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

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Abstract

Generally, rural credit markets in developing countries are characterized by market failures associated with imperfect information and 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. The concept of dynamic incentives is used to develop conditions that minimize the potential for strategic default when offering 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 article shows that the existence of an information exchange system, amongst input sellers, which mimics the role of a "credit score", can effectively deter default behavior by farmers receiving inputs on credit. Moreover, productivity shocks that affect the return to the use of inputs also affect the opportunity cost of repayment, and thus farmer's decision to repay.

Keywords: Microfinance; Asymmetric Information; Strategic Default; Dynamic Incentives; Agricultural Inputs.

JEL Classifications: C73, D82, G2, G20, O12, O16

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 smallholder 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 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 et al., 2003). Generally, credit markets in rural SSA are characterized by market failures associated with imperfect information in the presence of risk (Dorward et al., 1998, Poulton 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 loose the potential gain from trade by not completing the transaction. However, input provision on credit can potentially be facilitated if it is commonly known that failure to repay implies future inability to get input on credit. Essentially, when the interaction is repeated over an indefinite period of time, input on credit arrangements can be sustained as long as farmers value gains from future access to fertilizer more than the temporary gain from reneging on current debt contracts, and if the threat of being prevented from accessing future input on credit is credible.[i] However, when multiple input sellers exist in the market, how can one ensure credibility of the threat since farmers can potentially approach another provider after defaulting? This article adapts a game theoretic model drawn from the microfinance literature to answer this question, and then tests the model predictions using data from a framed field experiment conducted with farmers in rural Nigeria.

This article makes several important contributions to the literature on agricultural input loan provision (by private input suppliers) in developing countries. First, there is no study (the authors are aware of) that has focused explicitly on strategic default in cases in which private input suppliers would sell inputs on credit to farmers and collect payment after harvest. While such input on credit arrangements share some characteristics of microfinance, they also have their peculiarities such as being in-kind, less prone to moral hazard, and mostly threatened by strategic default. Consequently, we build on the microfinance literature and develop ideas about additional measures that can help alleviate strategic default problems in input on credit arrangements. Specifically, we extend previous work on the role of dynamic incentives in addressing strategic default by exploring the importance of information sharing among credit suppliers for the effectiveness of dynamic incentives in a rural developing country setting. This article is timely given the recent focus by policy makers and development practitioners on private sector led approaches to input market development in developing countries. It informs the likely strategies that are necessary to encourage the development of private sector led input on credit provision. This article also adds to the limited number of studies that use framed field experiments, and is also one among very few examples of an empirical application of the concepts of credit information sharing and dynamic incentives mechanisms.

The rest of the article is organized as follow. In section 2, we provide a summary of the relevant literature on strategic default. Section 3 presents the theoretical framework from which empirically testable hypotheses are drawn. 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. DEALING WITH STRATEGIC DEFAULT

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. This approach 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 mechanism effectively transfers 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.[ii]

There is a 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 strategic default without relying on the group incentives used in the microfinance literature. Using a model based on a single microfinance institution ("lender") and a group of micro entrepreneurs ("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 that punishment should instead 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. But in reality there are usually several lenders and information is rarely perfectly shared amongst them. Tedeschi's 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 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 (McIntosh and Wydick, 2009, Padilla and Pagano, 1997, Padilla and Pagano, 2000, Vercammen, 1995). The general conclusion is that credit information sharing substantially increases lending, and decreases borrowers' default (Djankov et al., 2007, Jappelli and Pagano, 2002, Luoto et al., 2007, de Janvry 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 (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*, 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 to identify 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. de Janvry et al. (2010) exploited the lack of awareness 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 existence and workings of the bureau.[iii] 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.

