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# What Do Credit Bureaus Do? Understanding Screening, Incentive, and Credit Expansion Effects

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Abstract: We develop a theoretical model that explains the primary empirical results emanating from a multi-year study of the impact of credit bureaus in Guatemala. Our theory 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, partially counteracting the first two effects. We create a simulation model that allows us to examine the relative magnitudes of these effects in relation to the order in which they occur.

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# 1. INTRODUCTION

A transformation is occurring in many developing countries 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] that 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.

Building from the results of field experiments that surrounded the implementation of a credit bureau in Guatemala and other empirical studies, our model analytically decomposes the overall impact of a credit information system into *three* effects. The first two effects lower borrower default rates: a screening effect and an incentive effect. While the two positive effects of credit bureaus have been

[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.

previously discussed in the literature, our model also derives a third effect--*the credit expansion effect*--that predicts equilibrium increases in loan size and a resultant *increase* in default. The credit expansion effect creates an offsetting behavior that is not unlike Peterson, Hoffer, and Millner's (1995) work on new airbag technology. They show how drivers use the safety coming from the airbag to buy more speed, with the empirical result that airbags are associated with more automobile crashes.

In the same way, the data from our previous empirical work and the theory presented in this paper show that lenders use the information from credit bureaus to expand credit, which counteracts much of the decline in defaults associated with better credit market information. While the data from our previous empirical study comes from credit-system-based field experiments in a developing country, Guatemala, we believe the theoretical model we present may also yield some insight into the causes of the 2008-09 U.S. financial crisis, where defaults dramatically increased even within the context of the world's most sophisticated credit information system. As a result, our research offers pertinent insights for the IFC and other international institutions that are currently financing the development of credit-information infrastructures in less-developed countries.[3] While such efforts are likely to lead to reductions in default from screening and incentive effects, the resulting lender expansion of credit that typically accompanies the implementation of such systems may counteract some of the stabilizing benefits that information systems bring to 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

[3] The IFC is promoting bureaus and registries in numerous developing countries including Egypt, Lebanon, Mongolia, Morocco, Pakistan, and Vietnam.

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.

The canonical treatment of asymmetric information in credit markets is due to Stiglitz and Weiss (1981), who model the incentives for borrowers to undertake risky investments that increase a borrower's expected payoff under limited liability but that 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. This approach to asymmetric information, and the corresponding empirical methods suggested by Karlan and Zinman (2009), are of interest when we consider the quantity of asymmetric information in a credit market as fixed, and consider the interest rate to be the only control parameter. Credit information systems, however open up the possibility of engendering a first-order reduction in the quantity of asymmetric information in the marketplace. Hence our model of the impact of credit information systems takes the interest rate as an endogenous variable determined through a competitive equilibrium and considers how it responds to a reduction in asymmetric information. This is in some ways the conceptual reverse of Stiglitz and Weiss, who examine how the unobserved attributes of those remaining in a credit market are affected by an exogenous change in interest rates.

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 Newman (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).

We now proceed to a summary of empirical results on credit bureau implementation, which we condense into a series of four stylized facts. From there we present our theoretical model, and we conclude with a discussion of the ramifications of our modeling environment for policy in credit market institutions.

## 2. SUPPORTING EMPIRICAL EVIDENCE

Related to this research, Luoto, McIntosh, and Wydick (2007) and de Janvry, McIntosh, and Sadoulet (2009) use field experiment data from a microfinance lender, Génesis Empresarial, one of the lending institutions participating in a credit bureau that was implemented across Guatemala in 2001. 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.

The 39 branches of Génesis Empresarial, a major microfinance lender, received the hardware and software necessary for the credit bureau in nine different waves between August 2001 and January 2003, providing a natural experiment to test the effects of the credit bureau on the lending portfolio of

Génesis. Luoto et al. (2007) provide a set of diagnostics demonstrating that the rollout of the bureau provides an admissible source of statistical identification, and proceed to test the branch-level impacts from the screening effect of the bureau on loan delinquency rates, finding a reduction in default of approximately two percentage points after the bureau was implemented in branch offices.

