determine $\overline{r_b}$ of equation (1). For the traditional banks we consider the commercial credit market and estimate the following equation using OLS [12]:

$$r_t^T = \alpha^T X_t^T + \beta^T r_{t-1}^T + \gamma^T L_t^T + \epsilon_t^T, \tag{7}$$

where $X_t^T = [1, IPI_t, IBR_t]'$ and IPI denotes the industrial production index calculated on monthly bases by the Department of National Statistics (DANE) and IBR the interbank rate calculated by Colombia's Central Bank (Banco de la República) . We use monthly data from March 2002 to August 2001 and take the logarithm of the commercial loans issued. The results from the regressions are presented below,

Table 1: Inverse Commercial Credit Demand Function Regression

Variable	Coefficient	t-statistic
$Constant$	0.049092	4.269936
IPI	0.000104	2.287487
IBR	0.183509	4.847803
L^T	-0.003569	-3.688066
r_{t-1}^T	0.847937	26.77454

Sources: DANE, Banco de la República and Superintendencia Financiera de Colombia. Authors' calculations.

As expected the commercial credit interest rate depends negatively on the amount of loans issued [13]. We calculate the elasticity parameter $\hat{\gamma}^T = -0.003569$. More production and an increase in the interbanking reference rate are associated with higher interest rates. The results also show that the one period autoregressive component of the regression is extremely important to determine the current interest rate behavior. Since the model developed here is static, we suppose that the exogenous variables assume the average value of the period studied. Hence, we can calibrate the parameter $\overline{r}^T$ of the simplified demand function (1) assumed in the model, by taking the expected value on both sides of equation 10 and replacing the average values for exogenous variables.

[12] Other variables where considered but where discard by the usual omitted variable test and in order to preserve the parsimony of the model. The complete results for the regressions are presented on Appendix B

[13] This partially validates the assumption that observed equilibrium interest rate correspond to demand function observations.

$$\overline{r}^T = \hat{\alpha^T} X + \hat{\beta^T} r^T = (0.04909, 0.0001, 0.18351) \begin{pmatrix} 1 \\ IPI \\ IBR \end{pmatrix} + 0.8479\ r^T$$
$$= 0.1865. \quad (8)$$

Similarly we apply the same procedure to the microcredit banking system. We estimate a OLS model to approximate the demand function for microcredit as follows,

$$r_t^M = \alpha^M X_t^M + \beta^M r_{t-1}^M + \gamma^M L_t^M + \epsilon_t^M. \quad (9)$$

We consider $X_t^M = [1, CPI_t, E_t]'$ as exogenous variables that affect the demand function for microcredit, where CPI denotes the Consumer Price Index calculate by DANE. The results from the regression are summarized in Table 2

Table 2: Inverse Microcredit Demand Function Regression

Variable	Coefficient	t-statistic
$Constant$	0.07163	3.3213
CPI	0.001292	3.76430
IBR	0.11264	2.4457
L^M	-0.034528	-3.49918
r_{t-1}^M	0.89053	25.6677
Adjusted R-squared	0.916663	
Number of observation	98	

Sources: DANE, Banco de la República and Superintendencia Financiera de Colombia. Authors' calculations.

Once again there is a negative sign of the coefficient associated with the microcredit loans issued, and the estimated parameter of equation (1) yields $\hat{\gamma}^M = -0.034528$.In this case, the CPI and the IBR have a positive relationship with the interest rate and once again the lagged value in the interest rate is a crucial determinant of its current value. Analogously to the previous case, we calculate the value for the parameter $\overline{r}^M = 0.442483$.

To calibrate the deposit supply function we follow a somehow similar procedure. We estimate the following inverse deposit supply function

$$r_t^D = \alpha^D X_t^D + \beta^D r_{t-1}^D + \gamma^D D_t + \epsilon_t^D. \quad (10)$$

The set of exogenous variables considered is $X^D = [1, IBR, ECI, NWI]$, where IBR denotes the interbanking rate, ECI is the expected consumption index calculated by FEDESARROLLO and NWI is the nominal wages index reported by DANE. The results from the regression are shown in Table 3.

