

Sustaining Input on Credit through Dynamic Incentives and Information Sharing: Lessons from a framed field experiment

Serge Adjognon, Lenis Saweda Liverpool-Tasie, Robert Shupp
Michigan State University

Abstract

Despite the potential benefits of providing inputs on credit, market conditions do not encourage the private sector to provide such credit to smallholder farmers. Generally, credit markets in rural areas of developing countries are characterized by market failures associated with imperfect information in the presence of risk. These failures persist due to weak contract enforcement institutions, thus increasing the potential for high strategic default rates. Knowing this, input suppliers are reluctant to provide inputs on credit to farmers, leading to a missing market problem. The concept of dynamic incentives is used to develop conditions that minimize the potential for strategic default and make it efficient for private input suppliers to offer agricultural inputs on credit to rural smallholder farmers. Using data collected through a framed field experiment that simulates a market for input on credit, the model predictions are tested. We show that the existence of an information exchange system between input sellers and the profitability of the input, are both important determinants of farmers' likelihood of repayment for inputs on credit.

1. INTRODUCTION

Increasing agricultural productivity is key for the structural transformation of societies and for poverty reduction (Johnston and Mellor 1961). One potential mechanism to increase agricultural productivity is the increased use of modern technologies, including fertilizer. While there are signs of an increase in fertilizer use in countries with subsidy programs or other concerted input support strategies, fertilizer use in Sub Saharan Africa (SSA) generally remains low (Sheahan and Barrett 2014).

Severe capital and credit constraints are one key reason for the low fertilizer use rates among poor farmers in many developing countries. Even when farmers believe that fertilizer use is profitable, they may be unable to purchase fertilizer because they lack cash, cannot obtain credit (e.g. due to lack of collateral) or cannot obtain fertilizer locally (Kelly, Morris et al. 2007). Thus, input on credit has been identified as a potential way to increase farmers' access to and use of modern inputs by solving both the credit and accessibility or availability constraints.

Despite the potential benefits of providing inputs on credit, market conditions often do not encourage the private sector to provide such credit to smallholder farmers (Kelly, Adesina et al. 2003). Generally, credit markets in rural SSA are characterized by market failures associated with imperfect information in the presence of risk (Dorward, Kydd et al. 1998, Poulton, Dorward et al. 1998, Sadoulet 2005, Tedeschi 2006). These failures persist because institutions for contract enforcement are weak, increasing the potential for high default rates among farmers. Knowing this, input suppliers are reluctant to provide inputs on credit to farmers. This leads to the missing market problem as both the input provider and the farmer lose the potential gain from trade by not completing the transaction. A key question then is "Can input provision on credit be facilitated if it is commonly known that failure to repay

implies future inability to get input on credit?” This paper adapts a game theoretic model drawn from the microfinance literature to answer this question. We then use an innovative lab-based field experiment, in rural Nigeria, to test the model. We find that input on credit arrangements can be sustained as long as farmers value gains from future access to fertilizer more than the temporary gain from renegeing on current debt contracts, and if the threat of being prevented from accessing future input on credit is credible.

This paper makes an important contribution to the literature on agricultural input loan provision by private input suppliers to small farmers in developing countries. In the literature, no study (the authors are aware of) has focused explicitly on strategic default in cases in which private input suppliers would sell input on credit to farmers and collect payment after harvest. Since such input on credit arrangements share some characteristics of microfinance but also have their particularities, we build on the microfinance literature and develop ideas about innovative and effective measures that can help alleviate strategic default problems in input on credit arrangements. This paper also add to the limited number of papers that use lab in field experiments, and is also one of the very few examples of empirical application of the concepts of credit information sharing and dynamic incentives mechanisms.

The rest of the paper is organized as follow. In section 2, we provide a summary of the relevant literature on strategic default. Section 3 presents the model of the missing market situation, proposes a repeated game model to enforce repayment and sustain trade, and draws empirically testable hypotheses from the theoretical model. Section 4 describes the experimental design used to gather data for the empirical analysis and section 5 presents and discusses the results of the empirical analysis. We conclude with a summary of the key findings and policy implications in section 6.

2. LITTERATURE REVIEW ON STRATEGIC DEFAULT AND SOLUTIONS

Strategies to overcome moral hazard and strategic default issues inherent to offering uncollateralized loans to poor people in developing countries is a longstanding problem in the microfinance literature. One strand of the literature focuses on the use of group lending and joint liability as a mechanism to overcome those issues. The model requires borrowers to sort themselves in groups. Loans are made to individuals, but the group as a whole is held jointly liable in case of default. The mechanisms effectively transfer screening and monitoring costs from the bank to borrowers, providing an effective way for banks to reduce adverse selection, moral hazard and enforcement problems. However, the success of group lending becomes limited when we care about the poorest (Armendáriz de Aghion and Morduch 2000), or when the group is either non-existent or too large to have the necessary information to ensure repayment (Tedeschi 2006). Therefore it has become a subject of interest to find mechanisms through which individual non-collateralized lending to the poorest could be sustained.¹

There is relatively large literature, with an early contribution from Besley (1995), which has discussed dynamic mechanisms through repeated interaction and reputation mechanisms as alternative ways to overcome strategic default without relying on group lending based on joint liability. The fundamental idea is that when a borrower depends on successive loans to keep his business functional, the threat of being denied future loans can provide incentives to avoid default in current period (Hulme and Mosley 1996, Armendáriz de Aghion and Morduch 2000, Tedeschi 2006).

Tedeschi (2006) focused on strategic default and default due to negative economic shocks and showed how dynamic incentives, in the form of additional or future loans, can reduce

¹ Details about the mechanism and limitations of group lending are provided in Stiglitz (1990), Armendáriz de Aghion (1999), Armendáriz and Gollier (2000), Sadoulet (1997), etc.

strategic default without relying on the group incentives used in the literature. Using a model based on a single microfinance institution (“lender”) and a group of microentrepreneurs (“borrowers”) who may well be farmers, he models the repeated lender-borrower relationship by endogenizing the amount of time that a borrower who defaults must remain without a loan. He shows that the optimal length of the punishment phase can be less than infinity, especially when an individual has much to gain from the lending relationship. He notes however, that punishment should only be sufficiently long to prevent a borrower from strategic default, but not so long as to unduly punish the borrower that experiences a negative economic shock. An important aspect of this model is that it assumes the presence of a single lender or perfect sharing of default information if multiple lenders are present. The paper does not discuss explicitly how this potential exchange of information between lenders may affect repayment behavior, nor does it empirically test the predictions.

As competition between lenders increases, the effectiveness of the dynamic incentive is weakened because the borrowers can take advantage of this competition and get loans from various sources. In such a case, coordination between lenders, in terms of credit information exchange can be an effective discipline device to mitigate various forms of moral hazard, and reduce strategic default (Padilla and Pagano 1997, Padilla and Pagano 2000). For example, communication and exchange of information was essential for the functioning of the *merchant guilds* that facilitated trade during the late medieval period (Greif, Milgrom et al. 1994), and the *Coalition* that enabled 11th century Maghribi traders’ to benefit from employing overseas agents despite the commitment problem inherent in these relations (Greif 1993). Ghosh and Ray (1999) also show the importance of communication between lenders in solving the issue of strategic default in individual lending. Moreover, there is a growing number of recent studies that provide theoretical and empirical evidence on the effect of credit information systems for mitigating problems of adverse selection and moral hazard in credit

markets (Vercammen 1995, Padilla and Pagano 1997, Padilla and Pagano 2000, McIntosh and Wydick 2009). The general conclusion is that credit information sharing substantially increases lending, and decreases borrowers' default (Jappelli and Pagano 2002, Djankov, McLiesh et al. 2007, Luoto, McIntosh et al. 2007, De Janvry, McIntosh et al. 2010).