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. This lack of awareness of the bureau at the time of its implementation is helpful in trying to decompose the different effects of a credit bureau empirically. de Janvry et al. (2009) exploit this lack of awareness among borrowers to isolate the incentive effects of bureaus via a field experiment. In the experiment, 573 Génesis borrowing groups were randomly selected from within 7 branches (the branches themselves randomly selected through stratified sampling) to receive a course that highlighted the existence and workings of the bureau. The training course focused both on the positive repercussions of a bureau (increased access to outside credit for those with good borrowing records) as well as the negative (heightened adverse consequences of failing to repay), and provided specific information about lenders using the bureau, when information was checked, and on whom. Following is a set of four stylized facts that emerge from the experimental study in Guatemala and other more macro-oriented empirical work on the impacts of credit bureaus:

EMPIRICAL FINDING #1: *Credit information-sharing substantially increases lending.* (Jappelli and Pagano, 2002; Djankov, McLiesh, and Shleifer, 2007; de Janvry et al., 2009). de Janvry et al. show that there is both an increase in the number of loans issued by each branch per month (from 30 to 45) as well as an increase in the average loan size: ongoing borrowers who take loans both before and after the bureau see loan sizes go up from $1,058 to $1,140 for individual borrowers, and from $872 to $1,080 for borrowers in solidarity groups. Figure 1 uses the staggered entry of the 39 branches of Genesis (which entered the bureau in nine waves) to show that within a month of beginning to use the bureau average lending volume per branch jumps almost 50%, from US$44,000 to US$63,000 per month.

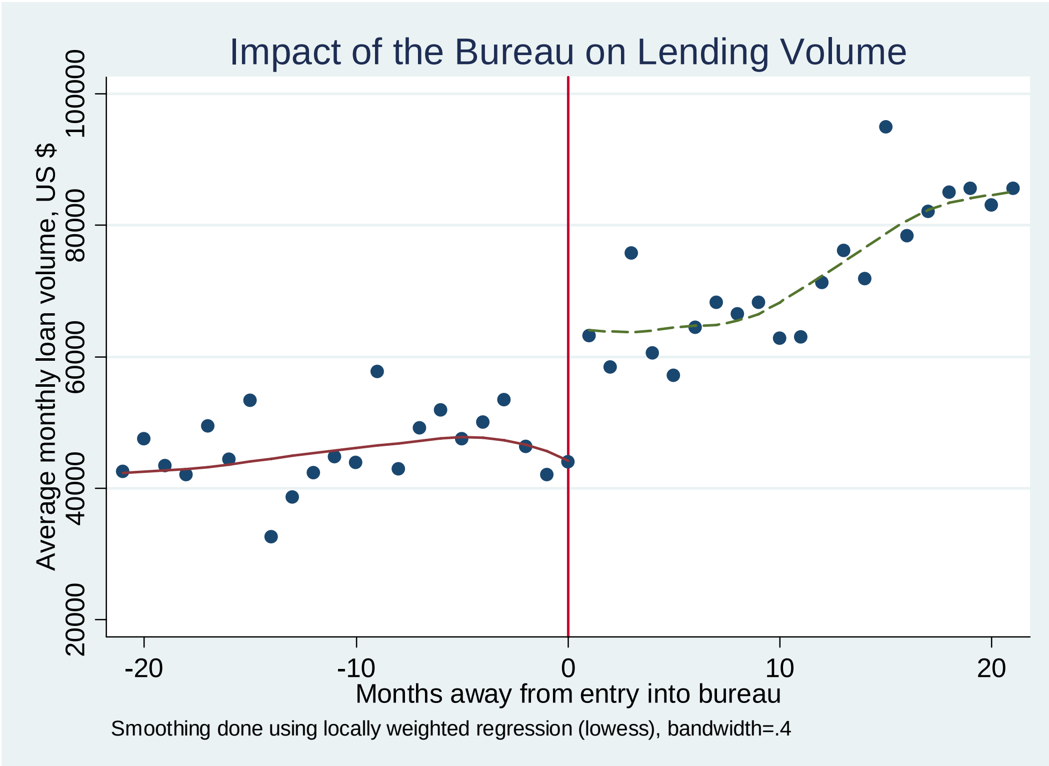


**Figure 1**

The dramatic level of credit expansion seen in the Guatemalan field experiment is consistent with macro-level cross-country work: Jappelli and Pagano find that the ratio of bank lending to GDP increases significantly and substantially under both positive and negative information sharing. Investigating determinants of credit in 129 countries, Djankov et al find information-sharing institutions to be associated with higher levels of private credit relative to per capita income.