Table 3: Inverse Deposit Supply Function Regression

Variable	Coefficient	t-statistic
$Constant$	-0.0411	-2.44529
IBR	0.16404	6.6282
IPN	0.0000846	3.0646
NWI	-0.0000122	-6.6595
D	0.002483	2.77982
r^D_{t-1}	0.79075	2.7798
Adjusted R-squared	0.986671	
Number of observation	98	

Sources: DANE and Superintendencia Financiera de Colombia. Authors' calculations.

The results of the regression show that the deposits rate depends positively on the amount of deposits supplied by households, hence the parameter from equation (2) is calibrated as $\hat{\gamma}^D = 0.002483$. An increase in the IBR or IPN is related to an increase in this interest rate, whereas, an increase in the nominal wages has a negative effect over it. Again we see that the effect of the lagged value of the deposit interest rate plays an important role in the determination of its current level. Following the same procedure explained above, we compute $\underline{r}^D = 0.01993$.

3.2 Provision Function

The current Colombian financial legislation sets the minimum provision level that applies to different types of credit depending on their credit risk scoring [14]. Loans are divided in five categories depending on their intrinsic credit risk and the time they are overdue. The five categories are:

- A Category or "normal risk"
- B Category or "acceptable risk, larger than normal"
- C Category or "sensible risk"

[14] The law that regulates the provision system is part of the financial organic law. In particular, Annex 2 of chapter II of *Resolución 100 de 1995* issued by the Colombian Financial Superintendency, specifies the minimum provision level required for each type of credit as presented in this paper. In the case of commercial loans this is calculated based on the Credit Risk Handling System (SARC), whereas for the microcredit loans no such system has been implemented yet.

- D Category or "significative risk"
- E Category or "non-repayment risk".

Usually banks calculate their provisions according to the expected losses given by an internal credit risk model previously approved by the Colombian Financial Superintendency[15]. Nonetheless, the regulator imposes the following provisioning percentages for microcredits and commercial credits[16]:

Table 4: Provisions

Category	Commercial	Microcredit
A	0.0153	0.028
B	0.03702	0.04
C	0.16005	0.2
D	0.3833	0.5
E	1	1

Sources: Superintendencia Financiera de Colombia. Authors' calculations.

As explained above, we consider screening level s as a continuous linear function that maps the banks portfolio onto $\mathbb{S} = [0, 5]$. For the construction of a provision function we fit a continuous curve that minimize the distance with respect to the observations presented in table 4 and has a rational basis[17]. The functions obtained for each type of credit is,

for commercial credits

$$Prov(s) = -0.254435 + \frac{1.25597}{s} \tag{11}$$

and for microcredits

$$Prov(s) = -0.215898 + \frac{1.24707}{s}. \tag{12}$$

In the case in which we the provision system includes monitoring and screening we suppose,

$$Prov(s, m) = -0.215898 + \frac{2.49414}{s + m}. \tag{13}$$

[15]In the colombia's regulatory framework there exists a general provisions that are not considered in this paper. In theory this would only shift the estimated provision curve upwards.

[16]As noted above, the comercial credit minimum provisions are calculated considering the SARC. In particular this credit risk system takes into account the size of the firm and the macroeconomic context. Also the categories that regulate provisions differ from the ones presented here. We calculated the matrix presented here using the credit rating homologation explained in Annex 3 of chapter II of *Resolución 100 de 1995* and assuming equal weights for each category, for large firms in the good macroeconomic scenario.

[17]We use the rational function basis $\left\{1, \frac{1}{x}\right\}$ to fit the curve.