In this article, we develop a theoretical model that 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 models in Padilla and Pagano (2000) and McIntosh and Wydick (2009) the article features a simple repeated game model of input credit and stresses the importance of information sharing amongst lenders, for farmers' repayment decision. The model also embeds the presence of a productivity shock that may affect farmers' repayment abilities or incentives. We then test the 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 $n_s = \{1, \ldots, N_s\}$ and a set of farmers $n_b = \{1, \ldots, N_b\}$. By assumption, the farmers need to buy inputs for agricultural production but they do not have the capital to pay upfront and thus must buy it on credit. The firms are agricultural input dealers or brokers who have inputs that they seek to sell. They consider selling on credit in addition to cash sales in order to maximize the volume of sales.[iv] We fix the price of the input and assume all farmers receive the same input bundle so that brokers maximize profits by selling more inputs bundles to farmers with a higher likelihood of repaying. In each stage of the game, each broker 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 on 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 i.e. that agricultural output is always higher with the use of the input than without. Output without using the input is denoted R_{none} but there is a random productivity shock $\eta = \{Good, Bad\}$ that is realized after the input has been acquired and used.[v] The return to the use of the input, $R_\eta = \{R_{good}, R_{bad}\}$, is assumed to be lower when the shock is bad and higher when it is good (i.e., $R_{good} > R_{bad} > R_{none}$).

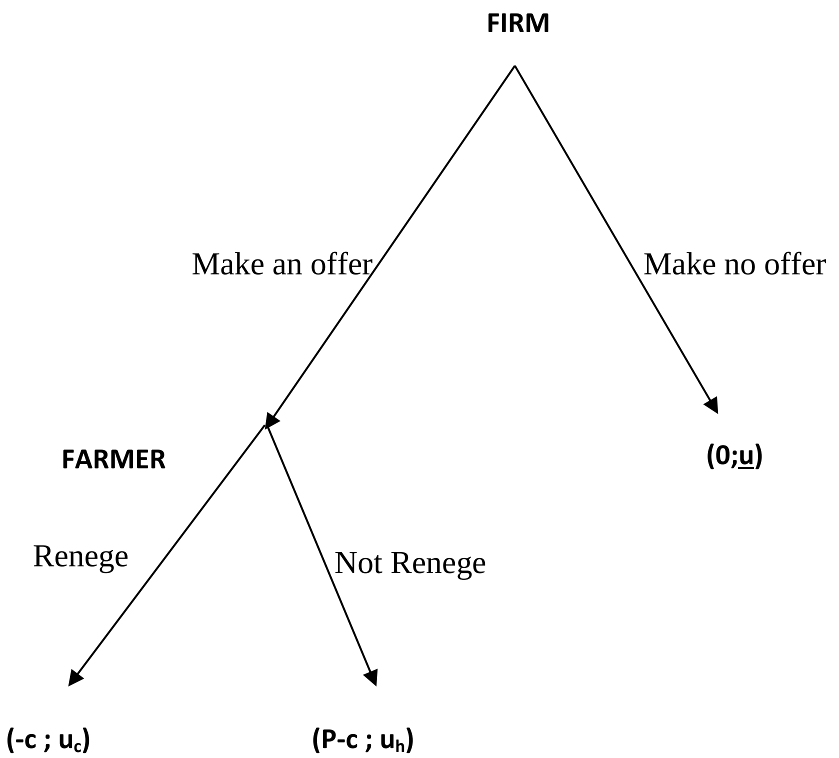
In every period of the game, the firm's strategy can be described by a function $\sigma_i^S\colon \mathrm{H}^t \to \{Offer, Not\ offer\}$ for all farmers i $\in$ n_b, where $\mathrm{H}^t = \{\mathrm{H}^t_{Public} \cup \mathrm{H}^t_{Private}\}$ is the set of information available to firm s, and which contains, up to time t-1, the repayment history of the all the farmers including farmer i. Notice that we distinguish between public and private information. The public information set for a firm j $\in$ n_s contains the repayment history for all farmers that firm j has not made an offer to in past periods and therefore does not know privately how they behaved in those periods. The private information set contains repayment information about those farmers firm j has made offers to in past periods and therefore has observed farmer repayment behavior. The farmer's strategy in each period (given he receives an offer) is a mapping σ_j^B from the realization of productivity shock η to the set of possible actions $\{Renege, Not\ renege\}$, 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 set.[vi]

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. P is the price at which the input is being sold to the farmer, and c is the cost of the input to the firm. The firm's reservation payoff in case of no transaction with a farmer is 0. We assume that the firm's 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 R_{none} if they do not receive an offer in that stage and thus do not use any of the input. If a farmer receives an offer, their payoff function is described by a mapping g: $\{R_{good}, R_{bad}\} \times \{Renege, Not\ renege\} \to \mathbb{R}$. Their payoff depends on their repayment decision and the realization of the productivity shock. We define $u_{h\eta}$, $u_{c\eta}$, and $\underline{u}$ to be the farmer's state contingent utilities from not reneging, reneging, and not using the agricultural input, respectively.

