The Supply and Demand Side Impacts of Credit Market Information

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Abstract

We utilize a unique pair of experiments to study the precise ways in which reductions in asymmetric information alter the outcome in a credit market. We formulate a general model in which the information set held by lenders, and what borrowers believe their lenders to know, enter separately. This model illustrates that non-experimental identification of the supply- and demand-side information in a market will be confounded. We then present a unique natural experiment, wherein a Guatemalan credit bureau was implemented without the knowledge of borrowers, and subsequently borrowers were given a randomized course describing the existence and workings of the bureau. Using this pairing of randomized and natural experiment, we find that the most powerful effect of new information in the hands of lenders is seen on the extensive margin, in their ability to select better clients. Changes in contracts for ongoing borrowers are muted. When borrower in group loans learn that their lender possesses this new information set, on the other hand, we see strong responses on both the intensive margin (changes in moral hazard) and the extensive margin (groups changing their composition to improve performance). We find some evidence that disadvantaged and female borrowers are disproportionately impacted. Our results indicate that credit bureaus allow for large efficiency gains, that these gains are augmented when borrowers understand the rules of the game, and that economic mobility both upwards and downwards is likely to be increased.

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I. INTRODUCTION

It has long been understood that asymmetric information plays a central role in determining credit market equilibria (Stiglitz & Weiss, 1981). Particularly in developing countries, where many borrowers lack credit histories and informal information-sharing mechanisms predominate, information problems may present a major obstacle to economic efficiency and mobility. This paper presents a unique confluence of data and identification in order to conduct an in-depth analysis of the ways in which a key institutional innovation, namely a credit bureau, has altered equilibrium lending outcomes. for one of Guatemala's largest microfinance lenders. We use the administrative data of one of Guatemala's largest microfinance lenders, as well as data from the new credit bureau which gives the behavior of all of these clients with *other* lenders. From these data we can assemble a comprehensive picture, not only of how the bureau alters behavior with a given lender, but with the credit system as a whole.

The second novel feature of this study is that the bureau was introduced in a staggered fashion without the knowledge of the borrowers. A year later, we conducted a large randomized educational campaign in which we instructed borrowers on the ways in which the bureau works, and the repercussions for their future access to credit. Hence we observe improvements in lender information and the corresponding changes in borrower behavior at different times. The resulting ability to disentangle the supply- and demand-side effects of information on credit market equilibria is, to our knowledge, unique to the literature.

Microfinance markets provide a good environment in which to look for natural experiments in the use of information. Because of a rapid increase in sophistication in these markets, they offer much starker changes in information-sharing agreements than developed credit markets, which typically have been sharing information for many years. The "microfinance revolution" has allowed poor people to gain access to loans even if they did not own assets that they could pledge as collateral (Morduch, 1999; Morduch and Armendariz de Aghion, 2005). As in any time-delayed transaction, success of the microfinance contracts requires that the lender be able to control adverse selection and moral hazard. Early microfinance lending operating in geographically monopolistic contexts could partially resolve this problem through the repetition of exchange with privately held reputation and dynamic incentives. Rising competition among lenders without information sharing, however, increasingly undermined the power of dynamic incentives, and disrupted this equilibrium. The response to this change, in several developing countries, has been to introduce credit bureaus which share information about borrowers repayment behavior and outstanding debts. In so doing, privately held information about reputation and indebtedness has been made public, leading to sharp changes in credit market equilibria and potential benefits for the two sides of the transaction.

In this paper, we take advantage of a rare opportunity to analyze this transformation of microfinance lending as reputation and information become public by combining a natural experiment with a randomized experiment. The natural experiment emerged when entry of a microfinance lender (Genesis Empresarial) into a credit bureau (Crediref) was done in a staggered fashion over the course of 18 months without informing borrowers that their behavior was being reported to the bureau. In this early phase, the credit bureau was thus only used by the lender as a client selection device. Subsequent to this, we set up a randomized experiment wherein we selectively informing jointly liable clients about how their lenders share information through a credit bureau system and the implications this can have for them. In this second phase we examine how Solidarity Groups (smaller groups with larger loans) and Communal Banks (larger groups with smaller loans) adjusted their behavior upon selectively learning of the existence of the credit bureau and its workings.

We find significant effects of informational changes on both the supply and demand side of the market. As might be expected, the strongest effect of improved information in the hands of lenders is seen through the screening of new clients, particularly individuals, and the ability to increase loan volumes faster than would otherwise have been the case. The bureau also causes a dramatic increase in the expulsion of existing clients. On the demand side, informing group members about the implications of a credit bureau induced a better repayment performance among members of solidarity groups, both through reduction in moral hazard and improved selection by the groups themselves. This demonstrates that credit bureaus are an efficient institutional innovation not only in assisting client selection by lenders and group borrowers alike, but that additional improvements are realized when borrowers clearly understand the implications of information sharing arrangements. Borrowers with good credit records are also able to take advantage of this information sharing to get access to more loans outside Genesis. However, use of reputation to access additional loans was differentially successful across categories of borrowers. It induced the more experienced clients to improve their credit records, but not the less experienced ones who in fact worsened their records when they exuberantly seized the opportunities opened to them by information sharing across lenders to increase their levels of indebtedness with outside lenders.

The paper is organized as follows. In Section II we provide background information on the transformations of microfinance lending leading to the emergence of credit bureaus, and Section III describes our paired experiments in more detail. Section IV presents a simple model of the two-sided selection process that generates the pool of individuals who receive loans, and the effects of this selection on estimates of the conditional mean. Section V analyzes the impact of improved information on the supply side through the staggered rollout of Crediref, and Section VI gives the corresponding changes when demand-side information improves. Section VII concludes on the impact of credit bureau information on borrower behavior.

II. Evolution of competition in microfinance lending

Microfinance markets provide an interesting forum in which to examine the effects of asymmetric information for several reasons. First, limited borrower liability exposes lenders to levels of adverse selection and moral hazard not seen in markets which rely on formal collateral. Second, the use of joint liability contracts for those borrowers who take group loans creates an intricate strategic dynamic between groups and lenders, each of whom bear some risk in the extension of loans to individual members. Finally, the explosive growth of microfinance itself means that markets in many developing countries have gone from near-monopoly to vibrant competition in the course of the past decade or so. As these markets mature, we typically see certain group members seeking larger loans than the joint liability system can credibly cover, and the inexorable drift towards greater competition and more individualized lending put a premium on mechanisms such as credit bureaus which allow lenders to adapt to these new realities. We now sketch this process of credit market evolution to place credit bureaus in context.

2.1. Non-competitive lending

Under the lender monopolies that characterized the early years of microfinance lending, several mechanisms were developed to solve problems of asymmetric information. Dynamic incentives were used to solve the moral hazard problem. This was done by making sure that borrowers were always kept credit constrained by the only loan supplier, and that a reputation of good repayment behavior would guarantee access to larger future loans.

Both moral hazard and adverse selection could be mitigated through the use of group lending, where the limited liability rule would induce members to engage in group self-selection & self-monitoring, making use of the local information available to them (Besley & Coate, 1995, Ghatak & Guinnane 1999). For individual loans, the adverse selection problem remained problematic. It was partially remedied by delegating selection to credit agents with access to local information, and giving them incentives to seek this information, reveal it truthfully to the lender, and align their objectives on those of the institution.

The insurance problem in taking loans, even without having to put collateral at risk, could also be partially solved through group lending. The joint liability rule implied that group members had an incentive to insure each others repayments. In principle, the insurance problem remained unaddressed for individual loans. In practice, for both individual and group loans, it was in the best interest of the lender to provide some kind of insurance for verifiable shocks. Thus, the repayment schedules on individual loans, and the joint liability rules on group lending, were not strictly enforced under all circumstances.

Joint liability contracts come under increasing strain as heterogeneity in loan sizes within a group increases. Further, those borrowers who take the largest loans generate the largest lender profits, and so new lending products were typically developed which allowed for 'internal graduation' to smaller groups, and eventually to individual loans. This opened up the possibility to cross-subsidize poorer clients with these large borrowers, but began to undermine group mechanisms in older, better-established lenders.

2.2. Competition without information sharing

The world of monopoly lending was soon undermined by entry of other lenders attracted by the industry's high profit rates. Rising created some negative effects for the incumbent lenders. It weakened the use of dynamic incentives to control moral hazard, as borrowers could find other sources of loans. It also worsened the adverse selection problem as information was not shared among lenders, allowing borrowers to hide bad repayment behavior and to over-borrow by cumulating many small loans from different sources.[1] And it weakened the possibility of cross-subsidization as better borrowers were snatched by competitors, canceling the source of rents that could be used for subsidies. At the same time, the better borrowers could still not move up the credit ladder toward better contracts as information on their reputation remained captive with the incumbent lender. It is in this context that many lenders organized to share information about their clients repayment performance (negative information) and also about levels of indebtedness with each of them (positive information). This is how credit bureaus were born and the practice of microfinance lending under public information was introduced.

The decision for a lender to join a credit information sharing system among a group of lenders involves a complex set of tradeoffs (Padilla & Pagano 1997). The benefits of doing so are a decrease in portfolio risk (Campion & Valenzuela, 2001), preventing clients from taking multiple loans and thus hiding their true indebtedness (McIntosh & Wydick, 2005) and the preservation of reputation effects during long-term lending relationships with clients (Vercammen 1995). The incentives to share information are also closely related to the level of competition; even if we do not see the kind of collapse of repayment quality predicted in Hoff & Stiglitz (1998), not only is the need to screen clients likely to increase with competition (Villas-Boas & Schmidt-Mohr, 1999), but the dispersion of information that results from a larger number of lenders makes it more difficult to do so. The interesting strategic tension arises because the advantage conferred on incumbents by a lack of information sharing can be an effective method for preventing entry (Marquez, 2001). Hence we are likely to see information sharing emerge as a strategic equilibrium only where lenders face a large pool of mobile, heterogeneous borrowers, and when the incumbents are relatively unconcerned about new entry (Pagano & Japelli, 1993).