In particular, Luoto et al. (2007) and de Janvry et al. (2010) 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. The credit bureau, called CREDIREF, was established to solve the problem of multiple loan contracting and hidden debt exacerbated in the late 1990s by the growth in the number of microfinance institutions (MFIs) in Guatemala. By allowing for positive and negative information sharing between participating lenders, CREDIREF was proved to have positive screening and incentive effects. Essentially, 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) took advantage of this for identifying the branch-level impacts from the screening effect of the bureau on loan delinquency rates. Their results indicate a reduction in default of approximately two percentage points after the bureau was implemented in branch offices. As for de Janvry et al. (2009), they exploited the lack of awareness² about the credit bureau 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

² 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 was helpful in trying to decompose the different effects of a credit bureau empirically.

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. The results of their empirical analysis indicate that while new clients recruited after the bureau have better repayment rates, this improvement in default was 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.

While Luoto, McIntosh et al. (2007) and de Janvry, McIntosh et al. (2010), focused on moral hazard due to multiple and hidden loan contracts (over-indebtedness), the theoretical model developed below characterizes ex-post moral hazard, or strategic default in the context of individual input loans made by private input suppliers to farmers in developing countries. Drawing insight from the theoretical models in Padilla and Pagano (2000) and McIntosh and Wydick (2009) we develop a simple repeated game model of input credit and stress the importance of information sharing for farmers' repayment decision. Our model also embeds the presence of a productivity shock that may affect farmers' repayment abilities or incentives. We then test our model predictions in the field using lab-in-the-field experimental methods referred to as a framed field experiment by Harrison and List (2004).

3. THEORETICAL FRAMEWORK AND EXPERIMENTAL HYPOTHESES

A simple model of input on credit

Our model considers a repeated matching game between a set of firms $n_s = \{1, \dots, N_s\}$ and a set of farmers $n_b = \{1, \dots, N_b\}$. By assumption, the farmers need to buy inputs for agricultural production but they do not have the capital to pay upfront. Therefore they can only buy it on credit. The firms are agricultural input dealers or brokers seeking to make more profit by increasing the volume of sales³. Therefore they are willing to give the inputs on credit to the farmers as long as they expect to be repaid at the end of the agricultural season. In each stage of the game, each firm is matched with every farmer and they play a 2-player sequential stage game. For each game the firm decides, at the beginning of the agricultural season, whether or not he should make an offer of input credit to the farmer. After harvest, the farmer decides whether to repay or not. We assume the use of the agricultural input is always profitable. That is it gives the farmer a return always higher than not using it. However, there is a random productivity shock $\eta = \{Good, Bad\}$ that is realized later during the agricultural season and therefore after the relationship between the firm and the farmer has already started⁴. The return to the use of the agricultural input $R_\eta = \{R_{good}, R_{bad}\}$ is assumed to be lower in the Bad state of nature than in the Good state. But agricultural output is always higher with the use of the input than without using inputs ($R_\eta > \underline{R}$).

In every period of the game, the firm's strategy can be described by a function $\sigma_i^S: H^t \rightarrow \{Offer, Not\ offer\}$ for all farmer $i \in n_b$, where $H^t = \{H_{Public}^t \cup H_{Private}^t\}$ is the set of information available to firm s , and which contains, up to time $t-1$, the repayment history of the all the farmers including farmer i . Notice that we distinguish between public

³ Note that this model can be generalized to any relation between demanders and suppliers of credit.

⁴ This can be thought of as a weather shock. A good weather implies higher productivity *ceteris paribus*.

and private information. Public information for a firm j , contains repayment history about all the other farmers that he has not made an offer to in some periods and therefore does not know privately how they behaved in those periods. Whereas private information is about the farmers he has made offers to and therefore has observed personally their repayment behaviors. As for the farmer, his strategy in each period that he receives an offer is a mapping σ_j^B from the realization of productivity shock η to the set of possible actions $\{Renega, Not renega\}$, for all firms j from which the farmer took an offer. When he does not receive any offer, his set of possible actions is the empty set⁵.

Finally, for each initiated transaction with a farmer, the firm gets a payoff of $P-c > 0$ if the farmer does not renege, and $-c < 0$ if the farmer does renege. The firm's reservation payoff in case of no transaction with a farmer is 0. We assume that each firm payoff function in the stage game is additively separable over all the transactions made with farmers in that stage. As for the farmers, they receive a reservation payoff \underline{R} from each firm they do not receive an offer from in that stage. But when they receive an offer, their payoff function is described by a mapping $g: \{R_{good}, R_{bad}\} \times \{Renega, Not renega\} \rightarrow \mathbb{R}$. Their payoff depends on their repayment decision and the realization of the productivity shock. We call $u_{h\eta}$, $u_{c\eta}$, and \underline{u} the farmer's state contingent utilities from not renegeing, renegeing, and not using the agricultural input, respectively.

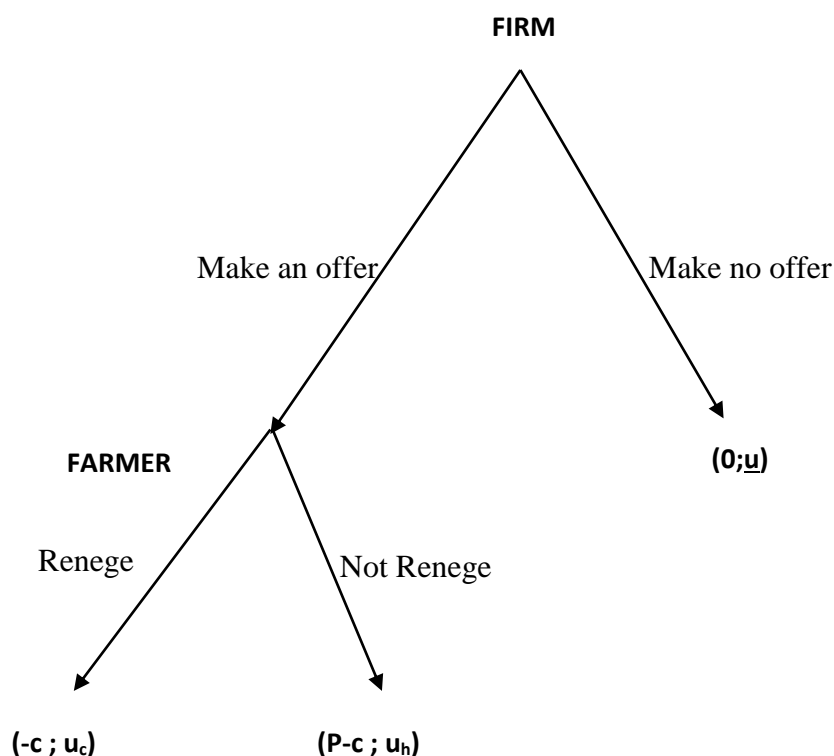
The missing market problem in a single period game

In a single period case, the game described above can be represented by the extensive form game in figure 1 for the matching between each farmer and each firm. As can be seen on the figure, in absence of an exogenously enforced social sanction, the farmers' dominant strategy

⁵ Later, in our experimental design, we impose the constraints that farmers can only accept one offer in each period, and firms can only make offer to a limited number of farmers. These assumptions only simplify the game for the participants without fundamentally changing the results.

is to take the loan from any firm that makes him an offer, and then renege. In anticipation of this, the firm's dominant strategy is to not lend in the first place and thus the market collapses (Conning and Udry 2007). Figure 1 shows that the Subgame Perfect Equilibrium for this game is (no offer, renege) which gives a payoff profile of $(0, \underline{u})$. This is clearly pareto inferior to the (offer, not renege) option which results in a profile of payoff of $(P-c ; u_h)$. This happens irrespective of the realization of the productivity shock. Also, since there is no previous stage, the information available to the firm at the beginning if the game is the empty set. Note that typically the loan might be secured or the firm could enforce the contract through the legal system causing the farmer's renege payoff to be greater than u_c . If this is high enough then the farmer has an incentive to not renege and the firm would make the offer and we would get to the pareto superior outcome. However, in our context, there is a high potential for default due mostly to the fact that the legal procedures for enforcing contracts are critically weak in most developing countries (Kelly, Adesina et al. 2003). Thus, the input provider and the farmer both loose the potential gain from trade.