EMPIRICAL FINDING #2: *Overall default decreases marginally after credit bureau introduction.* (Jappelli and Pagano, 2002; Luoto et al., 2007; de Janvry et al., 2009). Jappelli and Pagano find in a cross-country estimation that information sharing reduces at-risk loans by 3 to 4 percentage points over a base rate of 7.7 percent. Luoto et al. find a significant 3.3 percentage point decrease in the fraction of loans with any late intermediate payments, and also find that the trend on delinquency turns significantly negative when the bureau comes into use. de Janvry et al. disentangle this effect more closely, finding that while new clients recruited after the bureau have better repayment rates, this improvement in default is counteracted by an doubling in the probability of serious delinquency among ongoing borrowers whose loan sizes grew sharply subsequent to the use of the bureau. These ongoing borrowers with larger loans realized an increase in arrears (for loans more than two months late) from 2.0 to 4.3 percent. The overall effect in the Guatemalan experimental work is indicative of a marginal reduction in default, but this result is smaller and less robust than expected.

EMPIRICAL FINDING #3**:** *Credit Bureaus induce a wave of borrower turnover.* (Jappelli and Pagano, 2002; Cowan and De Gregorio, 2003; Miller, 2003; Luoto et al., 2007; de Janvry et al., 2009). Prior to the rollout of the Guatemalan credit bureau, 42% of Genesis clients were taking their first loan and 51% of borrowers did not take a subsequent loan. de Janvry et al. find both rates go up by about 14 percentage points. This means that there was a one-third increase in new borrowers and an almost one-quarter increase in the rate at which borrowers left the lending portfolio in the first cycle after the bureau came into use. Luoto et al. show the benefits of screening high-risk borrowers in terms of reduction in default. Cowan and De Gregorio find that bureaus provide information which is highly effective in allowing Chilean banks to screen out bad risks through credit scoring. In larger cross-country studies, Miller highlights the benefits of screening effects in preventing risky borrowers from obtaining loans, and Jappelli and Pagano find that as credit applicants with poor records are able to be screened from borrowing, smaller firms with good credit records benefit disproportionally, especially in countries with weaker business law.

EMPIRICAL FINDING #4: *Credit Information Systems have distinct screening and incentive effects. When the screening effect precedes the incentive effect, the screening effect is larger.* **(**de Janvry et al., 2009). The Genesis case featured an unannounced implementation of a bureau, which our team followed with a randomized training campaign intended to trigger incentive effects. The screening effects are found to be substantially larger, with the bureau having only muted impacts on repayment performance to Genesis. 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. Results also indicate that borrowing from other lenders increases by roughly 10 percentage points among borrowers in large communal banking groups.[4] Given the large cull of borrowers that accompanied the lender's use of the bureau, it is perhaps not surprising that the remaining borrowers have limited positive incentive effects from the bureau, because borrowers engaging in risky cross-lender borrowing had already been removed from the portfolio.

In what follows, we present a theoretical model that can explain these four empirical findings. Specifically, the model allows us a straightforward decomposition of screening effects (effects that mitigate adverse selection in credit markets), incentive effects (that mitigate moral hazard), and credit expansion effects (the expansion of lending as credit information increases). Our model motivates why a competitive profit-driven lender will increase loan sizes when asymmetric information is removed from the marketplace, and provides predictive power of the types of people screened into and out of the market when a bureau is implemented. Besides capturing these key features of the experience from our field experiments, we can use the model to extend our understanding of the potential impact of the introduction of bureaus in different contexts. We conclude by fitting parameters from the model using data from the field, and use it to perform a simulation of the impact of the bureau had the incentive effects been realized prior to the screening effects. The results of this simulation suggest that the impacts of a bureau can be brought forward in time by a publicity campaign which informs borrowers in advance as to the creation of a bureau.

[4] 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.

# 3. A MODEL OF CREDIT INFORMATION SHARING

*3.1 Moral Hazard with Incomplete Lender Information Sharing*

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, $\{V, r\}$.[5] 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

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

In a zero-profit Bertrand competitive equilibrium, this implies that the interest rate for any loan of size $V$ will be equal to $r = \left(F + pV\left(1 - \underline{R}\right)\right)/(1 - p)V$. Note that since $p = p_v\left(V_E + V\right)$, this means that

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

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

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

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 $\Gamma$ 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.[6] 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 $\rho_i$ and $G(\rho_i)$ is its associated distribution function. This makes the profit function of borrower *i* equal to

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

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:

[6] In our model, $\rho$ 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.

