<u>Online Appendix</u>
for

<u>Credit Market Consequences of Improved Personal Identification: Field Experimental Evidence from Malawi</u>

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Appendix A: Background on project partners, loan details, and full text of training script

Background on Cheetah Paprika (CP)

Extension services provided by CP consist of preliminary meetings to market paprika seed to farmers and teach them about the growing process, additional group trainings about farming techniques, individual support for growers provided by the field assistants, and information about grading and marketing the crop. The farmer receives extension services and a package of seeds, pesticides and fungicides at wholesale rates in exchange for the commitment to sell the paprika crop to CP at harvest time. Although CP is by far the largest paprika purchaser in the country, it does not provide credit to farmers because of the risks involved in contract enforcement.[1] CP has a staff of six extension officers and 15 field assistants in the locations chosen for the study. The staff maintain a database of all current and past paprika growers and handles the logistics of supplying farmers with the package of inputs as well as the purchase of the crop.

In July 2007, CP asked farmers in the study areas to organize themselves into clubs of 15 to 20 members to accommodate MRFC's group lending rules.[2] Most of these clubs were already in existence, primarily to ease delivery of Cheetah extension services and collection of the crop. During the baseline survey and fingerprinting period (August and September 2007), CP staff provided a list of paprika growing clubs in each locality to be visited in each week.

Background on MRFC and loan details

MRFC is a government-owned microfinance institution and is the largest provider of rural finance, with a nationwide outreach of 210,000 borrowers in 2007. To obtain the loan-financed production inputs, borrowers took an authorization form from MRFC to a pre-approved agricultural input supplier who provided the inputs to the farmer and billed MRFC at a later date. Sixty percent of the loan went towards fertilizer (one 50 kilogram bag of D-compound fertilizer and two 50 kilogram bags of CAN fertilizer); the rest went toward the CP input package: thirty-three percent covered the cost of nine bags of pesticides and fungicides (2 Funguran, 2 Dithane, 2 Benomyl, 1 Cypermethrin, 1 Acephate and 1 Malathion) and the remaining seven percent for

[1] In 2007, CP purchased approximately eighty-five percent of the one thousand tons of paprika produced annually in Malawi.
[2] A typical CP group has between 15 and 30 farmers and is organized around a paprika collection point. MRFC's lending groups have at most 20 farmers, so some of the CP groups participating in the study had to be split to be able to access MRFC's loans.

the purchase of 0.4 kilograms of seeds.[3] While all farmers that took the loan were given the CP package, farmers had the option to borrow only one of the two available bags of CAN fertilizer. Expected yield for farmers using the package with two bags of CAN fertilizer on one acre of land was between 400 and 600 kg, compared to 200 kg with no inputs.[4] In keeping with standard MRFC practices, farmers were expected to raise a 15 percent deposit, and were charged interest of 33 percent per year (or 30 percent for repeat borrowers).

Biometric training script

Benefits of Good Credit
Having a record of paying back your loans can help you get bigger loans or better interest rates.

Credit history works like trust. When you know someone for a long time, and that person is honest and fair when you deal with him, then you trust him. You are more likely to help him, and he is more likely to help you. You might let him use your hoe (or something else that is important to you), because you feel sure that he will give it back to you. Banks feel the same way about customers who have been honest and careful about paying back their loans. They trust those customers, and are more willing to let them borrow money.

MRFC already gives customers who have been good borrowers a reward. It charges them a lower interest rate, 30 percent instead of 33 percent. That means that for the loan we have described today, someone who has a good credit history would only have to pay back 8855, instead of 8971.[5]

Another way that banks might reward customers they trust is by letting them borrow bigger amounts of money. Instead of 7700 MK to grow one acre of paprika, MRFC might lend a trusted customer 15400, to grow two acres.

To earn trust with the bank, and get those rewards, you have to be able to prove to the bank that you have taken loans before and paid them back on time. You can do that by making sure that you give the bank accurate information when you fill out loan applications. But if you call yourself John Jacob Phiri one year, and Jacob John Phiri the next year, then the bank might not figure out that you are the same person, so they won't give you the rewards you have earned.

Costs of Bad Credit
But trust can be broken. If your neighbor borrows your radio and does not give it back or it gets ruined, then you probably wouldn't lend him anything else until the radio had been replaced.

