Lending in Developed and Developing Economies: Theory and Evidence from Hyderabad

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August 15, 2015

Abstract

The vast literature studying informal moneylending markets has been primarily empirical. Combining theoretical with empirical work is key to a complete understanding of the potential of credit to alleviate poverty. This paper aims to estimate the true costs of lending in developing economies, as well as to shed light on the differences between optimal lending mechanisms in developing and developed settings, and what drives these differences. In this paper, I propose two different models of lending which isolate two mechanisms: investment in lending to the "right types" ex ante (screening), and investment in punishing defaulters ex post (enforcement). The theory predicts that lenders will prefer to invest in punishing default, rather than screening ex ante, when they anticipate that cost of default will be low for borrowers, when cost of capital is high, and when people are poor, all plausible characteristics of developing settings. Poorer borrowers are punished more harshly for default than wealthier borrowers—if this were not the case, the lender would not extend credit to poorer borrowers. In addition, the equilibrium rate of repayment is high under both enforcement and screening. In fact, when the enforcement mechanism is used in equilibrium, wealthier borrowers are more likely to default than poor borrowers. I take these models to a detailed dataset of 610 households from Hyderabad, India, who hold at least one loan from a Hyderabad moneylender. I employ generalized method of moments techniques to estimate the structural parameters of each model. I then use these estimates to suggest that a model of enforcement, rather than screening, best explains the Hyderabad data: MFIs may be observed to punish default harshly (for example, by intimidating borrowers), and this has received much negative press, but the theory provides an explanation for why features of the developing environment may be driving this as an equilibrium lending mechanism.

*I thank Dilip Abreu, Chris Ahlin, Abhijit Banerjee, Emily Breza, Cynthia Kinnan, Greg Leiserson, Debraj Ray, Rajiv Sethi, and Chris Walters for helpful comments. Support from the National Science Foundation is gratefully acknowledged.

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1 Introduction

Credit as an instrument to alleviate poverty has been studied and explored in a number of creative 
ways for several decades now, but no strong consensus about its short-run and long-run effectiveness, 
or about its optimal design, has emerged from the extremely lively and active debate (the January 
2015 issue of AEJ: Applied Economics provides an excellent, though not exhaustive, overview of 
the literature). Yet although an extensive body of research has been devoted to studying the 
potential of credit to alleviate poverty, most of the work has focused on empirically identifying the 
benefits accruing to borrowers—does consumption increase? Does total access to credit increase? 
Do businesses grow? However, a complete understanding of credit as a policy tool requires an 
understanding of the true costs of lending. What is the true cost of capital in a given developing 
economy? What are the true costs of screening, monitoring, and enforcement?

In order to estimate these true costs, which are not directly observable, I develop a theory to 
characterize the lending mechanisms which emerge in equilibrium across different settings. The 
theory also tells us which borrower candidates are and should be approved for loans in equilibrium, 
and at what terms. In this paper, I focus on two particular kinds of approaches to lending: in the 
first approach, the lender expends resources to screen borrower candidates directly and to learn 
their "default type". In the second approach, the lender instead expends resources to influence 
a borrower’s default type—for example, the lender may make the environment more punishing 
of default by investing in intimidation tactics and other mechanisms to harrass and stigmatize 
defaulters. These two approaches can be thought of as screening and as enforcement, respectively.

Once the conditions which determine when a particular model of lending is used are characterized, 
I take the theory to data and use it to estimate the parameters of each model. I also generate 
testable predictions. The conditions shed light on questions beyond screening and enforcement 
costs. For example, does the optimal model for lending differ between developing and developed 
economies? What are the key differences between developing and developed economies that drive 
differences in lending? Do screening and enforcement have different impacts on credit’s impact on 
poverty and inequality?

The screening and enforcement lending models I build are enormously simplified (although I 
hope to greatly enrich the theory in future drafts. However, certain simplifications will be un-
avoidable). The general borrowing and lending setting is static, and has the following features. All 
individuals are risk neutral. Individuals vary in initial wealth endowment, as well as cost of default. 
Cost of default is modeled as the fraction of total wealth that a borrower loses if he chooses to 
default. Default is therefore strategic, not involuntary: a borrower repays if and only if he prefers 
repayment to default.

Initial wealth endowment is observable and exogenously given, but an individual’s cost of default 
cannot be observed by the lender. An individual’s demand for credit is exogenously given, and 
increasing in his wealth (the assumption about the relationship between wealth and size of loan 
demanded is motivated by empirical observations from, e.g., Aleem [1], but the exogenous demand 
for credit is an assumption I’d like to relax in future drafts). There exists a production technology 
which yields deterministic returns.

In the first model, a lender (acting as a local monopolist) may expend resources and set a level 
of screening rigor. Screening works in the following way: the lender chooses some cost of default, 
and then perfectly observes all individuals whose costs of default are lower than this threshold. The 
remaining borrowers are then known to have costs of default above the threshold. The lender must 
therefore decide how rigorously to screen, which borrower applicants to accept or reject, and what 
interest rates to offer accepted borrowers. Individuals then invest in the production technology, 
and borrowers who received loans decide whether to repay the loan or to default. All individuals
consume their remaining wealth at the end of the period.

In the second model, instead of using a screening mechanism, the lender instead can expend resources to set individual-specific costs of default. The higher the cost of default imposed, the more expensive for the lender. This is a fundamentally different approach to achieving high repayment rates—the screening approach aimed to identify which set of borrower applicants were good candidates for credit, and what contract terms were appropriate to offer them. This enforcement approach, by contrast, is less concerned about identifying the right individuals to receive credit ex ante, and more concerned with making sure everyone repays ex post. That is, instead of trying to learn about borrower type, the lender invests in influencing that type.

The main theoretical results are summarized as follows. The enforcement mechanism is more likely to emerge as an equilibrium lending practice when people are poorer, direct screening is costly, and costs of default in the status quo are low. These are plausible characteristics which distinguish developing from developed economies: for example, direct screening tends to be more costly in developing environments due to a lack of credit registries, borrowers typically lacking employment and financial histories, borrowers are more likely to be nomadic, borrowers are more likely to live in hard-to-access areas, and so on. Costs of default tend to be lower in developing economies because, again, there is no credit registry that collects reports of defaulters, borrowers are more likely to be nomadic, and so on. In addition, under the enforcement mechanism, the lender sets harsher punishments for poorer borrowers than for wealthier borrowers. Precisely because individuals are very poor in developing economies, a lender must impose harsh punishments of default in order to be able to extend them any credit at all. Poorer borrowers also face higher interest rates than wealthier borrowers.

The repayment rate is high under both screening and enforcement mechanisms, since in the first case, the low cost of default types are identified (and do not receive credit), and in the second case, a particularly high cost of default is imposed on poor borrowers. On average, the repayment rate will be higher under screening than under enforcement across all borrowers, but will be equally high for poor borrowers—when the enforcement mechanism is used, defaulters are likely to be wealthier borrowers. Interestingly, more people receive credit under the enforcement mechanism than under the screening mechanism.