[1] Nonetheless, McIntosh et al (2006) show that informal information-sharing agreements were able to prevent the wholesale collapse of credit markets which would have followed from competition under certain theoretical frameworks, such as Hoff & Stiglitz (1998).

2.3. COMPETITION WITH INFORMATION SHARING

With the introduction of a credit bureau allowing the sharing of positive information among lenders, the adverse selection problem could be partially resolved for the lender, especially in individual loans. Information sharing should help prevent clients from taking multiple loans and thus hiding their true indebtedness (McIntosh & Wydick, 2005). Moral hazard should also be held in check as new incentives were introduced for borrowers to improve their repayment performance that now influences access to loans across the whole participating microfinance industry (Vercammen, 1995). Information sharing should thus be a major source of efficiency gains for lenders (Jappelli & Pagano, 1999; Campion & Valenzuela, 2001). Improved performance should also open new opportunities to access more and better loans from others than the lender with whom reputation had been privately earned. This public information would allow good borrowers to shop for larger and cheaper loans, thus moving up the credit ladder on the basis of information about their past good behavior (Galindo & Miller, 2001).

Because lender profit cannot decrease from knowing more, a lenders want to join a bureau to learn what the other lender knows, but fears suffering from the response when the other lender learns. Nothing is lost by sharing information on bad clients to whom one would never lend again, whereas sharing information on one's most profitable clients carries great risk. For these reasons we expect negative information-sharing agreements to be easier to form than positive agreements.

The costs of introducing a bureau can be illustrated through casting this new information as a variant of the 'Hirshleifer effect' (Hirshleifer 1971). This refers to the situation in which the willingness to extend insurance can be eroded by the improvement of *ex ante* information. Since the willingness to extend limited-liability credit is tantamount to an insurance offer both by the lender and the group, reduction in the uncertainty over future borrower outcomes will certainly exclude certain individuals from the borrower pool, and may also result in an increase in the homogeneity of borrower groups. Hence while market efficiency will in general be enhanced, agents who were receiving implicit insurance through a lack of information, and those on whom the bureau contains negative information, will be harmed.[2]

III. THE GUATEMALA CASE: A RANDOMIZED AND A NATURAL EXPERIMENT.

In this section we give a brief outline of the institutions and contexts which allowed us to set up our paired experiments.

Guatemala's microfinance credit bureau, Crediref, was formed by five of the largest members of Redimif, the national association of MFIs. The impetus was concern over a rising level of default in the client base, and agreement by the three institutions that dominate microfinance lending in the capital city (Genesis, BanCafe, and Banrural) to all enter the credit bureau.[3] Concerns over use of the system for client cherry-picking among each others or by new entrants were alleviated through several simple mechanisms. First, only institutions that share information into Crediref are allowed to consult it, with the exception of a six-month trial period during which reduced-price checks can be run by prospective entrants. Secondly, the system does not allow users to identify the lender who issued the loan. To prevent lenders from using act of receiving credit from a high-tier lender as a quality signal, it is institutionally anonymous. Further, as mentioned, for group lending, only the total loan size and repayment performance are reported. By restricting the information observable, then, Crediref was able to overcome the strategic obstacles to the formation of a bureau. Since its inception in 2002, the bureau has continued to grow and now contains data from eight different lenders.[4]

Genesis extends loans to individuals, and to two types of groups: solidarity groups (SG), which number 3-5 people and feature relatively large loans; and communal banks (CB), with upwards of 30 people and small loans. The logic of borrower and group behavior is quite different in the two types of groups. Accordingly, the response to information about the role of a credit bureau can also be expected to be quite different. In CBs, loans are completely uncollateralized and so MFIs commonly used dynamic incentives to keep clients credit constrained and hence holding a high future valuation for the relationship with the

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[2] See 'The Economics of Privacy', Posner (1981) for a more general treatment.

[3] BanCafe and Banrural are both national full-service banks which only share microlending information in Crediref, and not information from their commercial banking divisions.

[4] For an analysis of the impacts of the lenders' use of Crediref, see Luoto et al. (2005).

lender. Internal control of behavior is difficult due to the large size of the group, loans are very small, group members have few other borrowing options inside Genesis, and their low asset endowments also severely limit their access to loans from other lenders. The situation is quite different in SGs. For them, internal control is made easier by the small size of the group, and the use of collateral and cosigning is common. While SG clients have access to much larger loans, they are also likely to be more informed about and attractive to outside lenders who will offer lower rates than an MFI on these high-volume loans. As the size of SGs decreases, the incentives become more similar to those under individual lending.

Genesis has 39 branches distributed over most of Guatemala. For technical reasons, it staggered the entry of its branches into Crediref over the period between March 2002 and January 2003. In addition, Genesis' clientele remained unaware of the existence and use of Crediref both in reporting information to other lenders and in checking credit records for client selection.[5] Group lending clients were made selectively aware of the existence and implications of a credit bureau through randomized information sessions that we organized over the period June to November 2004. For logistical reasons, we trained only SGs and CBs and not individual borrowers. This gave us a unique two-stage transition into microfinance lending under private and shared information.

Given the lack of information among Genesis clients about the existence and implications of a credit bureau, we designed a course to be administered by the Genesis in-house training staff. The design of the materials presented a challenge because nearly 50% of the Genesis clients are illiterate. We drew on experience from the training office and from the faculty of Universidad Rafael Landivar in order to develop materials that were primarily pictographic. We used the logos of the different lending institutions in combination with diagrams showing the flow of money and information in the lending process to illustrate when Genesis shares information on the clients and when it checks them in the bureau. The key focus of the information was to reinforce the fact that repayment performance with any one lender now has greater repercussions than previously. This point was made both in a negative fashion (meaning that repayment problems with any participating lender will

[5] See Luoto et al (2007) for details.

decrease options with other lenders) and in a positive fashion (emphasizing the greater opportunities now available for climbing the 'credit ladder' for those who repay well).[6]

In Section 5 we present results from the staggered entry, which changed lender information, and in Section 6 we discuss the impacts of the improvement of borrower understanding of the system. In order to organize thoughts, we first present a simple model of the two-sided selection process through which the pool of borrowers is determined.

IV. OBSERVED CREDIT MARKET OUTCOMES

Let f be a credit market outcome (loan sizes, repayment rates, probability of becoming a long-term client, and so on) defined on all potential borrowers. Z represents characteristics of the potential borrower that are observable as of the time of application, and X represents information over borrower quality that becomes observable as the lender has increasing experience with a given borrower. a represents characteristics that are private information to the potential borrowers, α is the information observed in the bureau, and α^B is what the borrower believes the lender to see. (Even though α^B is most likely equal to α, it will be useful later on to distinguish them.) Lenders attempt to use the information that they can observe (Z, α, and potentially X) to proxy for a. We can write the observed outcome as:

$$f = f\left(Z, X, a, \alpha, \alpha^B\right),$$

where f can be thought of either as the terms of a contract (loan sizes, interest rates) or the outcome of this contract (repayment rates, probability of continuing as a borrower).

4.1. BORROWER BEHAVIOR

Without moral hazard, a potential borrower's behavior would strictly depend on his characteristics and the terms of the loan contract. Under moral hazard on the part of the borrower, his behavior also depends on the information that the lenders have on him, or more precisely his knowing the information that the lenders have on him. Letting π^B the latent variable underlying the decision by the borrower to apply for a loan, this can be formalized as follows:

[6] As a cautionary tale of the unpredictable consequences of training programs, Schreiner (1999) finds that the randomized Unemployment Insurance Self-Employment Demonstration actually *discouraged* the most disadvantaged from entering self-employment.

$$\pi^B = \pi^B\left(Z, a, \alpha^B\right).$$

4.2. LENDER BEHAVIOR

From the applicant pool, a lender will select a borrower if his expected return from extending him a loan is positive. The return to the loan essentially depends on the borrower's behavior, i.e. is function of the borrower's characteristics Z and *a* and, if there is moral hazard behavior on the part of the borrower, on α^B (the lender knows what the borrower thinks the lender knows). However, the lender does not observe *a*, and hence needs to rely on the signal α to make the selection decision. Let π^L be the latent variable underlying the decision process; although the selection process follows this recursive structure, we define π^L over all potential borrowers:

$$\pi^L = \pi^L\left(Z, \alpha, \alpha^B\right).$$

With the use of two different notations for the signal itself, α, and the borrower's information on that signal, α^B, we clearly see that the signal influences the lender decision in two ways. First, the lender uses the signal as a proxy for the true unobserved quality of the borrower, and second, the lender takes into account the fact that the borrower may behave strategically in response to the existence of a public signal on his quality.

We can visualize the selection induced by the bureau from the lenders' side by thinking about the conditional distribution of π^L before and after α is revealed. Without this information, the lender will issue loans to any applicant for whom $\pi_0^L = \pi^L(Z, \varnothing, \varnothing) > 0$, and so offers contracts to the right half of the distribution of expected profits. Once α is observable, there will be a new distribution of expected profits, and there may be fixed costs of adjusting contracts to this new equilibrium. Let $\phi^L(\alpha, \pi_0^L \geq 0)$ represent the pdf of expected profits using the information in the bureau among borrowers who wanted loans and who were offered loans without the bureau, and $\phi^L(\alpha, \pi_0^L < 0)$ represent the pdf among those who wanted loans but were not offered loans without the bureau.

