Adverse Selection in Credit Markets: Evidence from South Indian Bidding Roscas

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Abstract: Bidding Roscas (rotating savings and credit associations) are financial institutions in which participants contribute at regular meetings and bid to receive the accumulated contribution. We use a natural experiment to test for information asymmetries in these Roscas. In September 1993, the Indian government imposed a ceiling on bids (and hence on interest rates). We compare the difference in default rates between early and late recipients before and after this policy shock. We find significant evidence of adverse selection. Our findings cannot be explained by moral hazard. We also find that adverse selection is more pronounced in urban areas and in newly established branches.

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1 Introduction

Information asymmetries are widely believed to be crucial impediments in financial markets. Yet the evidence of asymmetric information in insurance markets is mixed (Chiappori and Salanié (8)) and there is little empirical research testing for such asymmetries in credit markets (Ausubel (4), Karlan and Zinman (13), Ahlin and Townsend (1)).[1] In this paper we use a natural experiment in South India to test for asymmetric information. The rich institutional structure of the financial institution we study makes our identification strategy novel.

We ask if borrowers who are willing to pay a higher interest rate are riskier than those who are not. We find clear evidence that they are. In particular we are able to reject the null hypothesis that unobserved riskiness is unrelated to the interest rate a borrower is willing to pay. Further, by exploiting small sample variation in the data we are able to show that moral hazard does not explain this finding. Our results therefore strongly suggest that there is adverse selection in credit markets (Stiglitz and Weiss (20)). When riskiness is unobserved, selection could go either way, however. De Meza and Webb (9) show that safer borrowers may instead be willing to pay higher interest rates and derive opposite implications from Stiglitz and Weiss (20).[2] We find no evidence of their hypothesized advantageous selection.[3]

The context for our study is a financial institution called a Rosca (or Rotating Savings and Credit Association). These are popular in many developing countries. In a Rosca, a

[1] Our paper is most closely related to Karlan and Zinman (13) who find adverse selection among women but not among men using randomized experiments. In contrast, we find adverse selection in a sample that is predominantly male.

[2] Distinguishing between these two theories is difficult but important. According to Besley (5): "...both the Stiglitz-Weiss and De Meza-Webb analyses conclude that the level of investment will be inefficient, but they recommend opposite policy interventions as a solution. The conflicting recommendations would not be especially disquieting except that the differences between the models are not based upon things that can be measured with precision...So it is hard to know which of the results would apply in practice."

[3] This term advantageous selection is used by de Meza and Webb (10) in the insurance context, where it refers to how increasing premiums can lead to a safer pool of insurees.

group of people get together regularly, each contributes a fixed amount, and at each meeting one of the participants receives the collected contribution, also called the pot.[4] In random Roscas, the pot is awarded in each round by lottery. In bidding Roscas, the subject of our study, each pot is awarded to the highest bidder of an auction. Once a participant has received a pot he is ineligible to bid for another. Unlike textbook financial markets with a single interest rate, every participant in a bidding Rosca effectively pays a different interest rate. This variation in interest rates makes bidding Roscas particularly appropriate for this kind of a study.

Bidding Roscas induce participants to self select. In each round, of those participants who have not received a pot in any of the preceding rounds, the one who is willing to accept the highest loan interest rate receives the pot. So recipients of early pots demonstrate a willingness to pay higher interest rates than late recipients. The question is: are early recipients riskier or safer than later recipients? Since early recipients have more to repay, if they are riskier than later recipients, it would lead to higher default costs overall and hence *adverse* selection. On the other hand, if earlier recipients are safer than later recipients, the overall default costs would be lower, i.e. *advantageous* selection.[5]

To distinguish between adverse and advantageous selection, we exploit an exogenous policy shock.[6] In September 1993, the government unexpectedly imposed a bid ceiling (of 30% of the total pot). This effectively transformed the early rounds of bidding Roscas into random Roscas since many participants bid up to the ceiling but only one of them chosen by lottery receives the pot. At an extreme, if a Rosca is transformed from bidding to

[4] The rationale for Roscas and for the different formats we observe are analyzed by Anderson and Baland (2), Besley, Coate and Loury (6), Klonner (14) and Kovsted and Lyk-Jensen (16).

[5] The willingness to pay higher interest rates may be because of differences in riskiness and profitability of the investment technology (as in the Stiglitz-Weiss (20) and de Meza-Webb (9) models) or for other reasons (say, impatience) that by coincidence are correlated with risk. In the paper we assume that the private information is on project riskiness and profitability, but the results would go through if instead the private information was about the degree of borrower impatience (and the associated default risk).

[6] Eeckhout and Munshi (11) study the performance of bidding Roscas as matching institutions using the same natural experiment.

complete random, all else equal, the average riskiness of all recipients should be the same (implying a completely flat risk profile).

We first show theoretically how the policy shock will result in a different *flattening* of riskiness depending on whether there is adverse or advantageous selection. With adverse selection, the difference between the riskiness of early and late recipients becomes smaller as a result of the bid ceiling. In contrast, with advantageous selection, that difference would become larger. We therefore use a difference-in-difference specification to test between the models. Our null is that there is neither adverse nor advantageous selection.

The policy shock forms the basis of our identification strategy. Figure 1 shows a flattening of default rates for a particular Rosca denomination. Notice that the flattening is consistent with adverse selection but inconsistent with advantageous selection. But such a pattern could also arise for other reasons. In particular, aggregate shocks or changes in the composition of participants could reduce defaults by early recipients (relative to late). Or the changes in loan terms (earlier recipients typically receive more favorable terms after the policy shock), and the associated changes in moral hazard propensity, could be driving the observed pattern. We control for all these possibilities. In particular, we use the small sample variation in auction outcomes to aid identification. The amount of the winning bid at which a pot is awarded before the policy shock can be used to control for the changes in loan terms.

To summarize then, we find evidence of adverse selection, but no evidence of advantageous selection. Our estimates are robust to controls for aggregate shocks, changing composition of Roscas, different loan terms and moral hazard. We also show that adverse selection is context specific. It is more pronounced in branches that have been established more recently, are less remote and in larger cities. This is as expected: the Rosca organizer presumably is less effective at screening participants in newer branches and in more urban areas.

Finally, we contrast our paper with an empirical literature on repayment incentives in developing countries. Anderson et al (3) analyze how social collateral affects Rosca design in Kenya. Karlan (12) and others use default data from group lending programs to explore the role of social collateral in ensuring repayment. Since the bidding Roscas that we study are commercially organized, the participants do not bear the cost of defaults of others in their group.[7] So we would not expect social ties between Rosca members to reduce default rates.

We proceed as follows. In section 2, we provide background on bidding Roscas in South India, and on the policy shock. In section 3, we construct a simple model of bidding Roscas to illustrate the flattening result. In section 4, we discuss our identification strategy. In section 5, we discuss our results. We conclude in section 6.

2 Institutional Context

In this section we provide some background information on the bidding Roscas we study: how they work, how contributions are enforced, how we calculate default rates, and how default rates are affected by the policy shock.

Rules and Denominations

Bidding Roscas are sophisticated mechanisms that match borrowers and lenders. Each month participants contribute a fixed amount to a pot. They then bid to receive the pot in an oral ascending bid auction where previous winners are not eligible to bid. The highest bidder receives the pot of money less the winning bid and the winning bid is distributed among all the members as a dividend. Consequently, higher winning bids mean higher interest payouts to later recipients of the pot. Higher winning bids also effectively mean smaller loans for the winners of early pots. Over time, the winning bid falls as the duration for which the loan is taken diminishes.

[7] Participants are asked to provide cosigners (typically from *outside* the Rosca) to guarantee that they will continue to make contributions after receiving the pot. Bond and Rai (7) compare cosigned loans with group loans.

Example (Unrestricted Bidding) *To illustrate these rules, consider the following* 3 *person Rosca which meets once a month and each participant contributes* \$10. *Suppose the winning bid is* \$15 *in the first month. Each participant receives a dividend of* \$5. *The recipient of the first pot effectively has a net gain of* \$10 *(i.e. the pot less the bid plus the dividend less the contribution). Suppose that in the second month (when there are* 2 *eligible bidders) the winning bid is* \$12. *And in the final month, there is only one eligible bidder and so the winning bid is* 0. *The net gains and contributions are depicted as:*

Month	*1*	*2*	*3*
Winning bid	*15*	*12*	*0*
First Recipient	*10*	*-6*	*-10*
Second Recipient	*-5*	*12*	*-10*
Last Recipient	*-5*	*-6*	*20*

The first recipient is a borrower (he receives \$10 *and repays* \$6 *and* \$10 *in subsequent months, which implies a* 34 *percentage monthly interest rate). The last recipient is a saver (she saves* \$5 *for* 2 *months and* \$6 *for a month and receives* \$20, *a monthly interest rate of* 49 *percent).*

In South India, Roscas originated in villages and small communities where participants were well informed about each other and could enforce repayments (Radhakrishnan (19)). The bidding Roscas we study are larger scale: the participants typically do not know each other and the Rosca organizer (a commercial company) takes on the risk of default. Bidding Roscas are a significant source of finance in South India (where they are called chit funds). Deposits in regulated chit funds were 12.5% of bank credit in Tamil Nadu and 25% of bank credit in Kerala in the 1990s, and have been growing rapidly (Eeckhout and Munshi (11)). There is also a substantial unregulated chit fund sector.