3.3 Cost function

The cost function is modeled such that it reflects the monitoring and screening costs' behavior. If in practice screening costs are associated with filtering some type of risky debtors, one could think that marginally this costs are relatively constant. This means that distinguishing between an A and a B type debtor, is the same as comparing a D from an E type. Hence, it is reasonable to assume that the cost function $c(m, s)$ is linear on the screening level s. On the other hand, monitoring costs seem to increase more than proportionally as monitoring increases, because for a given screening level the resources spent on monitoring are marginally increasing. In particular we assume the following functional form,

$$c(s, m) = \kappa^b(m^{\rho_1} + s^{\rho_2})L^b. \tag{14}$$

From the previous discussion we suppose $\rho_1 = 1$ and $\rho_2 = 2$ [18]. We calibrate $\kappa = 0.001$ to illustrate the results [19].

The differences in the labor and administrative costs (LAC) between the traditional banking system and the microcredit banking system suggest that microcredit banks spend more resources in monitoring. Using data collected by the Colombian Financial Superintendency from January 2002 to July 2010, we compare these costs between the two banking systems. The data show that the microcredit banks' labor and administrative costs relative to their assets are more approximately 3.053 times higher in comparison with the traditional banks[20].

4 Results

In this section we present the main findings of the paper using the model calibrated with the colombian data as described in the previous section. We present the ROA -calculated as the bank's profits over its total loans- for both types of banks and compare them under different provisioning regulation scenarios.

In the case of the traditional bank, we find that the ROA_T is always greater when there are no provisions. This shows that when the available resources increase, the bank's profits grow more than proportionally in comparison with the increment in the credits issued (Figure 1). As the parameter $\underline{m}$ increases, the ROA_T initially grows for both scenarios showing that very

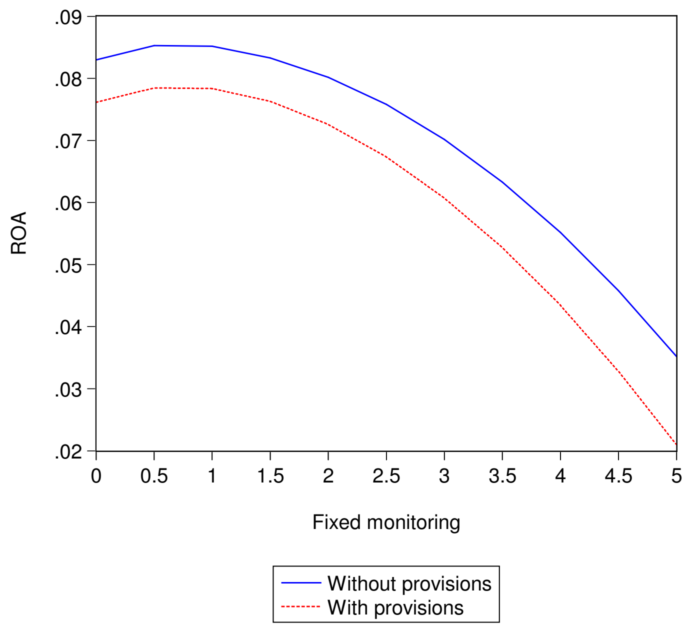
[18] If this parameters are reasonably modified, the main results of this paper do not vary qualitatively if $\rho_1 > \rho_2 \geq 1$.

[19] When κ is varied it mainly affects the level of the ROA^b of the banks, but the conclusions do not vary significantly.

[20] This calculation was carried out from January 2010 to July 2010, since it is a period where both assets and costs of the microcredit banks have stabilized.

low monitoring levels are not beneficial for the traditional bank. In fact the maximum ROA_T is attained for both scenarios near $\underline{m} = 0.71$. When provisions are imposed, the bank's profits are decreasing and eventually turn negative. This happens because the marginal costs of increasing monitoring, exceeds the marginal benefit[21].