<u>The missing market problem in a single period game</u>

In the single period case, each matching between farmer and firm in the game described above can be represented by the extensive form game in figure 1. As depicted, the farmers' dominant strategy 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 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 of the game is the empty set. 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 not to 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 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 the input-on-credit contract using dynamic incentives

As noted by Conning and Udry (2007), if the above interaction is repeated, it may be possible to generate incentives for the farmer to repay in every period, provided that the threat of no further loan activity is credible and sufficiently punishing. To illustrate, consider an infinitely repeated game where each round is the above stage game. Recall that, while in reality famers 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 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:

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

Recall that $\mathrm{H}^t = \mathrm{H}_{Public}^t \cup \mathrm{H}_{Private}^t$ 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 aspect 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, if default information is shared publicly amongst firms and all firms agree to collectively punish a defaulter, the farmer is forced to behave as if in an exclusive relationship with the firm.[vii]

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

$$\mathrm{V}_{\mathrm{h}\eta} = \mathrm{u}_{\mathrm{h}\eta} + \frac{\delta}{1-\delta} \tag{1}$$

where δ and u_h are, respectively, the discount factor and payoff from not reneging 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:

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

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 θ=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 θ=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 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:

$$\mathbf{V_{h\eta} \geq V_{c\eta}}, \qquad \boldsymbol{\eta = \{Good, Bad\}} \tag{3}$$

$$\mathbf{u_{h\eta} + \frac{\delta}{1-\delta} E_\eta u_h \geq u_{c\eta} + \frac{\delta}{1-\delta}\left[\theta E_\eta \underline{u} + (1-\theta) E_\eta u_h\right]} \tag{4}$$

This is equivalent to:

$$\boldsymbol{\delta} \geq \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{\theta}\frac{\left(E_{\eta}u_{\mathrm{h}}-E_{\eta}\underline{u}\right)}{\mathrm{u}_{\mathrm{c}\eta}-\mathrm{u}_{\mathrm{h}\eta}}} = \boldsymbol{\delta}_{\boldsymbol{\eta}}^{*} \tag{5}$$

Equations 5 demonstrates 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 the productivity shock is independently and identically determined in each round, the per-period forgone benefit from continuing to get inputs on credit ($E_{\eta}u_{\mathrm{h}} - E_{\eta}\underline{u}$) 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 ($\mathrm{u}_{\mathrm{c}\eta} - \mathrm{u}_{\mathrm{h}\eta}$) is in the current period. In particular, $\mathrm{u}_{\mathrm{c}\eta} - \mathrm{u}_{\mathrm{h}\eta}$ 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, $\mathrm{u}_{\mathrm{c},Good} - \mathrm{u}_{\mathrm{h},Good} > \mathrm{u}_{\mathrm{c},Bad} - \mathrm{u}_{\mathrm{h},Bad}$ and therefore, in the good state of the nature, δ_{η}^{*} is lower than in bad state of nature, *ceteris paribus*.

Many empirical hypotheses can be derived from equation 5. We focus on 2 main ones in this study:

<u>Hypothesis 1</u>: Equation 5 indicates that as θ increases, δ_{η}^{*} decreases for all η. 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 sufficiency 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**."

<u>Hypothesis 2</u>: Equation 5 also indicates that as ($u_{c\eta} - u_{h\eta}$) increases, δ_η^* increases for all η. 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.

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

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.

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).[viii] 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 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 round.[ix] 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 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 ago dealers to make offers.[x] 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 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).

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 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 necessarily spread out the offers across all farmers in each round. Consequently, while 1205 offers 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 an initial, though still weak, indication that communication and exchange of information can allow the market to perform better due to the reduced information asymmetry problem.