Figure 1: Extensive form representation of the farmer-trader theoretical game



Enforcement of input-on-credit contract using dynamic incentives

As mentioned by Conning and Udry (2007), if the interaction is instead repeated, it may be possible to generate incentives for the farmer to repay in every period, provided that the threat of loan non renewal is credible and sufficiently punishing. Now consider an infinitely repeated game where each round is the above stage game. Recall that, while in reality farmers and firms do not enjoy an infinite lifespan, an infinitely repeated game is equivalent to a finite horizon model with a constant probability of terminating the relationship every period (Greif 1993, Mas-Colell, Whinston et al. 1995).

In each period of the game, the threat of non-renewal implies that each firm is playing the following strategy with each farmer i they are matched with:

$$\sigma_i^S : \begin{cases} \text{if } H_i^t \text{ indicates No past default behavior by farmer } i, \text{ make him an offer} \\ \text{Otherwise, make no offer to farmer } i \end{cases}$$

Recall that $H^t = H_{Public}^t \cup H_{Private}^t$ contains both public and private information about the farmer. In this model where the market is competitive (several firms and several farmers), the public information part is crucial for sustaining cooperation, unless the firm and the farmer have an exclusive relationship. When farmers have the possibility to take input credit offers from other firms in subsequent periods, the expected punishment from default is less severe and may not be able to deter default. However when information is shared publicly amongst firms, the farmer is forced to behave as in an exclusive relationship with the firm, if all firms agree to collectively punish a defaulter. However, this presumes that other firms will punish a farmer who did not default them personally. In the absence of a strong legal system, this can be made possible through the emergence of institutions through which lenders who do not punish a defaulter are themselves sanctioned (Kandori 1992, Greif 1993, Conning and Udry 2007).

The farmers' response to the collective punishment is described as follow. At any period t, the present value of the lifetime expected utility to the farmer from never defaulting (V_h) given the realization of the productivity shock $\eta = \{Good, Bad\}$ is:

$$V_{h\eta} = u_{h\eta} + \frac{\delta}{1-\delta} E_{\eta} u_h \quad (1)$$

where δ and u_h are, respectively, the discount factor and payoff from not renegeing as defined earlier. $E_{\eta} u_h$ is the expected utility of the farmer for periods when he does not renege.

The present value of the lifetime expected utility from a one-time default is:

$$V_{c\eta} = u_{c\eta} + \frac{\delta}{1-\delta} [\theta E_{\eta} \underline{u} + (1-\theta) E_{\eta} u_h] , \quad \eta = \{Good, Bad\} \quad (2)$$

where θ is the probability that a defaulting farmer gets punished. θ is affected by the number of input sellers in the market and the efficiency with which information about defaulters flows between firms so that they can exclude the farmer from consideration. If $\theta=1$, that implies information flows perfectly between firms and it is guaranteed that a defaulter will never get input on credit from any other firm in subsequent periods. Likewise, if $\theta=0$, information does not flow between private firms and farmers can default and still get inputs on credit from other firms, depending on how many input firms there are. Eventually, the private information set alone will translate into a value of $\theta_{private}$ that is lower than when the firms have access to both the public and private information history.

According to the Nash Folk Theorem (Fudenberg and Tirole 1991, Mas-Colell, Whinston et al. 1995), cooperation between farmers and input suppliers can be achieved under the assumptions described above, as long as farmers are patient enough (δ is high enough).

The sustainability condition requires that:

$$V_{h\eta} \geq V_{c\eta} , \quad \eta = \{Good, Bad\} \quad (3)$$

$$\mathbf{u}_{h\eta} + \frac{\delta}{1-\delta} E_{\eta} \mathbf{u}_h \geq \mathbf{u}_{c\eta} + \frac{\delta}{1-\delta} [\theta E_{\eta} \underline{\mathbf{u}} + (1-\theta) E_{\eta} \mathbf{u}_h] \quad (4)$$

This is equivalent to:

$$\delta \geq \frac{1}{1 + \theta \frac{(E_{\eta} \mathbf{u}_h - E_{\eta} \underline{\mathbf{u}})}{\mathbf{u}_{c\eta} - \mathbf{u}_{h\eta}}} = \delta_{\eta}^* \quad (5)$$

Equation 5 means that in any period, only farmers with a discount factor greater than δ_{η}^* will not default and trade is sustainable only with those farmers. Assuming that productivity shock is independently and identically determined in each round, the per-period forgone benefit from continuing to get inputs on credit ($E_{\eta} \mathbf{u}_h - E_{\eta} \underline{\mathbf{u}}$) is fixed in each future period. Therefore, the minimum discount rate required to sustain trade depends mostly on how big the farmers' immediate gain from defaulting ($\mathbf{u}_{c\eta} - \mathbf{u}_{h\eta}$) is in the current period. In particular, $\mathbf{u}_{c\eta} - \mathbf{u}_{h\eta}$ can be interpreted as the opportunity cost of repaying for the input received on credit in the current period, and is a function of the realization of the productivity shock in that period. For risk averse farmers, $\mathbf{u}_{c,Good} - \mathbf{u}_{h,Good} > \mathbf{u}_{c,Bad} - \mathbf{u}_{h,Bad}$ and therefore, in the good state of the nature, δ_{η}^* is lower than in bad state of nature, *ceteris paribus*.

Equation 5 describes the conditions under which farmer will be willing to repay their input loans given that firms are adopting a multilateral punishment strategy. Many empirical hypotheses can be derived from this equation. We focus on 2 main ones in this study:

Hypothesis 1: Equation 6 indicates that as θ increases, δ^* decreases. That is, as the probability of being recognized as a defaulter by other firms increases, the minimum discount rate required for the farmer not to default decreases. This probability is related to the credibility and sufficient of the punishment threat, and is determined by many factors such as the number of input suppliers and the degree of communication between them. This leads to

the following testable hypothesis: “**As communication and exchange of information is facilitated amongst input suppliers, the probability of the farmer being caught and ostracized increases, and therefore, the probability of default by farmers decreases.**”

Hypothesis 2: Equation 6 also indicates that as $(u_{c\eta} - u_{h\eta})$ increases, δ_{η}^* increases. That is, as the opportunity cost of repaying increases, the minimum discount rate required for the farmer not to default increases. This leads to the second testable hypothesis: “**In the bad state of the nature (when productivity is lower due to some productivity shock), the probability of default by farmers receiving inputs on credit increases.**”

4. EXPERIMENTAL DESIGN AND PROCEDURES

Given that input-on-credit arrangements are not commonly observed in the setting of interest, it is difficult, if not impossible, to collect observational data to test our hypotheses. Therefore, we conduct a lab-based field experiment using randomly selected farmers in 10 different villages in Kwara State, Nigeria (see Table 1). The experiment is designed to simulate a multiple round market for inputs-on-credit and test the above hypothesized communication and profitability shock effects.

To test the communication and exchange of information effect, five out of the ten study villages were randomly selected to receive a communication treatment. In those five villages information regarding individual farmer default behavior was relayed to all creditors resulting in increasing the probability that a farmer is identified as a potential future defaulter. In the five non-communication treatment villages, creditors only knew the default behavior of the farmers to whom they made loans. Comparing farmers’ behavior in the communication treatment to that in the non-communication treatment tests for the hypothesized communication effect.

To test hypothesis 2 – the impact of productivity and profitability on default behavior – a round-level treatment was implemented. Specifically, in each round the weather could take on one of two states – good or bad. If the weather was good, productivity and profitability of farmers were high, and if the weather was bad productivity and profitability of farmers were low. Recall that the profitability shock hypothesis assumes that a higher net profitability reduces farmers’ incentives to default. Given this we expect lower levels of farmer default in rounds with good weather than in rounds with bad. In each round, the weather state was determined by the flip of a coin after credit decisions were made, but before repayment.