To estimate the parameters in these models, I use a dataset from Hyderabad, India, which contains detailed information about households—their household characteristics, any salaries and assets, expenditure, businesses, and any outstanding loans, including data on the size of the loan, the purpose, the interest rate, and the type of lender (e.g. friend, family member, moneylender, microfinance institution, etc.). (Data specifics will be discussed in Section 4.) I then use GMM techniques to estimate the supply side parameters (screening cost, enforcement cost, and cost of capital) and the distributional parameter of cost of default type. While it is difficult to say precisely which model "fits best", I use a simple notion of Euclidean distance to show that, at least in one sense, the enforcement model "fits the data best".

I emphasize that the results in this paper are particularly specific to the ingredients of the models. This is partly because I hope to develop the theory further (and thus these models are a first pass at the problem), but also because there are very steep theoretical and empirical challenges to studying these questions. First, modeling the complexity of informal lending markets is incredibly challenging. Lending in developing economies is less regulated and enforced by a formal legal structure, so the contracting environment can be almost limitlessly complicated (and there may be many contract interlinkages). Moreover, the structure of the supply side of credit markets is the subject of research in and of itself. The information structure in developing economies is also very complex—for example, research has posited that informal moneylending persists precisely because informal moneylenders have available to them unique information about borrowers, and unique
ability to enforce loan repayment. Accounting for networks adds even more dimensions to the problem. Thus, the sample of individuals who apply for loans from an MFI in the first place is already potentially very selected, for a number of different reasons.

Furthermore, the problem is dynamic—a key observation from empirical work across the world shows that borrowers and suppliers of credit build relationships over time. While the initial screening process may be arduous, and while it may be very difficult for the borrower not to default, if she does manage to build a solid history with a lender, there are certainly long-run gains. Of course, this impacts agent behavior only if agents are rational and forward-looking, which they may not be, at least not in the standard von Neumann-Morgenstern expected utility sense. Thus, we are dealing with, at the minimum, a dynamic, incomplete contracting problem with a complex supply side and agents operating outside of the expected utility framework. Even if tractability and empirical testability of the model were not important, informal lending presents a formidable theoretical challenge.

The next section reviews some of the relevant theoretical and empirical literature. Section 3 is devoted to the theory, and Section 4 describes the data. Section 5 outlines the empirical strategy. Section 6 will eventually include the parameter estimates and will analyze the fit of the models, as well as consider policy evaluation and counterfactuals. Section 7 concludes.

2 Literature Review

As discussed in the introduction, there is very little informal moneylending literature that incorporates both theory and empirics. The data for this paper is constructed from the raw dataset gathered by Banerjee et. al. [4], which conducts a randomized microfinance experiment to analyze the first-time impact of microfinance on agents' consumption and investment decisions, as well as its effects on women. The study is interested in demand for microcredit, and finds that households with existing businesses invest more in durable goods, but do not invest more in nondurables. Households who are not entrepreneurial invest in nondurables rather than durables.

Aleem [1] conducts an extremely detailed and interesting survey of informal moneylenders in Pakistan. This paper is one of very few to estimate lending costs. Aleem personally visits 14 moneylenders and asks them detailed questions about their screening process and their costs (of screening, capital, pursuing delinquent loans, and fixed costs). The paper is primarily concerned with testing whether the high and variable interest rates charged by moneylenders are usurious, or a reflection of lenders' costs. He finds that lenders charge at their average cost but above their marginal cost, and presents this as evidence of a monopolistically competitive lending structure. The main empirical findings from Aleem [1] are: first, interest rates decrease in wealth, second, loan sizes increase in wealth, third, there is very little default, and fourth, there is very little profit for lenders. These findings are echoed by a few other empirical papers (though these observations tend to be highly specific to the setting).

Hoff and Stiglitz [5] supports this monopolistically competitive view. The paper discusses various policies and theories which have been presented over the years. Policymakers initially thought the "solution" to high interest rates charged by seemingly exploitative moneylenders was to offer cheap institutional credit. Yet informal moneylenders have continued to thrive, while the institutions have struggled hugely with problems of default, supporting the theory that the high interest rates were not a result of pure monopolistic behavior, but rather accounted for the riskiness of default. Four big puzzles are described: the segmentation of credit markets, the coexistence of formal and informal lenders, the credit interlinkages in informal lending (for example, a shopkeeper who lends to a client), and the limited number of moneylenders in a given region despite the
high interest rates charged. Hoff and Stiglitz [5] argue that monopolistic competition stemming from imperfect information (screening costs) explains the high interest rates and low profits of moneylenders, as well as the limited number of moneylenders in a given region.

Banerjee [3] constructs a dynamic model of the lender’s problem with monitoring and screening technologies. The paper provides a valuable overview of robust empirical facts: first, sizeable gaps between lending and deposit rates within a sub-economy, second, high and variable interest rates within the same sub-economy, third, low levels of default, fourth, ex ante competition in markets (based on low levels of observed lender profit), interest rates that decrease in wealth and loan sizes that increase in wealth, and interest rates that decrease in loan size. Banerjee captures the low default levels and interest rates that decrease in wealth by introducing fixed and variable lending costs. The intuition is valuable, but the model quickly becomes intractable, and too abstract to test.

In short, the literature provides a detailed picture of what empirical facts a strong model should capture. The literature has largely focused on a monopolistically competitive structure stemming from screening costs and imperfect information.

3 The Lending Models

Because screening and enforcement are not observed, a theory of lending must first be developed in order to be able to estimate the costs faced by lenders. The models uncover which distinguishing features of developing versus developed economies drive differences in equilibrium lending practices, with a focus on comparing the use of harsh punishment of default to incentivize repayment, versus rigorous ex ante screening of borrower applicants. Because of this focus, I will shut down many realistic and important features of the world, at least in this first pass. The eventual goal is to enrich the theory to include particularly important features, such as dynamic incentives, limited liability, and endogenous demand for credit, as well as to relate the results to different market structures (e.g. different degrees of competition), and to identify which sets of borrowers and productive opportunities receive funding for each kind of lending mechanism.

3.1 Set Up of Model One: Screening

The borrower applicants: there is a measure 1 continuum of potential borrowers with utility described by $u(x) = x$, who vary in their exogenous initial wealth endowment $w_i$, their loan demand $l_i$, and their cost of default, $f_i$. Assume that an investment of size $I$ yields deterministic returns described by $y(I)$, where $y(I) \geq I$, $y'(I) > 0$. In this draft, I will make the heroic assumption of linearity: first, that $l_i = \lambda w_i$, and second, that $y(I) = AI$, $\lambda \in \mathbb{R}$, $A \geq 1$.

Default is strategic: if a borrower receives a loan of size $l_i$ at interest rate $r_i$, he repays if repaying at these terms is less costly than losing a fraction $f_i$ of his total wealth at the end of the period, which is the cost of default. This can be thought of as debt collection—the lender can seize a fraction of a defaulting borrower’s assets—or as an intimidation or harassment cost, where this cost is more severe for those with more to lose. Each borrower consumes his total remaining wealth at the end of the period.

Suppose that $w_i$ and $f_i$ are independent, and that $w \sim \text{uni}[0, W]$, while $f \sim \text{uni}[0, F]$, $W, F > 0$ and set exogenously.