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

As seen in (4), in contrast to the lender, the borrower's iso-profit curves are *positively* sloped for small $V$, specifically when $(1-p-p_v V_i)(\overline{R}-(1+r_i)) > p_v \Gamma \rho_i^{-1}$, 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

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

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. Remembering the subscript $i$ is suppressed on contract terms, Equation 5 spells out how variation in the equilibrium loan size and interest rate is driven by underlying heterogeneity in discount rates. 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 2a.[7]

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 $\rho_1$ in Figure 2A. The tangency point of this borrower's iso-profit curve to the zero-profit curve of the lender occurs at Point A. But as $\rho_i$ 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

[7] A detailed proof for the existence of equilibrium in this model is provided in McIntosh and Wydick (2005). We 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.

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 2A. 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.

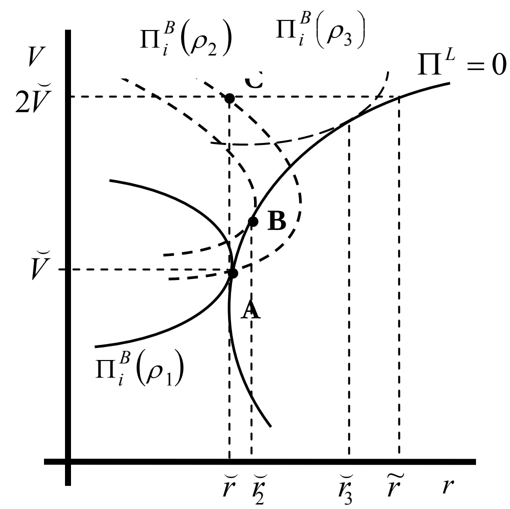


**Figure 2A**

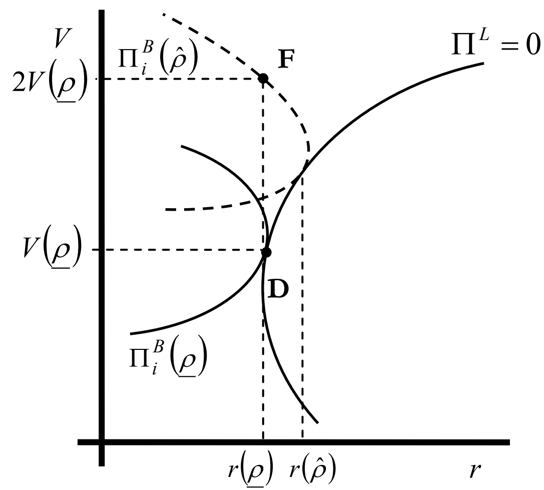


**Figure 2B**

From this full-information benchmark case, we can now consider the incentives of a single individual to take advantage of asymmetric information over debt from other lenders. Why should some borrowers seek to obtain loan contracts from multiple lenders? In the full-information context, a lender may oblige a borrower with higher $\rho$ 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 2A.[8] Moreover, because of the fixed costs associated with each loan, with full information borrowers will exclusively contract with a single lender. If a single borrower is able to take two separate loans, where the existence of the second loans is hidden from each of the two lenders, then the extra risk imposed by the high debt level of the borrower is not priced into the contract. As seen in Figures 1A and 1B, a high-$\rho$ borrower

[8] 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.

would choose to take separate loan contracts from different lenders, allowing him to avoid the interest rate premium that would otherwise be required on a single, larger loan.

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 this borrower contracting multiple loans to obtain separate loans of equal size. In Figure 1A, a borrower with rate of time preference $\rho_2$ would be indifferent between obtaining a single loan of size $\breve{V}$ at interest rate $\breve{r}$ or two separate loans of the same size, though he prefers a single loan at a higher interest rate $\breve{r}_2 > \breve{r}$. 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 where asymmetric information is ubiquitous.) Figure 2B shows the marginal borrower with $\rho_i = \hat{\rho}$, who is indifferent between multiple and single loan contracting if he were able to take a hidden loan. Consequently, borrowers with $\rho_i > \hat{\rho}$ present a hidden default risk to lenders, where we assume that $\underline{\rho} > \hat{\rho} > \overline{\rho}$.

*3.2 Introduction of a Credit Information System*

Having demonstrated that borrowers may choose to take advantage of hidden actions, we now consider the equilibrium contract under asymmetric information. In such markets, interest rates and loan sizes adjust endogenously to account for the possibility that any borrower, *ex-ante* to borrowing, may possess hidden debt. A credit information system is an institution that decreases the degree of asymmetric information between lenders in the credit market. The system's effectiveness determines the extent to which the market represents the full or the asymmetric information equilibrium.