Table 1: Experiment Villages in Kwara State, Nigeria

Local Government (LGA)	Village Name	Communication	Number of rounds
PATIGI	AGBOORO	Yes	10
PATIGI	CHAKYAGI	No	10
EDU	CHEWURU	Yes	11
EDU	CHIKANGI	No	10
EDU	CHIKANGI TIFIN	Yes	11
EDU	EFFAGI	No	10
EDU	GBARIGI	Yes	11
EDU	KPANGULU	No	10
PATIGI	KUSOGI GANA TSWALU	Yes	10
PATIGI	SHESHI TASHA	No	10

Each experimental session (one per village) involved 20 participants. Participants were randomly assigned to be either a farmer (who might receive inputs on credit), or a paid broker of an agro dealer (henceforth, agro broker).⁶ Each session had 4 agro brokers and 16 farmers and participants remained in the same role for the entire experiment. Each experimental session consisted of 10 or 11 rounds. After the 9th round in each village, a coin was flipped at the end of each round to determine whether to continue an additional round of the game or not. This is to establish a random stopping point of the game and reduce farmers’ incentive to

⁶ We use the term broker because this is more consistent with the fertilizer distribution system prevalent in the study area.

behave opportunistically in the last rounds. Interestingly, we never had more than 11 rounds in any village, and all the 3 villages for which the experiment went for an 11th round were communication treatment villages. Each round represents an agricultural season and the decisions made by participants were based on simulating the important aspects of actual input credit markets. As such, each round consisted of two periods – a pre-planting period and a post-harvest period. In the pre-planting period, the agro brokers offered inputs on credit to the farmers and the farmers decided which (if any) agro broker offer to accept. In the post-harvest period, farmers' harvest returns were determined (based on weather and input use) and farmers choose whether to repay the agro broker for the input or not. The possible decisions and their payoff implications for agro brokers and farmers are described in the following sections.

Decisions and Payoffs for Agro Brokers

Each of the four agro brokers in each village began each round with 300 kg of fertilizer to potentially be sold on credit to farmers. In the pre-planting period, the broker decided **for each farmer** whether to offer input on credit or not. To simplify the decisions, we assumed that the input comes in bags of 100kg and each farmer only needs 100kg. Therefore, an offer made to a farmer implied 100kg of input offered to the farmer by the broker. This means that the broker could make offers to at most 3 farmers in each round⁷. Once offered, each farmer could accept or decline the offer. In the post-harvest period, agro brokers received payments from the farmers to whom they made input loans. The value of the input loaned was set to N100 per kg. Thus a farmer who borrowed 100kg of fertilizer from an agro broker would be expected to repay N10,000. However, the actual amount received and the agro broker's commission/penalty depends on the farmers' repayment decision. The farmers had the option

⁷ Note that agro brokers did not have to make any offers, but if they did not they would not receive the base salary.

to: not repay at all (0% of amount owed), partially repay (50% of amount owed), or repay in full (100% of amount owed). The possible outcomes for an agro broker, from any given farmer who received inputs on credit, are summarized in the Table 2.

Table 2: Brokers' Commission/Penalty Schedule

Description		Amount/Value	
	Amount of fertilizer loaned	0	100kg/N10000
Repay in full	Amount collected	0	N10000
	Broker's commission/penalty	0	N2000
50% repayment	Amount collected	0	N5000
	Broker's commission/penalty	0	-N1500
0% repayment	Amount collected	0	N0
	Broker's commission/penalty	0	-N3000

Overall the agro broker's earnings from input sales during a round consist of two parts. First, a base salary of N3000 – paid if at least one farmer accepted an offer. This base salary was designed to incentivize agro dealers to make offers.⁸ Second, the commissions/penalties from the repayment of loans made to farmers (3 or less per broker). As shown in Table 2, the broker receives a N2000 commission for every sale where repayment is complete but a penalty is imposed every time he offers inputs to farmers who do not repay fully. If a repayment is partial the agro broker has to pay a penalty of N1500 to the input dealer. Similarly, if the farmer repays nothing, the agro broker has to pay a penalty of N3000 to the input dealer. Note that, given the penalties, it is possible for the agro broker to lose money in a

⁸ In fact, without this incentive (and because of the N50,000 payment given to ensure non-negative earnings discussed below) agro brokers might choose to sit out the game by not making offers once they made a single loan.

round. For example, assume that an agro broker makes offers to 3 different farmers and they all accept. The broker thus gets the base salary of N3,000. If all the farmers decide to fully default, the broker loses N3,000 per farmer or N9,000 total. Overall, the broker has a net loss of N6,000. In order to avoid the possibility that the broker owed us money at the end of the experimental session, every broker was promised N50,000, to be paid at the end of the session, provided that he had made at least one loan in any round. Net payments to agro dealers per round could vary from a loss of N6,000 as illustrated above to a net gain of N9,000 if three offers are accepted and fully repaid.

Decisions and Payoffs for Farmers

As described above, in each round farmers received offers from the agro brokers in the pre-planting period and, given that they received more than one offer, chose which one to accept. Note that, to simplify the game, farmers could only accept fertilizer on credit from one agro broker (100kg). Furthermore, fertilizer was assumed to always be advantageous for farmers in that using it always increased yields and thus payoffs. There was also no mechanism for farmers to get fertilizer in another way. This was done to ensure that all the farmers had the same resources available to them at the beginning of a round/season. In the post-harvest period, the weather for the season was determined via a coin-flip (a single coin flip applied to all farmers and individual farmers were invited to flip the coin) and this, along with whether they received fertilizer, determined harvest yields. As shown in Table 4, harvest yields were represented in terms of monetary returns to investment. Specifically, if the farmer used fertilizer and weather was bad they earned N13,000, while if the weather was good they earned N16,000. If they did not use fertilizer, the returns were much lower (N1,000) and were not dependent on the weather. After learning about the weather and resulting earnings, farmers that had received fertilizer chose a level of repayment (0%, 50%, or 100%). Recall

that the fertilizer on credit was worth N10,000 or N100/kg. The possible round earnings for a farmer are shown in Table 3.

Table 3: Farmers' payoff structure

Description		Amount/Value	
Amount of fertilizer received (kg)		0	100kg
Low Return to investment (Bad Weather state)		N1000	N13000
if full repayment	Amount paid	0	N10000
	Farmer's net payoff	N1000	N3000
if partial (50%) repayment	Amount paid	0	N5000
	Farmer's net payoff	N1000	N8000
if no repayment	Amount paid	0	0
	Farmer's net payoff	N1000	N13000
High return to investment (Good Weather state)		N1000	N16000
if full repayment	Amount paid	0	N10000
	Farmer's net payoff	N1000	N6000
if partial (50%) repayment	Amount paid	0	N5000
	Farmer's net payoff	N1000	N11000
if no repayment	Amount paid	0	0
	Farmer's net payoff	N1000	N16000

Information Treatment Variation and General Implementation

The communication treatment sessions differed from the non-communication sessions in that the agro brokers were given complete information about all farmers' past repayment behavior in the game. This was done through a record kept publicly on a board in front of all the participants (see table 2). The repayment record board was updated after each round, thus showing each farmer's repayment decision in previous rounds. This implies that when a farmer does not repay the credit taken from a specific broker in a specific round, all other brokers will know about it before they make credit offers in the following round. Farmers in these sessions were informed prior to the start of the game that their repayment behavior would be made public. The default record was presented to participants as shown in Table 4.

Table 4: Public repayment records used in treatment villages

	Farmer 1	Farmer 2	Farmer 3	Farmer 4	Farmer 5	Farmer 6	Farmer 16
Round 1									
Round 2									
Round 3									
Round 4									
Round 5									
Round 6									
Round 7									
Round 8									
Round 9									
Round 10									

The experiment was paper-based in that agro brokers and farmers made decisions using decision sheets (see appendix), but the data was recorded and payment amounts calculated using a computer. A team of six experimenters ran each session. Once all participants were present, the instructions were presented and questions answered. Participants were then separated into farmer and agro broker groups and received the appropriate decision sheets (broker sheet and farmer sheet). To give participants a chance to see the game in action and to ask questions an unpaid practice round was performed. During the experiment all decisions were anonymous in that brokers and farmers were assigned participant numbers and all decisions were entered on paper and communicated to other relevant participants via collection and transcription of decision sheets by the experimenters.