The data we use are from Shriram Chits and Investments Ltd., an established Rosca organizer with headquarters in Chennai. The company started its business in Chennai, the state capital located in the Northeast of Tamil Nadu. It began organizing Roscas in

1973 and has been expanding gradually over the state of Tamil Nadu since then, a process which is still ongoing. While the company operated 78 branches in late 1991, the number of branches has grown to 87 as of May 2005.

The most common Rosca denomination offered by Shriram in the early 1990s meets for 40 months (with 40 members) and has a contribution of Rs 250. This Rosca has a pot of Rs $10,000$. At that time, every year over five hundred Roscas were organized of this denomination alone (see Table 1).

The organizer also offers other Rosca denominations, some with shorter durations (e.g. 25 months), others with longer durations (e.g. 50 months), and some with higher contributions and some with lower contributions. In this way, the organizer can match borrowers and lenders into Roscas that vary based on investment size and horizon. In what follows, we will refer to a Rosca of duration n (in months) and contribution m as (n, m). Since all Roscas administered by the organizer meet once per month, n also equals the number of members. The available pot is nm. Our sample comprises those eleven denominations that were most popular around the time the policy shock, which will be discussed shortly, occurred. More precisely, we include all denominations of which Shriram started at least 40 Roscas between October 1992 and September 1994. The number of groups in the sample is set out in Table 1 and Table 2 contains more detailed information on the 78 branches in which the Roscas of our sample were organized.

Policy Shock

In September 1993 the Supreme Court of India enforced the 1982 Chit Fund Act, which stipulates a 30% ceiling on bids for every Rosca denomination. Since there was considerable uncertainty about when and if this law would ever be enacted, the 1993 ruling can reasonably be interpreted as an unanticipated policy shock (see Eeckhout and Munshi (11)). The ceiling effectively converted bidding Roscas into partial random Roscas: if several participants bid up to the ceiling only one of them receives the pot by lottery. This rule applied to all Roscas started after September 1993. Roscas that were started before September

1993 continued to operate under the old regime of unrestricted bidding.

Example (Restricted Bidding) *In terms of the previous example then the law capped bids at* \$9. *So in both the first and second month, bidding would go up to the ceiling. The first recipient contributes* \$10, *receives the pot less the bid,* \$21, *and also receives a dividend of* \$3, *which provides a net gain of* \$14 *in the first month. Each of the other participants contributes* \$10 *and receives a dividend of* \$3 *in the first month. So the payoffs are:*

Month	*1*	*2*	*3*
Winning bid	*9*	*9*	*0*
First Recipient	*14*	*-7*	*-10*
Second Recipient	*-7*	*14*	*-10*
Last Recipient	*-7*	*-7*	*20*

From this example, then it is clear that the ceiling substantially lowers the interest rate on borrowing for the first recipient (and hence the interest rate on savings for the last recipient). According to Eeckhout and Munshi (11), interest rates fell from $14-24\%$ *pre policy shock to* $9-17\%$ *post shock. This is in accordance with the stated objective of the policy which was to prevent usurious interest rates in Roscas. The ceiling also creates uncertainty about when a participant would receive the pot.*

Our sample consists of Roscas that started in the 12 months prior to the shock and in the 12 months after the shock. According to Table 1, there was a substantial decrease in the number of Roscas formed for several of the Rosca denominations, including a drop of 37.5 percent for the popular $(40, 250)$ denomination. Bidding reached the ceiling during the first half of the Rosca cycle after the policy shock in all 11 denominations. In denominations of shorter duration, the ceiling binds less often because the winning bid reflects an interest payment for a loan of shorter duration. At the other extreme, bidding reached the ceiling in roughly 98% of the first 30 rounds of the $(60, 1250)$ denomination.

Enforcement

Early recipients clearly have an incentive to drop out and stop making contributions. The organizer of the Roscas offers protection to participants against such defaults. If a recipient fails to make a contribution, the organizer will contribute the funds. The organizer receives two forms of payment. He acts as a special member of the Rosca who is entitled to the entire first pot (i.e. the first pot at a zero bid). He also receives a commission (usually $5 - 6$ percent) of the pot in each round.

Rosca participants do not put up any traditional collateral. Instead, the organizer relies on the promise of future financial access and outside cosigners provide incentives for participants to continue making contributions even after they have received the pot. In Roscas of longer durations, recipients in the first half of the Rosca have to provide three cosigners with a total monthly net income of fifteen percent of the pot, and recipients in the second half of a Rosca have to provide two such guarantors. In shorter duration Roscas all recipients have to provide two cosigners. Moreover the organizer uses alternative enforcement strategies as well. Company officials claimed to us that their relatively high collection rates are due to personalized collection efforts like home visits. Finally, the organizer tries to discourage risky participants by admitting only those people who can show they have a regular wage income. Company officials also told us that screening and enforcement procedures were not changed in response to the policy shock and that enforcement policies were the same across branches.

In contrast with the informal financial arrangements in village economies, in these organized urban Roscas social pressure plays no role in enforcing repayment. In each branch, interested individuals simply sign up to join a Rosca of a specific denomination, and a new Rosca commences once enough individuals have signed up. Since members of a particular Rosca have negligible losses from a default in their group, they have no incentive to select or monitor the other group members.

Defaults

We calculate the individual default rate of a member of Rosca i who receives the pot in round $t \in \{1, ..., n\}$ as

$$y_{ti} = \frac{\text{amount not repaid by round } t \text{ recipient}}{\text{amount owed by round } t \text{ recipient}}. \tag{1}$$

So $y_{ti} = 0$ if the recipient has made all contributions, and $y_{ti} = 1$ if the recipient has made no contributions after winning the pot. Partial defaults are observed in the data, which means that y_{ti} is often less than 1.[8]

We also calculate the total default rate for Rosca i as

$$x_i = \frac{\text{total amount not repaid by members of Rosca } i}{\text{total amount owed by members of Rosca } i}.$$

The total default rate gives the percentage of funds lent out in Rosca i that the company failed to collect from the Rosca's participants. It thus reflects the risk for the organizer associated with lending in Roscas. Notice that x_i can be written as a weighted average of individual default rates. Denoting by Q_{ti} the amount owed by the round t recipient in Rosca i, we can write

$$x_i = \frac{\sum_t y_{ti} Q_{ti}}{\sum_t Q_{ti}}.$$

The "weights" Q_{ti} are strictly decreasing in t because Q_{ti} equals $Q_{t+1,i}$ plus the net contribution due in round $t+1$.[9] Put differently, while the recipient of the round t pot owes another $n - t$ net contributions, the recipient of the next pot only owes $n - t - 1$ net contributions. This implies that individual default rates of early recipients affect the default costs of the organizer disproportionately.

[8] When a participant stops making contributions before receiving a pot, she is excluded from the group and replaced by another individual.

[9] According to the rules of a Rosca, the net contribution in round t equals m minus $\frac{1}{n}$ times the winning bid in round t. This is because each member receives an equal share of the winning bid as dividend in each round.

Between 10 and 25% of members are finance companies (institutional investors) which have a close business relationship with Rosca organizer. Since finance companies never default, all pots allocated to them are excluded from the analysis. With an average total default rate of 1.6 percent among customers other than finance companies, Shriam maintains an extraordinary collection record. To put this number into perspective, Ausubel (4) reports an average chargeoff rate of 4.5 percent in his study of credit card lending in the US.

We are interested in how default rates were affected by the bid ceiling. A dramatic change occurred in the timing of individual defaults (see Table 3). Before the policy change, the individual default rate of recipients during the first half of a group's duration averaged 1.74% while individual default rates of recipients during the second half of the cycle averaged 0.54%. The respective figures are 1.53% and 0.73% after the policy change. For the 752 groups of the $(30, 500)$ denomination this is illustrated in Figure 1. The profile of individual default rates by round is considerably flatter for the post policy shock groups. Although the average individual default rate remained virtually unchanged, the observed flattening of the timing of defaults resulted in a decrease in the total default rate in the sample. The average total default rate dropped by 18% from 1.71 percent to 1.41 percent (see Table 3).

As can be seen from Table 3, default rates were higher before the policy change for Roscas with large contributions, in the newer branches in the South and Northwest of the state of Tamil Nadu (the older branches are in the Northeast), in more remote areas and in smaller towns. These differences persisted till after the policy change.

3 Theory

In this section, we develop a model of bidding Roscas in which borrowers differ in terms of riskiness and profitability. In this model a Rosca provides financial intermediation between members of different profitabilities. Specifically, high profitability members will receive early pots to undertake their projects earlier. To do so, they compensate those members who wait through the price they pay for a pot. We analyze bidding behavior first in the absence of a ceiling (unrestricted bidding) and then in the presence of a bid ceiling (restricted bidding) when borrower types are private information. The purpose is to establish implications which can distinguish adverse selection from advantageous selection.

