Adverse Selection, Moral Hazard, and Credit Information Systems

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Abstract: We develop a model that derives "screening" and "incentive" effects of credit information systems that mitigate problems of adverse selection and moral hazard in credit markets. We also derive a "credit expansion" effect in which borrowers with clean credit records receive larger and more favorable equilibrium loan contracts. The credit expansion effect increases default rates, but does not overwhelm the reduction in portfolio default from screening and incentive effects. We create a simulation model which allows us to examine the relative magnitudes of these effects in relation to the order in which they occur. Our results indicate that a substantial portion of the positive effects of a bureau can be realized through the publicity of a bureau prior to its implementation. We then use loan-level data from the rollout of a credit information system used by a Guatemalan microfinance lender to show that this credit expansion effect partly, but not fully, counteracts the positive screening and incentive effects from the system.

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I. INTRODUCTION

A transformation is occurring in many parts of the developing world in which a borrower's personalized relationship with a sole provider of credit is being replaced by an impersonal relationship with a larger market of potential lenders. This transformation has arisen as the number of providers of microfinance and commercial credit has proliferated in the population centers of Asia, Africa, and Latin America, creating multiple borrowing options (Miller, 2003; Luoto, McIntosh, and Wydick, 2007). While a personalized credit relationship may check moral hazard problems via threats of credit termination and/or rewards for timely repayment, a proliferation of credit options increases the scope for asymmetric information problems in credit markets. This phenomenon has triggered the rapid emergence of credit information systems,[1] which allow lenders to share information about borrowers.[2]

In many ways the formation of credit information systems in the developing world is a bellwether of financial development: Institutions that facilitate credit information sharing add stability to financial systems. Moreover, in this transformation of the credit relationship from a personalized one to a relationship with a larger market, borrowers stand to gain from competition between lenders. Yet despite their increasing importance, too little is known about the specific effects of credit information systems on credit markets.

In this paper we contribute to an understanding of the effects of credit information systems by presenting a simple model that decomposes the overall impact of a credit information system into two distinct effects that lower borrower default rates: a screening effect and an incentive effect. The model also predicts equilibrium increases in loan size and a resultant *increase* in default for borrowers with clean credit records. We subsequently summarize results from fieldwork in Guatemala where we utilize both natural and

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[1] There are two principal types of credit information systems: *credit bureaus* (often called private credit registries), which involve the voluntary exchange of information among lenders, and *public credit registries* established by the state in which participation in the system is typically compulsory.

[2] Developing and transitional countries which now have private credit bureaus are (Africa): Botswana, Kenya, Namibia, Nigeria*, and South Africa; (Latin America): Argentina, Bolivia*, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras*, Mexico, Panama, Paraguay, Peru, and Uruguay; (Asia): India*, Indonesia*, Kyrgyzstan*, Malaysia, The Philippines, Sri Lanka, and Thailand; (Eastern Europe): Bosnia-Herzegovina, Bulgaria*, Czech Republic*, Estonia, Georgia*, Hungary, Lithuania*, Poland, Romania*, and Slovakia*; (Middle East): Egypt*, Israel*, Kuwait*, Pakistan, Turkey, and Saudi Arabia*. (Source: International Financial Corporation, World Bank Group). A current updated list is available at http://www.ifc.org/ifcext/gfm.nsf/Content/FinancialInfrastructure-PCB-List.
*Denotes first private credit bureau instituted since 2000.

randomized field experiments around the implementation of a credit information system that has facilitated information-sharing between microfinance providers. The empirical evidence yields considerable support for the effects we posit in our model, and some important general insights into the problems of adverse selection and moral hazard in credit markets.

Our work builds on seminal research in the field such as Jappelli and Pagano (1993), who demonstrate that credit information systems are likely to emerge in large, heterogeneous, and mobile pools of borrowers, and that such systems are a natural monopoly because of increasing returns to scale in information-sharing. Theoretical work by Padilla and Pagano (1997, 2000) and Vercammen (1995) analyzes the effects of information sharing between lenders in credit markets. The former suggests that the exchange of "blacklists" of defaulting borrowers between lenders can be an effective discipline device to mitigate various forms of moral hazard, reducing interest rates in credit markets, while the latter demonstrates that the sharing of shorter credit histories is optimal for mitigating moral hazard, preventing borrowers from free riding on good reputation. Subsequent empirical work by Brown, Jappelli, and Pagano (2007), using firm-level panel data in transition economies, has found that the cost of credit declines as information sharing increases between lenders.

In Section II of our paper, we attempt to bridge this literature on credit information systems through a model that yields predictions about the effects of credit information systems on a particular form of moral hazard, multiple loan contracting, that has become increasingly prevalent in developing countries with the proliferation of new sources of credit. We then carry out a simulation of our model on the effect of a credit information system on default rates. In Section III, we compare the predictions and simulations of our model with evidence obtained in the context of the rollout of a credit information system in Guatemala. Section IV concludes with a short summary, some policy implications of our results, and a generalization of the effects we derive to other contexts where asymmetric information problems exist.

II. A Model of Credit Information Sharing

The large literature on the asymmetric information problem in credit markets has taken several different approaches to modelling hidden actions and hidden information. The most well-known of this work is that of Stiglitz and Weiss (1981), who reveal the incentive by borrowers to undertake risky investments which increase a borrower's expected payoff under limited liability, but simultaneously reduce the expected payoff to the lender. Higher interest rates draw an increasingly larger proportion of risky investments into the pool of borrowers, creating conditions for a credit-rationing equilibrium. Subsequent work has highlighted other forms of *ex-ante* moral hazard, such as underinvestment in borrower activity complementary to credit (e.g. Boot, Thakor, and Udell, 1991), borrower negligence (e.g. Aghion and Bolton, 1997), and partial diversion of a loan from productive investment to present consumption (e.g. Wydick, 2001). Moral hazard may also occur *ex-post* to project outcome if a borrower simply reneges on a promise to repay. This kind of strategic default underlies the models of Banerjee and Neumann (1993) and Paulson and Townsend (2003).

The form of moral hazard that characterizes our model is multiple loan contracting, in which borrowers may obtain more advantageous credit terms through taking hidden loans from different lenders, with each lender possessing information over only his own contract with a borrower (Jappelli and Pagano, 2000; Bizer and De Marzo, 1992). Hidden loan contracts impose a negative externality because the unseen debt increases the probability of default on each loan. We build our analysis of credit information systems around this type of moral hazard because defaults associated with over-indebtedness are an increasingly grave phenomenon in parts of the developing world that have experienced a proliferation in sources of credit. The growing problem of multiple loan contracting has been well-documented, for example, in Turkey (Kaynak and Harcar, 2001), South Africa (Daniels, 2004), and Central America (McIntosh and Wydick, 2005).