Banks work the same way. If you take a loan and break the trust between yourself and the bank by not paying back the loan, then the bank won't lend to you again. This is especially true if you have a good harvest but still choose not to pay back the loan.

When you apply for a loan, one of the things that a bank does to decide whether or not to accept your application is to look in its records to see if you have borrowed money before. If you have borrowed but not paid back, then you will be turned down for the new loan. This is like you asking your neighbors if someone new shows up in the village and asks you to work for him. You might first ask around to see if the person is fair to his employees and

[3] The loan amount varied across locations because of modest differences in the transport cost for fertilizer. The cost of the CP package was the same in all locations.
[4] Yield is computed under the conservative assumption that farmers will divert one 50 Kg bag of CAN fertilizer towards maize cultivation. While larger quantities of inputs would result in higher output for experienced paprika-growers, the package described here was designed by extension experts to maximize expected profits for novice, small-holder growers.
[5] Loan amounts mentioned in the script are lower than actual loan amounts observed in the data because fertilizer prices rose somewhat in the time between the initial intervention (in Aug-Sep 2007) and loan disbursement (Nov 2007).

pays them on time. If you learn that the person does not pay his workers, then you won't work for him. Banks do the same thing by checking their records.

MRFC does not ever give new loans to people who still owe them money. And MRFC shares information about who owes money with other banks, so if you fail to pay back a loan from MRFC, it can stop you from getting a new loan from OIBM or another lender, also.

Remainder of script is administered to fingerprinted clubs only

Biometric Technology
Fingerprints are unique, which means that no two people can ever have the same fingerprints. Even if they look similar on a piece of paper, people with special training, or special computer equipment, can always tell them apart.

Your fingerprint can never change. It will be the same next year as it is this year. Just like the spots on a goat are the same as long as the goat lives, but different goats have different spots.

Fingerprints can be collected with ink and paper, or they can be collected with special machines. This machine stores fingerprints in a computer. Once your fingerprint is stored in the computer, then the machine can recognize you, and know your name and which village you come from, just by your fingerprint! The machine will recognize you even if the person who is using it is someone you have never met before. The information from the machines is saved in many different ways, so if one machine breaks, the information is still there. Just like when Celtel's building burned, people's phone numbers did not change.

Administer the following after all fingerprints have been collected:

Demo
Now, I can figure out your name even if you don't tell me. Will someone volunteer to test me? *(Have a volunteer swipe his finger, and then tell everyone who it was).*

The bank will store information about your loans with your fingerprint. That means that bank officers will know not just your name, but also what loans you have taken and whether or not you have paid them back. They will be able to tell all of this just by having you put your finger on the machine.

Before, banks used your name and other information to find out about your credit history. But now they will use fingerprints to find out. This means that even if you tell the bank a different name, they will still be able to find all of your loan records. Names can change, but fingerprints cannot.

Having your fingerprint on file can make it easier to earn the rewards for good credit history that we talked about earlier. It will be easy for the bank to look up your records and see that you have paid back your loans before. It will also be easier to apply for loans, because there will be no new forms to fill out in the future!

But, having your fingerprint on file also makes the punishment for not paying back your loan much more certain. Even if you tell the bank a different name than you used before, or meet a different loan officer, or go to a different branch, the bank will just have to check your fingerprint to find out whether or not you paid your loans before. Having records of fingerprints also makes it easy for banks to share information. Banks will share information about your fingerprints and loans. If you don't pay back a loan to MRFC, OIBM will know about it!

Appendix B: Details on biometric fingerprinting technology

In consultation with MRFC's management, fingerprint recognition was chosen over face, iris or retina recognition because it is the cheapest, best known and most widely used biometric identification technology. Fingerprinting technology extracts features from impressions made by the distinct ridges on the fingertips and has been commercially available since the early 1970s.

Loan applicants from fingerprinted clubs had the image of their right thumb fingerprint captured by an optical fingerprint scanner attached to a laptop. To maximize accuracy, farmers washed their thumbprints prior to scanning, and the scanner was also cleaned after each impression. During collection, about 2 per cent of farmers had the left thumbprint recorded (instead of the right) because the right thumbprint was worn out. (Many farmers grow tobacco, which involves thumb usage during seedling transplantation that can wear out a thumbprint over many years.)