Information: the initial wealth endowment $w_i$ is known to each borrower and observed by the lender. All individuals and the lender are familiar with the relationship between wealth and loan demand, as well as the linear production technology. Additionally, all individuals and the lender know the distributions of wealth and cost of default in the population.
The key asymmetric information is in the "cost of default" type: the lender does not observe each borrower’s cost of default, $f_i$. Moreover, a borrower learns of his own cost of default only once he receives a loan (if he doesn’t receive a loan, he doesn’t learn his own cost of default, but it’s irrelevant for him).¹

The lender: the lender is a monopolist who is approached by borrower candidates applying for loans of varying sizes, and decides first whom to accept and whom to reject. (Rejected borrowers invest their own wealth in the linear technology.) If the lender accepts a borrower requesting a loan of size $l_i$, she then sets an interest rate $r_i$. The lender faces cost of capital $c(L; \rho) = \rho L$ (that is, it costs the lender $\rho L$ to lend $L$ funds, because the lender does not have infinite funds), where $\rho > 0$.²

A screening mechanism is available to the lender. In particular, she can pay $\varphi \hat{f}$, $\varphi > 0$, and perfectly observe all $f_i < \hat{f}$ (the borrower applicants with low cost of default, who are less profitable to lend to). She then knows the remaining borrowers have cost of default $f_i > \hat{f}$.

Timing: The period proceeds as follows:
1. Each individual $i$ is endowed with initial wealth $w_i$, drawn from $\text{uni}[0, W]$, where $w_i$ is known to the individual and observed by the lender.
2. Each individual $i$ approaches the lender and asks for a loan of size $l_i = \lambda w_i$.
3. The lender pays for screening of rigor $\hat{f}$, which costs her $\varphi \hat{f}$. She then learns perfectly which of the borrower applicants has cost of default $f_i < \hat{f}$.
4. The lender decides which borrower applicants to accept, and which to reject. She sets an interest rate $r_i$ for each of the accepted borrowers.
5. Each accepted borrower learns his cost of default $f_i$.
6. Each individual invests as he wishes, and realizes the returns of those investments.
7. Borrowers who received a loan decide whether to repay or to default.
8. The individuals and the lender consume their end-of-period wealth.

Equilibrium: The equilibrium consists of the following elements:
1. Individuals: each individual $i$ in the population chooses a utility-maximizing level of investment. Each successful borrower applicant (an individual who receives a loan) must also have a strategy which optimally maps her state of the world (wealth, loan size, investment, cost of default, and interest rate) into the decision to repay or to default, where borrowers are utility-maximizing.
2. The lender: the lender chooses a screening rigor which maximizes her expected utility. She has a strategy which maps her information about a borrower conditional on screening rigor (cost of default type, wealth) into a decision about whether to accept or reject the borrower. If she accepts the borrower, she sets the interest rate to maximize her expected profit.

3.2 Set Up of Model Two: Enforcement

The set up of this model is identical in almost every respect to Model One, with one fundamental difference: the lender no longer uses the screening mechanism $\hat{f}$ to learn, to any extent, the cost of default types of borrower applicants. Instead of screening out borrower applicants ex ante based on cost of default, then, the lender invests in punishing default ex post. In particular, she can pay $c(f_i, w_i) = \pi w_i^2 f_i^2$ to set $f_i$ for individual $i$. It is harder to impose steep costs of default on richer

¹This informational structure means that the lender cannot design a menu of contacts to induce truthful revelation of cost of default type. If the borrowers knew their own $f_i$ at the point of asking for a loan, then it is possible that the lender may be able to set a menu of interest rates for each $l_i$ such that types $f_i$ truthfully select into each contract.

²This is an interesting contract which I will explore in later versions, but which I put aside for the time being.

2The unusual degree of functional form specification is due to the parameter estimation exercise in the second half of the paper.
individuals. (If a lender does not impose a cost of default on an individual, then that individual is believed to have cost of default \( f_i \sim \text{uni}[0, F] \).)

**Timing:** The period proceeds as follows:
1. Each individual \( i \) is endowed with initial wealth \( w_i \), drawn from \( \text{uni}[0, W] \), where \( w_i \) is known to the individual and observed by the lender.
2. Each individual \( i \) approaches the lender and asks for a loan of size \( l_i = \lambda w_i \).
3. The lender pays \( \pi w_i^2 f_i^2 \) to set \( f_i \) for individuals \( i \) of her choice.
4. The lender decides which borrower applicants to accept, and which to reject. She sets an interest rate \( r_i \) for each of the accepted borrowers.
5. Each individual invests as he wishes, and realizes the returns of those investments.
6. Borrowers who received a loan decide whether to repay or to default.
7. The individuals and the lender consume their end-of-period wealth.

**Equilibrium:** The equilibrium consists of the following elements:
1. Individuals: each individual \( i \) in the population chooses a utility-maximizing level of investment. Each successful borrower applicant (an individual who receives a loan) must also have a strategy which optimally maps her state of the world (wealth, loan size, investment, cost of default, and interest rate) into the decision to repay or to default, where borrowers are utility-maximizing.
2. The lender: the lender chooses a severity of punishment of default, \( f_i \), for some individuals \( i \), which maximizes her expected profit. She has a strategy which maps her information about a borrower conditional on \( f_i \) (or \( E(f_i) \)) into a decision about whether to accept or reject the borrower. If she accepts the borrower, she sets the interest rate to maximize her expected profit.

4 Results
4.1 Model One: Screening

Since returns to investment are deterministic: \( y(I) = AI, A \geq 1 \), an individual invests her entire wealth and any credit he receives. Thus, an individual \( i \) with wealth \( w_i \) and cost of default \( f_i \) (which he learns after getting a loan), who gets a loan \( l_i = \lambda w_i \) at interest rate \( r_i \), repays iff:

\[
f_i A[w_i + \lambda w_i] \geq r_i \lambda w_i \iff f_i \geq \frac{r_i \lambda}{A(1 + \lambda)}
\]

The first question is thus: given that a lender has set a screening rigor \( \hat{f} \), which borrowers does she reject? Which does she accept? What interest rate does she offer to the accepted borrowers?

Given \( \hat{f} \in [0, F] \), the lender can identify all borrower applicants with \( f_i < \hat{f} \). Thus, the lender will set the highest interest rate she can for these \( f_i \), without triggering default. Using the condition above, this means that:

\[
r_i = f_i \frac{A(1 + \lambda)}{\lambda}
\]

The lender offers this only to those \( f_i \) for whom she makes non-negative profit, however:

\[
f_i \frac{A(1 + \lambda)}{\lambda} \lambda w_i - \rho \lambda w_i \geq 0 \iff f_i \geq \frac{\rho \lambda}{A(1 + \lambda)}
\]

Thus, the lender rejects all \( f_i \in [0, \min \left\{ \frac{\rho \lambda}{A(1 + \lambda)}, \hat{f} \right\} \).
If $\hat{f} > \rho \frac{A}{A(1+\lambda)}$, the lender accepts $f_i \in \left[\rho \frac{\lambda}{A(1+\lambda)}, \hat{f}\right]$ and sets $r_i = f_i A(1+\lambda)$.