To conceptualize the effects of information sharing in credit markets, we develop a model that is both a simplification and extension of McIntosh and Wydick (2005). Here we consider the case of an oligopolistic industry of lenders engaging in Bertrand competition over a finite but large pool of borrowers indexed by $i \in \{1, 2 \ldots n\}$. Lenders offer loan contracts to borrowers at a fixed administrative cost *F*, where a contract is defined over the size of the loan and interest rate, $\{V, r\}$.[3] Upon receiving a loan, a borrower's project either succeeds or fails in returning a yield higher than the interest rate. More borrowing increases the payoff if a project is successful, but also increases the probability that the borrower will be unable to repay the entire loan. Total borrowing is equal to existing debt and the size of the proposed loan, or $V_T = V_E + V$. Existing debt, V_E, is known to the borrower, but in the absence of credit information sharing is hidden from the lender who is therefore forced to form expectations over the extent of existing indebtedness. A project fails with probability p yielding only $\underline{R} < 1$ per unit of borrowed capital. We assume borrowers have no collateral, and in this case are forced to default on this fraction $1-\underline{R}$ of the principal. A successful project yields a gross return of $\overline{R} > 1 + r$ with probability $1 - p$. The probability of project failure p is increasing in V_T such that $p = p_v V_T$, where $p_v > 0$. Assuming that the cost of capital to lenders is zero, this makes the lender's expected profit from a loan to borrower *i* equal to

$$\Pi_i^L = (1-p)(1+r)V + p\underline{R}V - V - F. \tag{1}$$

In a zero-profit Bertrand competitive equilibrium, this implies that the interest rate for any loan of size *V* will be equal to $r = (F + pV(1-\underline{R}))/(1-p)V$. Note that since $p = p_v(V_E + V)$, this means that the competitive equilibrium interest rate to any borrower is increasing in the (expected) level of debt carried by a borrower.

We derive the shape of the lender's iso-profit curves in $\{V, r\}$ space by totally differentiating (1) to obtain

$$\frac{dV}{dr} = \frac{V(1-p)}{(p_v V + p)(1 + r - \underline{R}) - r}. \tag{2}$$

[3] We will suppress the subscript *i* on contractual variables in our paper except for emphasis or in cases of ambiguity.

Because the numerator is positive, the slope of the lender's iso-profit curve is positive when *V* is large, and negatively sloped when *V* is small.

Borrower profits are generated from small enterprises with a uniform endowment that has zero opportunity cost. Borrower profits are equal to project payoff minus interest costs. Because the probability of project failure is increasing in a borrower's outstanding debt, a project failure signals that a borrower is more likely to be characterized by hidden levels of indebtedness than one who is free of default, and thus the borrower incurs an endogenous penalty Γ from default, the details of which we will describe shortly.

Borrowers differ only in the extent to which they value these future penalties, and hence in their willingness to engage in risky borrowing behavior for which they may realize short-term gain at a greater risk of long-term pain.[4] Specifically, each borrower is characterized by a rate of time preference $\rho_i \in [\underline{\rho}, \overline{\rho}]$ where $g(\rho_i)$ is the density function of ρ_i and $G(\rho_i)$ is its associated distribution function. This makes the profit function of borrower *i* equal to

$$\Pi_i^B = (1-p)\left(\overline{R}-(1+r)\right)V - p\Gamma\rho_i^{-1} \tag{3}$$

Totally differentiating borrower *i*'s profit function with respect to *V* and *r*, we obtain the slope of the set of borrower *i*'s iso-profit curves in $\{V, r\}$ space:

$$\frac{dV}{dr} = \frac{V(1-p)}{(1-p-p_v V)\left(\overline{R}-(1+r)\right) - p_v\Gamma\rho_i^{-1}}. \tag{4}$$

As seen in (4), in contrast to the lender, the borrower's iso-profit curves are *positively* sloped for small *V*, specifically when $(1-p-p_v V_i)\left(\overline{R}-(1+r_i)\right) > p_v\Gamma\rho_i^{-1}$, and negative otherwise. While lenders' iso-profit curves are increasing across *r*, borrowers' iso-profit curves are decreasing in *r*.

Using (2) and (4) and by substituting $p_v(V+V_E)$ for *p*, an equilibrium loan contract $\{V^*, r^*\}$ between a borrower and lender in Bertrand competitive equilibrium occurs at

[4] In our model, ρ can alternatively be viewed as social collateral, alternative income-generating options, or any other individual-level source of heterogeneity which affects borrowers welfare (but not lender profits) in the event of default.

$$V^* = \frac{\overline{R} - 1 - p_v\left(\Gamma\rho_i^{-1} + \left(\overline{R} - \underline{R}\right)V_E\right)}{2p_v\left(\overline{R} - \underline{R}\right)} \quad , \quad r^* = \frac{p_v\left(V^* + V_E\right)\left(1 - \underline{R}\right) + F/V^*}{1 - p_v\left(V^* + V_E\right)} \qquad (5)$$

if it satisfies $\Pi_i^B(V,r), \Pi_i^L(V,r) \geq 0$, where we assume that the return in the good state is sufficiently high that the equilibrium loan is always positive. With Bertrand competition between lenders, the equilibrium loan to any borrower *i* will occur at the tangency point between borrower *i*'s iso-profit curve and the lender's iso-profit curve where $\Pi_i^L = 0$, depending on a borrower's rate of time preference, as seen in Figure 1A.[5]

Why should some borrowers seek to obtain loan contracts from multiple lenders? Where this tangency point occurs depends on the future penalties imposed on borrowers for default, and the value different borrowers place on these future penalties. Consider the borrower with rate of time preference ρ_1 in Figure 1A. The tangency point of this borrower's iso-profit curve to the zero-profit curve of the lender occurs at Point A. But as ρ_i increases, borrower *i*'s indifference curve rotates clockwise, as seen in (4). The negatively-sloped portion of the curve becomes steeper and the positively sloped portion of the curve becomes flatter, resulting in a higher tangency point along the lender's zero-profit curve. This is illustrated by borrowers with different rates of time preference, where $\rho_1 < \rho_2 < \rho_3$ in Figure 1A. Thus in our model more impatient borrowers are riskier borrowers, demanding larger loans (and their potential for greater profit) in the present, while discounting the future consequences of default more heavily.