The Basic Economy

There are two agents and two periods. Each agent is initially endowed with a riskless income stream of \$1 per period and has access to an investment project of size 2. The project yields an expected (gross) rate of return of μ per period. We assume that for each participant μ is independently drawn from a common distribution with cumulative distribution H at the beginning of date 1.[10] Assume that H is smooth and strictly increasing on its support $[\underline{\mu}, \overline{\mu}]$. Moreover, μ is privately observed.[11] Assume that H is common knowledge and so H also represents the beliefs of each agent about the distribution of the other agent's rate of return μ. We assume that projects are risky, and their riskiness is related to their return. They fail with probability $\phi(\mu)$ and succeed with probability $1 - \phi(\mu)$. We shall assume that $\phi(\mu)$ is weakly monotonic, i.e. either $\phi'(\mu) \geq 0$ for all μ or $\phi'(\mu) \leq 0$ for all μ. In words, riskiness is either (weakly) increasing or decreasing in profitability. We shall assume further that there is a lower bound on $\phi'(\mu)$:

$$\phi'(\mu) > -2/\delta \tag{2}$$

We shall discuss both the reason for making this assumption and the consequences of relaxing it at the end of this section. Both agents are assumed to have additively separable, risk-neutral intertemporal preferences with common discount factor δ.

[10] In our model, as in Besley et al. (6), Kovsted and Lyk-Jensen (16) and Eeckhout and Munshi (11), participants differ in their ex ante valuation for a given pot. There is an alternative way of modelling Roscas (Klonner (14) and Klonner (15)) where members are identical ex ante and obtain private information before every auction. Our approach to testing between adverse and advantageous selection goes through if we assumed instead that participants were identical ex ante but each received a profitability draw of μ from the distribution H at each date.

[11] Kovsted and Lyk-Jensen (16), also assume private information, while this information is public in Besley et al (6). and Eeckhout and Munshi (11).

Both the agents form a bidding Rosca that meets at dates 1 and 2. Each member contributes \$1 at date 1 and there is an open-ascending bid auction. The winning bidder of the auction receives the pot of \$2 and, according to the rules, pays half of the price, p_1 say, to the other, losing bidder. Thus the winner receives $2 - p_1/2$. She needs additional finance of $p_1/2$ to undertake the investment project. As in Kovsted and Lyk-Jensen (16), we assume that each member has access to costly external funds to finance this difference between the amount received from the Rosca upon winning the auction and the cost of the project. Each dollar borrowed from this source causes an instantaneous disutility of $c > 1$. At date 2, the winner at date 1 contributes if her project succeeds. If her project fails, then the organizer contributes \$1. In either case the date 1 losing bidder is assured of \$2 at date 2 (there is no auction).

We are thinking of participation in the Rosca as an opportunity for a wage earner to undertake a risky entrepreneurial activity. The profitability and riskiness of this entrepreneurial activity is privately observed. The winner of the auction in our model effectively takes a loan of $1 - \frac{p_1}{2}$ and repays \$1 at date 2. The loser of the auction effectively lends $1 - \frac{p_1}{2}$ and is repaid \$1. So the higher is the price (i.e. the second highest bid), the higher is the interest rate (or equivalently the lower is the loan size).

Unrestricted Bidding

The bidding Roscas in our sample use an open ascending bid format. As is common in the literature on private value auctions (McAfee and McMillan (17)), we model this as an ascending clock auction, in which each bidder presses a button while the standing price increases continuously (as on a clock). Once a bidder releases her button, the auction ends and the price is equal to the stopout price of that bidder who first released her button. In such an auction, a participant's bid function is a stopout price that depends on her type. We will denote the equilibrium bid function as $b_0(\mu)$.

We shall show below that the equilibrium bid function $b_0(\mu)$ is increasing. In this equilibrium, an agent who observes profitability μ has expected utility:

$$\Pi^e(\mu) = H(\mu)\left(2\mu - \frac{c}{2}E\left[b_0(\widetilde{\mu})|\widetilde{\mu} \leq \mu\right] - \delta(1-\phi(\mu))\right) + (1-H(\mu))\left(\frac{1}{2}b_0(\mu) - \delta\right) + \delta 2\mu.$$

The random variable $\widetilde{\mu}$ denotes the other member's profitability drawn from the distribution H. The probability of winning the auction $\Pr(b_0(\mu) \geq b_0(\widetilde{\mu}))$ is $H(\mu)$ and the probability of losing the auction is $1-H(\mu)$. If the agent wins, then 2μ is the expected profit she earns instantly from winning the first pot and investing, and $\frac{c}{2}E\left[b_0(\widetilde{\mu})|\widetilde{\mu} \leq \mu\right]$ is the expected instantaneous disutility arising from having to finance $b_0(\mu)/2$. If the project succeeds, which happens with probability $1-\phi(\mu)$, she has to pay the Rosca contribution in the next round, which gives the term $-\delta(1-\phi(\mu))$. When a member of profitability μ loses the auction, she instantaneously consumes $b_0(\mu)/2$ and has to pay the contribution in the next round for sure, thus the term $\frac{1}{2}b_0(\mu) - \delta$. At the end of the second period both members have invested and earn an expected income of 2μ. Notice that the organizer insures the loser of the auction against default in the second round by the first round winner, and it is for that reason that both will invest.

We show that there is adverse selection if $\phi'(\mu) > 0$ and advantageous selection otherwise:

Proposition 1 ***(Unrestricted Bidding)***

A symmetric Bayesian Nash equilibrium exists in which:

(i) the equilibrium bid function $b_0(\mu)$ is strictly increasing

(ii) the early recipient is more profitable than the late recipient

(iii) If $\phi'(\mu) > 0$ (< 0) the early recipient is riskier (safer) than the late recipient.

All proofs are in the appendix.

The equilibrium characterized in Proposition 1 implies that the participant with higher profitability obtains finance first (which is socially efficient). The function $\phi(\mu)$ represents the relation between riskiness and profitability. When riskiness and profitability are positively related, $\phi'(\mu) > 0$, there is *adverse selection.* In contrast, when riskiness and profitability are negatively related, $\phi'(\mu) < 0$, there is *advantageous selection.* Since the first participant is riskier under adverse selection, default costs are higher than with advantageous selection. If $\phi'(\mu) = 0$ for all μ, all profitability types are of equal riskiness and there is neither adverse nor advantageous selection. We shall discuss the relationship between adverse/advantageous selection in our model of bidding Roscas and models of adverse/advantageous selection in credit markets at the end of section 3.

Restricted Bidding

In this section we model the implication of a ceiling on bids, which we denote as $\bar{b}$. At one extreme, if the ceiling is set very low, then it will always bind. Participants will both bid to the ceiling and the pot will be awarded by lottery (just as in a random Rosca).[12] The expected riskiness of the first recipient will be the same as the expected riskiness of the second recipient. The risk ordering will be flattened. At the other extreme if the ceiling $\bar{b}$ is set very high, then it will never bind and so the auction outcome will be the same as in the unrestricted case (Proposition 1).

If the ceiling $\bar{b}$ is set somewhere in between the extremes, then it will only bind sometimes. In such a case there exists a bidding equilibrium in which, as before, a participant's bid function is weakly increasing. We denote this equilibrium bid function (restricted by the ceiling) as $b_1(\mu)$. It is shown in Figure 2. This function is strictly increasing for profitabilities below a certain threshold denoted by μ'. For $\mu > \mu'$, on the other hand, $b_1(\mu)$ is flat and equal to the ceiling $\bar{b}$. If both participants bid to the ceiling, open bidding stops and both participants have an equal chance of winning the pot.[13] The ceiling binds when both participants receive a profitability draw exceeding μ' and in such a case the early

[12] Unlike a random Rosca (where the price is zero for every pot), here the price of the first pot is $\bar{b}$ and so the winner of the lottery makes a side payment of $\bar{b}/2$ to the loser.

[13] In practice, if both agents bid to the ceiling, they are invited to participate in the lottery (and either may decline). We model this decision. So here a strategy for each agent is not just a bid function but also the lottery participation decision (if invited). As we show in the proof of Proposition 2 an agent chooses to participate in the lottery if and only if she bids up to the ceiling.

recipient is of the same expected profitability (and hence the same expected riskiness) as the late recipient.

We collect these cases together in the following proposition:

Proposition 2 ***(Restricted Bidding)***

- *If the ceiling is sufficiently high,*

$$\bar{b} \geq \frac{2(2\overline{\mu} + \delta\phi(\overline{\mu}))}{1+c} \tag{3}$$

then the ceiling never binds and Proposition 1 applies.

- *If the ceiling is sufficiently low,*

$$\bar{b} \leq \frac{2(2\underline{\mu} + \delta\phi(\underline{\mu}))}{1+c} \tag{4}$$

then the ceiling always binds, both participants bid $\bar{b}$ and the early and late recipients have the same profitability and riskiness.

- *Finally, if neither (3) nor (4) hold, then a symmetric Bayesian Nash equilibrium exists, in which a unique threshold $\mu' \in (\underline{\mu}, \overline{\mu})$ exists such that:*

(i) the equilibrium bid function $b_1(\mu)$ is increasing below the threshold μ' and $b_1(\mu) = \bar{b}$ above the threshold μ'

(ii) the early recipient has lower profitability than the late recipient with probability $\frac{1}{2}(1 - H(\mu'))^2$

(iii) if $\phi'(\mu) > 0$ (< 0), the early recipient is of lower (higher) risk than the late recipient with probability $\frac{1}{2}(1 - H(\mu'))^2$.