In the following sections, we focus on farmers and brokers' behaviors and analyze the role of productivity 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

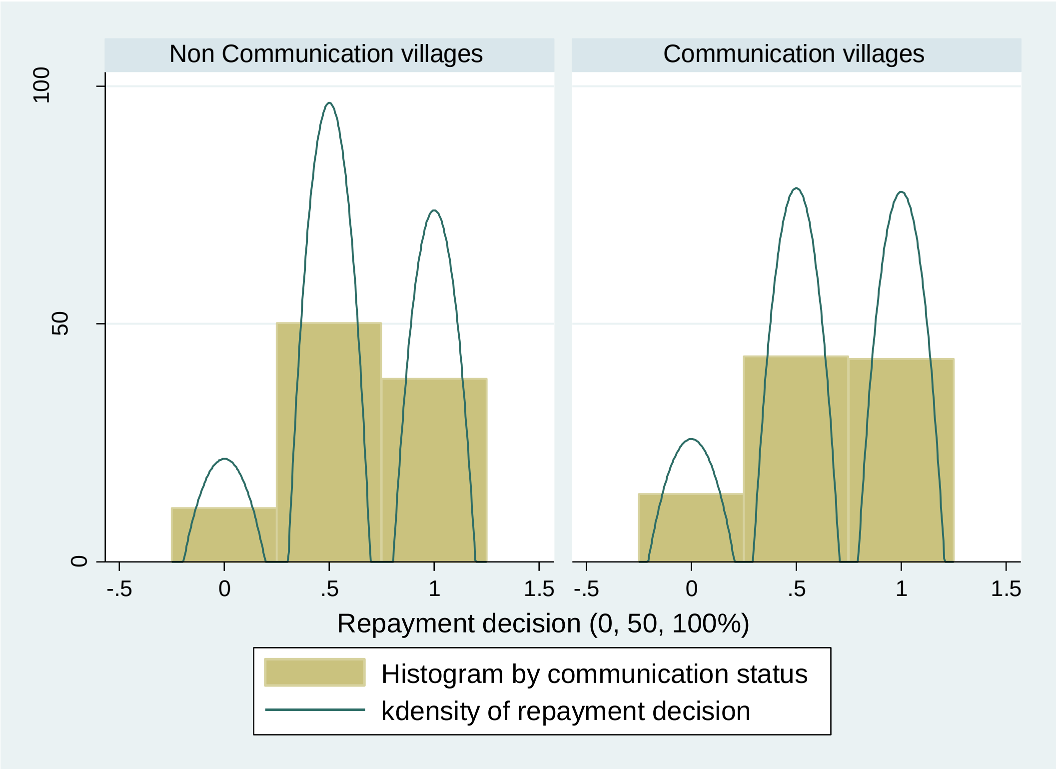
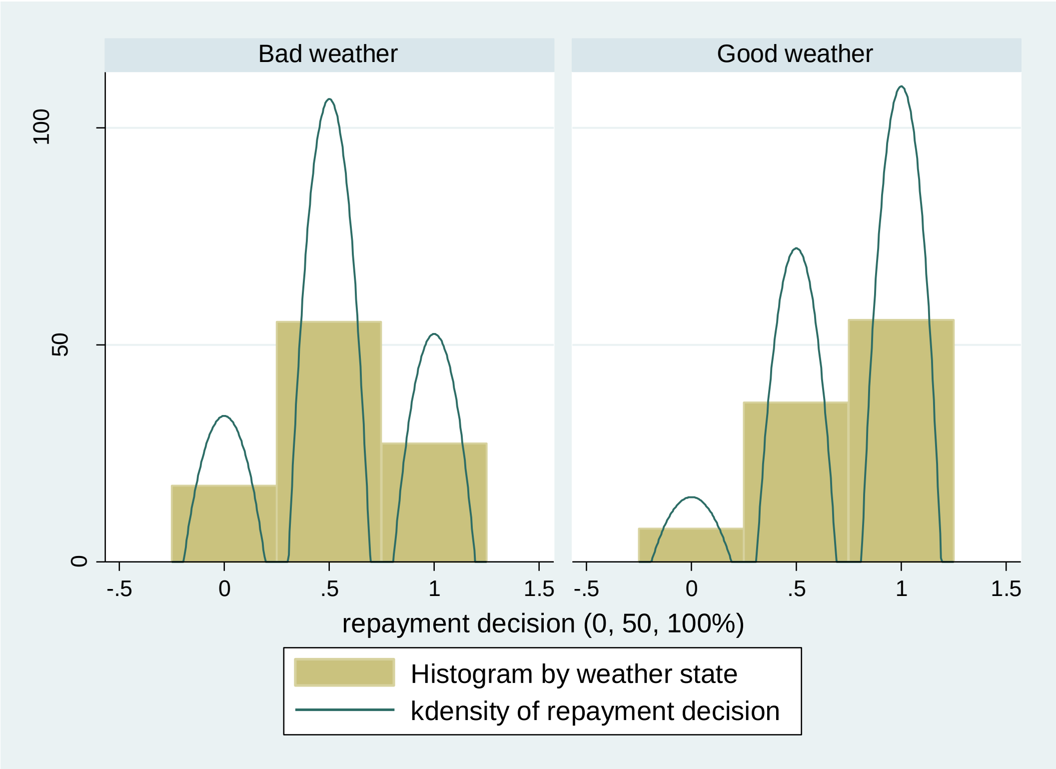