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[5] We also assume that the parameter p_v is sufficiently small that for all loan contracts $p = p_v V_T < 1$. It can easily verified that when the return in the good state, $\overline{R}$, is sufficiently high that the borrower's iso-profit curve bends backward at a higher level of V than that for the lender, which we assume. This implies that in the equilibrium loan contract, a marginal increase in V increases expected profit to the borrower, but not the lender.

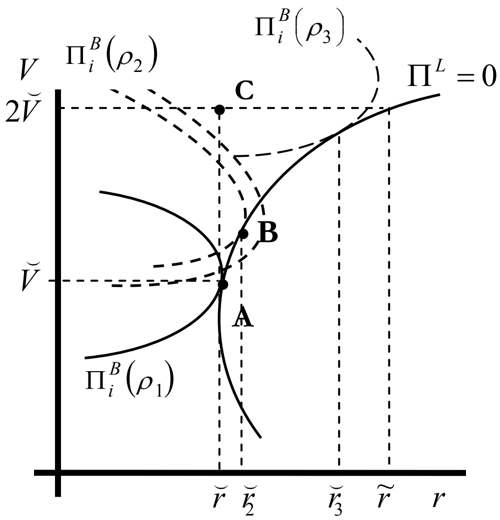

Figure 1A

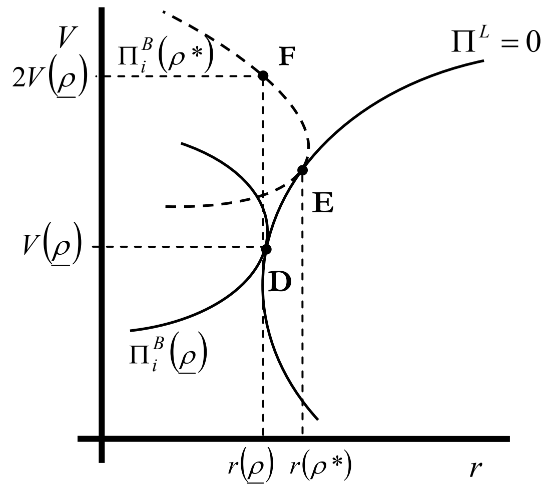

Figure 1B

In a full-information context, a lender may oblige a borrower with higher ρ by offering him a larger loan at a higher interest rate, which fully compensates the lender for the added risk, as seen by tangency point B in Figure 1A.[6] Moreover, because of the fixed costs associated with each loan, with full information borrowers will exclusively contract with a single lender. But with asymmetric information about borrower debt, a high-ρ borrower may choose to take separate loan contracts from different lenders, allowing the borrower to avoid the interest rate premium that would be required on a single, larger loan. This behavior has become ubiquitous in developing countries that have witnessed a proliferation of credit options, but where a lack of credit information allows for hidden debt.

Because the interest rate is a convex function of V^* (*i.e.* $\frac{dr^*}{dV^*}, \frac{d^2r^*}{dV^{*2}} > 0$), it is therefore most advantageous for borrowers contracting multiple loans to obtain separate loans of equal size. In Figure 1A, a borrower with rate of time preference ρ_2 is indifferent between obtaining a single loan of size $\breve{V}$ at interest rate $\breve{r}$ or two separate loans of the same size, though prefers a single loan at a higher interest rate $\breve{r}_2 > \breve{r}$.

[6] In practice some lending institutions are willing to negotiate higher interest rates for larger loans, while other institutions offer all loans of a given type at a single interest rate. Whether or not a lender is willing to grant larger loans at a higher interest rate is a choice that may depend on particular institutional frictions related to negotiation costs, and does not alter our fundamental point that borrowers have an incentive to conceal borrowing from multiple lenders. In practice some institutions establish a fixed interest rate at which they grant all loans, and will constrain loan sizes or reject applications for loans of excessive size.

However, a borrower with rate of time preference $\rho_3 > \rho_2$ strictly prefers obtaining two separate loans at interest rate $\breve{r}$, each of size $\breve{V}$ to a single loan at a higher risk-adjusted interest rate, $\breve{r}_3$. Because a borrower's rate of time preference is hidden, he may do this by soliciting two loans of size $\breve{V}$ from two lenders, each at interest rate $\breve{r} = p(\breve{V})(1-\underline{R})/(1-p(\breve{V})) < \tilde{r} = p(2\breve{V})(1-\underline{R})/(1-p(2\breve{V}))$ who misperceive the probability of default as $p(\breve{V})$ rather than $p(2\breve{V})$. (We will demonstrate shortly how lenders incorporate this expectation of hidden debt into account in the credit market equilibrium.) Figure 1B shows the marginal borrower with $\rho_i = \rho^*$, who is indifferent between multiple and single loan contracting. Consequently, borrowers with $\rho_i > \rho^*$ present a hidden default risk to lenders, where we assume that $\underline{\rho} < \rho^* < \overline{\rho}$.

When lenders share information about defaults, defaulting borrowers will receive less favorable equilibrium loan contracts than non-defaulting borrowers, thus making Γ endogenous in our model under negative information sharing. Because the probability of default is a function of total indebtedness, a default increases the *ex-post* probability of hidden debt having contributed to default. Moreover, because a borrower's rate of time preference is fixed, a past defaulter presents an *ex-ante* higher risk of default to a future lender. Letting *d* represent the state of having defaulted and ~*d* the state of no default, it is easily demonstrated using Bayes' rule that $E[V_E|d] = \dfrac{p(V_E > 0)\cdot p(d|V_E > 0)\cdot V^*}{p(V_E > 0)\cdot p(d|V_E > 0) + p(V_E = 0)\cdot p(d|V_E = 0)} >$

$E[V_E|\sim d] = \dfrac{p(V_E > 0)\cdot(1-p(V_E > 0))\cdot V^*}{p(V_E > 0)\cdot(1-p(V_E > 0)) + p(V_E = 0)\cdot(1-p(V_E = 0))}$. By (5) this means that the equilibrium loan contract for defaulting borrowers is worse than for non-defaulting borrowers so that $V_d^* < V_{\sim d}^*$ (the equilibrium loan size is smaller) and $r_d^* > r_{\sim d}^*$ (the equilibrium interest rate is higher), making $\Gamma = \Pi_i^B(V_{\sim d}, r_{\sim d}) - \Pi_i^B(V_d, r_d) > 0$.