Figure 1 illustrates the borrowers who are picked up and dropped. The discontinuous decision to acquire or eject clients will be determined by the points at which the fixed costs of taking either move exceed the revenue from doing so, resulting in selection *out* of a density

$\int_{-\infty}^{FC^-} \phi^L(\alpha, \pi_0^L \geq 0) d\alpha$ of 'bad' borrowers and selection *in* of a density $\int_{FC^+}^{\infty} \phi^L(\alpha, \pi_0^L < 0) d\alpha$ of 'good' ones. If it more costly to acquire new clients than to eject old ones, the lender's extensive margin will be more sensitive to negative information than positive. The use of a bureau may decrease the fixed cost of acquiring new clients, thereby increasing the overall density that receives loans

The interesting cases of lender switching from the demand side can be modelled using a two-lender world. We formalize the difference between α and α^B through the observation that a well-informed borrower will be able to infer α from *a*. Specifically, when lenders start using a bureau the borrowers know that each lender can now observe the experience X that the *other* lender has accumulated with a given borrower. Thus if a borrower has taken loans only from Lender 1, they know that lender will simply see X_1 when they look in the bureau, and so the *new* information revealed is $\alpha_1 = \varnothing$. If Lender 2 looks in the bureau in the same situation, however, he will see $\alpha_2 = X_1$. This means that for a borrower who takes loans from both lenders and who knows that both lenders use the bureau will have $\alpha^B = \{X_2, X_1\}$, and will have $\alpha^B = \varnothing$ if neither lender uses the bureau. The corresponding contracts observed for a given borrower (holding X and Z constant) can be written $\{f_1(X_2), f_2(X_1)\}$ and $\{f_1(\varnothing), f_2(\varnothing)\}$ in the case with and without the bureau, respectively..

From here we can characterize the possible borrower responses to knowing that lender information has changed. If a borrower takes no loans with or without the bureau, or takes a loan only from a single lender with and without the bureau, we do not need a two-lender modeol. In the more interesting cases, the bureau induces the relative profitability of loans from the two lenders to change in some way.

W assign Lender 1 as the 'inside' lender, from whom the borrower has already been taking loans.

- If borrower profit is maximized under the contracts $\{0, f_2(X_1)\}$, when the bureau is used Lender 2 offers contract that gives the borrower higher profits than the prebureau contract $\{f_1(\varnothing), 0\}$. This implies that the borrower must lie in Region A for Lender 2 in Figure 1, and this borrower will 'graduate' to the second lender.[7]

- If a borrower is credit-constrained under the offer from the inside lender without the bureau, then profit will be maximized under the contract $\{f_1(X_2), f_2(X_1)\}$, and so a borrower in Region A moves to using multiple lenders when the bureau is in use.
- If $\pi^L(Z,X) > 0$, both lenders are willing to make an offer to a borrower in the absence of the bureau, but if $\pi^L(Z,X,X_{-i}) < 0$ for either lender (meaning that the borrower is in Region B), then we have the situation described in McIntosh & Wydick (2005), where the bureau is used to restrict 'double-dipping'.

4.3. THE SELECTION PROCESS

An empirical analysis should take account of this two-sided selection process, and also account for estimation error. The system of equations is thus:

$$\pi^B = \pi^B\left(Z, a, \alpha^B\right) + \varepsilon^B \tag{1}$$

$$\pi^L = \pi^B\left(Z, \alpha, \alpha^B\right) + \varepsilon^L \tag{2}$$

$$f = f\left(Z, X, a, \alpha, \alpha^B\right) + u \tag{3}$$

where *f* is only observed for clients that have applied and been selected, i.e., agents for which $\pi^B \geq 0$ and $\pi^L \geq 0$. In this formulation, the distributions of ε^B, ε^L, and *u* are defined over the whole population.

If we could observe the population from which the applicants emerge and the selection process, we would estimate (1) identifying the applicant from the population, then (2) identifying the selected from the applicants, and then (3) for the observed clients. Because of the selection process, the conditional mean of the error term:

$$E\left(u \middle| \pi^B \geq 0, \pi^L \geq 0\right) \neq 0$$

[7] A canonical case of lender heterogeneity (from Navajas et al 2003) is that one lender has high fixed costs and low variable costs, giving a comparative advantage in large loans. In this case the greater mobility induced by the bureau allows lenders to pair with the lender specialized in providing loans of the right size, rather than becoming an informational hostage to the lender with whom they first established a relationship.

The correction terms depend on the distribution of the error terms. Assuming for example a trivariate normal distribution, the expression will depend on whether the two error terms ε^B and ε^L are correlated or not. If they are not correlated, i.e., $\mathrm{cov}(\varepsilon^B,\varepsilon^L)=0$, then:

$$E\left(u\left|\pi^B\geq 0,\pi^L\geq 0\right.\right)=-\gamma_B\frac{\phi\left(\pi^B(\cdot)\right)}{\Phi\left(\pi^B(\cdot)\right)}-\gamma_L\frac{\phi\left(\pi^L(\cdot)\right)}{\Phi\left(\pi^L(\cdot)\right)}=-\gamma_B\lambda_B\left(Z,a,\alpha^B\right)-\gamma_L\lambda_L\left(Z,\alpha,\alpha^B\right) \qquad (4)$$

In the more likely case of correlated error terms, $\mathrm{cov}(\varepsilon^B,\varepsilon^L)=\sigma$, one would consider using a bivariate probit method for estimating (1) and (2), wherein:

$$E\left(u_{ij}\left|\pi^B\geq 0,\pi^L\geq 0\right.\right)=\gamma_B M_{BL}+\gamma_L M_{LB}, \qquad (5)$$

with:

$$M_{BL}=\left(1-\sigma^2\right)^{-1}\left(G_B-\sigma G_L\right)$$

and $$G_B=\frac{E\left(\varepsilon_B\left|\pi^B\geq 0,\pi^L\geq 0\right.\right)}{\Phi\left(\pi^B(\cdot),\pi^L(\cdot)\right)}.$$

4.4. CONDITIONAL MEAN OUTCOMES AMONG BORROWERS

Given the selection process, the conditional mean on a credit market outcome *f*(.) among the clients is thus:

$$E(f)=f\left(Z,X,a,\alpha,\alpha^B\right)+\gamma_B M_{BL}\left(Z,a,\alpha,\alpha^B\right)+\gamma_L M_{LB}\left(Z,a,\alpha,\alpha^B\right). \qquad (6)$$

It might appear that the best way to separate the demand- and supply-side effects of credit market information would be to use data on all borrower application decisions and all lender selection decisions. Equation (6) tells us, however, that in the full-information world where α and α^B change together, this information is insufficient. Lenders can only choose borrowers from among the pool that applies, and borrowers will alter application decisions based on the degree to which the bureau reveals positive or negative information about them. Because we lack an exclusion restriction on the separate effects of these two kinds of information, non-experimental identification will be confounded.

Using (6), the causal effects that we would wish to estimate are:

$\frac{\partial f}{\partial \alpha^B}$ gives the moral hazard effect on the incumbent clients.

$\frac{\partial f}{\partial \alpha}$ gives the adjustment to the optimal contract when the lender uses the bureau.

$\gamma_B \frac{\partial M_{BL}}{\partial \alpha} + \gamma_L \frac{\partial M_{LB}}{\partial \alpha}$ gives the selection effect from the lender's use of the credit bureau.

$\gamma_B \frac{\partial M_{BL}}{\partial \alpha^B} + \gamma_L \frac{\partial M_{LB}}{\partial \alpha^B}$ gives the auto-selection effect of borrowers learning that the lender is using a CB.

The value of the unusual way in which the Guatemalan bureau was rolled out, combined with very detailed panel data on borrower behavior, is that we have the ability to identify each of these four terms separately. The staggered rollout of the bureau altered α, while changing α^B only minimally. Thus changes in outcomes among *new* borrowers who were screened before and after the bureau allow us to measure $\gamma_B \frac{\partial M_{BL}}{\partial \alpha} + \gamma_L \frac{\partial M_{LB}}{\partial \alpha}$, and changes in the contracts offered to *ongoing* borrowers give us $\frac{\partial f}{\partial \alpha}$. Correspondingly, the randomized training program changed α^B in an environment where the use of the bureau and hence α was constant. So we can examine changes in group composition induced by the training to measure $\gamma_B \frac{\partial M_{BL}}{\partial \alpha^B} + \gamma_L \frac{\partial M_{LB}}{\partial \alpha^B}$, and any shifts in behavior among ongoing clients give us $\frac{\partial f}{\partial \alpha^B}$.

4.5. Differential Impacts

The observed impact of the revelation of new behavior α from the bureau (and the resultant borrower inference α^B) is likely to be modulated by two factors in a systematic way. The first is through the influence of *X*, borrower information that was unobservable at the time of initial screening but which becomes observable as the lender's experience with a given client increases. Because the lender is naturally engaged in using its full information set (Z, X) to predict the relevant unobservable information *a*, the richer the information set in *X* becomes, the less residual unknown information remains. Thus for a client with a rich information set *X* we would expect to see a smaller lender response to observation of a given piece of information in the bureau than for a new borrower for whom $X = \varnothing$.

The second systematic source of variation will arise from the fact that Crediref reports information on *group* repayment behavior, rather than individual repayment. So a bureau record gives the repayment for a group loan and the size of the group that took that loan, but for groups greater than 1 there is no way to infer whether this specific individual has had a repayment problem, or indeed what is the total level of indebtedness of the individual.[8] For those who take solely individual loans, this oddity vanishes. For borrowers further down the ladder of credit, where all loans are taken in large groups, the bureau provides an exceedingly vague picture of borrower quality. One indication of this difference in quality is that Genesis is willing to pay the fixed costs of a check in the bureau (about $1) for over 60% of the recurring individual and solidarity group loans, but for less than 2% of recurring communal bank loans. Consequently, we find no impact of the lender starting to use the bureau on communal bank clients, and there should be a correspondingly insignificant decrease in the reduction in moral hazard for communal bank borrowers when they learn of the use of the bureau.