5. RESULTS AND DISCUSSION

5.1. GENERAL DESCRIPTION OF THE DATA

Distribution of the input credit offered and accepted throughout the games

As noted above, the experiment involved 16 farmers and 4 brokers per village, in 10 villages for 10 to 11 rounds. Overall, the 40 brokers that participated in the experiment made a total of 1205 input loan offers to farmers (see table 5). In the communication villages we observed more offers (614) than in the non-communication villages (591). Given that multiple brokers

may make offers to the same farmer and farmers can only accept one offer, some offers are necessarily rejected. Farmers, when they received offers during a round, got on average 1.34 offers. This indicates that brokers did not spread out the offers well in each round. Consequently, while 1205 offer were made, the total number of offers actually accepted was 892 or 74% of the total number of offers made by brokers. Breaking this down by communication treatment, in villages with communication, 76% of offers were accepted whereas in the non-communication villages, only 72% were accepted. Note that, in the communication villages more offers were made and a higher proportion were accepted resulting in more transactions relative to the non-communication villages. This is a first, though still weak, indication that communication and exchange of information allowed the market to perform better due to the reduced information asymmetry problem.

Table 5: Statistics about the offers made and received through the game

	Communication	Non-Communication	Total
Total number of offers	614	591	1205
Average number of offers per farmer (amongst farmers who received at least one offer)	1.31	1.36	1.34
Total number of offers actually accepted throughout the game	466 (76%)	426 (72%)	892 (74%)

In the following sections, we focus more closely on farmer and broker behaviors and analyze the role of weather shocks and communication treatments.

5.2. FARMERS' BEHAVIOR

Description of farmers' repayment behavior during the game

A key goal of this experiment was to evaluate how communication and exchange of information between brokers, as well as productivity shocks (weather), affect repayment decisions when farmers receive input on credit. Figures 2 and 3 describe the relationship between repayment behavior and our treatment variables. The pooled data contains 892 observations at the farmer level, with 47.3% observations with the good weather state, and 52.2% observations in the communication treatment villages.

Figure 2 (repayment behavior by communication treatment) indicates that the default rate – defined as the proportion of farmers who repay less than 100% – is higher in the no-communication treatment. More precisely, with no communication, 50.23% of farmers repaid half, while 11.27% did not repay anything, making the total default rate 61.5%. In contrast, with communication, the default rate, similarly defined, is 57.3%. This lower default rate in the communication treatment suggests that communication amongst input suppliers likely has a positive effect on farmers' repayment of input loans. We explore this later in more detail with an econometric model.

Figure 2: Histogram of repayment decisions by communication treatment status

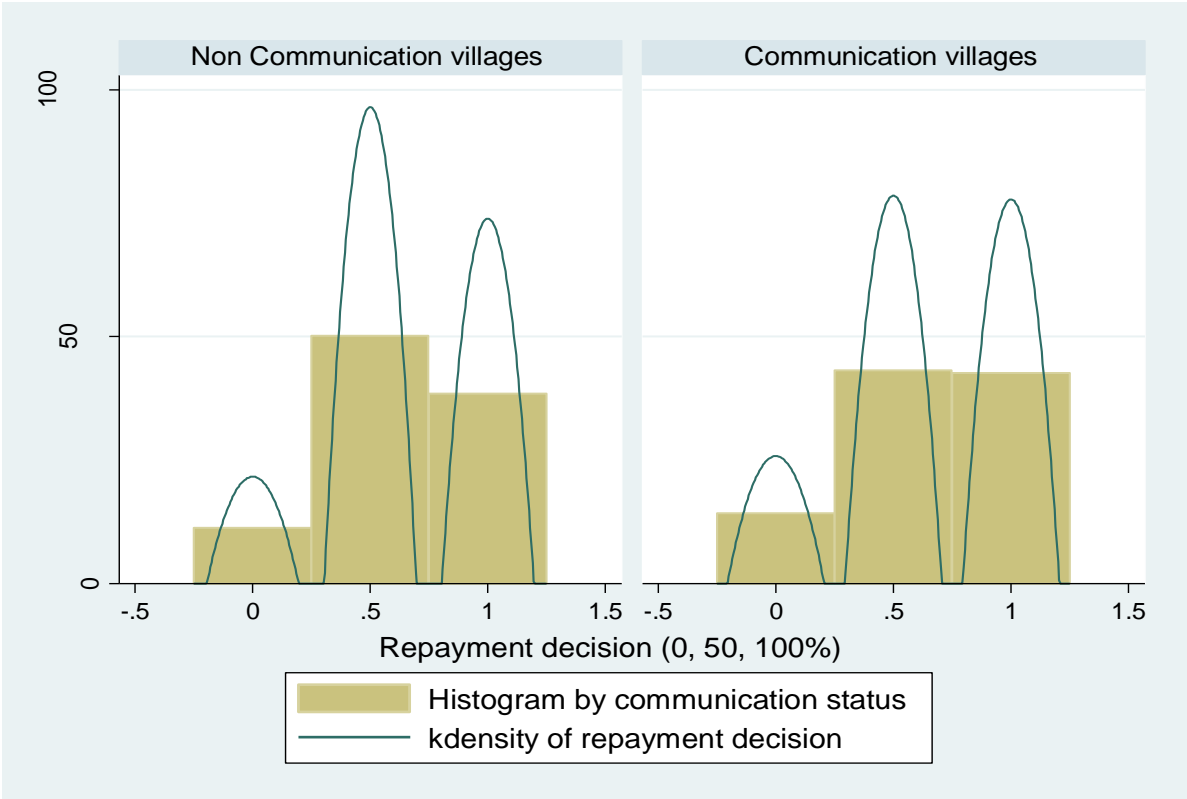
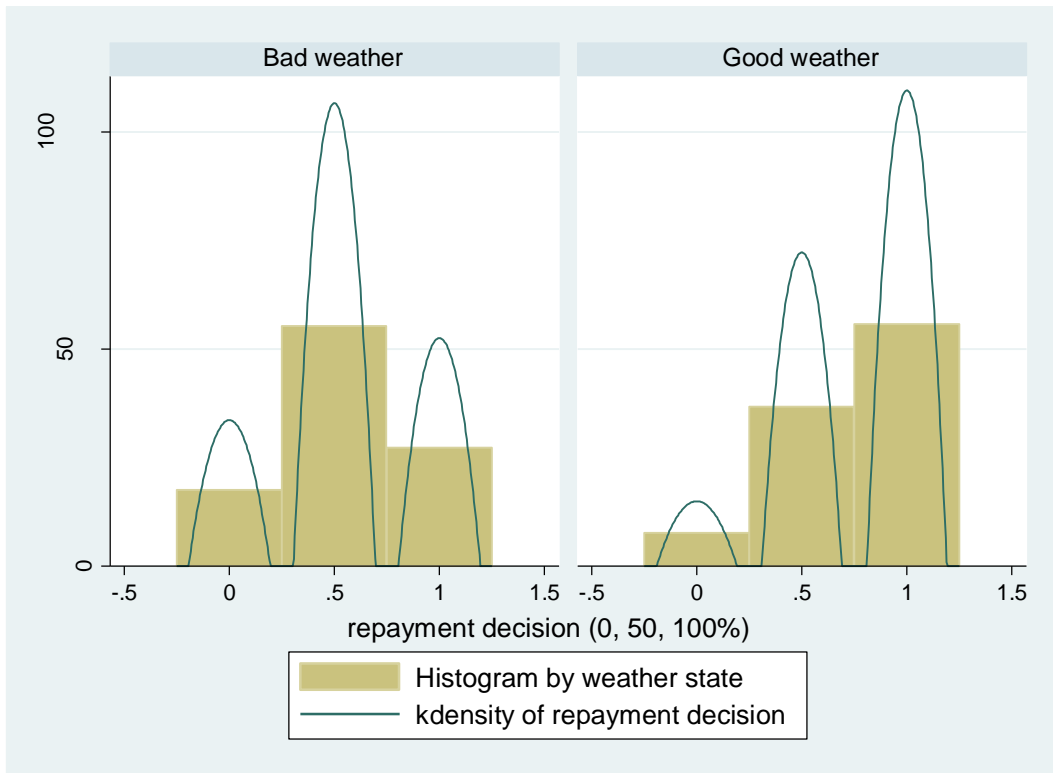


Figure 3 indicates that default rates are higher when the weather state is bad (negative shock). Again, defining ‘default’ as the proportion of farmers who did not repay fully (i.e. 100% of what was owed), the total default rate during bad weather rounds was 72.77% (55.32% repaid half while 17.45% did not repay at all). For good weather rounds, the default rate was lower at 44.31% (36.73% repaid half while 7.58% did not repay at all). This difference suggests, as hypothesized in the theoretical model above, that profitability shocks play an important role in farmers’ decisions to repay input loans.