While the benefits of negative information sharing have been well developed, our model considers the added advantage of lenders sharing positive information about borrowers when there exists the possibility of hidden indebtedness. In contrast to negative information, which primarily concerns records of defaults, positive information may provide data on outstanding debt, borrower characteristics, positive records of repayment, and loan histories. Lenders are typically willing to share negative information because the threat of being put on the list of defaulters promotes borrower discipline. But lenders may be less willing to share positive information because it exposes them to competition from other lenders over high-quality borrowers for whom they may enjoy informational rents. But with both positive and negative information sharing, borrowers may be punished not only by defaults, but by evidence of hidden debt. Ironically, while negative information reveals only past defaults (which may have been unavoidable), in our model it is positive information sharing that actually provides direct evidence of *ex-ante* borrower risk.[7]

We consider the problem of a lender screening borrowers who may carry existing debt V^E obtained from other lenders. Let α represent the probability with which the system exposes a multiple contracting borrower's hidden debt, V^E. Take as given for the moment that these exposed borrowers are then denied secondary loans (an assumption we will justify shortly). As seen in Figure 1B, let $\rho^*(\alpha) \in (\underline{\rho}, \bar{\rho})$ equal the lowest value of ρ_i, given α, for which the expected payoff to borrower i from seeking multiple loans is higher than from a single loan, *i.e.*

$$\begin{aligned}\Pi_i^B &= (1-\alpha)\left[\left(1-p\left(2\tilde{V}\right)\right)\left(\bar{R}-(1+\tilde{r})\right)\left(2\tilde{V}\right)+p\left(2\tilde{V}\right)\Gamma\rho_i^{-1}\right]+\alpha\left[\left(1-p\left(\tilde{V}\right)\right)\left[\left(\bar{R}-(1+\tilde{r})\right)\tilde{V}\right]+p\left(\tilde{V}\right)\Gamma\rho_i^{-1}\right] \\ &> \left(1-p\left(\breve{V}\right)\right)\left[\left(\bar{R}-(1+\breve{r})\right)\breve{V}\right]+p\left(\breve{V}\right)\Gamma\rho_i^{-1}.\end{aligned} \tag{6}$$

where $\{\breve{V},\breve{r}\}$ and $\{\tilde{V},\tilde{r}\}$ are the most favorable contracts available to a borrower i seeking single and multiple loan contracts. By definition then, we know that for $\forall\rho_i(\alpha) \geq \rho^*(\alpha)$, $\{2\tilde{V},\tilde{r}\} \succ \{\breve{V},\breve{r}\} \succ \{\tilde{V},\tilde{r}\}$, and for $\forall\rho_i(\alpha) < \rho^*(\alpha)$, $\{\breve{V},\breve{r}\} \succ \{\tilde{V},\tilde{r}\},\{2\tilde{V},\tilde{r}\}$, and thus from (6) we know that $\frac{d\rho^*(\alpha)}{d\alpha} > 0$. Without restricting

[7] Padilla and Pagano (2000) argue that the value of negative information sharing yields a greater disciplinary effect on borrowers than full (positive and negative) information sharing. Moral hazard in their model involves non-contractible effort levels by borrowers. Sharing only default information makes future borrowing directly contingent upon performance, while sharing positive and negative information reduces borrower discipline as risk is not just assessed by performance but also by borrower characteristics. In contrast, our model focuses on moral hazard in multiple loan contracting, such that positive information directly reveals evidence of borrower risk.

ourselves to distributional assumptions on the support of $g(\cdot)$, this makes the expected default rate on a new loan equal to

$$\bar{p} = \frac{\int_{\underline{\rho}}^{\rho^*(\alpha)} p(\breve{V}) g(\rho_i) d\rho_i \breve{p} + (1-\alpha) \int_{\rho^*(\alpha)}^{\bar{\rho}} p(2\tilde{V}) g(\rho_i) d\rho_i \tilde{p}}{\int_{\underline{\rho}}^{\bar{\rho}} g(\rho_i) d\rho_i - \alpha \int_{\rho^*(\alpha)}^{\bar{\rho}} g(\rho_i) d\rho_i}. \tag{7a}$$

Letting $\gamma \equiv 1 - G(\rho^*(\alpha))$ be the probability of multiple loan contracting, we can write

$$\bar{p} = \frac{(1-\gamma)\breve{p} + \gamma(1-\alpha)\tilde{p}}{1-\gamma\alpha}, \tag{7b}$$

where $\breve{p}$ and $\tilde{p}$ are the expected probabilities of default for borrowers who have single and multiple loans at information-sharing level α.[8]

Positive and negative information sharing in our framework thus creates three types of borrowers: "exposed borrowers," those who are screened from multiple loan contracting and as a result possess single loan contracts that are inferior to their perfect-information contract, "defaulting borrowers," those who have defaulted on a previous loan, and "clean borrowers," borrowers with clean credit records. While the latter may have hidden debt, this becomes less likely as α increases. Let d continue to be the state of default, h be the state of being exposed with hidden debt, and $c = \sim d \cap \sim h$ be the state of being a clean borrower with no default and no exposure of hidden debt, with corresponding subscripts on V and r. This leads to the first proposition from our model:

PROPOSITION 1: *Increased positive information sharing between lenders leads to larger equilibrium loans at lower interest rates for both clean and defaulting borrowers.*

[8] Our model implicitly makes the following assumptions in the interest of tractability: 1) Lenders consider default on a borrower's previous loan and information on current debt with other lenders, whether in default or not; 2) Lenders know γ(α), but loan terms for an individual borrower provide no added information about the probability of hidden debt. 3) All borrowers not detected with existing debt remain in the market because each borrower has identical borrowing options and α is assumed to be the same for all lenders.