What about for borrower applicants whose type was not identified following the screening process, and who therefore have $f_i \geq \hat{f}$? The lender solves:

$$\max_{r_i} \Pr \left[ f_i \geq \frac{r_i \lambda}{A(1+\lambda)} \mid f_i \geq \hat{f} \right] r_i \lambda w_i - \rho \lambda w_i$$

Since $f_i \geq \hat{f} \sim \text{uni} [\hat{f}, F]$, this maximization problem is:

$$\max_{r_i} \frac{F - \frac{r_i \lambda}{A(1+\lambda)}}{F - \hat{f}} r_i \lambda w_i - \rho \lambda w_i$$

$$\text{FOC}_{r_i} : \quad \frac{F}{F - \hat{f}} \lambda w_i - \frac{2 \lambda^2 w_i}{(F - \hat{f}) A(1+\lambda)} r_i = 0$$

$$r_i = \frac{FA(1+\lambda)}{2 \lambda}$$

(The objective function is concave in $r_i$, so this is a maximum.)

Note that at this $r_i$, the probability of repayment, conditional on $f_i \geq \hat{f}$, is:

$$\Pr \left[ f_i \geq \frac{r_i \lambda}{A(1+\lambda)} \mid f_i \geq \hat{f} \right] = \frac{F}{F - \hat{f}}$$

where

$$\frac{F}{F - \hat{f}} \leq 1 \iff \hat{f} \leq \frac{F}{2}$$

Moreover, given $\hat{f} \leq \frac{F}{2}$, this yields non-negative profit for the lender if and only if:

$$\frac{FA(1+\lambda)}{2 \lambda} \lambda w_i - \rho \lambda w_i \geq 0 \iff \frac{AF^2(1+\lambda)}{4 \left( F - \hat{f} \right) \lambda} \geq \rho$$

Thus, if the above condition holds, the lender sets $r_i = \frac{F A(1+\lambda)}{2 \lambda}$ for individuals with $f_i \geq \hat{f}$, conditional on $\hat{f} \leq \frac{F}{2}$. Otherwise, the lender rejects all individuals with $f_i \geq \hat{f}$.

What if the lender wants to set $\hat{f} > \frac{F}{2}$? In that case, the lender optimally sets $r_i = \frac{\hat{f} A(1+\lambda)}{\lambda}$. This guarantees that probability of repayment is 1 for $f_i \geq \hat{f} > \frac{F}{2}$. To see this, observe that setting $r_i = \frac{\hat{f} A(1+\lambda)}{\lambda}$ and guaranteeing repayment by all $f_i \geq \hat{f}$ dominates setting a slightly higher interest
rate at the cost of causing some borrowers to default ($\varepsilon > 0$): 

$$\hat{f} A(1 + \lambda) w_i - \rho \lambda w_i > \frac{F - \left( \hat{f} + \frac{\varepsilon}{A(1 + \lambda)} \right) \left( \frac{\hat{f} A(1 + \lambda)}{\lambda} + \varepsilon \right) \lambda w_i - \rho \lambda w_i}{F - \hat{f}} \iff$$

$$\hat{f} A(1 + \lambda) w_i - \rho \lambda w_i > \left( 1 - \frac{\varepsilon}{A(1 + \lambda)} \right) \left( \frac{\hat{f} A(1 + \lambda)}{\lambda} + \varepsilon \right) \lambda w_i - \rho \lambda w_i \iff$$

$$0 > -\frac{A(1 + \lambda)}{F - \hat{f}} \left( \frac{\hat{f} A(1 + \lambda)}{\lambda} + \varepsilon \right) \lambda w_i + \lambda w_i \iff$$

$$0 > \left[ 1 - \frac{\hat{f}}{F - \hat{f}} - \varepsilon \frac{A(1 + \lambda)}{F - \hat{f}} \right] \lambda w_i$$

But the last condition holds, since $\hat{f} > \frac{F}{2} \Rightarrow \frac{f}{F - \hat{f}} > 1$.

This yields non-negative profit for the lender if and only if:

$$\hat{f} A(1 + \lambda) w_i - \rho \lambda w_i \geq 0 \iff \frac{\hat{f} A(1 + \lambda)}{\lambda} \geq \rho$$

which is just a condition that the optimal interest rate is weakly greater than the cost of capital.

Now that we know the optimal lending decisions and contract terms given screening rigor $\hat{f}$, what screening rigor does the lender choose in the first place?

There are two cases: $\hat{f} \in [0, \frac{F}{2})$, and $\hat{f} \in [\frac{F}{2}, F]$.

Let’s start with Case 1: suppose the lender sets $\hat{f} \in [0, \frac{F}{2})$. (Assume cost of capital is such that $\frac{AF^3(1+\lambda)}{d(F-f)^2} \geq \rho$, so that the lender does want to lend to those with cost of default $f_i \geq \hat{f}$.) Then the lending decision and interest for each type $f_i$ is described by the table below:

<table>
<thead>
<tr>
<th>$f_i$</th>
<th>lending decision</th>
<th>interest rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0, \frac{\lambda}{A(1+\lambda)}$</td>
<td>reject</td>
<td>n/a</td>
</tr>
<tr>
<td>$\frac{\lambda}{A(1+\lambda)}, \hat{f}$</td>
<td>accept</td>
<td>$r_i = f_i \frac{A(1+\lambda)}{\lambda}$</td>
</tr>
<tr>
<td>$\hat{f}, F$</td>
<td>accept</td>
<td>$r_i = \frac{F}{2} \frac{A(1+\lambda)}{\lambda}$</td>
</tr>
</tbody>
</table>

Then what is the optimal screening rigor, conditional on it being less than $\frac{F}{2}$? The lender solves:

$$\max_{\hat{f} \in [0, \frac{F}{2})} \int_0^{\hat{f}} \left[ f_i A(1 + \lambda) - \rho \lambda \right] E[w_i] df_i + \int_{\hat{f}}^{F} \left[ \frac{\hat{f}}{2} \frac{F}{F - \hat{f}} A(1 + \lambda) - \rho \lambda \right] E[w_i] df_i - \varphi \hat{f} F$$

This can be re-expressed as:

$$\max_{\hat{f} \in [0, \frac{F}{2})} A(1 + \lambda) E[w_i] \left[ \frac{\hat{f}^2}{2} - \left( \frac{\rho \frac{\lambda}{A(1+\lambda)}}{2} \right)^2 \right] - \rho \lambda E[w_i] \left[ \hat{f} - \rho \frac{\lambda}{A(1+\lambda)} \right]$$

$$+ \left( F - \hat{f} \right) \left[ \frac{\hat{f}}{F - \hat{f}} \frac{F}{2} A(1 + \lambda) - \rho \lambda \right] E[w_i] - \varphi \hat{f}$$
But note that the objective function is **convex** in \( \hat{f} \). Thus, conditional on \( \hat{f} \in [0, \frac{F}{2}] \), \( \hat{f}^* = 0 \). If \( \hat{f}^* = 0 \), the lender just solves, for each \( i \):

\[
\max_{r_i} \frac{F - r_i A(1+\lambda)}{F} r_i \lambda w_i - \rho \lambda w_i
\]

So:

\[
r_i |(\hat{f}^* = 0) = \frac{F A(1 + \lambda)}{2} \lambda
\]

and the lender’s expected utility is:

\[
\left[ \frac{1}{2} F A(1 + \lambda) - \rho \lambda \right] W \geq 0 \iff \frac{F A(1 + \lambda)}{\lambda} \geq \rho
\]

What is the optimal screening rigor, conditional on \( \hat{f} \in [\frac{F}{2}, F] \)? (Assume \( \hat{f} \frac{A(1+\lambda)}{\lambda} \geq \rho \), so that the lender accepts borrowers with \( f_i \geq \hat{f} \).)