The first pot is allocated to the higher profitability member with certainty only if at least one member's profitability is no bigger than μ'. If, on the other hand, both participants have profitability draws exceeding μ' which happens with probability $(1 - H(\mu'))^2$ a lottery occurs, and the early recipient has lower profitability than the late recipient with probability $\frac{1}{2}$. In this sense, with a binding ceiling, the bidding Rosca no longer induces an ex-post efficient allocation.

With unrestricted bidding the equilibrium bid function $b_0(\mu)$ is increasing. With restricted bidding, participants with profitability exceeding a threshold μ' bid at the ceiling $\bar{b}$. We also show (below) that the bid ceiling shifts down the entire bid function (so $b_1(\mu)$ is lower than $b_0(\mu)$). This is depicted in Figure 2 and proved as:

Proposition 3 ***(Comparing Bid Functions)***
In the symmetric equilibria characterized in Propositions 1 and 2, a member of profitability $\mu \in [\underline{\mu}, \overline{\mu}]$ chooses a strictly smaller stopout price in an auction with restricted bidding, that is $b_0(\mu) > b_1(\mu)$ for all $\mu \in [\underline{\mu}, \overline{\mu}]$.

Testable Implication

Another more important effect of introducing a ceiling on bids occurs whenever a lottery takes place in the first round. Proposition 1 states that the recipient of the first pot always has higher profitability than the recipient of the second pot. With the ceiling in place, however, the recipient of the first pot has a lower profitability than the recipient of the second pot with probability $\frac{1}{2}(1 - H(\mu'))^2$ if the ceiling sometimes binds (Proposition 2). It is this reordering of types that we will use to identify the slope of the ϕ function. More precisely, conditional on the first pot being allocated through a lottery, the recipient of the first pot has lower profitability than the recipient of the second pot with probability $\frac{1}{2}$, while the probability of this event is zero when there is no ceiling on bids in place.

The ceiling makes the average riskiness of participants more equal over time. This insight is summarized as:

Proposition 4 ***(Testable Implication)***
Provided the ceiling binds sometimes or always, Propositions 1 *and* 2 *imply:*
(i) If $\phi'(\mu) > 0$, then the difference between the riskiness of early and late recipients is positive with both unrestricted and restricted bidding but smaller in the latter case.
(ii) if $\phi'(\mu) < 0$, then the difference between the riskiness of early and late recipients is negative with both unrestricted and restricted bidding but higher (that is less negative) in

the latter case.

In other words, restricted bidding flattens the risk profile in both cases. So our empirical strategy (which we discuss in detail in section 4) will be to take the difference between early and late recipients before and after the ceiling is imposed. We then take the difference between these differences. This should be positive in the case where $\phi'(\mu) > 0$ and negative in the case where $\phi'(\mu) < 0$.

Stiglitz-Weiss and de Meza-Webb

We now turn to the connection between adverse/advantageous selection in our model of bidding Roscas and the adverse/advantageous selection in models of credit markets by Stiglitz-Weiss (20) (henceforth SW) and de Meza-Webb (9) (henceforth DW).

So far we have generalized the SW model by allowing participants to differ in their profitability. We have associated the adverse selection when $\phi'(\mu) > 0$ with SW since it is the riskier borrowers who are willing to pay higher interest rates. But strictly speaking, SW make the special assumption that all borrowers have the same profitability μ and just differ in their riskiness. It is straightforward to see that the riskier participant will bid more for the first pot because she is less likely to pay the contribution in the second round. So the SW special assumption will lead to adverse selection with unrestricted bidding, a flattening of the risk profile under the ceiling and the same testable implication as in Proposition 4.

In their model of credit markets, DW assume that riskiness and profitability are negatively related. When $\phi'(\mu) < 0$, we find advantageous selection if assumption (2) holds. We associate this advantageous selection with DW since it is the safer borrowers who are willing to pay higher interest rates.

For the sake of completeness, we will briefly discuss what the model predicts if assumption (2) does not hold. Suppose that:

$$\phi'(\mu) < -2/\delta \text{ for all } \mu$$

Under this alternative assumption, there is an equilibrium with restricted bidding in which the less productive riskier participant takes the first pot. Effectively the alternative assumption leads to adverse selection of the SW kind: the riskier participant is willing to pay more for the pot than the safer participant. The reason is that the benefit from the higher chance of defaulting on the round 2 contribution for the risky participant outweighs the higher profitability of the safer participant. With restricted bidding the risk profile is flatter under the alternative assumption and so the testable implication (Proposition 4) goes through as before.

4 Identification

Our identification strategy is based on the flattening effect, as summarized in Proposition 4 and the assumption that, other things held constant, a member's default rate as defined in equation 1 is increasing in the member's riskiness, ϕ. The flattening effect on the risk profile immediately carries over to groups with $n > 2$ members.

In this section we first illustrate our basic identification strategy in the context of an ideal experiment. We then proceed to discuss how an empirical analysis can account for various factors in the data which potentially flaw the basic identification strategy. In the course of this discussion, the specification used for the empirical analysis is gradually derived. As we shall see both the policy shock and small sample variation in winning bids will be crucial to our identification strategy.

The Ideal Experiment

An ideal experiment would be characterized by the following four properties:

1. There are groups with restricted and unrestricted bidding, which start and end at identical dates.

2. The expected default rate of the recipient of a pot is independent of aggregate shocks, i.e. transitory economic conditions that affect all individuals who are Rosca members.

3. Individuals who sign up for a Rosca membership are randomly assigned into groups with restricted and unrestricted bidding.

4. The expected default rate of the recipient of a pot does not depend on the terms at which the pot is obtained.

Suppose we have the ideal experiment: data from groups with unrestricted and groups with restricted bidding, where all groups are from the same Rosca denomination, that is all groups are of identical duration and contribution per round. The sign of the slope of the ϕ-function is then identified through the econometric specification

$$y_{ti} = \alpha_t + \xi \; after_i + \beta \; after_i \; late_t^{\tau} + u_{ti}, \tag{5}$$

where $t \in \{1, ..., n\}$ denotes the round of receipt of the pot, and $i \in \{1, ..., I\}$ indexes Roscas of a particular denomination. The unit of observation y_{ti} is the individual default rate of the recipient in round t of Rosca i. The intercept term α_t is round specific. The dummy variable $after_i$ equals one if Rosca i started after the policy shock and zero otherwise. The dummy variable $late_t^{\tau}$ is an indicator for whether the recipient in round t was a late (as opposed to and early) recipient. Here $\tau \in (0, 1)$ determines a "cutoff round" that separates early from late recipients, where, qualitatively, early recipients correspond to the recipient of the first, and late recipients to the recipient of the second pot in our theoretical model. To be precise, $late_t^{\tau}$ equals one if $t > \tau n$. The interaction term $after_i \; late_t^{\tau}$ interacts the indicator for before/after policy shock with the indicator for early/late receipt of the pot. To give an example, when $n = 40$ and $\tau = 0.5$, specification (5) relies on the difference in defaults between recipients of pots up to and after round 20. For identification, τ has to be chosen such that flattening of the risk profile occurs around round $n\tau$. A sufficient condition for this is that a lottery occurs in round $n\tau$ (assuming this is an integer) in at least some of the groups with restricted bidding.

The least-squares estimate of β is the difference between (i) the difference in the average default rate of recipients of early and late pots with unrestricted bidding and (ii) the difference in the average default rate of recipients of early and late pots with restricted bidding.

Loosely speaking we shall think of β as the *treatment effect* of the policy shock. When all members are of equal riskiness, flattening of types does not affect the average riskiness of the recipient in a given round. As a consequence, the riskiness of a given round's recipient is identical before and after the policy shock. This implies that the difference in defaults between late and early recipients is the same in Roscas with restricted and unrestricted bidding. Thus the null hypothesis of no selection ($\phi'(\mu) = 0$ for all μ) can be tested through the statistical hypothesis $\beta = 0$.

Recall that, according to Proposition 4, flattening through a ceiling on bids decreases the average profitability of early recipients and increases the average profitability of late recipients. Thus with adverse selection, $\phi'(\mu) > 0$ for all μ, early recipients are relatively less risky with restricted than with unrestricted bidding. Consequently, a point estimate of β significantly bigger than zero indicates the presence of adverse selection, while a point estimate of β significantly smaller than 0 indicates advantageous selection.

To conclude this subsection, notice that identification of selection through the empirical specification (5) is ensured if any of the following two subsets of conditions 1 through 4 holds: $\{1, 3, 4\}$ or $\{2, 3, 4\}$. This is because simultaneity of restricted and unrestricted groups (property 1) takes care of aggregate shocks. On the other hand, when there are no time-dependent aggregate shocks (property 2), simultaneity of restricted and unrestricted groups is not needed.

In the data set underlying this paper, we do not have an ideal experiment as characterized in properties 1 through 4. More precisely, with the given data scenario, a robust identification strategy has to account for departures from all four properties of the ideal experiment. We now address departures from each of these four properties and show how our identification strategy accounts for them such that the test for no adverse selection remains unbiased.

Aggregate Shocks and Non-simultaneity of Unrestricted and Restricted Groups

We first address properties 1 and 2. As to the former, unrestricted and restricted groups do not occur simultaneously. In particular, all unrestricted groups in the data start before September 30, 1993, while all restricted groups start after that month. On the other hand, Rosca members may have been subject to transitory aggregate shocks unobserved by the researcher, which is a departure from property 2. We accommodate these concerns by exploiting the fact that unrestricted and restricted groups in our sample overlap.