First we consider what happens when lenders share negative information about defaults. In this case, even if lenders cannot directly observe outside debt, they have a proxy for it in a borrower's repayment record. Because they are suspected of having external debt, defaulting borrowers will receive less favorable equilibrium loan contracts than non-defaulting borrowers. We can cast the negative information in a bureau (repayment history) in this simple static environment as a signal on the probability of a borrower having outside debt. Let *d* represent the state of having defaulted and ~*d* the state of no default. In the pure asymmetric information case lenders observe neither $V_E$ nor *d*, while with a negative information sharing bureau *d* becomes observable. Noting from before that $p(d \mid V_E > 0) > p(d \mid V_E = 0)$, for two otherwise observationally equivalent individuals where one has outside debt and the other does not, it is easily seen using Bayes' rule that once the bureau allows *d* to be observed,

$$E[V_E|d] = \frac{p(V_E > 0) \cdot p(d|V_E > 0) \cdot V^*}{p(V_E > 0) \cdot p(d|V_E > 0) + p(V_E = 0) \cdot p(d|V_E = 0)} >$$

$$E[V_E|\sim d] = \frac{p(V_E > 0) \cdot (1 - p(V_E > 0)) \cdot V^*}{p(V_E > 0) \cdot (1 - p(V_E > 0)) + p(V_E = 0) \cdot (1 - p(V_E = 0))}.$$

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).

Negative information sharing can therefore easily be thought of as defining the magnitude of Γ, the pecuniary reward for not defaulting. Without negative information sharing, Γ is limited to the punishment capability of the lender writing the defaulted loan. Stronger negative information sharing generates a larger difference for those who have and have not defaulted, and so

$\Gamma = \Pi_i^B\left(V_{\sim d}, r_{\sim d}\right) - \Pi_i^B\left(V_d, r_d\right) > 0$ will be larger. This will increase loan sizes and decrease interest rates for non-defaulters relative to the no negative information sharing case.

While the benefits of negative information sharing have been well developed, our model also allows us to consider the added advantage of lenders sharing *positive* information about borrowers when the possibility of hidden indebtedness exists. 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.[9]

We consider the problem of a lender screening borrowers who may carry existing debt obtained from other lenders. Let $\alpha \in [0, 1]$ represent the quality of credit information sharing in the system; we model good information sharing through the probability with which the system exposes a multiple contracting borrower's hidden debt, if such exists. Let $\left\{\breve{V}^*, \breve{r}^*\right\}$and $\left\{\tilde{V}^*, \tilde{r}^*\right\}$ be the equilibrium loan contracts that are taken by a borrower with single loans and multiple loans respectively in an incomplete-information market characterized by lender information-sharing level $\alpha$.. Our model implicitly makes the following assumptions in the interest of tractability: 1) Lenders consider default on

[9] 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.

a borrower's previous loan and information on current debt with other lenders, whether in default or not; 2) Lenders know $\gamma(\alpha)$, 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 $\alpha$ is assumed to be the same for all lenders; 4) Exposed borrowers are denied secondary loans.

Let $\hat{\rho}(\alpha) \in (\underline{\rho}, \bar{\rho})$ now equal the lowest value of $\rho_i$, given $\alpha$, for which the expected payoff to borrower $i$ from seeking multiple loans is higher than from a single loan, *i.e.*

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

By definition then, we know that for $\forall\rho_i(\alpha) \geq \hat{\rho}(\alpha)$, $\left\{2\widetilde{V}^*, \widetilde{r}^*\right\} \succ \left\{\breve{V}^*, \breve{r}^*\right\} \succ \left\{\widetilde{V}^*, \widetilde{r}^*\right\}$, and for $\forall\rho_i(\alpha) < \hat{\rho}(\alpha)$, $\left\{\breve{V}^*, \breve{r}^*\right\} \succ \left\{\widetilde{V}^*, \widetilde{r}^*\right\}, \left\{2\widetilde{V}^*, \widetilde{r}^*\right\}$, and thus from (6) we know that $\frac{d\hat{\rho}(\alpha)}{d\alpha} > 0$. Without restricting ourselves to distributional assumptions on the support of $g(\cdot)$, this makes the expected default rate on a new loan equal to

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

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

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

where $\breve{p}$ and $\widetilde{p}$ are the expected probabilities of default for borrowers who have single and multiple loans at information-sharing level $\alpha$. While McIntosh and Wydick (2005) derive the equilibrium contracts and lender profitability in an asymmetric information setting, this paper provides an exploration of how credit information systems will alter that equilibrium, and disentangles their diverse and counteracting effects as information systems are implemented in the credit market.