V. THE LENDER BEGINS USING THE BUREAU.

The staggered entry of Genesis' branches into the credit bureau provides us with a natural experiment in alteration of *lender* information. Luoto et al (2007) perform tests of the impacts of this staggered entry using aggregated data, and provide evidence for the fact that the rollout was a valid natural experiment and that borrowers did indeed know very little as to the workings of the bureau. Using loan-level data, we can measure several interesting effects that are not visible using branch-level data. Firstly, because we can observe whether each loan is issued to a new or to an ongoing borrower, we are able to disentangle the screening effects of the bureau on the extensive margin from changes in contracts on the intensive margin. Secondly, we can track the differences over time between borrowers who entered Genesis before and after the bureau was being used, and so measure the longer-term effects of improved information. Finally, because we also observe the credit officer who issues each

[8] While this system appears anomalous, there are good reasons to think that this will be a standard feature of credit reporting systems in microfinance markets. The first is that the data management software of many smaller lenders never tracks loans at the individual level, and so they may be unable to prepare reports on group loans for each member of the group. Secondly, in some Latin American countries (such as Peru) have taken the approach that, since a loan is technically made to a group, there should be no legal recourse available to lenders against delinquent individuals as long as the *groups* to which they belong successfully repaid the loan.

loan, we can examine changes of behavior at the level of the individual who actually makes loan screening decisions.

The results of the first exercise are given in Tables 1 and 2. Table 1 measures changes on the extensive margin, or $\gamma_B \frac{\partial M_{BL}}{\partial \alpha} + \gamma_L \frac{\partial M_{LB}}{\partial \alpha}$, by measuring changes in the lending contracts observed on first loans which were issued before and after the bureau. The regressions use branch and month fixed effects, and robust standard errors clustered at the branch level. For loans given to individual clients, where we would expect the effects of new information to be strongest, we see a sharp decrease in the share of loans that were charged late fees, and this is accomplished despite the fact that the average loan size to individuals increased weakly. Loans more than 2 months delinquent, which would be technically under default, are not changed. For group borrowers, on the other hand, we see that the improvement in repayment performance is weaker (now insignificant), and that there has been a decrease in loan sizes of almost 20%. Hence the pure adverse selection effect of the bureau is to improve interim repayment performance strongly among individual borrowers while not decreasing loan sizes, while group performance is improved less strongly and only through a large decrease in loan sizes to new borrowers.

Table 1b places these relatively modest changes in new client behavior in context by demonstrating the enormous changes in selection in and selection out induced by the use of the bureau. For individual loans, we see that the bureau induces a symmetric change in the percentage of all borrowers who are kicked out and who leave; both figures increase by roughly 17 percentage points. In other words, there is a period of great upheaval in the client base triggered by the use of the bureau. Figure 2 shows the large increase in new individual clients that occurs for roughly six months after the bureau is implemented. For solidarity groups, the picture is somewhat more nuanced; individuals within these groups are much more likely to be expelled, but the groups themselves become more durable as a result of the bureau. The net effect of a large decrease in enrolment of new members into old groups and a large increase in expulsions from old groups is the dramatic decrease in group size illustrated in Figure 3. There is, however, a corresponding explosion in the number of completely new solidarity groups that are formed, indicating that the bureau causes the lender to change from growing the group loan client base through forcing existing groups to approve new members to simply creating new groups. In other words, they rely less on joint liability as a screening tool when they have recourse to the bureau.

Table 2 carries out the reverse exercise; we include only borrowers who took loans both before and after the bureau was being used in their respective branch. Because we include borrower-level fixed effects, the treatment effect now measures changes in contracts for ongoing clients. Since we have limited the sample to those for whom $\pi^{B}(Z,a)\geq 0$, $\pi^{L}(Z)\geq 0$, and $\pi^{L}(Z,\alpha)\geq 0$, we follow a consistent cohort through the implementation of the bureau and so the marginal effect of the use of the bureau gives a picture of the continuous impact $\frac{\partial f}{\partial \alpha}$. For the solidarity group borrowers, we see a small increase in loan sizes with no corresponding worsening of repayment performance. For individual borrowers, on the other hand, we see the only indication of a *negative* impact of the bureau (from the lender's perspective): loan volumes increase but so does default. There are two ways of thinking about this otherwise surprising result. The first would take into account the enormous increase in the screening of new clients that is transpiring as the bureau is being introduced, and argue that through some multi-tasking problem, the credit officers have neglected the ongoing clients and hence allowed repayment to deteriorate. A more likely explanation, however, is provided by the extremely low mean default rate among these ongoing clients; 2% versus an institutional average of over 4%. If we think of default as following a Markov process, whereby any borrower with a negative realization in the previous period is screened out, then it is natural to suspect that this result arises from mean reversion. Nonetheless, the conclusion is that the tremendous improvement in information on new clients is not matched by a corresponding improvement in information for existing clients, implying that the information in X may allow lenders to do a reasonable job of proxying for the information revealed through α.

Having, in Table 1, calculated the impact of the information in the bureau on first loans, we wish to understand how the subsequent performance of clients differs depending on whether they were *initially* selected before or after the bureau. Table 3 shows the results of this analysis. Individual borrowers selected with the bureau are half again as likely as those selected before the bureau to go on to take subsequent loans: the mean probability is .44 and the increase in this probability for those selected with the bureau is .23, with a t-statistic of almost nine. These subsequent loans are taken somewhat sooner, and the size of these loans is roughly 12% larger. Therefore we see strong evidence that the improvement in performance of individual borrowers extends well beyond the first loan. Group borrowers, on the other hand, show no differences in taking subsequent loans depending on whether they were selected with or without the bureau. This is consistent with the joint liability mechanism providing a richer information set when group borrowers are screened.

One way of summarizing the joint effects of lender information on the intensive and extensive margin is to use the credit officer as the unit of analysis. In this way we can measure efficiency effects of the bureau as well, by examining whether a given employee is able to increase the number of new borrowers whose applications they process in a given period of time (here, in a month). Table 4 uses lender and month fixed effects and examines the impact of the bureau on a variety of outcomes. There is very large increase in the number of new borrowers (double) and new loans (4 on a basis of 5.8). This increase arises from increases in individual clients and group clients in similar proportions. The average size of the first loan issued by Genesis *doubles* when they begin using the bureau, but the number and volume of loans to old clients were not affected in any significant way. The total effect among all clients is thus an increase in the number of new loans by 1.9 on a basis of 7.12 and an increase in the portfolio growth of 20%, although not precisely measured. The growth of loans to both individuals and groups in the whole institution increased sharply as a result of the use of the bureau.

Using the data from the bureau, we ran a number of regressions (not shown) to test for whether improvements in Genesis' information caused changes in Genesis' clients' behavior with *other* lenders. Given that borrowers knew little about this change, we do not expect to see shifts induced by borrowers seeking out new opportunities (for this, see the next section). However, it is possible that changes in the contracts offered by Genesis would have altered demand with other lenders. The data structure for this analysis is not ideal, because Guatemalan law stipulates that the bureau can only keep a two-year window of data on borrower behavior. For this reason we could only observe outside borrowing behavior for the latter third of the branches of Genesis entering the bureau, but in no case did we find any significant impacts.

Our results suggest that improvements in information on the supply side of the market lead to major adjustments on the extensive margin, with virtually no intensive effect for ongoing borrowers. In other words, the lender learns very useful information about individuals borrowers to whom they have not given loans before, and they learn useful negative information about ongoing borrowers. However, given that they decide to continue to lend to a borrower once they have looked in the bureau, there is little improvement in their ability to increase loan sizes without seeing a corresponding decrease in repayment performance. For solidarity group borrowers, the bureau induces a strong swing toward smaller groups and new clients, and also appears to allow lenders to increase loan sizes without causing problems. There is a huge increase in employee efficiency at the lender, with the average credit officer moving from screening six new borrowers to ten new borrowers per month.

VI. BORROWERS LEARN THAT THE LENDER IS USING THE BUREAU.

The population used in this analysis consists of all the credit groups from seven branches selected from the 39 branches of Genesis to represent the variety of Genesis clients.[9] Within each of these seven branches, we randomly selected a predetermined number of groups for treatment, the others forming the control groups. Table 5 gives the treatment/control structure, and presents relevant statistics at the branch level for the selected branches.

Once selected, groups were notified that they were eligible to receive a free information session, and they were requested by their credit officer to appear at a specific time and place in order to receive the information. Attendance was entirely voluntary, and if a group did not show up the first time, two subsequent efforts were made to call it for the session. The percentage of chosen units that were in fact treated varies from 31% to 100% across branches, with an average response rate of 62%. The lowest saturation came from the branch of El Castaño in Guatemala City, a neighborhood branch which saw problems during

[9] This selection was done by randomly selecting one branch in each of seven groups of similar branches constituted by credit officers with intimate knowledge of the institution. However, despite the randomization, the average characteristics of the groups from these selected branches do not perfectly match those of the non-selected branches. We therefore limit the analysis to the groups from the selected branches.

the course of the study. Excluding El Castaño and its corresponding control, we are left with a remaining overall response rate of 69%.

The information sessions took place over a period of four months, from July to November 2004, with the order in which groups were called randomly defined. The timing of the treatment is thus specific to each treated group and we assign the median of the treatment dates within each branch to the control groups.

The quality of the randomization can be gauged from Table 6. Comparing the mean values of group-average characteristics such as age, marital status, education, gender, and ethnicity, we find no evidence of significant differences between the selected and control groups. Looking at Table 7 on repayment performance of the 1549 loans taken between January 2003 and June 2004, the situation is, however, less ideal. The selected groups perform better than the control groups, and the groups actually treated even more so. Hence, the *de facto* selection of groups in the field does appear to have favored good groups that were experiencing less repayment problems. The selection effect present in the decision to attend the information sessions is strongly positive: groups that had lower default to begin with were the ones that chose to attend.