To illustrate, consider the Rosca denomination $(40, 250)$ and groups that started between October 1992 and September 1994. The overlap of unrestricted and restricted groups in such a sample ranges between 39 months for two groups that started in September and October 1993, respectively, and 17 months for two groups that started in October 1992 and September 1994, respectively. To account for transitory aggregate shocks, we augment (5) by quarterly dummies. Toward that, we introduce the dummy $quarter_{ti}$, which equals one for all observations from the same quarter. To give an example, for the (40,250) denomination and start dates between October 1992 and September 1994, the period covered by such a sample is 63 months, from October 1992 to December 1997. With a partition of that time period into quarters, we arrive at 21 dummy variables (starting with the last quarter of 1992 and ending with the last quarter of 1997). Since, in the presence of an intercept term, all except one of these dummies are identified, $quarter_{ti}$ equals zero for all observations from the last quarter of 1992. Indexing quarters by j, we can now rewrite (5) as

$$y_{ti} = \alpha_t + \xi \ after_i + \beta \ after_i \ late_t^{\tau} + \gamma_j \ quarter_{ti} + u_{ti} \tag{6}$$

and, as a consequence, identification of the treatment effect β is solely based on differences in defaults of contemporaneous recipients of pots.

Different Member Characteristics in Unrestricted and Restricted Groups

In this subsection we address property 3 of the ideal experiment: random assignment into unrestricted and restricted groups. In our data, individuals are not randomly assigned into unrestricted and restricted groups. Instead, there were only unrestricted groups before September 30th of 1993, and only restricted ones after that date. Ideally for the researcher, an identical set of individuals signed up for each denomination before and after that date. As we have discussed earlier, the policy shock was unanticipated so we are not confronted with a selection problem arising from a deliberate choice by prospective Rosca members whether to join a Rosca prior to September 1993 that they anticipated would be restricted after September 1993.

There are, however, other plausible reasons for why the characteristics of members of restricted groups of a certain denomination might be different from those of members of unrestricted groups of that denomination. In this connection, Eeckhout and Munshi (11) show that for an individual of a given type ex-ante expected utilities from a membership in a Rosca with restricted and unrestricted bidding are different. This can result in different pools of members in restricted and unrestricted groups of a certain denomination for at least two reasons. First, an individual of a given type may choose to join a different denomination when confronted with restricted instead of unrestricted bidding. Second, if prospective Rosca members have finance options other than Roscas, be it lending from a money lender or saving in a bank, an individual who chooses to sign up for a certain Rosca denomination when bidding is unrestricted may choose not to join a Rosca and seek other forms of finance instead when bidding is restricted. This latter argument could, at least in principle, also work conversely: an individual for whom other sources of finance dominate a Rosca membership with unrestricted bidding may decide to join a Rosca when bidding is restricted.

We explore this issue in the context of the theoretical model developed in Section 3, in which both points just raised amount to different distribution functions for unrestricted and restricted groups, respectively. Denote the distribution of profitabilities for a given denomination with unrestricted and restricted bidding by H_0 and H_1, respectively. Under the null hypothesis of our test for no adverse selection, the risk profile is completely flat both before and after the policy shock, which continues to holds when H_0 and H_1 are different because, in that case, all profitability types are of identical riskiness. This implies that a change in the pool of members does not bias our statistical test for no adverse selection, $\beta = 0$ in (6).

Default Rate Depends on Loan Terms

We now address departures from Assumption 4. In general, observed defaults may not only be a function of a borrower's inherent riskiness, but also of the terms at which the loan is obtained. In this section we shall show that the small sample variation in these bidding Roscas allows us to compare default rates of participants before and after the policy shock controlling for loan terms.

In a bidding Rosca with n members, the terms for the recipient of the pot in round t consist of two components. The first component is the price at which that pot is obtained. We will slightly abuse notation and denote this price by b_t. In a Rosca, in which each member contributes one Rupee at each meeting, that price determines the *net amount received*, $R_t = n - \frac{n-1}{n} b_t$. In our model of a two period Rosca there is only one auction. The price in that auction equals the stopout price of the low profitability bidder, or equivalently $b_1 = b(\mu_{2:2})$.

The second component of the loan terms is the vector of prices in all remaining rounds of the Rosca, $\mathbf{b}_t = (b_{t+1}, ..., b_{n-1})$. Notice that b_n always equals zero since there is no auction in the last round. That vector determines the *repayment burden* of the round t recipient. This is because in a Rosca with an individual contribution of one Rupee per round the net payment that recipient has to make equals $1 - b_s/n$ in each round after receiving the pot, i.e. for $s = t+1, ..., n-1$. As a consequence, the (aggregate) repayment burden faced by the round t recipient equals $Q_t \equiv n - s - \frac{1}{n} \sum_{s=t+1}^{n-1} b_s$.

In what follows, we will discuss at some length how the net amount received is accounted for by our identification strategy. Later, we will return to the repayment burden.

Net Amount Received

Let R_t be the net amount received by a winner of a round t pot in a Rosca, i.e. $R_t = n - \frac{n-1}{n} b_t$. R_t may affect a recipient's expected rate of default for at least two reasons. First, in the absence of any kind of moral hazard, the success of the borrower's project may depend on the amount she is able to invest from the pot, where, most likely, the project has higher chances of succeeding when more is invested. We will refer to this as the *size effect*. This mechanical effect can confound tests of asymmetric information (Karlan and Zinman (13)). Second, if the borrower can choose between projects of identical expected return but different riskiness, or if the success of a project is a function of effort, the borrower will choose a riskier project or supply less effort as R_t decreases. This is the classic moral hazard (MH) situation in Stiglitz and Weiss (20) among others. To clarify terminology, we will refer to a change in defaults that results from a change in R_t as the *size/MH effect* on defaults, which will prove useful because we cannot identify size and moral hazard effects separately.

In the presence of a size/MH effect, specification (6) does not unambiguously identify a selection effect on defaults because two effects that are caused by the policy shift are confounded. The first direct one is a cap on bids which together with its additional impact on bidders' strategic behavior (see Proposition 3), results in a higher loan size on average in restricted groups. The second indirect effect of the cap is the flattening of the risk profile (see Proposition 4). As a consequence, the coefficient β in (6) captures the sum of the size/MH and the selection effect. To give an example, assume that $\phi'(\mu) = 0$ and as hypothesized above a higher loan size results *ceteris paribus* in a lower rate of default. Then average defaults of early recipients will be smaller with restricted bidding simply because they receive more money on average from the pot. As a consequence we will find a positive estimate of β, erroneously indicating the presence of adverse selection.

The obvious remedy is to condition on the price paid by the recipient. In this case, we only compare pre vs post shock recipients who receive the pot at identical conditions. A concern arising in this connection is that such conditioning may introduce selection. To illustrate, in terms of our simple model, conditioning on low bids in pre shock groups means conditioning on low profitability types. Since all profitability types are of identical riskiness under the null hypothesis, however, such selection does not bias our test for no adverse selection.

In econometric terms, we include b_{ti} into specification 6. Doing so in a linear fashion, we obtain

$$y_{ti} = \alpha_t + \xi \; after_i + \beta \; after_i \; late_t^{\tau} + \gamma_j \; quarter_{ti} + \psi_t b_{ti} + u_{ti}. \tag{7}$$

Notice that we allow the coefficient for b_{ti} to be round- specific.

Repayment Burden

We now turn to the second component in the terms that the recipient of the round t pot faces, the repayment burden Q_t. Clearly Q_t induces a size effect because both numerator and denominator of our measure of the default rate (see equation 1) are affected by Q_t. To see this rewrite (1) as

$$y_{ti} = \frac{Q_{ti} - \min(Q_{ti}, Z_{ti})}{Q_{ti}},$$

where Z_{ti} denotes the maximum amount recipient i can repay, or repayment potential for short. For constant repayment potential, which, in the absence of moral hazard, is determined by i's type, y is clearly (weakly) increasing in Q. To summarize, the (mechanical) size effect of repayment burden, Q_t, on the rate of default, y, is positive. To account for this, we will condition on the repayment burden by adding the term $\zeta_t Q_{ti}$ to the right hand side of (7),

$$y_{sti} = \alpha_t + \xi \; after_i + \beta \; after_i \; late_t^{\tau} + \gamma_j \; quarter_{ti} + \psi_t b_{ti} + \zeta_t Q_{ti} + u_{ti}. \tag{8}$$

5 Results

In this section, we estimate equation (8) for the eleven Rosca denominations in our data sample. The objective of this empirical exercise is twofold. First, we seek to identify if selection is adverse or advantageous (or neither). Second, we want to identify determinants of adverse/advantageous selection that can be inferred from branch locations or denomination characteristics. We use Roscas that were started after September 1992 and before October 1994 (the two year period around the implementation of the policy shift). This has the advantage of taking care of potential seasonality of membership in Roscas as well as providing a sufficiently large number of observations. The latter is especially crucial for our analysis since default is a low probability event in our sample.