Figure 1: ROA Traditional Bank



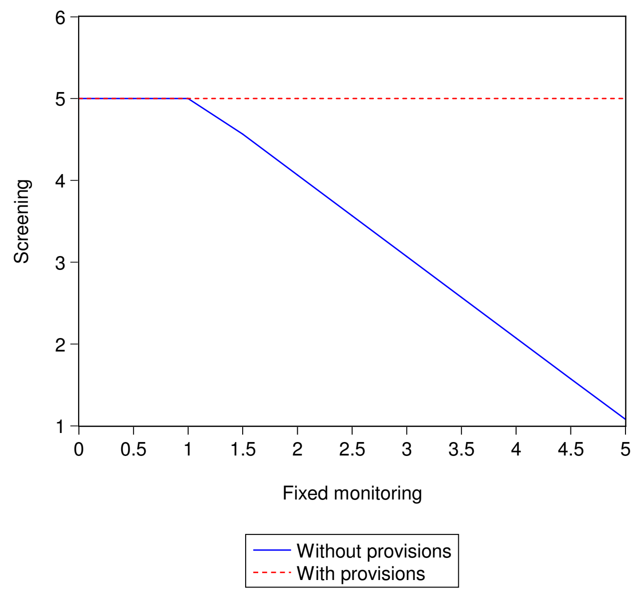
Source: authors calculations.

Figure (2) shows the optimal screening levels when the fixed monitoring parameter is changed. We observe that in the model with provisions, the optimal screening level is always at its maximum, this means that only the debtors that exhibit a low risk profile are accepted by the traditional bank (the ones that reflect an A credit rating). In contrast, in the model where there is no provisioning, as monitoring increases there is a substitution effect that leads to the decrease of screening. In fact when the monitoring parameter surpasses $m = 5$ the screening level is equal to zero (a screening level related with F credit type debtors).

The results for the microcredit bank are markedly different. Due to the higher average interest rates, the ROA_M is significantly higher for the microcredit model without provisioning in comparison with the ROA_T in the traditional model for the same scenario (Figure (1) and Figure(3)). Note that when no provisions are imposed, the risky profile debtors (associated with credit ratings E and F) would have access to the financial system through the microcredit bank and this bank will be highly profitable (Figure (3)). This is accompanied with high

[21]Note that for both scenarios, since the cost function $c(m, s, L)$ is unbounded and the repayment function $p(m, s)$ is bounded by 1, when $\underline{m} \to \infty$, the optimal values of credit supply and demand will tend to zero.

Figure 2: Optimal screening for the Traditional Bank



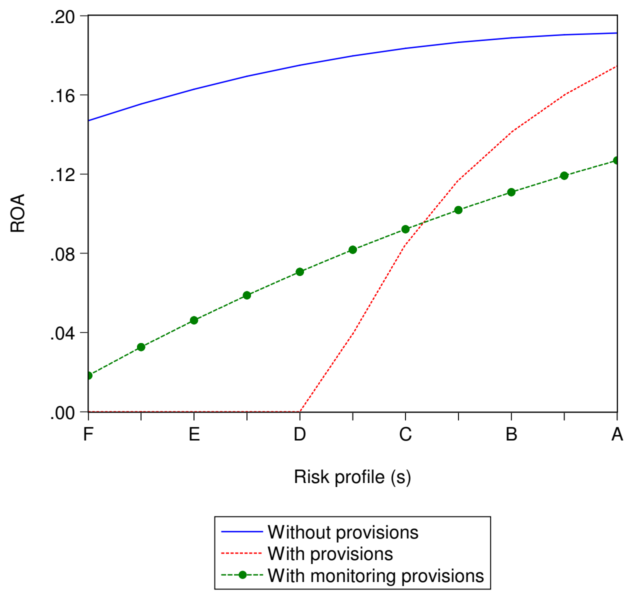
Source: authors calculations.

levels of monitoring that might be unattainable in practice [22]. The model with provisioning dependant on both screening and monitoring, exhibits a similar behavior. In this scenario, the microcredit bank is profitable for all risk type debtors (Figure(3).In contrast, the model in which provisions only depend on screening, the microcredit bank is unable to operate when the customers have risky profiles. In fact, only after their profiles replicate a portfolio with better credit rating than D, the bank starts issuing loans. This results show that a provision system that does not take into account the positive effect of monitoring on the repayment probabilities, can ruin the microcredit bank's business. If one wants to broaden the access to the financial system by extending credits to people with riskier profiles, its necessary to recognize the difference with the traditional banking system and accordingly apply distinct regulatory policies that enhance the intermediation activity instead of occluding it.