An additional view of the selection effects present among non-compliers comes from comparing the evolution of the repayment performance of non-compliers to that of control groups. This is done by estimating a difference-in-differences regression on loan repayment performance, similar to the impact regressions run elsewhere in the paper, comparing the non-compliers to the controls:

$$y_{lgt} = \alpha_g + \alpha_t + \delta T_{lgt} + u_{lgt} \tag{8}$$

where y_{lgt} is an indicator of repayment performance on loan *l* from group *g*, with its last payment made at time *t*, α_g and α_t are group and time fixed effects, and u_{lgt} the unobserved component. The "treatment" variable T_{lgt} is set equal to 1 if *g* is a non-complier group and $t \geq \tau_g$, the treatment date.[10] Column 3 in Table 8 reports the estimated parameters δ for the two measures of repayment performance. These results indicate no significant

[10] As explained above, since none of these groups was treated, the treatment date is set to the median date of all information sessions in the branch.

selection effects, suggesting that while the non-compliers had in average worse repayment performance than the control groups, they exhibit no significant intention to treat effect.

Because of this relatively high non-response rate and apparent selection in compliance, our analysis focuses on an intention to treat effect (ITE) rather than the treatment effect on the treated (TET). It gives a downward estimation of the impact of acquiring the information on the functioning of a credit bureau. To the extent that a non-experimental program would have a similar compliance rate, the ITE is also the quantity of interest for an institution considering a similar information program.

In addition, we conduct the impact analyses in the remainder of the paper using differencing techniques to remove any fixed differences between units. Before we present these results, we verify, using false DID tests, that no spurious treatment effects are present in the selected groups. The false treatment effects regressions are estimated by dividing the pre-treatment time period into two equal halves, and checking for differences between selected for treatment and control groups between these two periods using group fixed effects and month dummies:

$$y_{lgt} = \alpha_g + \alpha_t + \delta FT_{lgt} + u_{lgt} \tag{9}$$

The observations include all loans completed between January 16, 2003 and May 16, 2004. and the "false treatment" is set to take place in the middle of the pre-treatment period, such that $FT_{lgt} = 1$ if the group g has been selected for treatment, and $t \geq$ September 16, 2003. None of the false intention to treat effects featured in the first two columns of Table 8 are significant, indicating that there are no serious biases in using double differences.

6.1. Evidence on moral hazard, selection in groups, and outside borrowing

The instantaneous impact of the information program on inside repayment isolates the moral hazard effect that arises from the desire to use reputation from a given microfinance agency to leverage credit from other sources. Since group composition takes time to change, there should be only the moral hazard effect present in the discontinuity, and hence in the short run our experiment represents an instrument for the value that clients place on outside credit. Over time, the repercussions of changes in group membership undertaken due to the bureau begin to have their own effects upon inside repayment, adding adverse selection to moral hazard effects.

An important aspect of the treatment was to inform the Genesis clients of the potential use of their good track record in past borrowing to access outside loans from other lenders. Many MFIs are, in fact, reluctant to join a credit bureau precisely for this reason that they may lose their best clients to competitive lenders. At the same time, the credit bureau reveals to the institution the total of outstanding debt of the client, reducing the potential usage of double dipping to obtain a level of credit beyond repayment capacity. We, therefore, expect the effect of information to induce an increase in outside borrowing from clients that are most constrained by what Genesis can offer them. Whether the clients can properly judge their own ability to sustain higher indebtedness is, however, not sure. For the lender that looks at the information contained in the credit bureau, a clean slate during a short two-year period is also not a guarantee that the borrower is a solid client. Hence, while a good record in the credit bureau can be used for getting access to outside credit, it does not guarantee success in this endeavor.

In practice the analysis is complicated by the fact that the information sessions will only have an impact insofar as they impart previously unknown information. As a general matter, knowledge of the workings or indeed the existence of Crediref was very low among clients; not one of 184 clients surveyed in 2003 was aware that information was being shared between MFIs. That said, certainly some clients would have possessed better information, or at least more realistic expectations, over the process of information sharing. Such clients will appear to have a lower impact (and hence a smaller moral hazard response) simply because they learned less from the sessions. A causal impact of the treatment, then, is composite of the amount that was learned and how what was learned effects behavior.

6.2. The Intensive Margin: Discontinuous Impact within a Loan Cycle.

In isolating the moral hazard effect, we are aided by the fact that a group loan is made to a fixed group of people, and so within a single loan cycle there is no turnover. Thus, an analysis performed *within* the loan cycle where information sessions occurred contains only the effects of the treatment on the behavior of a given set of individuals. The analysis is done separately for solidarity groups and communal banks. The observations are the different intermediate payments made on the loans that were active at the time of the treatment. Because repayment problems tend to come only after a certain time is elapsed, we control for where in the loan cycle the repayment takes place. A complication occurs in that loans are of different length and require various numbers of intermediate repayments. To make these repayments comparable, we therefore divide the length of each loan cycle in 10 equal intervals of time, that we refer to as deciles, and we control for the deciles rather than the rank of the repayment. We thus estimate:

$$y_{plt} = \alpha_l + \alpha_t + \beta_d D_{plt}^d + \delta T_{plt} + u_{plt} \tag{10}$$

where y_{plt} is an indicator of performance for payment *p* made at time *t* on loan *l* that was active at time of treatment. The deciles dummy variable D_{plt}^d is equal to 1 if the payment belongs to decile *d*. The treatment variable, defined at the payment level, T_{plt} is set equal to 1 if the payment *p* is in loan *l* taken by a group *g* that was selected for treatment and $t > \tau_g$, the treatment date for group *g*.

We see in the results reported in column 1 of Table 9 that there was no significant change in performance on intermediate payments for the loan in progress in both SG and CB.

However, there were significant improvements in the final repayment performance, but only for SG. There was a decline in the percentage of delinquent payments of 18% in the treatments relative to the controls, and while the fall in the amount of late fees assessed is not significant, it is large in percentage terms. This indicates that SG, with a smaller number of members over which collective control can be exercised, are in a better position than larger CB in controlling moral hazard behavior among members. Thus the immediate message taken away from the information session was the perils of loan delinquency, and not of missed intermediate payments.[11]

[11] Although Crediref does in fact report on these intermediate payments, we encountered widespread confusion among credit officers as to how to interpret this data, and so the clients were probably correct in presuming that it was the final repayment status of the loan that mattered most.

6.3. IMPACT ACROSS LOAN CYCLES.

We have data on repayment behavior from Genesis for one year after the intervention. Over this intermediate time frame, we expect the moral hazard impacts to dominate although, in groups that take one or more loans after having received the information, repayment behavior is also plausibly being effected by the selection response of group members. These impacts are measured by estimating the repayment performance at the loan level over the long period 2002-2005. We used both OLS difference-in-difference and group fixed effects estimators:

$$y_{lgt} = \alpha_t + \alpha S_g + \delta T_{lgt} + u_{lgt} \quad (11)$$

or

$$y_{lgt} = \alpha_t + \alpha_g + \delta T_{lgt} + u_{lgt} \quad (12)$$

where y_{lgt} is a measure of repayment performance of loan *l* of group *g* with last payment at time *t*, S_g a dummy variable indicating that the group *g* was selected for treatment, and T_{lgt} the treatment variable equal to 1 if the group *g* was selected for treatment and $t > \tau_g$, the treatment date for group *g*. We also do two TET estimations in which non-compliers are omitted.

Results are reported in Table 10. The strongest evidence of impact is seen in the probability of having a delinquent loan, with an ITE of 4 to 10 and a TET of 5 to 11 percentage points. OLS estimates are strongly significant, and fixed effects somewhat less so. The other indicator shows improvement as well, although the t-statistics are low. Throughout, the ITE is almost exactly the TET times the share of selected clients that actually complied, which is consistent with no residual selection effects and no spillover effects. Separating SG and CB, we see that moral hazard and adverse selection improvements were exclusively confined to SG, with no change in the repayment performance of CB.

6.4. THE EXTENSIVE MARGIN: IMPACT ON GROUP COMPOSITION.

Analysis of the adverse selection effect of the treatment is most easily accomplished by looking directly at the characteristics of the individuals who are leaving and joining groups subsequent to the information sessions. While it would be possible to look at the change of the average characteristics of groups over time, the severe autocorrelation that would inevitably be present in such averaged measures makes this an unattractive approach. The characteristics of the specific individuals who come and go from groups, on the other hand, provide a discrete and clear-cut response to the information sessions.

In response to the understanding of the use of Crediref, new clients are undoubtedly selected for their desirable features associated to good repayment. Dropouts, however, may either exit the group freely, in which case selection is on desirable features associated with good repayment, or they may be expelled by the group, in which case selection is on the undesirable features associated with bad repayment.

To establish which individual characteristics are associated with good repayment behavior by a group, we estimated the correlations between having a delinquent last payment and ever making a late payment with client characteristics, from a simple cross-sectional regression on the pre-treatment period:

$$y_{lgt} = \alpha_t + \overline{X}_{lg}\beta + u_{lgt} \tag{13}$$

where $\overline{X}_{lg}$ is a vector of average characteristics of the member of group *g* participating to loan *l*. Results reported in Table 11 show that bad repayment behavior is associated with being divorced, female, younger, and having not banked previously with any of the Crediref member institutions.

We now examine these average characteristics among those leaving (dropouts) and those entering (new clients) groups in each borrowing cycle before and after the treatment. New members are defined as members that join a group after the first loan of the group, and dropout members those that quit the group before the last loan. Members that do not participate to a particular loan cycle, but return to the group for a subsequent loan are not counted as dropout and new at their temporary exit. We used both OLS difference-in-difference and branch fixed effects estimators:

$$\overline{z}_{lgt} = \alpha_t + \gamma SG_g + \alpha S_g + \delta T_{lgt} + u_{lgt}, \tag{14}$$

and

$$\overline{z}_{lgbt} = \alpha_t + \alpha_b^{SG} + \alpha_b^{CB} + \delta T_{lgt} + u_{lgbt} \tag{15}$$

where $\overline{z}_{lgt}$ is the characteristic of interest (number of new / dropout members, average demographic characteristic of the new /dropout members) for the loan *l* taken by group *g* at time *t*, SG_g is an indicator variable for Solidarity Groups, S_g a dummy variable indicating that the group *g* was selected for treatment, and α_b^{SG} and α_b^{CB} are branch fixed effects for SG and CB respectively.