PROOF: Since by using Bayes' rule $p(V_E > 0|c) = \gamma(1-\alpha)/(1-\gamma\alpha)$ and since by the convexity of $r(V_T)|\Pi^L = 0$ we have $V_E = V^*|V_E > 0$, then $E[V_E|c] = \frac{\gamma(1-\alpha)}{1-\gamma\alpha}V^*$. Substitution of $E[V_E|c]$ into the expressions for V^* and r^* in (5) and differentiating yields $\frac{dV_c^*}{d\alpha} > 0$ and $\frac{dr_c^*}{d\alpha} < 0$, respectively, or that the equilibrium loan size (interest rate) increases (decreases) for clean borrowers as positive information sharing increases. Again using Bayes' rule, the expected level of indebtedness for defaulting borrowers is $E[V_E|d] = \frac{\gamma(1-\alpha)p(d|V_E > 0)V^*}{\gamma(1-\alpha)p(d|V_E > 0) + (1-\gamma)\cdot p(d|V_E = 0)}$, which when similarly substituted into (5) yields $\frac{dV_d^*}{d\alpha} > 0$ and $\frac{dr_d^*}{d\alpha} < 0$, or that the equilibrium loan size (interest rate) likewise increases (decreases) for defaulting borrowers with greater positive information sharing. □

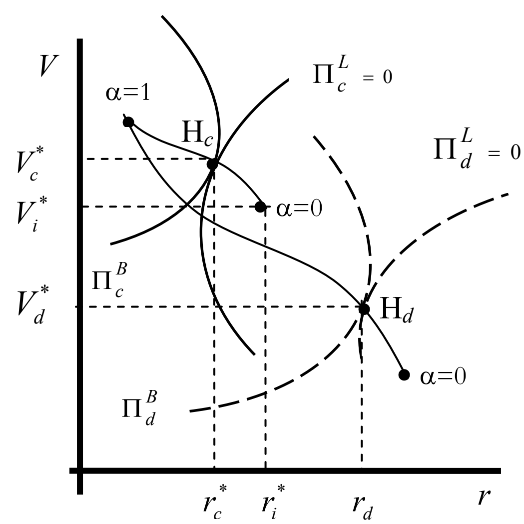

Figure 2

The intuition to the second part of the proposition is that greater positive information sharing allows lenders to screen applicants with hidden debt more effectively so that default becomes a weaker signal of hidden indebtedness. This makes the expected level of hidden debt among defaulting borrowers as well as clean borrowers lower, allowing access to better credit terms. This is illustrated in Figure 2 where the equilibrium loan contracts for clean and defaulting borrowers both improve as α increases. As α approaches one (perfect positive information sharing), contracts to clean and defaulting borrowers become equal since in both cases expected existing debt falls to zero.

Decomposition of Screening, Incentive, and Credit Expansion Effects.

By examination of (6) we see that an increase in α decreases the likelihood of multiple loan-taking, so that $\frac{d\rho^*}{d\alpha} > 0$ and thus $\gamma_\alpha < 0$. In other words, positive information sharing reverses the incentive for some borrowers to take multiple loans. This leads us to our second proposition:

PROPOSITION 2: *Credit information systems that facilitate positive and negative information sharing between lenders yield three distinct effects*: 1) *a screening effect*, 2) *an incentive effect*, and 3) *a credit expansion effect*.

PROOF: Differentiation of the default rate in (7b) with respect to α, holding V_E constant, yields

$$\frac{\partial \hat{p}}{\partial \alpha} = \frac{\left(\gamma(1-\gamma) - \gamma_\alpha (1-\alpha)\right)(\breve{p} - \tilde{p}) + p_\alpha (1-\gamma\alpha)^2}{(1-\gamma\alpha)^2} \tag{8}$$

where $p_\alpha \equiv p_v \frac{\partial V_c^*}{\partial \alpha}$. Note that γ_α represents the change in the fraction of defaulting borrowers with hidden debt in response to the probability of being detected. By setting $\gamma_\alpha = p_\alpha = 0$ we can isolate the screening effect in 8(a) to obtain

$$\left.\frac{\partial \overline{p}}{\partial \alpha}\right|_{\substack{\gamma_\alpha = 0 \\ p_\alpha = 0}} = \frac{\gamma(1-\gamma)(\breve{p} - \tilde{p})}{(1-\gamma\alpha)^2} < 0. \tag{8a}$$

While maintaining $p_\alpha = 0$, we can subtract the screening effect in (8a) from total effect in (8) to isolate the incentive effect in (8b):

$$\left.\frac{\partial \overline{p}}{\partial \alpha}\right|_{p_\alpha = 0} = \frac{-\gamma_\alpha (1-\alpha)(\breve{p} - \tilde{p})}{(1-\gamma\alpha)^2} < 0. \tag{8b}$$

Subtracting the screening and incentive effects from (8) and substituting for p_α yields the credit expansion effect in (8c) which we know from the proof of PROPOSITION 1 is greater than zero:

$$\frac{\partial \overline{p}}{\partial \alpha} = p_v \frac{\partial V_c^*}{\partial \alpha} > 0. \ \square \tag{8c}$$

The borrower *screening effect* of a credit information system seen in (8a) mitigates adverse selection problems and reduces portfolio default rates. It is the direct change in the default rate resulting from the ability to screen risky borrowers $(\rho_i > \rho^*)$ from the portfolio as α increases. The borrower *incentive effect* in (8b) also reduces default rates by mitigating problems of moral hazard. As α increases, more borrowers choose to take single rather than multiple loan contracts, thus reducing the higher default associated with hidden debt. This can be seen in the borrower's switching condition in (6) where higher levels of α change the behavior of some borrowers in the neighborhood of ρ^*; thus the effect is increasing in the magnitude of the derivative γ_α.[9] The credit *expansion effect* occurs as borrowers are given larger equilibrium loans. Because default is an increasing in loan size, this credit expansion increases default rates, but does not overwhelm the stronger effect on default of lower expected debt:

PROPOSITION 3: *The overall effect of information sharing will be a reduction in default rates.*

PROOF: Since default is strictly a function of outstanding debt, we must show that although the credit expansion effect results in larger loan sizes, the total level of debt declines for a borrower as α increases. From PROPOSITION 1 we know using Bayes' rule that $\frac{\partial E[V_E]}{\partial \alpha} < 0$. Substituting the expression for V^* in (5) into the probability of default, $p = p_v\left(V_c^* + V_E\right)$, and differentiating yields $\frac{\partial p}{\partial V_E} = \frac{-p_v\left(\overline{R} - \underline{R}\right)}{2p_v\left(\overline{R} - \underline{R}\right)} + 1 = \frac{1}{2}p_v > 0$. Thus because the screening effect is larger than the credit expansion effect and the incentive effect has the same sign as the screening effect, the net effect from information sharing must be a reduction in the default rate. □

[9] It is interesting to consider the effect of the system on the lender providing *original* loans to borrowers who then seek a hidden second loan from a *subsequent* lender. From the first lender's perspective the equilibrium default rate in (7b) is $\overline{p} = ((1-\gamma) + \gamma\alpha)\breve{p} + \gamma(1-\alpha)\widetilde{p}$, while (8) becomes $\frac{\partial \hat{p}}{\partial \alpha} = (\gamma - \gamma_\alpha(1-\alpha))(\breve{p} - \widetilde{p}) + p_\alpha$. The original lender receives a passive benefit from the system in that subsequent lenders reduce the level of hidden debt within the original lender's portfolio. The decomposition of this term into screening, incentive, and credit expansion effects proceeds in similar fashion to our case in which we focus on subsequent lenders screening for hidden debt. The full impact of the use of a bureau by all lenders is a composite of these two terms, which is algebraically more cumbersome but yields similar intuition to 8a-c.