Positive and negative information sharing together in our framework create 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 $\alpha$ increases. Let *d* continue to be the state of a borrower in default, *e* be the state of being exposed with hidden debt, and $c = \sim d \cap \sim e$ 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 which corresponds to EMPIRICAL FINDING #1:

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

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 $E[V_E|c] = \dfrac{\gamma(1-\alpha)}{1-\gamma\alpha}V^*$. Substitution of $E[V_E|c]$ into the expressions for $V^*$ and $r^*$ in (5) and differentiating yields $\dfrac{dV_c^*}{d\alpha} > 0$ and $\dfrac{dr_c^*}{d\alpha} < 0$, 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 $E[V_E|d] = \dfrac{\gamma(1-\alpha)p(d|V_E > 0)V^*}{\gamma(1-\alpha)p(d|V_E > 0) + (1-\gamma)\cdot p(d|V_E = 0)}$, which when similarly substituted into (5) yields $\dfrac{dV_d^*}{d\alpha} > 0$ and $\dfrac{dr_d^*}{d\alpha} < 0$, or that the equilibrium loan size (interest rate) likewise increases (decreases) for defaulting borrowers with greater positive information sharing. □

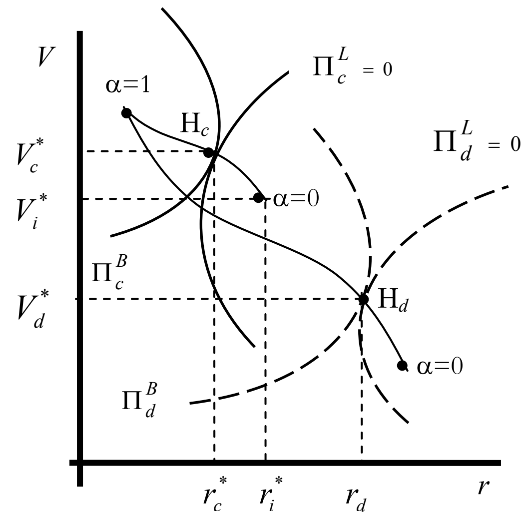


**Figure 2**

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 $\alpha$ increases. As $\alpha$ approaches one (perfect positive information sharing), contracts to clean and defaulting borrowers become equal since in both cases expected existing debt falls to zero.

*3.3 Decomposition of Screening, Incentive, and Credit Expansion Effects.*

By examination of (6) we see that an increase in $\alpha$ decreases the likelihood of multiple loan-taking, so that $\frac{d\hat{\rho}(\alpha)}{d\alpha} > 0$ and thus $\gamma_\alpha < 0$. In other words, positive information sharing reverses the incentive for some borrowers to take multiple loans. Empirical Findings #1 and #3 are thus explained through our second proposition:

PROPOSITION 2: *Credit information systems that facilitate positive and negative information sharing between lenders yield three distinct effects*: 1) *a <u>screening effect</u> that arises from improved borrower selection*, 2) *an <u>incentive effect</u> that comes from fear of detection*, and 3) *a <u>credit expansion effect</u> whereby larger loans create a perverse effect on default rates.*

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

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

where $p_\alpha \equiv p_v \frac{\partial V_c^*}{\partial \alpha}$. Note that $\gamma_\alpha$ 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

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

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):

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

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

$$\frac{\partial \overline{p}}{\partial \alpha} = p_v \frac{\partial V_c^*}{\partial \alpha} > 0\,. \;\square \qquad (8c)$$

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 $(\rho_i > \hat{\rho})$ from the portfolio as $\alpha$ increases. The borrower *incentive effect* in (8b) also reduces default rates by mitigating problems of moral hazard. As $\alpha$ 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 $\alpha$ change the behavior of some borrowers in the neighborhood of $\hat{\rho}$; thus the effect is increasing in the magnitude of the derivative $\gamma_\alpha$.[10] 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, which is consistent with what we discover in Empirical Finding #2.