If the provisions include monitoring and screening, the optimal monitoring level is higher in comparison with the other two scenarios. This shows that a regulation focus in this manner would motivate microcredit banks to further increase the repayment proportions, favoring the financial system in general (Figure (4)) .

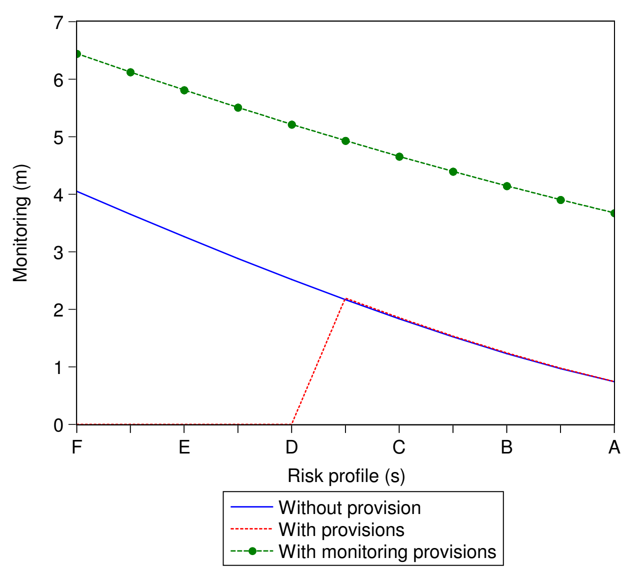
[22]The scaling of monitoring has been done such that its effect over the repayment proportion is the same as the effect of scoring (which is calibrated with the mapping into the credit rating space). Therefore if $m > 10$ it implies that the repayment portion is very close to one, $p(10, 0) = 0.9999546$. In practice achieving this repayments levels is unlikely.

Figure 3: ROA for the Microcredit Bank



Source: authors calculations.

Figure 4: Optimal Monitoring for the Microcredit Bank



Source: authors calculations.

5 Conclusions and Recommendations

In this paper we develop a simple microeconomic model to study traditional and microcredit banking systems. In particular we analyze the effect that different provision systems might have over both bank schemes. The results show that when the model was calibrated according to the Colombian financial data, the provisioning system that only takes into account the risk profiles of the debtors, prevents the access of some of them to the financial system and hinders the operation of microcredit banks given some adverse market conditions. In contrast when both monitoring and screening are considered, the microcredit bank is profitable for any type of debtor they face.

This model is a first step in studying the microcredit and traditional banks interactions. In fact, there are very interesting foreseeable extensions of the model. In the paper we intrinsically assume that the banking systems exist independently, hence there is no relation between them. A possible generalization of the model using game theoretic tools is to model the strategic interactions between potential debtors and the both types of banks. In a different direction, it is also important to further investigate the way banks compose their portfolio optimally such that it reflects a given credit screening. In this sense, not only the mean debtor but also the variance associated with the distinct risk profile might play an important role.

In terms of policy recommendations, the results of the model show that there are fundamental differences between the two type of banks business and consequently, different regulatory policies should govern over them. Ideally provisioning has to match the bank´s expected losses. Since the microcredit banks use micro finance technology to enhance their monitoring activity and elevate the loan repayment levels, this should be taken into account when thinking about a provisioning system for this type of banks. The model shows that this can broaden significantly the access to the financial system of a population otherwise excluded from it, without sharply increasing the credit non- repayment levels.

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