Figure 3 indicates that default rates are higher when the weather state is bad (negative shock). Again, defining 'default' as the proportion of farmers who did not repay fully (i.e. 100% of what was owed), the total default rate during bad weather rounds was 72.77% (55.32% repaid half while 17.45% did 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. Overall, the descriptive analysis of farmer behavior is consistent with the hypotheses derived from the theoretic model.

Figure 3: Histogram of repayment decision by weather state



<u>Econometric model</u>

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.

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

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.[xi] 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% lower when input suppliers are able to communicate and exchange information about repayment history.[xii] 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 et al. (2007), and de Janvry et al. (2010).

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

	ORDERED PROBIT		PROBIT	
VARIABLES	**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
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

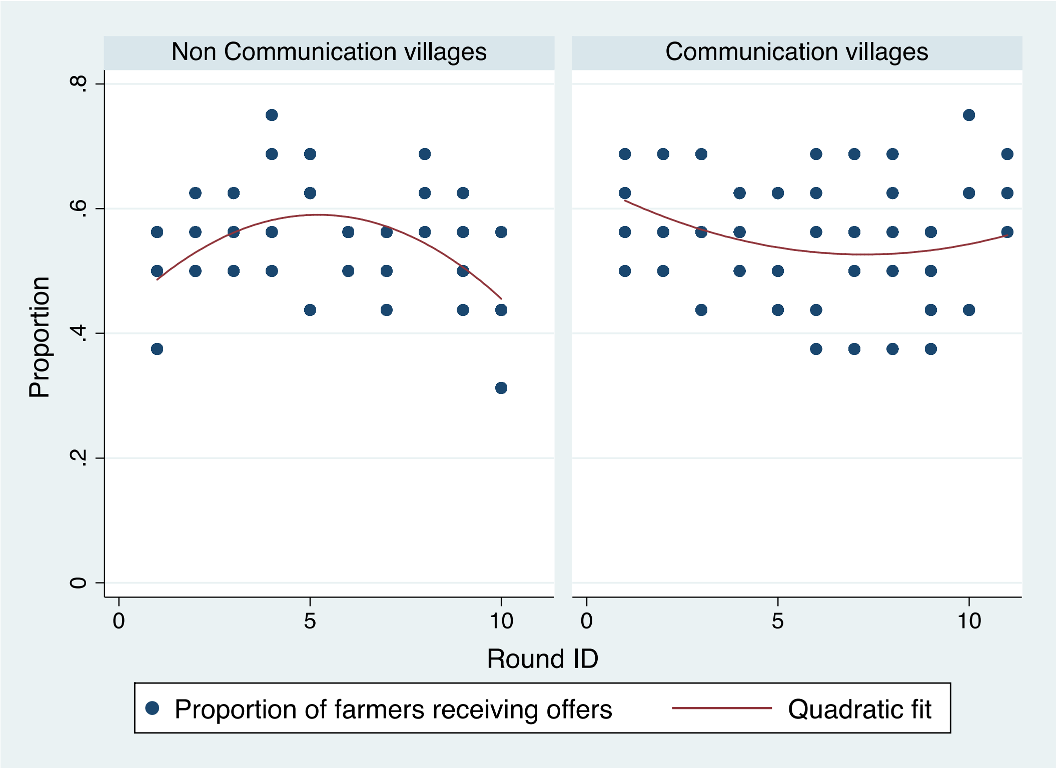
Similarly, both the Probit and Ordered Probit regressions indicate a positive and significant effect of weather state on farmers' repayment decisions. In fact, the Probit margin estimates indicate that default rates are 38% higher when the weather is bad. This is also consistent with our research hypothesis 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' actions 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. It appears that 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.[xiii]