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 $\alpha$ 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, $p = p_v(V_c^* + V_E)$, and differentiating yields $\frac{\partial p}{\partial V_E} = \frac{-p_v(\overline{R} - \underline{R})}{2p_v(\overline{R} - \underline{R})} + 1 = \frac{1}{2}p_v > 0$. 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. □

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.

[10] 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.

*3.4 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, $\alpha$ = 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 12th month, but to visually isolate screening and incentive effects, we assume borrower awareness of the system begins only in the 36th month.

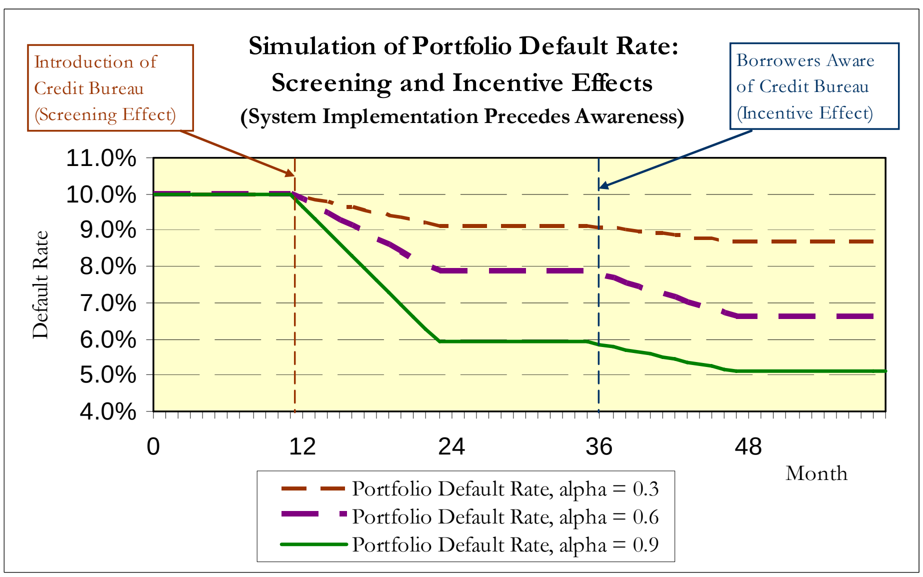


**Figure 3**

As seen in Figure 3, given our parameter assumptions, *screening* effects (the first dip in default rates) are larger as $\alpha$ 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 $\alpha$ 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 $\alpha$, because when $\alpha$ is very small the probability of discovery is too small to deter marginal borrowers from hidden debt; when $\alpha$ 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 $\alpha$. 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 $\alpha \to 1$, the total effect on default reduction is maximized, but comes exclusively from the screening effect which continues to increase but at a diminishing rate.

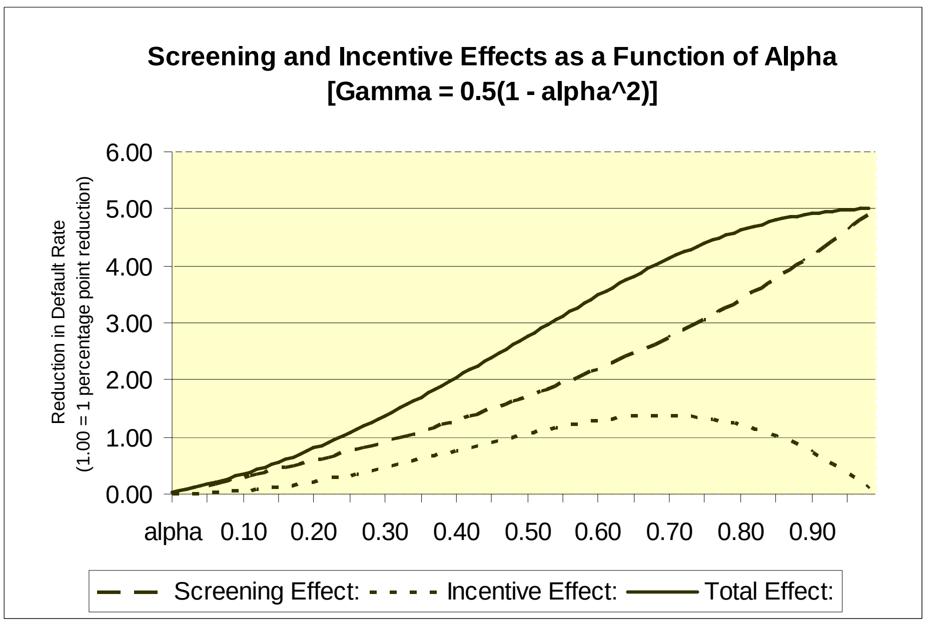


**Figure 4**

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.[11] 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.