The sample means reproduced in Table 3 foreshadow our later regression results. As elaborated in the preceding section, our identification strategy is based on the change in the difference of defaults between early and late recipients around the policy shock. Accordingly, the last four columns of this table give individual default rates by round averaged over the first and second half of the duration of each group, respectively. Let k index the Rosca denomination, where $k \in \{1, ..., 11\}$. So column 3 for instance displays the average default rate for early recipients before the policy shock which is calculated as:

$$\frac{1}{\sum_{k=1}^{11} \frac{n_k}{2} I_{k0}} \sum_{k=1}^{11} \sum_{t=1}^{n_k/2} \sum_{i=1}^{I_{k0}} y_{kti},$$

where n_k is the duration of denomination k and I_{ks} denotes the number of Roscas of denomination k started before ($s = 0$) and after ($s = 1$) the policy shock.

For the entire sample, the difference between early and late defaults shrunk from $1.74 - 0.54 = 1.2$ percent for Roscas that started before the shock to $1.53 - 0.73 = 0.80$. This gives a difference-in-difference of 0.4 (see column 7) which hints at adverse selection. This pattern is illustrated in Figure 1, where the default rate is graphed by round for the popular $(30, 500)$ denomination. While default rates are similar in later rounds of such Roscas pre and post ceiling, early recipients defaulted considerably more often in the pre ceiling Roscas.

Table 3 suggests that the magnitude of the double difference differs across sample partitions. For instance there is no flattening of the risk profile with smaller contributions. There is less flattening in recently established branches (relative to well established ones). There is also less flattening in branches established in smaller and more remote towns (relative to larger towns and less remote towns) respectively suggesting that there may be differences in adverse selection between rural and urban areas.

Next we turn to the regression analysis to establish whether these findings hold when several factors which potentially confound our measure of selection are taken into account. At the end of section 4, we showed that the specification (8) ensures identification in the absence of an ideal experiment. Here we adapt specification (8) to the 11 denominations in our sample indexed by k to estimate:

$$y_{kti} = \alpha_{kt} + \xi_k \ after_{ki} + \beta \ after_{ki} \ late^{\tau}_{kt} + \gamma_j \ quarter_{kti} + \psi_{kt} b_{kti} + \zeta_{kt} Q_{kti} + u_{kti}. \quad (9)$$

Notice that, except for the aggregate shock terms, we incorporate denomination-specific controls for bid b_{kti} and repayment burden Q_{kti} throughout.[14]

The OLS results for the treatment effect (which is the coefficient on the interaction term $after_{ki} late^{\tau}_{kt}$) with alternative sets of controls are in Table 4. With no controls included, the statistically significant point estimate is 0.0036. This roughly corresponds to the 0.4 percentage points by which the difference in defaults between early and late recipients fell (Table 3). The two numbers are not exactly equivalent because the regression in Table 4 includes denomination-round specific intercept terms α_{kt} and denomination specific policy shock terms $\xi_k after_{ki}$. When controls for loan size, repayment burden and aggregate economic conditions are added, we obtain an almost identical positive point estimate of 0.0037 significant at the 1% level. This confirms that selection in this credit market is adverse rather than advantageous. At first glance this might suggest that controlling for

[14] In principle, could estimate (9) by OLS and/or by a Tobit specification (since the default rate is censored at 0 and 1). For the present application the results from an OLS specification are of primary interest since they are based on changes in the conditional expected value of actual defaults as opposed to changes in the unobserved default propensity variable. More practically, given that (9) implies a total of $1,251$ right hand side variables and that $121,943$ observations are used, it was computationally infeasible to maximize the associated likelihood function.

the aggregate shocks, winning bid and repayment burden is unimportant. But columns 3 to 8 illustrate that the results vary when subsets of the controls are deliberately omitted. For instance, when only loan size (through the winning bid) is controlled for in column 4 the treatment effect of the policy experiment disappears. We take this as evidence for the importance to control for all three factors included in (9) for the subsequent, more detailed analysis.

To identify to what extent the treatment effect differs by participant characteristics, we augment (9) by additional terms:

1. We partition the set of denominations into two groups by contribution: small-contribution groups with $m \leq 500$ and large-contribution groups where $m > 500$. The interaction term $after_{ki}\ late^{\tau}_{kt}\ large_{kti}$ is added to the right hand side of (9). Notice that this is a triple interaction term: it interacts indicators for before-after, early-late and large-small contributions. Since the contribution chosen by a prospective Rosca member is almost proportionally related to her income on average (see Table 1 of Eeckhout and Munshi (11)), the coefficient on this interaction term indicates whether adverse selection is more pronounced among the rich.

2. We include the interaction term $after_{ki}\ late^{\tau}_{kt}\ n_k$, which controls for the duration of a group. Since loan terms are different in groups of different durations, we will not attribute a significant coefficient associated with this regressor directly to differences in adverse selection. Instead, we view it as a control which ensures robustness of the estimates of the (other) coefficients of interest.

3. We include several observable characteristics of the branch where a group is administered. In particular, we allow for a different magnitude of the treatment effect for groups administered in towns with a population of less than $300,000$. We further partition branches by remoteness from a metropolitan center, where, as in Table 2, a branch is considered remote if it is more than 100 kilometers away from large cities with a population of at least $500,000$. To see how the lender's experience interacts

with selection, we interact the treatment effect with a dummy variable that equals one for the 40 branches that are located in the Northeast of Tamil Nadu, where the company started its business in 1973.

4. Finally, we tackle the potential problem of resorting of Rosca members (see Section 4). We attempt to do this by including an interaction term, which captures the change in membership for each denomination (see Table 1) around the policy shift. A significant estimate provides evidence for an impact of resorting on our measure of adverse selection.

Results of an OLS estimation of this augmented specification are in Table 5.[15] The results are presented with alternative cutoffs. In the left panel a cutoff of one half is used.[16] The base treatment effect is estimated positive at 0.0133 and significant at the 6% level. For Roscas with contributions larger than Rs. 500, however, the (aggregate) treatment effect amounts to 0.0163, which is different from zero at conventional significance levels (p-value 1.6%).[17] The negative although insignificant coefficient of the interaction term $after_{ki}\ late_{kt}^{\tau}\ n_k$ suggests that the treatment effect is smaller in groups of longer duration. The next set of results in Table 5 (rows $4-6$) are the most interesting. The treatment effect is reduced by 0.4 and 0.26 percentage points for branches located in small and remote towns, respectively. These coefficients are significant at the 1% and 6% level.

[15] As with the initial econometric analysis, estimation of a Tobit model was computationally infeasible.

[16] In the right panel of Table 5, we present results using an early-late cutoff of one third instead. This earlier cutoff potentially increases the power of our test for no selection because the relative frequency of lotteries is higher during the first third than during the first half of Roscas after the policy. But the more unequal balance of the number of observations from early and late rounds works to reduce the power of the test. This set of results serves as a useful robustness check of the findings obtained so far. All results obtained for a cutoff of one half are confirmed qualitatively.

[17] Since Table 5 gives the subgroup treatment effects at zero duration, it raises the question of whether the subgroup treatment effects are still significant if evaluated at the sample mean duration (of 38.7 months). We do find that subgroup treatment effects are still significant. For instance, the treatment effect for a Rosca of 38.7 months with large contributions with a branch in a large town that is not remote and recently established with zero attrition is 0.00745 and significant (p-value 0.0046).

Further, the estimated treatment effect is discounted by another 0.39 percentage points for established branches, a reduction that is significant at the 1% level. Finally, as far as we are able to test, attrition does not appear to systematically interfere with our approach to measure selection: the coefficient is negligible in magnitude and far from being significant at conventional levels.

These results suggest that adverse selection is more pronounced in urban areas and in recently established branches. According to the Rosca organizers, identical policies to screen participants (and admit only those with regular salaries) are in place in all branches. Our findings can be explained as follows. Screening could be less effective in urban areas where participants tend to move more often. Further, well established branches' Rosca organizers could have had more time to detect and exclude riskier participants. So unobserved riskiness that is positively related to the willingness to pay could be more of a problem in urban areas and newer branches.

The importance of including controls is highlighted through a comparison of the double difference in Table 3 and the results of the regression analysis in Tables 4 and 5. As discussed previously, the average treatment effect for the entire sample in Table 4 is almost identical to the double difference in Table 3. Further, the treatment effect for the partitions of the sample in Table 5 are mostly the same as the qualitative findings in Table 3. An important caveat however is for the role of organizer's experience. The double difference in column 7 of Table 3 is positive and more than twice as big for established branches, while we find a significantly negative corresponding coefficient in Table 5. Clearly it is the latter which we would expect to see.

We close this section by asking how much adverse selection contributes to the difference in total default rates across partitions of the sample. We do this by comparing the difference in total default rates across a partition with differences in the treatment effect across the same partition in Table 6. If they are of the same sign then adverse selection explains some of the difference in total default rates. This is the case in the first two rows. But if they are of different signs (as in the last two rows) that provides evidences that the difference in average riskiness exceeds the effect of adverse selection.

We find that large contribution denominations have higher total defaults both before and after the policy change and more pronounced adverse selection than small contribution denominations, but the latter effect is not statistically significant. For lender experience we find more recently established branches have higher total default rates and the treatment effect is estimated at 0.4 percentage points higher than for more established branches. So adverse selection significantly contributes to higher total defaults when the Rosca organizer is lacking local experience.

The opposite pattern emerges for rural vs. urban branches (when the sample is partitioned based on the size and remoteness of the towns in which branches are located). Here we see higher total defaults in small and remote towns while the treatment effect is significantly smaller in these settings. From this we conclude that higher total defaults in more rural areas are due not to more pronounced adverse selection but rather to higher average riskiness of borrowers. This makes intuitive sense: rural Rosca participants are exposed to weather-related risks that urban Rosca participants are insulated from.