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 repayment 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 repayment 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 repayment scores, were the weights are the inverse of how far back repayment was made.

$$\textit{Credit Score}_t = SCORE_{t-1}/1 + SCORE_{t-2}/2 + SCORE_{t-3}/3 + ... + SCORE_{t-11}/11 \qquad (7)$$

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

The empirical model was specified as follow:

$$\boldsymbol{Prob(Y_t = 1) = A + B.X_t + e_t} \qquad (8)$$

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

*** p<0.01, ** p<0.05, * p<0.10 $^{+}$ p<0.15

The model was estimated for the whole sample and separately for each 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 the likelihood of getting input on credit 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 do not seem to have been able to implement such punishment mechanism.

Since all brokers collect information on farmer behavior over time, we would expect the extra repayment information received by brokers in the communication villages to be more important in the earlier rounds of the game. In later rounds, brokers in the non-communication villages have also collected information as they experience the behavior of farmers after giving them offers. Consequently, we expect to see a stronger effect of the credit score on the chances of getting an offer in communication villages in round 2 compared to non-communication villages. 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 presented in table 8 reflect the general results that the credit score is a significant and positive determinant of the likelihood of getting an input on credit offer. But in addition, the results from table 2 indicate a stronger and statistically significant interaction effect between communication treatment and the credit score variable.

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	0.069***	-0.015
	[0.634]	[0.005]	[0.633]
Communication			0.018
			[0.934]
Interaction Credit score * Communication			0.084**
			[0.033]
Constant	0.081	0.098	0.081
	[0.577]	[0.523]	[0.576]
Observations	80	80	160

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

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 article theoretically and empirically examined 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 consistent 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 (Tedeschi, 2006, Ghosh and Ray, 1999, 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 famers in a rural developing country setting.

Questions on how such input on credit arrangements can be implemented in practice are legitimate. 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 (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. 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 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, our results indicate that it is important 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. Index based insurance schemes targeted at private input suppliers in developing countries are an option to be explored to encourage input suppliers to engage in credit arrangements with smallholders engaged in agricultural activities with non-trivial production risks and uncertainty due to weather.

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.

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ENDNOTES

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[i] This is a direct implication of the Folk theorem.

[ii] Details about the mechanism and limitations of group lending are provided in Stiglitz, 1990, Besley and Coate, 1995, Armendáriz de Aghion and Morduch, 2000, etc.

[iii] 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.

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

[v] This can be thought of as a weather shock. Good weather implies higher productivity *ceteris paribus*.

[vi] Later, in our experimental design, we impose the constraints that farmers can only accept one offer in each period, and firms can only make offers to a limited number of farmers. These assumptions only simplify the game for the participants without fundamentally changing the implications of the model and the consequent empirical hypotheses.

[vii] Note that the collective punishment assumes that firms in competition have incentive to punish farmers who defaulted any of the firms even if they have not been cheated on personally. Greif, 1993, and Kandori, 1992 describe reasons and institutions that can guarantee this.

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

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

[x] 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.

[xi] The insignificance of the round dummies implies that farmers behaving in a particular way during specific rounds did not drive the communication and weather effects. 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 form 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).

[xii] 18% is higher than the effect found in the descriptive analysis because the weather state was not controlled for.

[xiii] 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. This happens only if each of the 4 brokers make their 3 offers to all different farmers.