Similar patterns emerge from estimation of the post-treatment change in characteristics by the two methods (Table 12). The strongest effect is a very sharp *decrease* in the percentage of women in groups, resulting from an exodus of women accompanied by a decrease in entry of new women to groups selected for receiving the information on Crediref. Seen from the perspective of free exit, this would imply that women were the better clients and were choosing to leave sub-par groups after the treatment. However, given the correlations measured in Table 11, a more likely story is that female repayment problems are more common and so the increase in male membership is a function of increasing group selection and discipline.

6.5. BEHAVIOR WITH OTHER CREDIREF LENDERS.

Information on Genesis clients became available to outside lenders in 2002, and hence their credit records have been used to determine their access to loans with other lenders. However, to the extent that clients were not aware of this possibility before the information sessions, they did not explicitly use their reputation to search for other loans. To measure the effect of this awareness, we analyze a number of indicators of external borrowing seen in the Crediref records.

Crediref collects information once a month on each of the loans taken by an individual. For group loans, the recorded information is on the total loan to the members of the group, not on the individual share in the group loan, meaning that the recorded level of indebtedness is the total amount taken out by the group, and the recorded repayment performance is also the performance of the group. We characterize a client's outside (non-Genesis) borrowing by the number of loans taken. We will characterize the repayment performance of each completed loan by whether there has been any late payment during its cycle. These SG and CB clients of Genesis do not have enough individual loans to make a separate analysis of individual and group loans. In this analysis, we only consider Genesis clients that were members of a group at time of treatment, and their treatment status is that of the group to which they belonged.[12]

The date recorded for each loan in Crediref is the date of the last data entry, which corresponds to the closing date of the loan (except for the current loans which have their last transaction recorded in June 2005). In this analysis we consider as pre-treatment all loans completed before the treatment date. Using a DID method, we estimate the following equation:

$$\Delta_{ig} = \alpha + \delta S_g + u_{ig}$$

where Δ_{ig} characterizes the change in outside loans reported in Crediref from the pre-treatment to the post-treatment period of individual *i* from group *g*, α represents the average change in outside borrowing for the members of the control groups, and S_g a dummy variable indicating that the group *g* was selected for treatment. The parameter δ measures the ITE effect of the information sessions. We use change in number of loans and whether individual *i* started taking outside loans after the treatment date.

Results are reported in Table 13. The interpretation of the observed changes is confounded by the fact that Crediref was rapidly expanding during this period. As more and more MFIs and Banks were joining the credit bureau, the information thickened and the number of reported loans increased without implying an actual increase in borrowing. The changes observed for the control clients can, however, serve as a reference for interpreting the magnitude of the DID measure of impact. Considering all 5419 clients together, there is no significant effect on the number of loans taken, but there is a 29% (calculated as 107/363*100) increase in the number of members that are reported taking an outside loan for the first time. For the SG members, there is a striking absence of effect of the sessions on

[12] When clients belonged to two groups, they were considered treated if at least one of their groups was treated. About 3% of the control SG clients (20% of the control CB) changed group, joining a treated group after the treatment date. We also perform the analysis by attributing them the status of treated starting from the date they joined the treated group. Results are very similar and not reported here.

their taking outside loans. We searched for heterogeneity among these SG members, along their relationship with Genesis (contrasting old and new clients, with many or few loans) and their past performance in Genesis and with their recorded outside loans, and found no group that increased its engagement outside of Genesis.

By contrast CB members increased the number of outside loans by 47% and increased by 31% the number of new entrants in outside borrowing. This difference may be due to SG members being already more engaged in outside borrowing (18% of the SG members had records of outside borrowing prior to the treatment, while only 12% of the CB members had any), meaning that they were less constrained and thus less eager to take on the opportunity or more informed of the existence of Crediref, implying that the information sessions had less impact on them.

Who among the CB members responded to the information by engaging into outside borrowing? The bottom rows of Table 13 report the contrast in ITE for good Genesis clients (never had a delinquent repayment) and bad clients (had at least a delinquent repayment) as well as for more experienced clients (had 4 or more loans with Genesis) and less experienced clients (had 3 or less loans with Genesis). Good CB clients respond to information about their public reputation by increasing the number of loans taken outside (+13%) and the number of them taking outside loans increases by 11%. By contrast, bad clients, with knowledge that their defaults in repayment is public information, are not able to increase their outside borrowing. The impact of information in inducing outside borrowing is stronger on the less experienced clients (who increase the number of loans by 12% while 16% start taking outside loans) than it is on their more experienced counterparts who do not change their outside borrowing. We will see later that increased borrowing by these less experienced clients can have a perverse effect on their repayment performance.

Table 14 reports the impact of the information sessions on the change in performance on outside loans:

$$y_{libt} = \alpha_b + \alpha_t + \delta T_{lit} + u_{lit}$$

where y_{libt} is a measure of performance for the loan *l* taken by individual *i* from branch *b* last recorded in Crediref at time *t*. The treatment variable T_{lit} is equal to 1 if individual *i* was member of a group selected at time of treatment and $t \geq \tau_i$, the treatment date. We also report the average pre-treatment performance $\overline{y}_0 = \sum_{lib,t<\tau_i} y_{libt}$ and the average change in performance in the control group $\overline{y}_1^C - \overline{y}_0^C = \sum_{l,ib\notin S,t\geq\tau_i} y_{libt} - \sum_{l,ib\notin S,t<\tau_i} y_{libt}$.

The performance is measured by a binary variable indicating whether there was any late repayment during the loan cycle. Note first that there has been an important decline in repayment problems even for members of the control groups, from its occurrence in 17% of the reported loans to 6% on average in the post-treatment period. The absence of overall impact of information on performance hides an interesting heterogeneity by type of borrower, notably among CB members. We saw that it is the less experienced Genesis clients who started to aggressively take outside loans. Yet, it is precisely them who worsened their repayment performance. To the contrary, the more experienced Genesis clients did not increase their loan taking in spite of an acquired public reputation, and they improved their repayment performance as defaults undermining reputation are now more costly. This indicates that the opportunity revealed by the information for clients to use their good reputation to access outside loans may end up with a deterioration of credit record when taken by less experienced borrowers.

VII. CONCLUSION.

We analyze the impact of the introduction of a credit bureau on borrower behavior, a transition from private reputation to public reputation in the microfinance industry.. This institutional change is symptomatic of an effort by the microfinance industry to broaden an "honesty equilibrium" in the face of rising competition. We combined for this a natural experiment in Guatemala consisting in the staggered entry of a large microfinance lender into a credit bureau (with use of bureau information in the first stage only for selection, without informing borrowers), with a randomized experiment to provide information to groups of borrowers about the existence of the credit bureau and its implications for them, and with access to administrative data on client records from both the microfinance lender and the credit bureau. The randomized experiment allows to measure how knowledge of the rules of operation of the credit bureau affects the behavior of members of credit groups both with the initial microfinance lender and with other lenders. By analyzing the behavioral response across successive loan cycles, we are able to evidence the roles of information on the supply and demand side separately. We also analyze the impact of public reputation on access to loans from other lenders and on borrowers' repayment performance on these loans.

The use of the bureau by the lender results in a strong reduction in adverse selection, and a correspondingly large improvement in performance indicators at the borrower and credit officer level. When group loan borrowers learn about the rules of operation of a credit bureau, the repayment performance of (small) SGs improves, but that of (large) CBs does not. This improvement in SGs is due to both the curbing of moral hazard behavior (as isolated in the current loan cycle) and to improved group selection. Improved group selection is done by shedding the weaker members, in particular women with average inferior repayment performance. In Hirschman's (1970) terminology, selection is due to "voice and loyalty" with groups expelling bad performers, as opposed to "exit" whereby good performers leave poorly performing groups, seeking better options.

Additional sources of heterogeneity in impacts are the length of experience that a borrower has with Genesis before they learn of the use of the bureau, and their quality as a borrower during that time. SG members with good repayment performance before treatment leave Genesis and take larger group loans. This gives evidence of some graduation toward outside borrowing, indicating that the credit bureau indeed opens new options to the better performing SG borrowers. Results are quite the opposite for members of CBs. There, members with good performance records took more outside loans. This is done by clients with good Genesis performance that they can now value externally as they know that it is public. Impact on performance was, however, sharply contrasted among more and less experienced borrowers. Clients with a long experience in borrowing from Genesis do not take more loans, but improve their repayment performance. By contrast, clients with limited experience are drawn into taking more outside loans and tend to fail to perform on these loans, worsening their repayment records. Hence, information about public reputation can be a two-edged sword, putting at risk of unrestrained borrowing exuberance those with limited experience in taking loans.

New information over the workings of a credit bureau has a powerful effect on borrower behavior. The outside lenders extended this new credit knowing the reputation on pre-existing indebtedness and performance of the borrowers' groups. The fact that we find strong differences across characteristics observable in the bureau on these outside loans implies that the use of a credit scoring model could improve lender efficiency in making multiple loans. The borrowers who were taking loans most similar to those offered at much lower rates by the top-tier lenders in Crediref (SG) did not rush out to take new loans; rather they engaged in a systematic improvement of their records in both inside and outside lenders. By reporting on group loan behavior, the bureau suffers from some informational efficiency loss, but actually bolsters the collective incentives that have led to the extension of uncollateralized credit to the poor on a joint liability basis. In short, ensuring that the individuals covered by a bureau are well-informed as to its working is a straightforward way for MFI lenders of increasing loan efficiency among top-tier group borrowers (SG) and to induce all bad borrowers to improve their performance. It also allows to deepen pro-poor capital markets for good borrowers (CB) and to strengthen the rungs on the credit ladder (SG). However, and not unexpectedly with an efficiency-enhancing institutional innovation, it leads to the shedding of weaker group members by enhanced incentives for groups to reduce AS, and to mistaken increase in indebtedness by less experienced severely constrained members (CB).