The lending decision and interest for each type \( f_i \) is described by the table below:

<table>
<thead>
<tr>
<th>( f_i )</th>
<th>lending decision</th>
<th>interest rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 0, \rho \frac{A(1+\lambda)}{\lambda} )</td>
<td>reject</td>
<td>n/a</td>
</tr>
<tr>
<td>( \rho \frac{A(1+\lambda)}{\lambda} ), ( \hat{f} )</td>
<td>accept</td>
<td>( r_i = f_i \frac{A(1+\lambda)}{\lambda} )</td>
</tr>
<tr>
<td>( \hat{f}, F )</td>
<td>accept</td>
<td>( r_i = \hat{f} \frac{A(1+\lambda)}{\lambda} )</td>
</tr>
</tbody>
</table>

Now, the lender solves:

\[
\max_{\hat{f} \in [\frac{F}{2}, F]} \int_{\rho \frac{A(1+\lambda)}{\lambda}}^{\hat{f}} [f_i A(1 + \lambda) - \rho \lambda] E[w_i] df_i + \int_{\hat{f}}^{F} \left[ \hat{f} A(1 + \lambda) - \rho \lambda \right] E[w_i] df_i - \varphi \hat{f} F
\]

which can be re-written:

\[
\max_{\hat{f} \in [\frac{F}{2}, F]} A(1+\lambda) E[w_i] \left[ \frac{\hat{f}^2}{2} - \left( \frac{\rho \frac{A(1+\lambda)}{\lambda}}{2} \right)^2 \right] - \rho \lambda E[w_i] \left[ \hat{f} - \rho \frac{\lambda}{A(1+\lambda)} \right]
\]

\[
+ \left[ F - \hat{f} \right] \left[ \hat{f} A(1 + \lambda) - \rho \lambda \right] E[w_i] - \varphi \hat{f} F
\]

This is concave in \( \hat{f} \). Then the following condition characterizes the (interior) maximum:

\[
FOC_{\hat{f}} : -A(1+\lambda)E[w_i] \hat{f} + FA(1+\lambda)E[w_i] - \varphi F = 0
\]

\[
\hat{f}^* = \frac{E \left[ A(1+\lambda)E[w_i] - \varphi \right]}{A(1+\lambda)E[w_i]}
\]

\[
= F \left( 1 - \frac{2\varphi}{A(1+\lambda)W} \right)
\]

where

\[
1 - \frac{2\varphi}{A(1+\lambda)W} \geq \frac{1}{2} \iff W \geq \frac{4\varphi}{A(1+\lambda)}
\]
Then, the lender’s expected utility is:

\[
EU^{\text{lender}}_{f^* > F} = \frac{A(1 + \lambda)WF}{4} - \varphi F + \frac{\varphi^2 F}{A(1 + \lambda)W} + \frac{W\rho^2 \lambda^2}{4A(1 + \lambda)F} - \frac{\rho \lambda W}{2}
\]

which beats not screening at all if this is greater than \( \left[ \frac{1}{2} F \right] A(1 + \lambda) - \rho \lambda \frac{W}{2} \) (basically, if \( \varphi \) low enough, prefer to screen fairly rigorously (above \( \frac{F}{2} \))).

The results are summarized below.

**Result 1:** Optimal screening rigor is interior when, loosely, the direct cost \( \varphi \) is not too high, there are enough wealthy people (\( W \) is high enough), investments are sufficiently productive (\( A \) high enough), and capital is somewhat expensive (\( \rho \) is high, so the lender needs to be more careful about who to give funds to).\(^3\)

Then the solution is:

\[
f^* = F \left( 1 - \frac{2\varphi}{A(1 + \lambda)W} \right) \in \left( \frac{F}{2}, F \right)
\]

and the lender makes the following lending decisions:

<table>
<thead>
<tr>
<th>( f_i )</th>
<th>lending decision</th>
<th>interest rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0, ( \frac{\lambda}{A(1 + \lambda)} )</td>
<td>reject</td>
<td>n/a</td>
</tr>
<tr>
<td>( \frac{\lambda}{A(1 + \lambda)}, f^* )</td>
<td>accept</td>
<td>( r_i = f_i \frac{A(1 + \lambda)}{\lambda} )</td>
</tr>
<tr>
<td>( f^*, F )</td>
<td>accept</td>
<td>( r_i = F \left( 1 - \frac{2\varphi}{A(1 + \lambda)W} \right) \frac{A(1 + \lambda)}{\lambda} )</td>
</tr>
</tbody>
</table>

**Result 2:** There is perfect repayment, since everyone who receives a loan repays. Those with \( f_i \in \left[ \rho \frac{\lambda}{A(1 + \lambda)}, f^* \right] \) have their types discovered exactly by the lender, and are given exactly the "right" lending terms, which lead to probability 1 of repayment. This is a relatively large mass of people, since screening is rigorous (\( f^* > \frac{F}{2} \)). Moreover, those with \( f_i \geq f^* \), even though their types are not known exactly, also repay with probability 1, since the lender sets an interest rate such that the individual with the lowest cost of default in this set of people repays with probability 1 (thus, everyone else certainly repays with probability 1, because they have even higher costs of default).

**Result 3:** Individuals with the lowest cost of default do not get credit. Specifically, those \( i \) with \( f_i \in \left[ 0, \rho \frac{\lambda}{A(1 + \lambda)} \right] \) can only invest their own initial wealth endowment.

**Result 4:** This interior, rigorous screening is more likely to be optimal when the population of individuals is sufficiently wealthy (\( W \) is high enough), or if screening costs are low (\( \varphi \)), or if the technology is sufficiently productive (\( A \) is high).

---

\(^3\varphi, W, A, \rho : \frac{A(1 + \lambda)F}{4} - \varphi F \frac{2}{W} + \frac{2\varphi^2 F}{A(1 + \lambda)W^2} + \frac{\varphi^2 \lambda^2}{2A(1 + \lambda)F} > 0 \)
4.2 Model Two: Enforcement

Now, the lender does not screen borrower applicants ex ante. As Model One demonstrates, a lender who uses a screening approach expends resources to learn the cost of default type of borrower applicants, in order to accept the "right" borrowers (those with higher cost of default) and reject those whose costs of default are too low, and to offer accepted borrowers appropriate credit terms (terms which lead the borrower to repay).

In Model Two, which explores an enforcement approach to lending, the lender can instead expend resources to influence how costly it is for various individuals to default. In particular, the lender can set a cost of default $f_i$ for individual $i$ at cost $c(f_i|w_i) = \pi w_i^2 f_i^2$. (If a lender does not impose a cost of default on an individual, then that individual is believed to have cost of default $f_i \sim \text{uni}[0, F]$.)

We know from the analysis in the previous section that, given known $f_i$, if it is profitable for the lender to accept $i$, then the lender optimally sets:

$$r_i^* = f_i \frac{A(1 + \lambda)}{\lambda}$$

Then the lender sets $f_i$:

$$\max_{f_i} f_i A(1 + \lambda) w_i - \rho \lambda w_i - \pi w_i^2 f_i^2$$

$$\text{FOC}_{f_i} : f_i^* = \frac{A(1 + \lambda)}{2\pi w_i}$$

(The objective function is concave in $f_i$, so this is indeed a maximum.)