Upon scanning, the fingerprint image was enhanced and added to the borrower database. We purchased the VeriFinger 5.0 Software Development Kit from Fulcrum Biometrics and had a programmer develop a data capture program that would allow the user to (i) enter basic demographic information such as the name, address, village, loan size and the unique BFIRM identifier, (ii) capture the fingerprint with the scanner and (iii) review the fingerprint alongside the demographic information.

Appendix C: Variable definitions

Data used in this paper come from two surveys: a baseline conducted in August-September 2007 and a follow-up survey about farm outputs and other outcomes conducted in August 2008. We also used administrative data about loan take-up and repayment, obtained from MRFC's internal records.

Baseline characteristics (from baseline survey)

Male equals 1 for men and 0 for women.
Married equals 1 for married respondents and 0 for respondents who are single, widowed, or divorced.
Age is respondent's age in years. In regressions, we use dummies for 5-year age categories rather than a continuous measure of age.
Years of education is years of completed schooling, and is top-coded at 13. In regressions, we use dummies for years of completed schooling, rather than a continuous measure of education.
Risk taker equals 1 for respondents who report that they frequently take risks, and 0 for respondents who do not.
Days of hunger last year is the number of days in the 2006-2007 season that individuals reduced the number of meals they ate per day.
Late paying previous loan equals 1 for respondents who report paying back a previous loan late, and 0 for respondents who do not.
Income SD is the standard deviation of income between the self-reported best and worst incomes of the 5 most recent years.
Years of experience growing paprika is the self reported number of seasons in which the respondent has grown paprika before the season studied in this project.
Previous default equals 1 for respondents who report that they have defaulted on a previous loan and 0 otherwise.
No previous loans equals 1 for respondents who report that they have not had any other loans from formal financial institutions (including micro lenders, savings and credit cooperatives, and NGO schemes) and 0 otherwise.

Take-up and repayment (from administrative data)

Approved equals 1 if the respondent was approved by MRFC for a loan and 0 otherwise.
Any loan equals 1 if the respondent borrowed money from MRFC and 0 otherwise (this could differ from *Approved* if the respondent chose not to take out the loan after it was approved by MRFC).
Total borrowed is the amount owed to MRFC, in Malawi kwacha (MK 145 = $US 1). This includes the loan principal and 33 percent interest charged by MRFC.

Balance is the unpaid loan amount remaining to be paid to MRFC. The balance includes principal and accumulated interest, and is reported in MK.
Fraction paid is the amount paid on the loan, divided by the *total borrowed* defined above.
Fully paid equals 1 if the respondent has completely repaid the loan and 0 if there is an outstanding balance.

We examine different versions of the variables *Balance*, *Fraction paid*, and *Fully paid* that vary by the date at which loan repayment status is measured. One set of variables refers to loan repayment status as of September 30, 2008, which is the formal due date of the loan. Another set of variables refers to "eventual" repayment as of the end of November 2008. MRFC considers loan repayment status at the end of November 2008 as the final repayment status of the loan, and makes no subsequent attempts to collect loan repayments after that point.

Land use and inputs (from follow-up survey)

Fraction of land used for various crops is the land used for the given crop, divided by total land cultivated.
Seeds is the value of paprika seeds used by the respondent, in MK.
Fertilizer is the value of all chemical fertilizer used by the respondent on the paprika crop, in MK.
Chemicals is the value of all pesticides and herbicides used by the respondent on the paprika crop, in MK.
Man-days is the amount of money spent on hired, non-family labor for the paprika crop, in MK.
All paid inputs is the total amount of money spent on inputs for the paprika crop, in MK. Mathematically, it is the sum of *Seeds*, *Fertilizer*, *Chemicals*, and *Man-days* defined above.
KG manure is the kilograms of manure applied to the paprika crop.
Times weeding is the number of times the paprika crop was weeded, by the respondent or hired labor.

Output, revenue and profits (from follow-up survey)

KG of various crops is the self-reported kilograms harvested of each crop.
Market sales is the amount of MK received from any sales of maize, soya, groundnuts, tobacco, paprika, tomatoes, leafy vegetables, and cabbage between April and August, which encompasses the entire main harvest and selling season for these crops.