6 Conclusion

We have used a natural experiment to distinguish between adverse and advantageous selection. This experiment involved imposing a bid ceiling on bidding Roscas which effectively made the early rounds more like random Roscas. The experiment did not substantially change overall default rates. But the difference between early and late defaulters changed substantially. This is what we use for identification of asymmetric information. We also use the small sample variation in auction outcomes to control for moral hazard (and other effects of different loan terms). We are thus able to identify a significant adverse selection effect. Further, we find that the adverse selection effect is more pronounced where we would expect it to be: in urban areas and in recently opened branches.

7 Appendix

Proof of Proposition 1:

For $b_0(\mu)$ to be a Bayesian Nash equilibrium agent 1 must be playing a best response to agent 2 (who has profitability draw $\widetilde{\mu}_2$ and is bidding $b_0(\widetilde{\mu}_2)$). Suppose agent 1 also determines her stopout price according to $b_0(\cdot)$ but pretends to be of type μ, which may or may not be her true type μ_1,the relevant part of agent 1's expected utility is

$$\Pi(\mu,\mu_1) = F(\mu)\left(2\mu_1 - \frac{c}{2}E\left[b_0(\widetilde{\mu}_2)|\widetilde{\mu}_2 \leq \mu\right] - \delta(1-\phi(\mu_1))\right) + (1-F(\mu))\left(\frac{1}{2}b_0(\mu) - \delta\right) \tag{10}$$

where $\widetilde{\mu}_2$ denotes member 2's profitability as random variable distributed according to H. $F(\mu)$ equals $\Pr(b_0(\mu) \geq b_0(\widetilde{\mu}_2))$, the probability of winning the auction if pretending μ, when $b_0(\cdot)$ is increasing. $2\mu_1$ is the expected profit she earns instantly when winning the first pot and investing. $\frac{c}{2}E\left[b_0(\widetilde{\mu}_2)|\widetilde{\mu}_2 \leq \mu\right]$ is the expected instantaneous disutility arising from having to finance $b_0(\mu_2)/2$. If she invests and the project succeeds, where the latter occurs with probability $(1-\phi(\mu_1))$, she has to pay the Rosca contribution of one in the subsequent round. Thus the term $-\delta(1-\phi(\mu_1))$, which is the discounted expected disutility from having to pay the next contribution when she wins the first auction. Notice that the organizing company insures the other member against such a default.

When she pretends μ and loses the auction, she instantaneously consumes $b_0(\mu)/2$ and has to pay the contribution in the next round for sure, thus the term $-\delta$.

A necessary condition for $b_0(\cdot)$ to represent a Bayesian Nash equilibrium of this bidding game is that

$$\mu_1 = \operatorname{argmax}_{\mu\in[\underline{\mu},\overline{\mu}]} \Pi(\mu,\mu_1) \text{ for all } \mu_1 \in [\underline{\mu},\overline{\mu}]. \tag{11}$$

Taking the derivative of $\Pi(\mu,\mu_1)$ with respect to μ gives

$$\frac{\partial\Pi(\mu,\mu_1)}{\partial\mu} = f(\mu)\left(2\mu_1 + \delta\phi(\mu_1) - (1+c)\frac{1}{2}b_0(\mu)\right) + (1-F(\mu))\frac{b'(\mu)}{2}. \tag{12}$$

Evaluating this at $\mu = \mu_1$ and setting it equal to zero gives an ordinary first-order differential equation. Moreover, the RHS of (12) gives the boundary condition $2\overline{\mu} + \delta\phi(\overline{\mu}) - (1+$

$c)\frac{1}{2}b_0(\overline{\mu}) = 0$. The unique solution to this boundary value problem is

$$b_0(\mu) = \widehat{b}(\mu) + \int\limits_{\mu}^{\overline{\mu}} \widehat{b}'(t) \left(\frac{1-F(t)}{1-F(\mu)}\right)^{1+c} dt,$$

where $\widehat{b}(\mu) = 2(2\mu + \delta\phi(\mu))/(1+c)$. (Note that $\widehat{b}(\mu)$ is the price which makes a participant indifferent between winning and losing, and since losing bidders can push up the winning bid, the equilibrium bid schedule exceeds $\widehat{b}(\mu)$). It is readily verified that b_0 is strictly increasing if and only if assumption (2) holds. To determine whether b_0 also satisfies a sufficient condition for a Bayesian Nash equilibrium, we seek to determine whether (10) is pseudoconcave in μ around μ_1 for all $\underline{\mu} \leq \mu_1 \leq \overline{\mu}$ (see Matthews, 1995). This requirement is equivalent to the condition,

$$\text{for all } \underline{\mu} \leq \mu_1 \leq \overline{\mu},\ -(\phi(\mu_1) - \phi(\mu)) \leq \frac{2}{\delta}(\mu_1 - \mu) \text{ if and only if } \mu \leq \mu_1 \tag{13}$$

which clearly holds globally if assumption 2 holds. Finally, since $b_0'(\mu) > 0$, that immediately implies parts (*ii*) and (*iii*) of the proposition. **QED**

Proof of Proposition 2:

The proof proceeds as follows. First we consider the interior case: the ceiling sometimes binds and neither (3) nor (4) hold At the very end of the proof, we consider the extreme cases: when (3) holds and the ceiling never binds and when (4) holds and the ceiling always binds.

Before the beginning of this auction, agent 1, say, observes a profitability of μ_1 and assumes that the other member is playing a strategy characterized by:

(*i*) $b_1'(\mu) > 0$ for all $\mu < \mu'$ and $b_1(\mu) = \overline{b}$ for all $\mu \geq \mu'$

(*ii*) when invited, a bidder of profitability μ chooses to participate in the lottery if, and only if, $\mu \geq \mu'$.

If participant 1 also determines her stopout price according to $b_1(\cdot)$ but pretends to be of type μ, which may or may not be different from μ_1,the relevant part of member 1's expected utility, is

$$\Pi(\mu,\mu_1) = \begin{cases} F(\mu)\left(2\mu_1 - \frac{c}{2}E\left[b_1(\widetilde{\mu}_2)|\widetilde{\mu}_2 \leq \mu\right] - \delta(1-\phi(\mu_1))\right) \\ \qquad\qquad + (1-F(\mu))\left(\frac{1}{2}b_1(\mu) - \delta\right), \text{ if } \mu < \mu' \\ F(\mu')\left(2\mu_1 - \frac{c}{2}E\left[b_1(\widetilde{\mu}_2)|\widetilde{\mu}_2 \leq \mu'\right] - \delta(1-\phi(\mu_1))\right) \\ + (1-F(\mu'))\frac{1}{2}\left(\left(2\mu_1 - \frac{c}{2}\overline{b} - \delta(1-\phi(\mu_1))\right) + \left(\frac{1}{2}\overline{b} - \delta\right)\right), \text{ if } \mu \geq \mu'. \end{cases} \tag{14}$$

The interpretation of terms is analogous to the case of unrestricted bidding, except for $\frac{1}{2}\left(\left(2\mu_1 - \frac{c}{2}\overline{b} - \delta(1-\phi(\mu_1))\right) + \left(\frac{1}{2}\overline{b} - \delta\right)\right)$, which is the expected utility from participating in the equal-odds lottery conditional on the other member also joining the lottery.

A necessary condition for $b_0(\cdot)$ to represent a Bayesian Nash equilibrium of this bidding game is that

$$\mu_1 = \text{argmax}_{\mu \in [\underline{\mu},\overline{\mu}]}\, \Pi(\mu,\mu_1) \text{ for all } \mu_1 \in [\underline{\mu},\overline{\mu}] \tag{15}$$

For $\mu < \mu'$, this implies that the derivative of $\Pi(\mu,\mu_1)$ with respect to to μ evaluated at $\mu = \mu_1$ has to equal zero. This gives, as for unrestricted bidding (see equation 12),

$$\frac{\partial \Pi(\mu,\mu_1)}{\partial \mu} = f(\mu)\left(2\mu_1 + \delta\phi(\mu_1) - (1+c)\frac{1}{2}b_1(\mu)\right) + (1-F(\mu))\frac{b_1'(\mu)}{2} = 0 \tag{16}$$

an ordinary first-order differential equation. Moreover, an individual of profitability μ' has to be indifferent between participating and not participating in the lottery when invited. This gives the boundary condition

$$2\mu' + \delta\phi(\mu') - (1+c)\frac{1}{2}b_1(\mu') = 0 \tag{17}$$

The unique solution to this boundary value problem is

$$b_1(\mu) = \widehat{b}(\mu) + \int_{\mu}^{\mu'} \widehat{b}'(t)\left(\frac{1-F(t)}{1-F(\mu)}\right)^{1+c} dt, \;\; \mu \leq \mu',$$

which is strictly increasing for $\mu < \mu'$ if and only if assumption (2) holds.