The proposition demonstrates that larger equilibrium loans dampen, but do not overwhelm, the reduction in the default rate from a lower level of hidden debt in the portfolio. Even after credit expansion, borrowers in the portfolio have lower expected default rates.

Model Simulation

To better understand the effects of credit information systems, we carry out a simulation of portfolio default rates based on our model. Here we focus on the nature of screening and incentive effects. To calibrate the simulation we set $p_\alpha = 0$, $\breve{p} = 0.05$, $\tilde{p} = 0.15$, and $\gamma(\alpha) = \frac{1}{2}(1-\alpha^2)$ so that $\gamma_\alpha = -\alpha$, which yields a baseline default rate (with $\alpha = 0$) of 10.0%. In Figure 2, we simulate the portfolio default rate in (7b) with three levels of information sharing, α = 0.30, 0.60, and 0.90.

We assume loans upon which arrears in payments may occur in any month and a portfolio default rate based on a 12-month moving average of overdue loans. In our first simulation, we assume a credit information system is implemented in the 12[th] month, but to visually isolate screening and incentive effects, we assume borrower awareness of the system begins only in the 36[th] month.

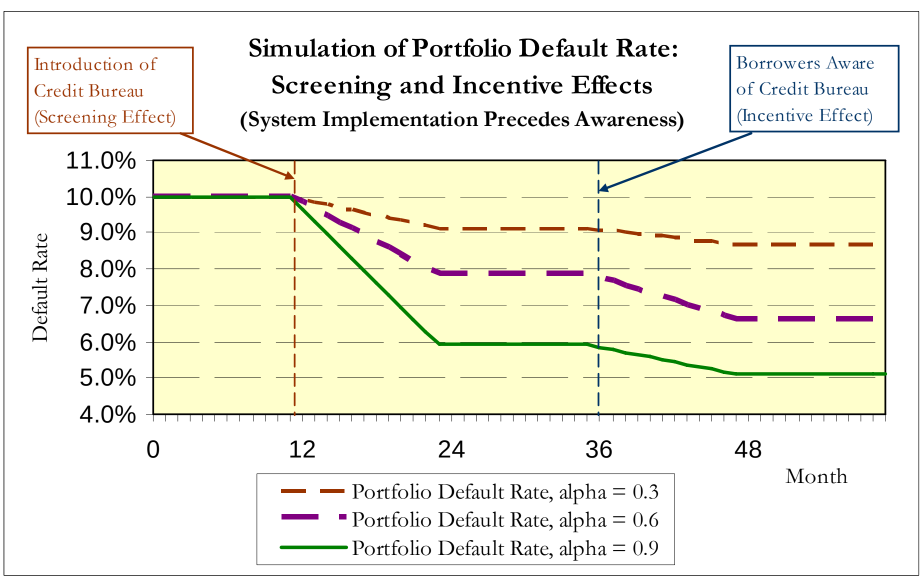

Figure 3

As seen in Figure 3, given our parameter assumptions, *screening* effects (the first dip in default rates) are larger as α increases, reducing the equilibrium default rate by approximately 0.88, 2.14, and 4.09

percentage points for $\alpha = 0.30$, 0.60, and 0.90. *Incentive* effects at these corresponding levels of α amount to a reduction in default of 0.43, 1.28, and 0.81 percentage points, respectively. Incentive effects are larger, however, at intermediate levels of α, because when α is very small the probability of discovery is too small to deter marginal borrowers from hidden debt; when α is very large, most borrowers who are tempted with multiple loan contracting have already been purged from the portfolio before the incentive effect can take hold.

Figure 4 reveals the magnitude of screening and incentive effects as a function of α. It illustrates that under our parameter assumptions, the incentive effect is largest when $\alpha = 0.701$, bringing about a default rate reduction on its own of 1.38 percentage points. However as $\alpha \rightarrow 1$, the total effect on default reduction is maximized, but comes exclusively from the screening effect which continues to increase but at a diminishing rate.