Figure 3: Histogram of repayment decision by weather state



Overall, the descriptive analysis of farmer behavior is consistent with the hypotheses derived from the theoretic model. An econometric analysis was also conducted to account for any round effects and interactions between weather state and communication.

Econometric model

To test the prediction of the dynamic incentives theoretic model, the determinants of a farmer's repayment decision using the communication treatment and weather states as explanatory variables was estimated with the following specification.

$$Y_{it} = \beta_0 + \beta_1 * T1_{it} + \beta_2 * T2_{it} + \beta_3 * (T1_{it} * T2_{it}) + \sum_2^{11} \delta \cdot Round_t + \varepsilon_{it} \quad (6)$$

where:

Y_{it} represents the observed repayment decision made by farmer i in round t

T1 is the binary communication treatment variable that takes value 1 if a farmer resided in a communication village and 0 otherwise. Similarly, T2 is the binary weather state variable that takes value 1 when the weather is good and 0 otherwise. We also include an interaction term between the communication and weather state variables to see if they influence each other's effect on repayment behavior of farmers. Finally round dummies were included to control for rounds effects on farmers' behaviors.

β_1 , β_2 , and β_3 , are the parameters to be estimated, while ε_{it} is the random error term.

We estimated the parameters of equation 7 above both as an Ordered Probit Model and a Probit model. For the Ordered Probit analysis, the dependent variable is the categorical repayment decision variable with values 0 (when no repayment was made at all), 0.5 (when 50% repayment was made), and 1 (when full repayment is made).

For the Probit analysis, the repayment decision variable is binary and takes values 1 when full repayment was made, and 0 otherwise. As such, this specification captures the probability of repaying fully, and is consistent with the definition of default used in the descriptive analysis section above.

Given that both our treatment variables were randomly assigned to farmers per round or village, our key explanatory variables are not correlated with the errors of any past, present, or future round, resulting in unbiased estimates via the strict exogeneity assumption (Wooldridge 2010). Standard errors are clustered at the farmer level to account for the fact that farmer decisions across rounds are correlated.

Econometric results

Table 6 presents the results of both the Ordered Probit and Probit regressions. Round effects

are hardly significant in both regressions and overall the results are consistent with the theoretic model predictions and the descriptive analysis presented above.⁹ Specifically, with regard to communication, the results of the Probit and Ordered Probit models estimation are consistent with each other, and show a positive and significant coefficient for the Communication treatment variable. In particular, the margin reported for the Probit model indicates that farmer default rates are 18%¹⁰ lower when input suppliers are able to communicate and exchange information about repayment history. This result is not only consistent with our research hypothesis but also with the findings in Greif (1993), Ghosh and Ray (1999), as well as Luoto, McIntosh et al. (2007), and de Janvry, McIntosh et al. (2010).

Table 6: Estimation results for the determinants of farmers' repayment behavior

VARIABLES	ORDERED PROBIT		PROBIT	
	Coefficient	P-value	Marginal effects	P-value
Repayment decision	0, 50%, 100%.		100% or not	
Good Weather state (1/0)	0.895***	0.000	0.381***	0.000
Communication village (1/0)	0.308**	0.026	0.183***	0.003
Interaction	-0.424**	0.017	-0.185**	0.013
Round ID = 2	-0.228	0.139	-0.126*	0.070
Round ID = 3	-0.219	0.214	-0.021	0.778
Round ID = 4	-0.189	0.255	-0.011	0.871
Round ID = 5	-0.277*	0.096	-0.073	0.316
Round ID = 6	-0.234	0.175	-0.064	0.377
Round ID = 7	-0.135	0.443	-0.029	0.695
Round ID = 8	-0.375*	0.053	-0.078	0.293
Round ID = 9	-0.128	0.467	-0.047	0.542
Round ID = 10	-0.141	0.448	-0.013	0.864

⁹ The insignificance of the round dummies imply that the communication and weather effects were not driven by farmers behaving in a particular way during specific rounds. In particular it indicates that the random stopping point method used during the experiment was effective in mitigating farmers' natural incentive to default in the last rounds of the game when they do not expect any future income from the relationship. We also run the regression without including the last round and the conclusion remain the same. It also might indicate that there is no significant learning effects (i.e., the farmers do not appear to be changing their behavior across rounds due to learning how the game works).

¹⁰ This number is higher than the effect found in the descriptive analysis because the weather state was not controlled for.

Round ID = 11	0.161	0.527	0.069	0.492
Number of Observations	892		892	

*** p<0.01, ** p<0.05, * p<0.1

Similarly, both the Probit and Ordered Probit regressions indicate a positive and significant effect of weather state on farmers' repayment decisions. In fact, the Probit margin estimates indicate that default rates are 38% higher when the weather is bad. This is also consistent with our research hypothesis and can be attributed to the fact the opportunity cost of repayment is higher in bad weather since yields are low. Finally, the interaction between communication and weather state is negative and significant in both the models. This implies that even though the weather state matters, it matters less in communication treatments than in non-communication treatments. This has the interesting implication that even though one cannot control the weather state, if one increases the credibility of the threat of termination through communication and information exchange, farmers' repayment decisions become less sensitive to weather shocks.

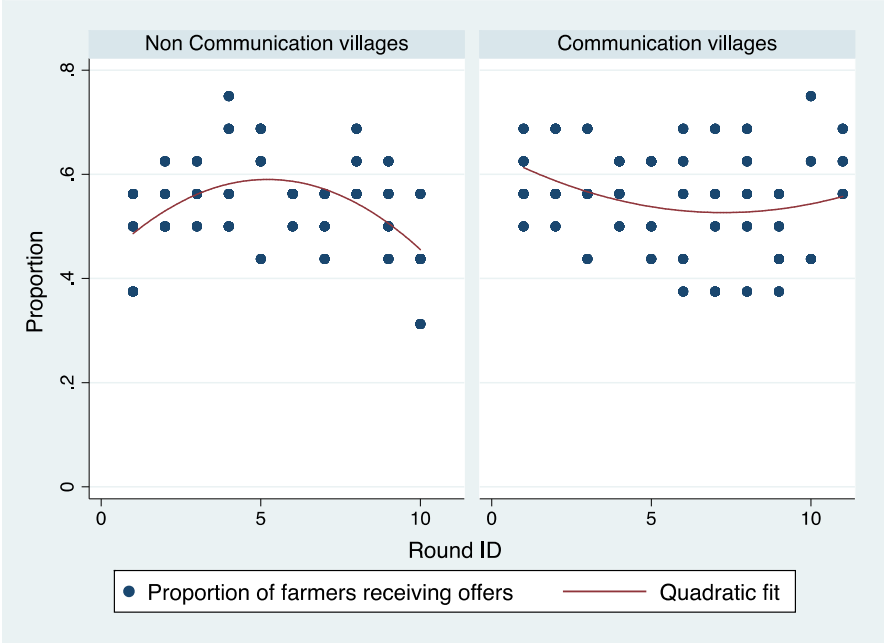
5.3. BROKERS' BEHAVIOR

Proportion of farmers receiving input on credit throughout the rounds

In this section, we explore the brokers' behaviors during the game and the rational behind them. Figure 4 presents how the proportion of farmers receiving offers changes over time in both the communication and non-communication treatments. Specifically, it shows a quadratic fit by treatment group and clearly indicates that in the communication villages, the proportion of people receiving offers decreases in the early rounds of the game, then picks up in the later rounds of the experiment, while the opposite occurs in the non-communication villages. In the communication treatments, the exchange of information between brokers allows them to effectively implement the multilateral punishment strategy and ostracize

defaulting farmers quickly. Once it is clearly established that defaulting is being detected and punished with high probability, the proportion of farmers receiving offers increases again and trade is sustained.