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

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. This is consistent with our Empirical Finding #4. In the case of our field experiment, when the screening effect preceded the incentive effect, the screening effect was larger. However, in practice if a population of borrowers fully expects that their current borrowing behavior to be recorded and shared among lenders in a future system, we might expect incentive effects to outweigh the subsequent screening effect.

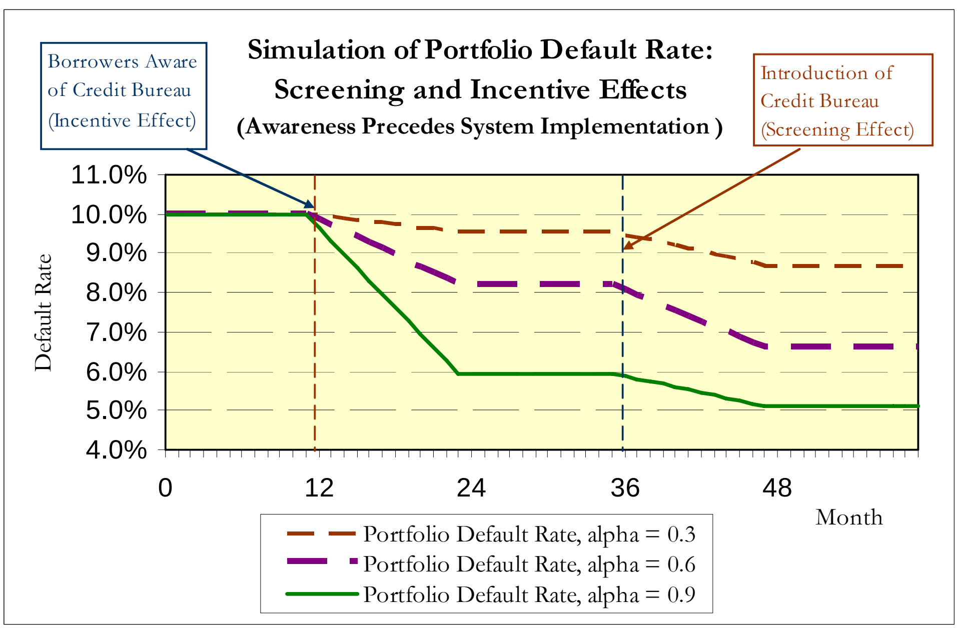


**Figure 5**

## 4. CONCLUSION

We present a theoretical model that 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. Indeed, these three effects can be extended in a general way to other contexts where internet technology has 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 passing informational screening. This "trust" created by the system induces an offsetting behavior 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. Our field experiment evidence from Guatemala shows that the introduction of the bureau induces a strong screening effect and a more muted incentive effect. However, the Guatemalan evidence on the introduction of a bureau featured a screening effect of the bureau that 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 the effect on moral hazard 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.[12] We illustrate here a somewhat surprising way of pulling these benefits forward in time as credit bureaus come to be implemented in developing countries: 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.

What can we learn from these results about the effect of credit information systems on credit markets in industrialized countries? Clearly the sophisticated credit scoring mechanisms operating in economies such as the United States have come to serve both important screening and incentive functions. But indeed it may be that the *credit expansion effect* was one of the subtle contributors to 2008 financial crisis in the United States. The widespread commercial use of the internet and internet-accessed credit scoring mechanisms by lenders increased dramatically during the 1990s. For example, in 1995 Freddie Mac and Fannie May began to recommend the use of FICO (Fair Isaac Corporation) credit scores in the evaluation of US mortgage loans. Better information on existing debt and credit scores likely contributed to the confidence that banks and secondary mortgage holders had in exposing consumers to heavier debt loads, and in pricing these debts in the secondary market. This increased use of credit scoring based on both positive and negative credit information coincided with a 10-year period that saw a dramatic increase in the level of outstanding U.S. consumer credit from US$1.02 trillion in 1995 to US$2.21 trillion in 2005 (Federal Reserve Board), setting the stage for the resulting crisis. The model presented here motivates the possibility that the seeds of the financial crisis were sown by the same informational innovations that improved the efficiency of credit markets. This introduces a note of caution into our understanding of the impact of credit bureaus on systemic credit market risks.

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[12] 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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