It is, moreover, readily verified that, for $\mu > (<)\mu'$, interim expected utility from participating in the lottery when invited is strictly bigger (smaller) than not participating. A strategy consisting of bidding

$$b_1(\mu) = \begin{cases} \widehat{b}(\mu) + \int\limits_{\mu}^{\mu'} \widehat{b}'(t) \left(\frac{1-F(t)}{1-F(\mu)}\right)^{1+c} dt & \text{if } \mu < \mu' \\ \bar{b} & \text{if } \mu \geq \mu' \end{cases}$$

and participating in the lottery if, and only if, $\mu \geq \mu'$ thus satisfies necessary conditions for a symmetric Bayesian Nash equilibrium.

To determine whether b_1 also satisfies a sufficient condition for a Bayesian Nash equilibrium, we seek to determine whether (14) is pseudoconcave in μ for all $\underline{\mu} \leq \mu_1 \leq \overline{\mu}$. It is straightforwardly verified that this is in fact the case provided condition (13) holds.

If the ceiling binds then riskiness and profitability are the same for the early and late recipient. If it does not, then since the equilibrium bid function $b_1(\mu)$ is weakly increasing, the early recipient has higher profitability and either higher or lower riskiness (depending on $\phi'(\mu)$).

Finally, note that (17) implies that μ' is defined by:

$$\frac{2(2\mu' + \delta\phi(\mu'))}{1+c} = \bar{b} \tag{18}$$

Now if $\mu' \geq \overline{\mu}$, then (18) implies the condition (3) for the extreme where the ceiling never binds. On the other hand, if $\mu' \leq \overline{\mu}$ then the the ceiling always binds, and (18) gives condition (4) for this extreme. **QED**

Proof of Proposition 3:

Recall that, in the bidding equilibria characterized in Propositions 1 and 2, a bidder in the auction of the first round determines her stopout price according to the function

$$b_0(\mu) = \widehat{b}(\mu) + \int\limits_{\mu}^{\overline{\mu}} \widehat{b}'(t) \left(\frac{1-F(t)}{1-F(\mu)}\right)^{1+c} dt$$

with unrestricted, and according to

$$b_1(\mu) = \begin{cases} \widehat{b}(\mu) + \int\limits_{\mu}^{\mu'} \widehat{b}'(t) \left(\frac{1-F(t)}{1-F(\mu)}\right)^{1+c} dt, & \mu < \mu' \\ \bar{b}, & \mu \geq \mu' \end{cases}$$

with restricted bidding. We obtain

$$b_0(\mu) - b_1(\mu) = \begin{cases} \int\limits_{\mu'}^{\overline{\mu}} \widehat{b}'(t) \left(\frac{1-F(t)}{1-F(\mu)}\right)^{1+c} dt, & \mu < \mu' \\ \int\limits_{\mu'}^{\mu} \widehat{b}'(t)dt + \int\limits_{\mu}^{\overline{\mu}} \widehat{b}'(t) \left(\frac{1-F(t)}{1-F(\mu)}\right)^{1+c} dt, & \mu \geq \mu', \end{cases}$$

which is clearly strictly positive for all μ when assumption (2) holds. **QED**

Proof of Proposition 4: Follows directly from Propositions 1 and 2.

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Table 1. Descriptive Statistics for the Sample by Denomination

Members			20	25	25	30	40	40	40	40	40	50	60
Contribution			500	400	1,000	500	250	500	625	1,250	2,500	1,000	1,250
Pot			10,000	10,000	25,000	15,000	10,000	20,000	25,000	50,000	100,000	50,000	75,000
Groups	Before Shock[1]		138	135	85	395	1,188	60	219	17	26	151	34
	After Shock[2]		188	135	102	357	742	39	147	24	26	107	19
	Increase (%)		36.2	0.0	20.0	-9.6	-37.5	-35.0	-32.9	41.2	0.0	-29.1	-44.1
Ceiling binding (%)[3]	Before Shock	Early[4]	7.1	24.6	28.1	40.5	79.1	83.2	71.9	82.2	71.4	91.6	98.4
		Late[5]	1.7	0.0	0.0	0.0	1.8	3.8	0.4	0.6	0.4	4.8	13.3
	After Shock	Early	18.6	44.0	42.4	57.2	72.7	87.9	69.8	83.8	67.2	91.9	97.9
		Late	3.8	0.3	0.4	0.6	3.8	7.2	3.8	7.9	5.2	14.2	27.0

[1] Groups that started between October 1992 and September 1993
[2] Groups that started between October 1993 and September 1994
[3] For pre policy shock groups, winning bid is no smaller than 0.3 times the pot; for post policy shock groups, reported winning bid equals 0.3 times the pot
[4] All those rounds before half of the rosca cycle is completed
[5] All those rounds after half of the rosca cycle is completed

	Number of Branches		Number of cities with population >500,000*	Average Distance to city with population >500,000 (km)**
	Total	In towns with population <300,000*		
Entire Sample	78	40	3	68
Established Branches	40	13	1	30
Recent Branches	38	27	2	108

* Source: Census of India, 1991

** Source: Census of India 1991 and own calculations based on road maps

Table 3. Rates of default (%)*.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		total default rate		individual default rate				
		before shock	after shock	before shock		after shock		double difference**
				early	late	early	late	
entire sample		1.71	1.41	1.74	0.54	1.53	0.73	0.40
by contribution	≤ 500 Rs.	1.33	1.24	1.63	0.64	1.87	0.90	0.02
	> 500 Rs.	2.00	1.56	1.88	0.43	1.20	0.56	0.81
by experience	recent	1.96	1.92	1.86	0.62	1.88	0.87	0.23
	established	1.48	0.94	1.62	0.47	1.15	0.58	0.58
by remoteness	<100 km from city with population >500,000	1.45	1.09	1.57	0.51	1.27	0.71	0.50
	≥ 100 km from city with population >500,000	2.33	2.30	2.11	0.61	2.17	0.77	0.10
by size of town	Population < 300,000	2.47	2.12	2.26	0.71	2.14	0.80	0.21
	Population ≥ 300,000	1.38	1.13	1.48	0.47	1.22	0.69	0.48

* see footnotes to Table 1.
** Calculated as ((3)-(4)) – ((5)-(6))

Table 4. OLS results for β, $\tau = 0.5$, with alternative sets of controls.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Estimate	0.00355	0.00372	0.00242	0.00008	0.00620	0.00219	0.00451	0.00253
	Std.	0.00079	0.00135	0.00125	0.00091	0.00084	0.00128	0.00131	0.00099
	p-Value	0.000	0.006	0.053	0.934	0.000	0.087	0.001	0.011
Controls	*Aggr. Shocks**	No	Yes	Yes	No	No	Yes	Yes	No
	*Winning Bid***	No	Yes	No	Yes	No	Yes	No	Yes
	*Repayment Burden***	No	Yes	No	No	Yes	No	Yes	Yes

* 24 quarterly dummies from 93, first quarter, to 98, fourth quarter
** Controls are in logs and interacted with 11 denomination-specific dummies
All specifications include 78 branch fixed effects

Table 5. OLS results with Interaction Terms.*

	$\tau = 0.5$			$\tau = 0.33$		
Interaction Term	Estimate	Std	p-value	Estimate	Std	p-value
after late	0.01333	0.00705	0.059	0.02395	0.00879	0.006
after late large	0.00303	0.00237	0.201	0.00497	0.00281	0.077
after late duration	-0.00024	0.00022	0.274	-0.00063	0.00028	0.024
after late (*small town*)	-0.00401	0.00127	0.002	-0.00461	0.00117	0.000
after late remote	-0.00256	0.00134	0.057	-0.00214	0.00124	0.086
after late established	-0.00394	0.00127	0.002	-0.00448	0.00118	0.000
*after late attrition** (%)*	-0.00005	0.00008	0.530	-0.00015	0.00010	0.135

* All footnotes to Table 4 apply

** Percentage increase in number of groups of the same denomination

Table 6. Differences in total default rates and differences in the extent of adverse selection

		difference in total default rate before shock[1]	difference in treatment effect[2]
contribution	large - small	0.67	0.30
experience	established - recent	-0.48	-0.40 **
remoteness of branch	remote - not remote	0.88	-0.26 *
size of town	small town - large town	1.09	-0.39 **

[1] obtained from Table 3
[2] in percentage points; see column 1 of Table 5
* significant at the 10% level
** significant at the 1% level

Figure 1. Average default rate by round, pre (dotted) and post (solid) ceiling, Denomination (30,500)

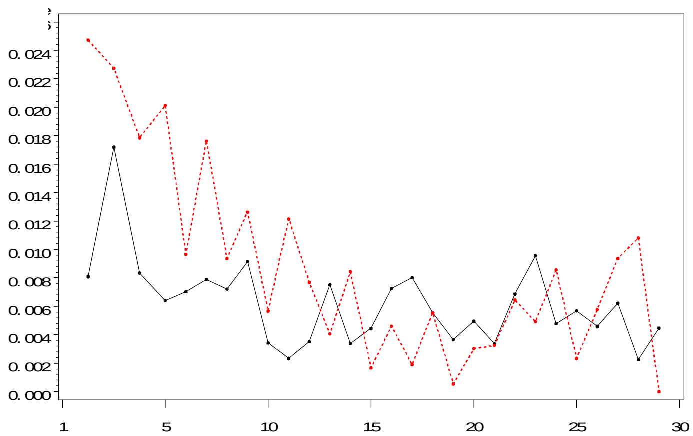

Figure 2. Equilibrium bid functions with unrestricted (solid line) and restricted bidding (dashed line)