Figure 4: Patterns of offers throughout the rounds of the game



However, in the non-communication treatments, the proportion of farmers receiving offers of input loans increases in the earlier rounds. This is likely because at that early stage, brokers do not have much information about farmer’s repayment history and learn about farmer credibility at a slower rate than in the communication villages. Without communication, brokers appear to have kept trying new farmers randomly each round, only avoiding those that had not repaid them in previous rounds. Farmers were then able to take advantage of this delay in information acquisition because they could default 4 times (one for each broker) before potentially being completely ostracized. This likely explains why the proportion of farmers receiving offers increases in the earlier rounds, and then decreases only in the later

rounds of the experiment when sufficient information was gathered about all farmers' repayment behavior.¹¹

Brokers' Punishment strategy

As discussed earlier, the main underlying assumption of the dynamic incentives model is that brokers are collectively engaged in a multilateral punishment strategy. To test whether the brokers were actually using this punishment mechanism during the experiment, we estimated a Probit regression to test the effect of farmers' repayment history on their probability of receiving an input loan in a particular round. Specifically, we compute a credit score for each farmer that is updated in each round and takes into account all the history of offers received and repayments made. For each observation (farmer and round), we first create a score for the repayment made ($SCORE_t$). It is zero if the farmer did not get any offer (or got one, but did not accept) in that round. For farmers who took offers, the score takes on a value of 10, -5, or -10 for full, partial, and no repayment respectively. Then for each farmer i in round t , we create a credit score by weighting or discounting the sum of past scores, where the weights are the inverse of how far back repayment was made.

$$Credit\ Score_t = SCORE_{t-1}/1 + SCORE_{t-2}/2 + SCORE_{t-3}/3 + \dots + SCORE_{t-11}/11 \quad (7)$$

This method puts less weight on older repayment behavior and penalizes more recent default behavior.

The empirical model was specified as follow:

$$Prob(Y_t = 1) = A + B.X_t + e_t \quad (8)$$

where Y_t is the binary dependent variable taking values 1 when the farmer received an offer in round t , and 0 otherwise while X_t is the vector of explanatory variables in round t , and

¹¹ Also notice that in every round, a maximum of 12 farmers, representing 75% of farmers in the game in each village, can receive [an](#) offer of input credit. And this happens only if each of the 4 brokers make their 3 offers to all different farmers.

includes the farmer's updated credit score at time t, the communication treatment status of the village, the interaction between communication and credit score, and round dummies.

Table 7: Determinants of receiving input loan offer as function of past repayment by communication treatment

VARIABLES	Coefficients [P-values]		
	Non Communication Villages	Communication Villages	All
Credit score	0.009 [0.144]	0.026*** [0.001]	0.009 [0.129]
Communication			0.013 [0.875]
Interaction Credit score * Communication			0.017 [0.101]
Round dummies			
Round ID = 2	0.165 [0.373]	-0.028 [0.890]	0.069 [0.617]
Round ID = 3	0.217 [0.212]	-0.066 [0.754]	0.077 [0.572]
Round ID = 4	0.305* [0.097]	-0.016 [0.937]	0.145 [0.291]
Round ID = 5	0.335 [0.131]	-0.063 [0.757]	0.136 [0.364]
Round ID = 6	0.194 [0.261]	-0.104 [0.588]	0.046 [0.719]
Round ID = 7	0.091 [0.655]	-0.224 [0.178]	-0.066 [0.614]
Round ID = 8	0.313 [0.145]	-0.127 [0.523]	0.093 [0.524]
Round ID = 9	0.113 [0.579]	-0.308 [0.130]	-0.097 [0.499]
Round ID = 10	-0.095 [0.641]	-0.138 [0.477]	-0.116 [0.404]
Round ID = 11		-0.028 [0.909]	0.108 [0.617]
Constant	-0.063 [0.657]	0.221 [0.120]	0.072 [0.506]
Observations	800	848	1,648

*** p<0.01, ** p<0.05, * p<0.1

The model was estimated for the whole sample and also disaggregated by subsamples of communication treatment. The results presented in table 7 indicate that in the communication

villages, past repayment behavior (captured by credit score) is a significant and positive determinant of likelihood of getting input loan in current periods. Farmers who have defaulted in the past are less likely to receive an offer in the current period in the communication villages. But this is not the case in the non-communication villages. This result is consistent with the idea that the punishment mechanism is more effectively implemented when input suppliers are able to communicate and exchange information about farmers. In the communication villages, such information sharing is more easily done, allowing brokers to effectively punish defaulters by not offering them input credit in subsequent periods. Brokers in the non-communication villages did not seem to have been able to implement such punishment mechanism.

Moreover, we would imagine that the extra repayment information received by brokers in the communication villages would matter the most in the earlier rounds of the game. The reason is that in later rounds, brokers in the non-communication villages also collect information as they experience the behavior of farmers after giving them offers. In that sense we should expect to see, in round 2 of the game, that credit score affects much more the chances of getting offer in communication villages compared to non-communication villages in the second round of the game. We test this by running equation model 9 for round 2 only where credit score reflect only the repayment behavior in round 1. The results are presented in table 8 below.

Table 8: Determinants of receiving input loan offer as function of past repayment by communication treatment for round 2 only

VARIABLES	Coefficients [P-values]		
	Non Communication Villages	Communication Villages	All
Credit score	-0.015 [0.634]	0.069*** [0.005]	-0.015 [0.633]
Communication			0.018 [0.934]
Interaction Credit score * Communication			0.084** [0.033]
Constant	0.081 [0.577]	0.098 [0.523]	0.081 [0.576]
Observations	80	80	160

*** p<0.01, ** p<0.05, * p<0.1

The results presented in the table reflects the general results to the extent that credit score is a significant and positive determinant of the likelihood of getting input credit offer. But in addition, the results from table 2 do indicate a stronger and significant interaction effect between communication treatment and the credit score variable.

From a policy point of view, this result speaks to the importance of information sharing mechanisms and institutions, for the effectiveness of dynamic incentive mechanisms.

6. CONCLUSION AND IMPLICATIONS

This paper theoretically and empirically examines the importance of communication and information exchange (about repayment history) on the effectiveness of dynamic incentives in input credit arrangements. The theoretic model predictions were tested using experimental data collected from farmers in rural Nigeria. Econometric results using both Probit and Ordered Probit approaches support the model's predictions. We find consistent evidence that information exchange among input suppliers reduces default among farmers in input on credit

arrangements. Productivity shocks also affect default rates, though importantly this tends to be less significant when there is information exchange among input suppliers.

The findings of this study are in line with the literature on microfinance which has established a positive role of dynamic incentives and information sharing for the success of microfinance in situations where scoring mechanisms, collateral requirements, and sound legal systems are non-existent or weak (Ghosh and Ray 1999, Tedeschi 2006, McIntosh and Wydick 2009). This study makes a contribution to this literature by providing additional evidence of the importance of information sharing for the effectiveness of dynamic incentives using experimental methods in the specific context of input credit for farmers in a rural developing country setting.

Questions on how such input on credit arrangements can be implemented in practice are legitimate. Furthermore, the costs and other potential issues related to sharing information between input suppliers are also important. If the cost of information exchange is too high, this will increase the cost of the loan to the farmers. Therefore, it might be difficult to sustain this input on credit arrangement without some external subsidies (may be from governments or development NGOs), unless the input is so profitable for farmers that they are willing to pay a high enough price for the input loan. This represents a threat to input loans to the poorest. According to Morduch (2000) input suppliers providing loans to people in more remote areas may have to make a decision to either curtail outreach to these clients or face the fact that full financial self-sufficiency may not be possible.

However, it may be possible to leverage the microfinance experience. Information sharing is already being incorporated as part of microfinance best practices. The establishment of Credit bureaus by microfinance institutions in several regions of the globe serves as evidence

(Campion and Valenzuela 2001, de Janvry, McIntosh et al. 2010). Input suppliers themselves might also benefit from such a concept by establishing “input credit bureaus” that collect repayment history information about farmers to whom they provide input loans. Such information can then be shared within the network of input suppliers and play the same role as consumer credit scores in developed countries.