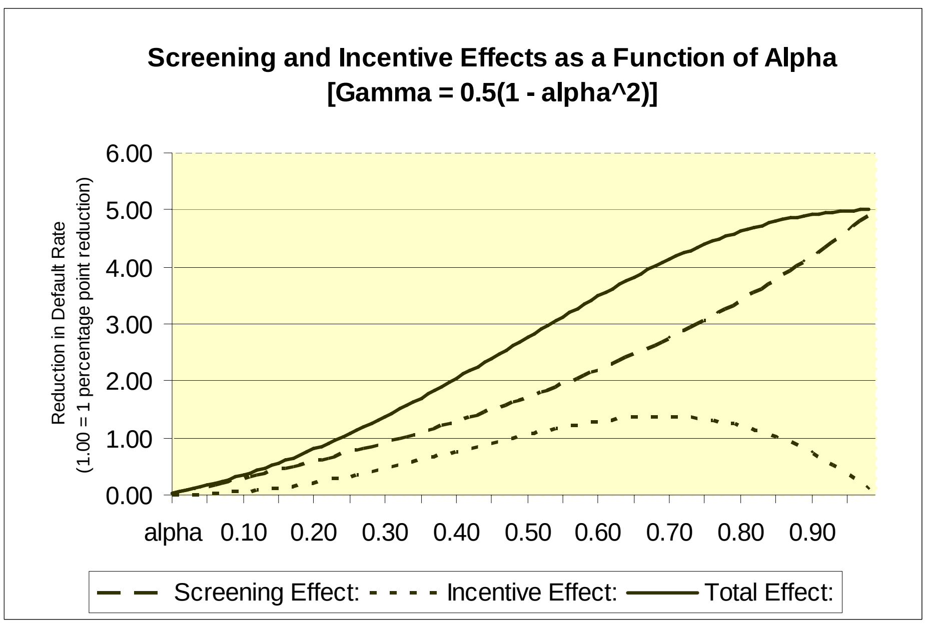

Figure 4

Normally we would think of the screening effect as the initial and larger effect of a credit information system with the incentive effect both subsequent and smaller. This, however, need not be the case.[10] It is conceivable that borrowers might become aware (or purposely be informed) of the impending use of the system, and that current behavior may have implications for future credit terms. Figure 5 shows that when the timing is reversed--awareness of lender information sharing occurs in the 12th month and actual implementation of the system occurs in the 36th month--the incentive effect not only precedes the screening effect, but given our simulation parameters is larger in magnitude. Moreover, the magnitudes of the screening effect (given $\alpha = 0.30$, 0.60, and 0.90) are equal to 0.45, 1.80, and 4.05 while those of the subsequently occurring screening effect are 0.86, 1.62, and 0.85, displaying a similar magnitude and pattern to the incentive effect when awareness of the system is subsequent to implementation.

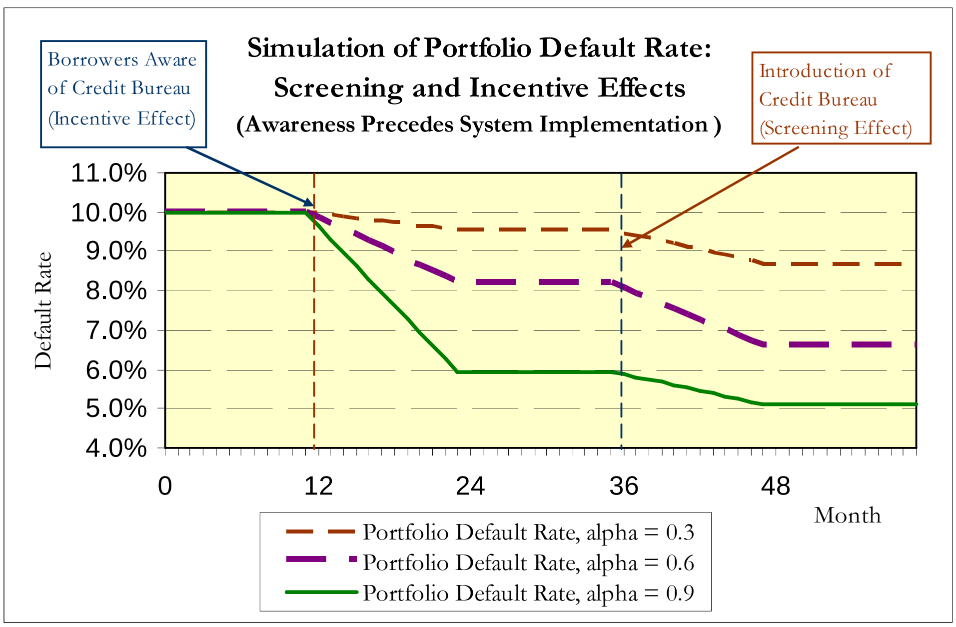

Figure 5

III. Empirical Evidence

In our empirical section we analyze results from the implementation of a credit information system in Guatemala to compare with the predictions of our model. Our data come from a microfinance lender, Génesis, which was one of the lending institutions that began to use the bureau when it was implemented. In contrast to public credit registries, which are established by the state and where lender participation is

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[10]Reversing the order so that awareness of the bureau occurs before implementation produces an initial incentive effect in which γ increases from $\gamma(0)$ to $\gamma(\alpha)$ and a secondary screening effect in which screening increases from 0 to α in (7b).

typically mandatory, credit bureaus are private networks in which lenders voluntarily share information. By the late 1990s the burgeoning growth in the number of microfinance institutions (MFIs) in Guatemala had exacerbated problems of multiple loan contracting and hidden debt to an extent that the country's major MFIs joined to establish *CREDIREF*, a credit bureau allowing for positive and negative information sharing between participating lenders. By 2003 the bureau held data on over 120,000 borrowers from six major MFIs, with more institutions being incorporated into the system each year.

Much of the evidence we present in support of the effects derived from our model is taken from Luoto, McIntosh, and Wydick (2007) and de Janvry, McIntosh, and Sadoulet (2007). The 39 branches of Génesis Empresarial, a major microfinance lender, received the hardware and software necessary for the credit bureau in ten different waves between August 2001 and January 2003. However, a preliminary field survey with 184 borrowers in six branch offices of Génesis found that borrowers were remarkably poorly informed as to the presence of the credit bureau: Not a single borrower in the survey knew the name of the bureau or had any detailed knowledge of whether Génesis shared information with others about their credit history. This lack of awareness of the credit bureau at the time of its implementation, and the way the new credit bureau was rolled out in a staggered manner through the branch offices of the lender is helpful in the decomposition of the effects of a credit bureau.

Luoto, McIntosh, and Wydick (2007) uses this natural experiment to isolate the screening effects of the system. Here, the staggered rollout of the bureau across the branches of Génesis is utilized to analyze the screening effect on repayment. Using branch and month fixed effects, the results uncover a significant decrease in the percentage and number of late payments, and a smaller and insignificant decrease in the months by which these payments were late. A summary of these results is provided in Table 1.

Impact on Branch-level Repayment	Pre-bureau Mean	Impact of Rollout
% Loans with a Payment Ever Late	58.80	-3.33
		(2.2)*
# of Payments Assessed a Late Fee	10.17	-1.31
		(3.7)*
Months by which Late Payments Late	1.06	-0.22
		(0.46)

Robust T-statistics in parentheses, *=95% significant, **=99% significant

1: Estimates taken from Luoto, McIntosh, & Wydick (2007), Intention to Treat estimated at branch level using branch and month fixed effects.

Table 1

Upon bureau implementation, de Janvry et. al. show that the average loan size increased by US$264 over a base of US$669 after credit bureau rollout. Our theory indicates that this credit expansion should have negative effects, but that these negative effects will not overwhelm the improved abilities conferred through the bureau. In the present paper we estimate the relationship between loan size and the default rate, as given by the credit expansion effect in (8c). Table 2 uses data on individual borrowers, isolating the credit expansion effect by focusing on changes in repayment after the bureau came into use. The regression includes fixed effects at the branch, month, and loan-rank level (whether a loan is a first loan, second loan, etc.).