Note that the optimal cost of default to impose on wealthier individuals is lower.

Then the lender lends to $i$ such that:

$$\frac{A^2(1 + \lambda)^2}{4\pi} - \rho \lambda w_i \geq 0 \Leftrightarrow \hat{w} = \frac{A^2(1 + \lambda)^2}{4\pi \rho \lambda} \geq w_i$$

So, the lender imposes cost of default and lends to $i$ with wealth $w_i \leq \hat{w}$ at interest rate given by:

$$f_i^* = \frac{A(1 + \lambda)}{2\pi w_i}$$

$$r_i^* = \frac{A^2(1 + \lambda)^2}{2\lambda \pi w_i}$$

Do individuals with wealth $w_i > \hat{w}$ get credit? Yes, for individuals $i$ such that the condition below holds:

$$\frac{FA(1 + \lambda)}{4\lambda} \lambda w_i - \rho \lambda w_i \geq 0$$

$$\frac{FA(1 + \lambda)}{4\lambda} \geq \rho$$

That is, all wealthier individuals $w_i > \hat{w}$ get credit at $r^* = \frac{FA(1+\lambda)}{2\lambda}$ as long as the lender receives non-negative profit from lending to these borrowers, knowing only that $f_i \sim \text{uni}[0, F]$.
Result 5: The lender prefers to impose an individual cost of default $f_i$ on poor borrowers $w_i \leq \bar{w}$, rather than lend to everyone under the prior that $f_i \sim \text{uni}[0, F]$, if the condition below holds:

$$\frac{A(1 + \lambda)}{\pi} > Fw_i$$

That is, if the prior belief is that the cost of default is low, the environment is productive, and the cost of setting punishments for default is not too high, the lender will prefer to set high, individual-specific punishments for default when lending to poor borrowers, and will lend to wealthier borrowers without expending resources to set high punishments for default.

Poor borrowers are less likely to get credit in this setting if the lender does not raise the punishment for default for them.

Result 6: Poorer borrowers face higher interest rates than wealthier borrowers if, for $w_i \leq \frac{A^2(1+\lambda)^2}{4\pi \rho \lambda} = \bar{w}$:

$$\frac{A^2(1 + \lambda)^2}{2\lambda \pi w_i} > \frac{FA(1 + \lambda)}{2\lambda}$$

$$\frac{A(1 + \lambda)}{F\pi} > w_i$$

$$\frac{1}{F} > \frac{A(1 + \lambda)}{4\rho \lambda} : w_i = \bar{w}$$

This is more likely if $F$ is small (costs of default in the status quo are low), the economy is not very productive ($A$ is small), and costs of capital are high ($\rho$ is high). These all seem likely in a developing economy.

Result 7: Loosely speaking, the lender prefers the enforcement mechanism to the screening mechanism when:

1. People are poor: $W$ is low.
2. The cost of influencing punishments for default is relatively lower than the cost of screening ($\pi$ small relative to $\varphi$)—this
3. Costs of default, $F$, are believed to be low.

These seem to be key characteristics of developing (versus developed) economies: people are poorer, screening is likely to be very costly (due to lack of credit registry, borrowers lacking histories, borrowers being nomadic, borrowers living in hard-to-access areas, and so on), and costs of default are likely to be low (there is no credit registry to report default to, borrowers may be nomadic, and so on).

Thus, enforcement may be used more commonly by lenders in developing economies, while screening may be used more commonly by lenders in developed economies. Because individuals are very poor in developing economies, a lender may have to impose harsh punishments of default in order to extend them any credit at all.

Result 8: Repayment is high under both screening and enforcement mechanisms, since in the first case, the low cost of default types are identified, and in the second case, a particular high cost of default is imposed on poor borrowers. On average, the repayment rate will be higher under screening than under enforcement across all borrowers, but will be equally high for poor borrowers—when the enforcement mechanism is used, defaulters are likely to be wealthier borrowers.
5 Data

5.1 The Dataset

The dataset is compiled from baseline data gathered by Banerjee et. al. [4] for their randomized experiment conducted in conjunction with the microfinance institution Spanadana in Hyderabad, Andhra Pradesh, India. 120 "slum areas" in Hyderabad were selected as being good candidates for first-time exposure to microfinance–residents were poor, but not "the poorest of the poor", and also were not nomadic. Baseline surveys were conducted in 2005. The baseline data consists of household composition (e.g. family size, education, employment, home construction, access to electricity and facilities such as latrines, ownership of land and residential status, assets, monthly expenditures, and so on), loan data (loan size, interest rate, lender type, and so on), and business data (whether the household owns a business, monthly profits, number of employees, and so on), for 2500 households with at least one woman between 18 and 55. There are too many variables to discuss explicitly. I use a limited subset, which I describe below.

Because Banerjee et. al. focused on studying the impact of introducing microcredit in a new market on borrower behavior—in business, consumption, investment, and in social issues—the dataset includes a lot of variables that are not relevant for this paper. Since my goal is to estimate distribution and supply side parameters of lending models, I primarily need data on interest rates and loans offered by informal moneylenders. The 2500 households in question do not all have outstanding loans; of the 1875 households who do have at least one loan, 696 report at least one of those loans as being drawn from an informal moneylender in Hyderabad (as opposed to an outside moneylender). Hyderabad moneylenders are by far the most common source of lending in the dataset—loans from friends, the second most common source, are more than three times less frequent. Furthermore, about half of the households who report having no loan claim that they need a loan but cannot get one, suggesting that screening mechanisms may hinder borrowers from transacting even in the informal sector. (Unfortunately, I do not have data on loan demands for these households; I am restricted to the data for households who were accepted by some lender.)

Households report holding anywhere from one to eleven outstanding loans. Ideally, I would incorporate this in the theory, but unfortunately I am unable to distinguish between different Hyderabad moneylenders in the dataset. That is, households who hold eleven loans might hold many, if not all of those loans with the same lender; we might expect that succeeding loans would be granted at lower interest rates, once a relationship has been established. Since this is not observable in the data, I use only the first loan reported by households. However, a basic check indicates that households with some wealth level and many loans do not appear to receive lower interest rates than households with a similar wealth level but few loans, suggesting that this may only be a minor concern.

Of the 696 households who report borrowing from an informal moneylender in Hyderabad, 643 also report the weekly interest rate. For these 643 households, I include a variety of wealth measures: I look at total monthly salaries, total monthly expenditures, expenditure on home repair, whether or not the household holds a "ration shop card" (a card given to extremely poor families for purchase of subsidized basic groceries), and household assets. The assets data is particularly detailed—households report owning subsets of a set of 41 standard goods, including pots, saris, jewelry, bicycles, color television, cars, electricity, landlines, and stoves. Additionally, I include measures of believed wealth: households were asked if they thought of themselves as being poor, how they would rank themselves on a "financial ladder", and what they believed their maximum repayment capacity to be. I also include several household characteristics, primarily, age of head of
household and family size. While literacy and birthplace (village, town, or city) seemed like natural controls, closer examination revealed that there was almost no variation—almost all individuals in the survey were literate and born in a city. Finally, my loan data consists of loan size, interest rate, loan purpose, and number of days between applying for and receiving the loan. The data on whether or not lenders asked for collateral was too incomplete to be used. After dropping households who do not have this full vector of data, I am left with a final sample size of 610 vectors of observations, each from a distinct household.