Alternatively, the input suppliers can rely on local village level retailers to distribute their product to farmers in very remote areas. Given that credit bureaus cannot be established everywhere, village level retailers with necessary social capital can be a potential solution since they have information about the farmers living in their communities. Also, they can more easily exchange information about repayment history with local retailers in neighboring villages to ensure defaulters do not get input loans from nearby village. This is possible because people in very remote rural areas usually know each other – they typically go to the same markets, health care facilities and places of worship. Also, with the promotion of the use of Information and Communication Technology (ICT) in rural areas, this communication and exchange of information between local retailers from different villages could be facilitated to ensure effectiveness of the dynamic incentive and solve strategic default issues. Finally it might help to think about ways to combine input credit arrangements with agricultural insurance schemes so that farmers who are unable to repay due to negative economic shocks do not face harsh punishment from input suppliers.

Appendix 1

Broker's ID:

Village name:

ROUND N*:

Farmers ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Total
Fertilizer Offer made (0kg, 100kg)																	
Offer Accepted/declined (1=yes/0=No)																	
Final sale realized (in Naira)																	
Farmer's Repayment behavior (0, ½, 1)																	
Net payoff to brokers (in Naira)																	

Appendix 2

Farmers' ID:

Village name:

ROUND N*

Brokers ID	1	2	3	4	Total
Offer received					
Accept/Decline (Please circle for YES and cross for NO)					

Source....

Amount owed			
Weather state (good/bad)			
Money received after harvest			
Repayment decision (please circle one)	0%	50%	100%
Net payoff to farmer			

Appendix 3

Implementation and sequence of actions in each round of the game

The experiment was run by a team of 6 enumerators. At the beginning of the experiment, the enumerators first identified the selected participants in the village. The selected participants who were not available were replaced by other people randomly drawn from the list of the village household heads. Then the previous instructions were presented and explained to all participants. Then the participants were separated into farmers and brokers group and received the appropriate sheets (broker sheet and farmer sheet) on which they are supposed to indicate their decisions throughout the game. Then a trial round called round 0 was executed to allow participants to get a better sense of what is going to happen during the experiment. Participants were aware that the round 0 is just a practice and that their answer to that round would not count for the payoff they would receive at the end of the game. After making sure everyone had completely understood the rules of the game, the real experiment starts with round 1 and goes down according to the following steps:

1. Broker makes offer to the farmers
2. Enumerators collect the brokers sheets then transfer offers made onto the farmers' sheets
3. Enumerators give farmers their sheets so they can examine the offers received from each broker, and make their accept/decline decisions
4. Enumerators collect the farmers sheets and transfer accept/decline decisions onto the brokers sheets
5. Enumerators calculate the amount owed by farmers to each brokers and translate onto the farmers sheets.

6. A farmer takes his turn and will flip the coin publicly to determine the weather state.
This is also communicated to all players and translated onto the farmers sheets
7. Enumerators give farmers their sheets so they can make repayment decision
8. Enumerators collect the farmers' sheets and transfer repayment decision onto the brokers' sheets
9. Enumerators calculate payoffs for both farmers and brokers, and translate onto their respective sheets.

In the communication treatment villages, farmer's total repayment is reported on the brokers' public board for all the brokers to see before the beginning of the following round when they decide again offer to be made.

REFERENCES

Armendáriz de Aghion, B. and J. Morduch (2000). "Microfinance beyond group lending." Economics of transition **8**(2): 401-420.

Besley, T. (1995). "Savings, credit and insurance." Handbook of development economics **3**: 2123-2207.

Campion, A. and L. Valenzuela (2001). "Credit bureaus: a necessity for microfinance? Microenterprise Best Practices." Development Alternative, Inc., Bethesda, Maryland.

Conning, J. and C. Udry (2007). "Rural financial markets in developing countries." Handbook of agricultural economics **3**: 2857-2908.

de Janvry, A., et al. (2010). "The supply- and demand-side impacts of credit market information." Journal of Development Economics **93**(2): 173-188.

De Janvry, A., et al. (2010). "The supply-and demand-side impacts of credit market information." Journal of Development Economics **93**(2): 173-188.

Djankov, S., et al. (2007). "Private credit in 129 countries." Journal of financial Economics **84**(2): 299-329.

Dorward, A., et al. (1998). Smallholder cash crop production under market liberalisation: a new institutional economics perspective, CAB International.

Fudenberg, D. and J. Tirole (1991). "Game theory. 1991." Cambridge, Massachusetts **393**.

Ghosh, P. and D. Ray (1999). Information and enforcement in informal credit markets, Boston University, Institute for Economic Development.

Greif, A. (1993). "Contract enforceability and economic institutions in early trade: The Maghribi traders' coalition." The American economic review: 525-548.

Greif, A., et al. (1994). "Coordination, commitment, and enforcement: The case of the merchant guild." Journal of political Economy: 745-776.

Harrison, G. W. and J. A. List (2004). "Field experiments." Journal of Economic Literature: 1009-1055.

Hulme, D. and P. Mosley (1996). Finance against poverty, Psychology Press.

Jappelli, T. and M. Pagano (2002). "Information sharing, lending and defaults: Cross-country evidence." Journal of Banking & Finance **26**(10): 2017-2045.

Johnston, B. F. and J. W. Mellor (1961). "The role of agriculture in economic development." The American economic review: 566-593.

Kandori, M. (1992). "Social norms and community enforcement." The review of economic studies **59**(1): 63-80.

Kelly, V., et al. (2003). "Expanding access to agricultural inputs in Africa: a review of recent market development experience." Food Policy **28**(4): 379-404.

Kelly, V. A., et al. (2007). Fertilizer use in African agriculture: Lessons learned and good practice guidelines, Washington, DC: World Bank.

Luoto, J., et al. (2007). "Credit information systems in less developed countries: A test with microfinance in Guatemala." Economic Development and Cultural Change **55**(2): 313-334.

Mas-Colell, A., et al. (1995). Microeconomic theory, Oxford university press New York.

McIntosh, C. and B. Wydick (2009). What do credit bureaus do? understanding screening, incentive, and credit expansion effects. Economics.

Morduch, J. (2000). "The microfinance schism." World development **28**(4): 617-629.

Padilla, A. J. and M. Pagano (1997). "Endogenous communication among lenders and entrepreneurial incentives." Review of Financial Studies **10**(1): 205-236.

Padilla, A. J. and M. Pagano (2000). "Sharing default information as a borrower discipline device." European Economic Review **44**(10): 1951-1980.

Poulton, C., et al. (1998). "The revival of smallholder cash crops in Africa: public and private roles in the provision of finance." Journal of International Development **10**(1): 85-103.

Sadoulet, L. (2005). "Learning from Visa®? Incorporating insurance provisions in microfinance contracts." Insurance against poverty. Oxford University Press, Oxford: 387-421.

Sheahan, M. and C. B. Barrett (2014). "Understanding the agricultural input landscape in sub-Saharan Africa: Recent plot, household, and community-level evidence." World Bank Policy Research Working Paper(7014).

Tedeschi, G. A. (2006). "Here today, gone tomorrow: Can dynamic incentives make microfinance more flexible?" Journal of Development Economics **80**(1): 84-105.

Vercammen, J. A. (1995). "Credit Bureau Policy and Sustainable Reputation Effects in Credit Markets." Economica **62**(248): 461-478.

Welfare-increasing reputation effects arise in credit markets when adverse selection gives rise to borrower reputation formation incentives that mitigate moral hazard problems. This paper shows that welfare stemming from reputation effects will diminish over time as the private information of borrowers is revealed to lenders in the form of lengthening credit histories. Aggregate borrower welfare may therefore decrease over time unless reputation effects can be sustained. Restricting a lender's access to a borrower's credit history via credit bureau policy is shown to be one method of sustaining reputation effects and preventing a decline in welfare.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data, MIT press.