We demonstrate that bureaus are effective in improving outcomes in a credit market. Since they are a relatively low-cost intervention, this implies that they should be made a part of efforts to achieve financial deepening in developing countries. Their use appears to be almost universally to the benefit of lenders, and in a competitive market, this should lead to lower interest rates for borrowers over time. The losers from the introduction of a bureau are those borrowers who are screened out a result of the information, and ongoing borrowers who may lose insurance opportunities as a result of the winnowing of the borrower pool. We show that group reporting can in fact reinforce the group mechanisms that underlie microfinance lending. The ultimate outcome is efficiency gains for the innovating institutions, gains for the more capable economic agents, and increased social differentiation.

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Table 1a. Extensive margin of staggered rollout: Performance of first loans

	Borrower pays late fees > 1% of principal	Loan more than 2 months delinquent	Average loan size per borrower
Individual loans			
Treatment Effect	-0.053	0.008	648
	(4.12)**	(0.55)	(1.12)
Observations	12792	12792	12792
R-squared	0.02	0.01	0.02
Number of branches	36	36	36
Mean of dependent variable	0.23	0.08	6863.57
Solidarity Group loans			
Treatment Effect			
	0.01	(0.01)	1018.96
	(0.44)	(0.28)	(1.92)
Observations	5412	5412	5412
R-squared	0.02	0.02	0.05
Number of branches	35	35	35
Mean of dependent variable	0.13	0.11	3933

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%
All regressions run with branch & month fixed effects, robust standard errors clustered at branch

Table 1b. Impact of bureau on screening borrowers in and out

	Individual Borrowers	**Borrowers within ongoing Solidarity Groups**	**Entire Solidarity Groups**
Leaving	**Fraction leaving**	**Fraction leaving**	**Fraction leaving**
First time screened	0.1765	0.1894	-0.4090
	(8.53)**	(6.76)**	(7.33)**
Subsequent screenings	-0.0633	-0.0054	-0.1935
	(1.61)	(0.64)	(2.91)**
Observations	14389	56132	56132
R-squared	0.04	0.05	0.04
Number of branches	33	33	33
Entering	**Fraction entering**	**Fraction entering**	**Fraction entering**
ITE	0.1687	-0.0104	0.1828
	(4.82)**	(2.60)**	(4.06)**
Observations	11630	56132	56132
R-squared	0.04	0.04	0.05
Number of branches	33	33	33

Table 2. Intensive margin of staggered rollout: Performance of ongoing borrowers

	Borrower pays late fees > 1% of principal	Loan more than 2 months delinquent	Average loan size per borrower
Individual loans			
Treatment Effect	0.029	0.022	618
	(1.79)	(3.42)**	(2.10)*
Observations	11117	11117	11117
R-squared	0.04	0.02	0.19
Number of borrowers	3235	3235	3235
Mean of dep. variable	0.120	0.020	8207
Solidarity Group loans			
Treatment Effect	-0.001	0.012	1344
	(0.04)	(1.55)	(6.66)**
Observations	9057	9057	9057
R-squared	0.02	0.02	0.30
Number of group loans	1216	1216	1216
Mean of dep. variable	0.05	0.03	6719

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%
All regressions run with individual and month fixed effects, dummies for loan cycle, robust standard errors clustered at branch level.

Table 3. Impacts of the bureau on the future behavior of newly selected borrowers

	Probability of taking subsequent loan	Months until subsequent loan taken	Growth in size of subsequent individual loan
Individual loans			
Treatment effect	0.228	-0.121	0.12
	(8.58)**	(1.79)	(2.27)*
Observations	12792	5686	5686
R-squared	0.12	0.04	0.05
Mean of dependent variable	0.44	1.99	1.37
Number of branches	36	36	36
Solidarity Group loans			
Treatment effect	0.071	0.09	0.046
	(1.11)	(0.58)	(0.42)
Observations	4782	2631	2631
R-squared	0.17	0.05	0.08
Mean of dependent variable	0.55	1.59	1.37
Number of branches	35	35	35

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%
All regressions run with branch & month fixed effects, robust standard errors clustered at branch level.

Table 4. Staggered rollout: Behavior of credit officers

			Individual loans		Group loans	
	Number of new loans	Total new lending (Qz)	Number of borrowers	Average loan size (Qz)	Number of borrowers	Average loan size per capita (Qz)
New borrowers						
Treatment effect	2.513	22,957	0.964	1,612	3.084	1,933
	(8.46)**	(7.27)**	(4.86)**	(4.26)**	(4.57)**	(9.90)**
R-squared	0.11	0.09	0.08	0.04	0.02	0.08
Mean of dep. variable	2.42	20,876	1.54	4,123	4.23	1,160
Pre-existing borrowers						
Treatment effect	-0.641	-5,716				
	(1.50)	(0.65)				
R-squared	0.08	0.06				
Mean of dep. variable	4.7	66,887				
All borrowers						
Treatment effect	1.872	17,242				
	(3.25)**	(1.72)				
R-squared	0.10	0.07				
Mean of dep. variable	7.12	87,763				

Absolute value of t statistics in parentheses

* significant at 5%; ** significant at 1%

All regressions include credit officer and time fixed effects, robust standard errors clustered at branch level.

Table 5. Implementation of the randomization

Branch Name	Number of Solidarity Groups	Number of Communal Banks	% selected for treatment	% actually treated	% of treated in selected
Chimaltenango	141	209	25	18	71
Cuilapa	104	28	49	27	54
Santa Lucia	122	37	71	41	58
Salama	175	128	60	37	62
Poptun	95	69	38	38	99
El Estor	22	0	82	50	61
El Castano	77	0	93	29	31

Table 6. Comparison of pre-treatment covariates

	Solidarity Groups			**Communal Banks**		
Group characteristic:	Control groups mean	Selected groups mean	Selected - control difference	Control groups mean	Selected groups mean	Selected - control difference
Loan amount per capita	830	844	14	311	297	-13
(in US$)	[66]	[58]	(0.15)	[9]	[8]	(3.19)
Percent divorced	1.48	1.40	-0.07	1.63	0.00	-1.63
	[0.57]	[0.52]	(0.10)	[0.89]	[0.00]	(1.84)
Percent widowed	4.11	4.81	0.69	4.40	8.12	3.72
	[0.52]	[1.51]	(0.41)	[1.24]	[1.71]	(1.87)
Average education[1]	1.06	1.05	-0.01	0.72	0.66	-0.05
	[0.05]	[0.02]	(0.25)	[0.05]	[0.04]	(1.84)
Percent female	42.17	45.56	3.38	100.00	100.00	
	[3.13]	[2.37]	(1.09)	[0.00]	[0.00]	
Average age	37.89	37.60	-0.29	37.73	38.14	0.40
	[0.89]	[1.27]	(0.45)	[0.74]	[0.95]	(0.38)
Percent indigenous	57.66	61.27	3.62			
	[8.17]	[9.20]	(0.91)			
Percent rural	23.72	26.94	3.21			
	[10.29]	[6.96]	(0.68)			
Number of observations	214	233		176	127	

Standard errors in brackets, absolute value of t-statistics in parentheses; t-tests compare mean values of selected groups and control groups.

more.

Table 7. Comparison of pre-treatment outcomes

Outcome	Control groups mean	Selected groups mean	Selected - control difference	Treated groups mean	Treated - control difference
Borrowers pays late fees > 1% of principal	9.21	3.33	-5.88	1.36	-7.86
	[2.40]	[0.48]	(2.27)	[0.44]	(3.18)
Loan more than 2 months delinquent	12.03	2.25	-9.78	0.72	-11.31
	[4.12]	[0.69]	(2.20)	[0.30]	(2.73)
Observations	672	877		586	

Standard errors in brackets; absolute value of t statistics in parentheses; t-tests compare group outcomes for selected or treated groups to outcomes for control groups.
All outcomes in percent.

Table 8. Counterfactual tests

	False Treatment Effects (Two pre-treatment periods)		Selection Effects (Non-compliers versus control groups)
Outcome	SGs	CBs	
Borrowers pays late fees > 1% of principal	-4.20	0.80	2.70
	(1.24)	(0.31)	(1.21)
Loan more than 2 months delinquent	-4.00	-2.00	0.60
	(1.04)	(1.57)	(0.28)
Observations	1233	669	2286

Absolute value of t-statistics in parentheses;
Analysis conducted at the loan level, with group and time fixed effects.
All coefficients multiplied by 100.

Table 9. Discontinuous impacts of information within a loan cycle

Outcome:	Intermediate payments ITE	Final payment only Mean value Control	Mean value Selected	Difference ITE
Solidarity Groups:				
Delinquent payment[1]	-4.99	27.67	9.98	-17.70
	(1.50)	[7.53]	[1.92]	(2.45)
Amount of late fees (US$)	-0.47	9.02	1.17	-7.85
	(0.36)	[6.37]	[0.68]	(1.19)
Number of observations	4711	175	266	
Communal Banks:				
Delinquent payment[1]	0.41	10.67	7.31	3.37
	(0.54)	[4.15]	[1.19]	(0.76)
Amount of late fees (US$)	-0.17	1.22	0.72	-0.49
	(1.36)	[5.79]	[0.22]	(0.60)
Number of observations	3739	192	168	

Absolute value of t-statistics in parentheses, standard errors clustered at the branch level in brackets;
Analysis conducted at the loan payment level, using loans that were active at the time of the treatment. Regressions on intermediate payment performance include loan and time fixed effects, and dummy variables for payments deciles.
[1] Coefficients multiplied by 100.