Because "wealth" is an ambiguous concept, especially for very poor families, I construct three measures. Wealth is important in my models primarily because it contributes to the cost of default and the ability to repay. Thus, I build wealth indices that attempt to capture the spirit of "appropriable" versus "non-appropriable" wealth, as well as repayment ability. Indices help to manage "scale" issues which cause problems when estimating parameters of the four basic models.

Purchase data is available in the dataset for 37 of the 41 items. I take means over purchase prices for each item, identify the bundle of assets and the quantity of each asset that a given household owns, and calculate the total value of asset holdings. I then build the empirical cdf $F(x) = \Pr(X \leq x)$ for total monthly salaries, total monthly expenditures, and total monthly salaries, and assign a household with $x$ monthly salary the number $F(x)$. For example, a household with the highest monthly salaries would be assigned the number "1". To account for some drastic outliers, I smooth the lowest 5% and the highest 5% of the cdf. I then weight each index equally in the final index: $w_1 = \frac{1}{3}F(\text{sal}) + \frac{1}{3}F(\text{exp}) + \frac{1}{3}F(\text{assets})$.

The second index is constructed from each household's own evaluation of wealth, specifically belief about maximum repayment capacity and a household's ranking of itself on a financial "ladder" from 1 to 10 where 3 is the modal answer. Empirical cdfs are constructs as in the first index, and the two measures are equally weighted.

Finally, the third wealth measure is simply total monthly salaries of each household.

The correlation of the first two indices is 0.2, of the second two is 0.26, and of the first and third is 0.24. It turns out that the second index is the strongest measure for the purpose of this estimation exercise. This makes sense, since the second index is largely based off of a household's capacity for repayment, and this is the kind of wealth measure that interests a lender.

How is a household’s cost of default measured? That is, how is $f$ captured in the data? Since the theoretical essence of this borrower type is appropriability of a borrower’s total wealth, I proxy for $f$ first by calculating the fraction of each borrower’s asset holdings that is appropriable, as well as weighing any land holdings or property ownership (since lenders will often ask borrowers to put up deeds as collateral). I consider business assets and equipment, such as auto rickshaws, valuable items such as cars and jewelry, and major durables such as fridges, computers, and other technology to be appropriable, while electricity, landlines, saris, and other measures of wealth such as total expenditures are considered non-appropriable. Next, I calculate maximum repayment capacity as a fraction of total loan size for each household. The $f$ I build for each household is the sum of these two measures.

In the first two models, the lender uses a screening mechanism to learn about a borrower’s private cost of default. I use "number of days between applying for and receiving the loan" as a proxy for screening rigor, and assign each household a number corresponding to the empirical cdf. The index for loan size is also built upon the empirical cdf.

Frustratingly, interest rates are reported as weekly rates (where interest is simple). However, cycle of repayment tends to be quarterly. I therefore index $r$ in three ways—first, by leaving it as is, second, by using its empirical cdf, and third, by transforming it into a simple quarterly gross interest rate (since $r$ is gross interest rate in the models). I approximate a quarter as being 10 weeks. Thus, I multiply the weekly interest rate reported in the data by ten (e.g., 5% becomes
50%, or 0.5), and add 1.

In sum, the final dataset for 610 distinct households consists of: three measures of wealth, an index for loan size, three measures of interest rates, cost of default, and screening rigor, as well as family size and age of head of household.

It is worth noting that, while some of these approaches may appear quite ad hoc, such improvisation is necessary, given the uniqueness of the dataset and the abstract nature of the variables in even the most basic of informal lending models.

5.2 Summary Statistics

The households in the subset of "first loans" are extremely representative of households in the general dataset. 38% of all loans in the dataset and 37% of all "first loans" come from a Hyderabad moneylender, making them the most popular source for loans. The second most popular lending source is a friend (14% and 15% of the dataset and subset of "first loans", respectively). The most common reason to take a loan was health (19% of total loans; 21% of "first" loans), and the second reason was marriage (15% of all loans and of "first" loans). The mean weekly interest rate across all loans is 3.69%; in the subset of first loans it is 3.65%. The mean number of days between applying for and receiving a loan across all loans is 9 days; in the subset of first loans, it is about 9.5 days. In short, there seems to be virtually no difference in terms of loan characteristics between the whole sample of loans and the subsample of first loans, and therefore the approach of considering only first loans seems reasonable. Looking at households who hold at least one loan versus households with no loans, we see that the populations are fairly similar in terms of household characteristics. For example, total monthly salary in both populations is about 4500 rupees, with a standard deviation of about 5000 rupees. Total monthly expenditure of households with no loans is about 4800 rupees with a standard deviation of about 4200 rupees, whereas for households with at least one loan, it is about 4500 rupees with a standard deviation of 7800 rupees. The mean cost of default of households with no loans is 0.26 with a standard deviation of 0.16; for those with at least one loan, the mean is 0.25 with a standard deviation of 0.15. Family size is mean 5 people with a standard deviation of 2 both in and out of sample. In both populations, about 75% of households hold ration cards. Almost everyone in both populations is literate and born in a city.

A minor difference between the two populations appears to be belief about maximum repayment capacity. The mean maximum monthly repayment capacity (as reported by households) of households with no loans is 773 rupees with a standard deviation of 630; for households with at least one loan, the mean is 810 rupees and the standard deviation is 838 rupees. Lastly, comparing households with their "first" loan from a Hyderabad moneylender (in sample) with households who draw on other lending sources (out of sample): the mean interest rate from Hyderabad lenders is 4.11 (with a standard deviation of 2.09), and from other lending sources is 3.76 (with a standard deviation of 2.33). The mean loan size from Hyderabad lenders is 20352 rupees (with a standard deviation of 26933), while from other lending sources is 23561 (with a standard deviation of 43159). The mean monthly salary for households borrowing from Hyderabad lenders is 4250 rupees (with a standard deviation of 2630); for those drawing on other lending sources, the mean is 4236 rupees (with a standard deviation of 3970). Mean number of days between applying for and receiving a loan in sample is about 8 days (with a standard deviation of 18), whereas out of sample it is about 11 days (with a standard deviation of 16). Finally, mean cost of default is 0.25 both in sample and out of sample.
6 Estimation

I take the following steps. First, I estimate parameters of both Model One (the screening model) and Model Two (the enforcement model), using moments inspired by the theory. Next, I do some basic goodness-of-fit comparisons, which provide suggestive evidence that the enforcement mechanism is a better fit for the Hyderabad data. Finally, I do some basic back-of-the-envelope calculations with the estimated structural parameters to demonstrate how this work can inform policy analysis.

I assume that the econometrician observes wealth $w$ with error, where the error is independent from $w$ and across agents (we can think of this as human reporting or rounding error). The theory implies that the analytic expressions for each choice variable should perfectly predict the outcomes, if the inputs are observed without any error. I assume that the error structure with which the econometrician observes the data (namely, the purely random human reporting/rounding error) is such that the expectation of each first-order condition is zero, so that these first-order conditions are valid moment conditions. While this is a strong assumption (one might think that individuals who are similar along certain observables are also more likely to err in reporting in the same way), it is not entirely implausible– rounding error is probably fairly independent and random.