Table 2

Effect of Loan Size on Default for Ongoing Individual Borrowers:

Dep var: Loan more than 2 mos delinquent	OLS	IV, using bureau as instrument	OLS
Loan Size ('000 US $)	-0.135	17.065	0.025
	(1.39)	(2.09)*	(0.32)
Bureau in Use			3.74600
			(3.88)**
Bureau in use * Loan size			-0.00100
			(3.01)**
# obs	11,184	11,184	11,184

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

Linear probability models with robust standard errors clustered at the branch level, and branch, month, and loan-rank fixed effects.

Mean of dependent variable in sample prior to bureau is 1.2%.

The first column shows the raw correlation between loan size and delinquency. Since loan size is increased for those deemed to be good risks, endogeneity between the variables should bias this relationship downward. In Column 2 we present an instrumental variable estimation of loan delinquency which utilizes the rollout of the bureau as an instrument for loan size. In line with our theory, the instrumental variable estimation shows the increase in loan delinquency from higher loan sizes, where these higher loan sizes are generated from predictions based on the introduction of the credit bureau. Our point estimate of 17.065 in Table 2 implies that the increase in average loan size from for ongoing borrowers increases loan delinquency by 3.63 percentage points. The third column of Table 2 is an OLS estimation that utilizes a dummy variable representing existence of the credit bureau, which estimates a similar 3.74 percentage point increase in delinquency.

Hence despite the decrease in overall delinquency illustrated in Table 1, default for individual borrowers who continue to take loans after the bureau actually *rises* as a result of the expanded access to credit engendered by the bureau. The estimation also includes an interaction term between loan size and the use of the bureau which shows that the sensitivity of delinquency to loan size is less steep after introduction of the bureau, meaning that better screening makes delinquency less sensitive to loan size than it was before. Thus larger loans are given and the larger loans yield a higher default rate *ceteris paribus*, but default becomes less sensitive to loan size after the bureau. What this implies is that lenders appear to optimize their use of a credit information system via increased profits from larger loans rather than simply by lower defaults. This makes sense--it is hard to imagine that optimal use of the new information provided by such a system would strictly be used to minimize default if the expansion of (now lower-risk) credit lies in the interest of the lender.

Equation 8b in our model suggests that we should witness further reduction in default via borrower awareness of the system, the incentive effect. de Janvry, McIntosh, and Sadoulet (2007) analyzes such an event via a field experiment, wherein a randomized group of Génesis borrowers were given a course on the workings of the bureau. Point estimates indicate that after awareness of the bureau, delinquency falls by roughly a full percentage point and default falls by about one and one-half percentage points, yet both results are statistically insignificant. The (possible) small decrease in delinquency is consistent with the theoretical predictions from our model when borrowers become aware of the system after its implementation. Results also indicate that borrowing from other lenders increases by roughly 10 percentage points among borrowers in large communal banking groups. The expansion of credit by *other* lenders illustrates that there are credit-constrained borrowers in the pool for whom a well-informed credit system as a whole is willing to offer more than their current lender will offer alone. This is the outside lender analogy to the "credit expansion" effect, whereby willingness to offer credit to high-quality Génesis borrowers expands as a result of the bureau. Given that those with hidden debt have already been purged from the portfolio, this increase in outside lending results from high-quality, credit constrained individuals realizing that they are no longer as constrained.

Taken together, this set of empirical results suggest a strong screening effect, a weaker incentive effect, and a counter-acting credit-expansion effect which occurs in the context of an improvement in the lender's ability to expand credit with a reduced probability of default.

IV. CONCLUSION.

We present a theoretical model which predicts the effects of credit information systems on equilibrium contracts and decomposes its overall impact into three separate effects: a screening effect that mitigates adverse selection, an incentive effect that mitigates moral hazard, and a credit expansion effect that causes higher default rates from larger loans. These three effects can be extended in a general way to other contexts in which internet technology has dramatically increased the potential for agent information-sharing among principals in a market. Examples of this kind include automobile insurance firms pooling records across states, buyers and sellers sharing ratings information from past transactions on *eBay*, or law enforcement institutions sharing criminal records across jurisdictions. In each of these examples, principals first derive a screening effect by curtailing their interaction with some high-risk types. Secondly, principals benefit because awareness of the system induces some agents on the margin to improve their behavior. But more subtly, the increased confidence of principals over agent quality induces principals to extend riskier contracts to the agents who have passed informational screening. This "trust" created by the system induces a perverse effect on outcomes which is analogous to our "credit expansion" effect.

We demonstrate theoretically that the first two (positive) effects will overwhelm the latter (negative) effect, such that the overall effect of information sharing on repayment is positive. A variety of empirical evidence demonstrates considerable support for the hypotheses generated by our model. We find that the relationship between loan size and repayment problems is significantly weaker when a bureau is in use than when it is not, and we cite work conducted in the Guatemalan environment which illustrates a strong adverse selection effect and a more muted moral hazard effect of the introduction of a bureau. This result is in contrast with Karlan and Zinman (2007), who find moral hazard to be the dominant force in South African credit markets. However, the Guatemalan evidence on the introduction of a bureau featured a screening effect of the bureau which preceded the incentive effect in time. Our theoretical model allows us to simulate what would have happened had the incentive effect come first and the screening effect thereafter. Interestingly, we find that the impact of the "first" intervention is similar and dominant regardless of whether the screening precedes information about the system or vice versa, and hence that the incentive effect of the bureau may have been dominant had the incentive effect preceded the screening effect.

One of the factors that makes a credit bureau an attractive intervention from a policy perspective is its modest cost compared to its substantial benefits, which other work related to this project has demonstrated.[11] We illustrate here a somewhat surprising way of pulling these benefits forward in time: If a group of lenders can credibly signal that they *intend* to introduce a credit bureau in the future, our simulations suggest that the incentive effect will allow them to capture a large majority of the future impact of the system almost immediately. This suggests that broadcasting credible statements about the future implementation of information-sharing systems may be an inexpensive and rapid way to bring stability to markets plagued by information asymmetries.

[11] See Luoto, McIntosh, and Wydick (2007) for a cost-benefit analysis of the CREDIREF system, in which in is determined that implementation of the system within the Génesis branch offices yielded a net present value to the microfinance institution of US$185,570 over three years with an annual internal rate of return of 96.5%, generated primarily from lower defaults.

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