Table 10. Impact of information across loan cycles

Outcome	OLS DID All ITE	All TET	All ITE	Group fixed effects All TET	SG ITE	CB ITE
Borrowers pays late fees > 1% of principal	-6.27	-7.98	-1.92	-3.24	-3.35	-1.93
	(1.20)	(1.58)	(0.68)	(1.46)	(0.99)	(1.11)
Loan more than 2 months delinquent	-9.90	-11.48	-3.69	-4.58	-6.46	-0.01
	(1.77)	(2.00)	(1.37)	(1.77)	(1.53)	(0.00)
Observations	3857	3191	3857	3191	2466	1391

Absolute value of t-statistics in parentheses, standard errors clustered at the branch level.
Analysis conducted at the loan level, with time fixed effects.
[1] Coefficients multiplied by 100.

Table 11. Correlations between group repayment and individual characteristics in Solidarity Groups

	Borrower pays late fees > 1% of principal	Loan more than 2 months delinquent
Number of members	1.65	0.07
	(1.33)	(0.03)
Divorced ratio	-2.87	20.52
	(1.13)	(1.21)
Widowed ratio	-6.78	-0.63
	(2.22)	(0.07)
Average education	3.64	0.16
	(1.52)	(0.21)
Female ratio	-0.58	-0.44
	(0.70)	(0.24)
Average age	-0.86	-1.18
	(7.46)**	(3.32)*
Average age squared	0.01	0.02
	(5.31)**	(3.39)*
Banking w/ Crediref institution ratio	-3.41	-2.55
	(2.22)	(3.27)*
Observations	1230	1230

Analysis conducted at the loan level. Absolute value of t-statistics in parentheses.
All coefficients are multiplied by 100.

Table 12. Compositional impacts of information

	OLS DID		Branch-level fixed effects	
	New clients ITE	Dropouts ITE	New clients ITE	Dropouts ITE
Number of members	0.32	0.04	0.19	-0.08
	(1.01)	(0.50)	(0.69)	(1.66)
Percent divorced	-1.25	0.93	-0.67	-5.97
	(1.77)	(0.08)	(2.25)	(0.84)
Percent widowed	-4.27	0.93	-1.52	-5.97
	(0.83)	(0.08)	(0.95)	(0.84)
Average education	0.03	0.05	-0.07	0.06
	(0.55)	(0.27)	(2.98)	(0.49)
Percent female	-17.32	7.38	-5.41	12.35
	(1.79)	(1.95)	(1.96)	(3.40)

Analysis conducted at the loan level, using time fixed effects. Each regression run separately to explain the number or the average characteristic of new / dropout clients for the loan.
Absolute value of t-statistics in parentheses.

Table 13. Impact of information on change in outside borrowing

	Number of clients	Change in number of loans	Start taking outside loan
All clients			
Control groups		0.261	0.363
		(1.64)	(6.34)
ITE	5419	0.077	0.107
		(1.77)	(2.64)
By type of clients			
Solidarity Group member			
Control groups		0.359	0.364
		(8.50)	(11.77)
ITE	1247	-0.038	0.083
		(0.25)	(1.00)
Communal Bank member			
Control groups		0.232	0.363
		(1.15)	(5.00)
ITE	4172	0.110	0.114
		(2.15)	(3.40)
Heterogeneity among Communal Bank members			
Less experienced clients - ITE	2717	0.120	0.161
		(2.98)	(4.39)
More experienced clients - ITE	1455	0.145	0.025
		(0.97)	(0.83)
Good client - ITE	3572	0.127	0.112
		(2.21)	(4.59)
Bad client - ITE	600	0.037	0.130
		(0.37)	(1.55)

Analysis at the client level; OLS of change in outside borrowing, with standard errors clustered at the branch level. Experienced (less experienced) clients are clients having had at least 4 (less than 4) loans with Genesis. Good (bad) clients had no (at least one) delinquent repayment before.

Absolute value of t-statistics in parentheses.

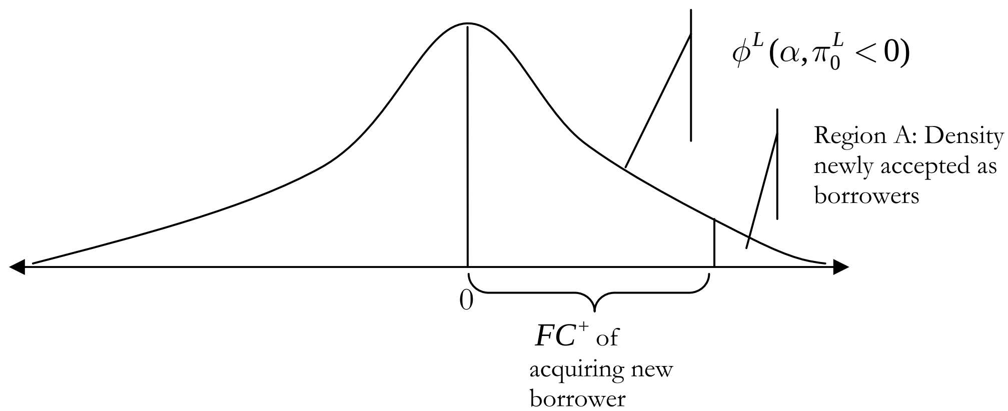
Table 14. Impact of information on the performance of outside loans

	Number of loans	Ever missed a payment Pre-treatment average	Pre-post change in control groups	ITE
All	4811	0.170	-0.109	0.002
				(0.11)
By type of clients				
Solidarity Group members	1314	0.197	-0.125	-0.063
				(1.27)
Communal Bank members	3497	0.160	-0.103	0.021
				(1.77)
Heterogeneity among Communal Bank members				
Experienced clients	1658	0.155	-0.079	-0.020
(4 or more loans inside)				(2.81)
Less experienced clients	1839	0.169	-0.126	0.043
(3 or less loans inside)				(1.79)

Analysis at the loan level, with time and branch fixed effects and standard errors clustered at the branch level. Absolute value of t-statistics in parentheses

Figure 1.

Density among Current Non-borrowers



Density among Current Borrowers

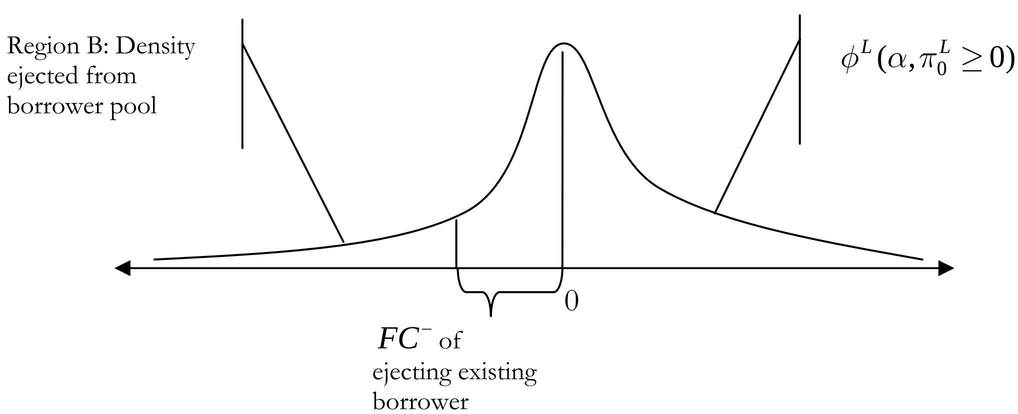


Figure 2. The increase in new individual loans when the bureau is used.

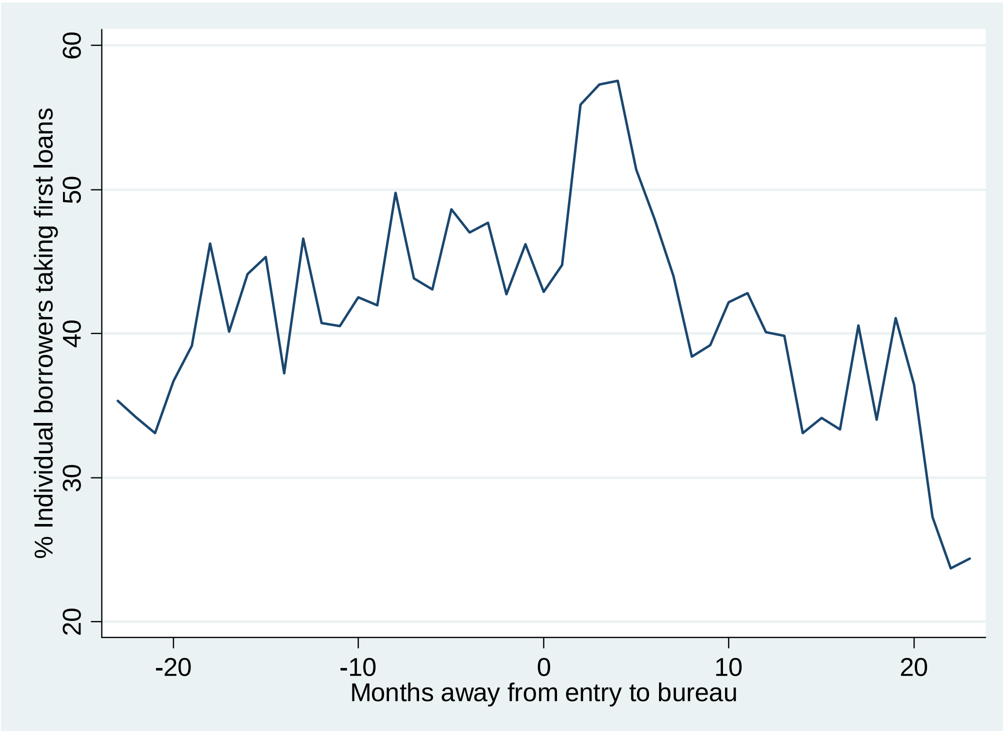


Figure 3. The decrease in the size of solidarity groups when the bureau is used.