I estimate a set of parameters $\Theta_j$, $j \in \{1, 2\}$ for each model $j$, using standard GMM techniques. Let $m_j = [m_{jk}(\Theta)]$ be the stacked vector of moment conditions for model $j$, where $E[m_{jk}(\Theta)] = 0$ and where $k$ identifies the moment condition in model $k$. Let $W$ denote the weighting matrix for these moment conditions. I employ the usual two-step approach by first obtaining a consistent estimate of $\Theta$, by setting $W$ initially to be the identity matrix, and then calculating an estimate of the variance-minimizing (optimal) weighting matrix, and then re-estimating $\Theta$ to minimize $m_k W_{opt} m_k$.

6.1 Model One: Screening

Let $\Theta_1 = \{\varphi, A, \lambda, \rho\}$. The four moment conditions suggested by the theory are:

M1 : $r_i = f_i A (1 + \lambda) \frac{1}{\lambda}$

M2 : $E(f_i | i \text{ gets credit}) = \frac{1}{2} \left[ \frac{\rho \lambda}{A(1 + \lambda)} + \left( 1 - \frac{2\varphi}{A(1 + \lambda) W} \right) F \right]$

M3 : $E(\hat{f}_i) = \left( 1 - \frac{2\varphi}{A(1 + \lambda) W} \right) F$

M4 : $L_i = \lambda w_i$

The first moment condition is based off the condition for the equilibrium interest rate of those borrowers who get credit. The second moment condition is based off the expected average cost of default type who gets credit in equilibrium. The third moment condition is based off the condition for the lender’s optimal screening rigor. The final moment condition is given by loan demand.

6.2 Model Two: Enforcement

Let $\Theta_2 = \{\pi, A, \lambda, \rho\}$. The four moment conditions are:
\[
M1 : f_i = \frac{A(1 + \lambda)}{2\pi w_i}
\]
\[
M2 : r_i = \frac{A^2(1 + \lambda)^2}{2\lambda \pi w_i}
\]
\[
M3 : L_i = \lambda w_i
\]
\[
M4 : E(f_i|\text{enforced}) = \frac{2\rho \lambda}{A(1 + \lambda)}
\]

The first moment condition is based off the condition for the cost of default type imposed by the lender on an individual with wealth \(i\). The second moment condition is based off the equilibrium interest rate of those who get credit. The third moment condition is given by loan demand. The final moment condition is the expected cost of default type of the subset of borrowers whose type gets enforced by the lender.

7 Results

7.1 Parameter Estimates

GMM estimation of the first, screening model following the empirical strategy outlined in the previous section yields the following results (\(N = 628\), standard errors are in parentheses):

<table>
<thead>
<tr>
<th>S: Parameter</th>
<th>Estimate</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\varphi)</td>
<td>29.143 (2.182)</td>
<td>[24.87, 33.42]</td>
</tr>
<tr>
<td>(A)</td>
<td>13.47 (0.46)</td>
<td>[12.56, 14.38]</td>
</tr>
<tr>
<td>(\lambda)</td>
<td>4.86 (0.32)</td>
<td>[4.23, 5.48]</td>
</tr>
<tr>
<td>(\rho)</td>
<td>4.87 (0.33)</td>
<td>[4.22, 5.5]</td>
</tr>
</tbody>
</table>

GMM estimation of the second, enforcement model yields the following results:

<table>
<thead>
<tr>
<th>E: Parameter</th>
<th>Estimate</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\pi)</td>
<td>0.07 (0.02)</td>
<td>[0.03, 0.09]</td>
</tr>
<tr>
<td>(A)</td>
<td>13.37 (0.46)</td>
<td>[12.46, 14.27]</td>
</tr>
<tr>
<td>(\lambda)</td>
<td>4.8 (0.32)</td>
<td>[4.18, 5.42]</td>
</tr>
<tr>
<td>(\rho)</td>
<td>2.02 (0.04)</td>
<td>[1.94, 2.11]</td>
</tr>
</tbody>
</table>

7.2 Goodness of Fit

What is the fit of Model 1 versus the fit of Model 2? That is, in this setting, does it seem more likely that the lender is expending resources to screen the population to determine an appropriate set of borrowers and correspondingly appropriate interest rates, or is the lender investing in enforcement by setting harsh punishments for default for certain borrowers?

It is difficult to pinpoint a rigorous strategy for comparison of these two models, in terms of fit. I therefore consider primitive measures such as sum of squared residuals. This is reasonable as a first pass, because the focus is on matching shape, distribution, comparative statics, and variation, rather than numerical value. The two frameworks are fundamentally different; my goal at this point is only to identify which framework seems to capture the spirit of the data.
The figure below represents the fit of the screening model in predicting interest rates. Households are along the $x$-axis, and the $y$-axis is the interest rate. Actual interest rates are plotted in red, while predicted interest rates are plotted in blue:

The figure below represents the fit of the enforcement model in equilibrium interest rates. Again, the $x$-axis is households, and the $y$-axis is the interest rate. The actual interest rates are plotted in red, while the predicted are plotted in blue:
As a last quick check, a simple OLS regression of interest rates on wealth and loan size verifies that equilibrium loans are indeed increasing in wealth, and the reduced-form estimate is fairly close to the structural estimate, so the exogenously-given loan demand function seems reasonable:

![Enforcement--red is actual interest rate](Image)

| Table 9: OLS Regression of Loan Size on Wealth |
|-----------------|-----------------|-----------------|-----------------|
| Regressor       | OLS Estimates   | Robust SEs      | Confidence Intervals |
| Wealth          | 0.228***        | 0.04            | [0.149, 0.308]    |
| Constant        | 0.327***        | 0.023           | [0.281, 0.373]    |

Notes: This table reports the OLS estimates of the role that wealth plays in determining loan size

*significant at 10%. **significant at 5%. ***significant at 1%

8 Conclusion

There are many limitations to this research. First of all, structural estimation is subject to many inherent limitations–model misspecification is always an underlying concern. However, the focus here is not so much to estimate magnitudes as to propose a benchmark framework for informal moneylending markets which has been lacking in the literature. The model is very basic. There are no dynamics, and wealth is assumed to be uncorrelated with private cost of default. But the goal here is simply to establish a starting point for applied theorists interested in informal lending. The literature has hitherto largely focused on joint liability and the use of screening mechanisms. My results suggest that an enforcement mechanism has theoretically different implications, and that a model where lenders focus on ex post control of default, rather than ex ante control of default,
best explains the behavior of Hyderabad moneylenders, and perhaps lending behavior in developing
economies more generally. Thus, it may be useful to further explore such mechanisms and consider
policies not focused on lowering screening costs. The overarching goal of this paper is to ask whether
there is some underlying informal lending mechanism that can unite the vast empirical literature by
generating the set of common elements observed across that literature. The findings indicate that
such a mechanism may actually rely more on a lender’s enforcement technology, rather than on her
screening technology as is commonly believed. While very preliminary, this paper suggests that
further exploration of the enforcement mechanism could be valuable in constructing a benchmark,
testable model of informal lending.

9 References


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