Profits is the value of *Market sales*, plus the value of unsold crop estimated based on the farmer's reported quantity, valued at district average price reported by the EPA office (*Value of unsold harvest*, defined below), minus *All paid inputs* as defined above.
Value of unsold harvest is the value, in MK, of the difference between the kg harvested and the kg sold of each crop. We use district average prices, as reported by the EPA office.

Appendix D: The Model

By virtue of the experiment, the credit contract is kept fixed, so our goal here is not to solve for the optimal contract in the presence of both information asymmetries (Gesnerie, Picard and Rey, 1988 or Chassagnon and Chiappori, 1997 for risk averse agents), but rather to derive the agents' optimal behavior with and without dynamic incentives.

Agents (or farmers) are risk-neutral and decide how much to borrow for cash crop inputs and how much to invest. We assume that they do not have collateral or liquid assets, so the maximum they can invest in cash crop production is the loan amount.

We introduce the possibility of adverse selection by allowing farmers to differ in the probability p (unobserved by the lender) that cash crop production is successful. Production is given by $f_S(b)$ when successful and by $f_F(b)$ when it fails, which happens with probability $1-p$. The amount b denotes total cash crop inputs invested. We assume that $f_j(b)$, $j \in \{F, S\}$ satisfies the usual properties $f_j(0)=0$, $f_j'(b)>0$ and $f_j''(b)<0$.

We model moral hazard by allowing borrowers to divert inputs instead of investing them in cash crop production. The decision to divert inputs is not observable by the lender. If they decide to divert, they earn q per unit of input diverted, which can be interpreted as the secondary market price for inputs or the expected return if these inputs are invested in another crop. Given the arrangement to buy the cash crop (paprika) in the experiment, we assume that the lender can only seize cash crop production but not the proceeds from diverted inputs. To simplify matters, we assume that the choice of diversion is binary, that is, either all or nothing is diverted.[6]

Following the experiment, the credit contract offered by the lender is given by a loan amount b and gross interest rate R, regardless of whether the lender can use dynamic incentives. We assume that the loan size b can take on two values, b_L and b_H where $b_L < b_H$.[7] We also assume that even when cash crop production fails, the borrower has enough funds to cover loan repayment provided that the small amount b_L is borrowed and inputs are not diverted. More formally, $f_F(b_L) = b_L R$. This assumption and the fact that $f_F(0)=0$ implies that if the borrower chooses to invest the large amount b_H in paprika production but the crop fails, then the borrower defaults because by concavity of $f_F(\cdot)$, $f_F(b_H) < b_H R$. Finally, we assume that if the crop succeeds, the large loan size yields higher farm profits than the smaller loan size. If we let

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[6] One can extend the model to the case where diversion is a continuous variable but the intuition is already captured in the simpler version presented.

[7] This assumption is in accord with the actual details of the loan package, where the most important determinant of loan size is whether the farmer chooses to have the loan fund one vs. two bags of CAN fertilizer. We can think of b_H including two bags, and b_L only one.

$y_S(b_k) = f_S(b_k) - b_k R$, for $k \in \{L, H\}$ denote net profits from successful cash crop production, this assumption can be expressed as $y_S(b_H) > y_S(b_L)$.[8]

We assume that there are two periods and no discounting, although the model could easily be extended to an infinite horizon setting with discounting. The timing within a period follows the set-up of the field experiment: the borrower first learns whether the lender can use dynamic incentives; then the borrower decides how much to borrow and whether to divert inputs; then paprika production takes place; the loan is repaid if sufficient funds are available and finally the borrower consumes any remaining income.

In what follows, we take the credit contract as given and characterize optimal borrower behavior with and without dynamic incentives. Then we briefly discuss the optimality of the credit contract and compare the predictions of the model to those of other models in the literature.

Borrower behavior without dynamic incentives

Since the lender is forced to offer the same contract in each period, lifetime optimization coincides with period-by-period optimization. In a given period, the borrower chooses how much to borrow b and whether to divert inputs D by solving the following problem:

$$v(p) = \max_{b \in \{b_L, b_H\}} \left\{ \max_{D \in \{0,1\}} Dqb_H + (1-D)py_S(b_H), \max_{D \in \{0,1\}} Dqb_L + (1-D)py_S(b_L) \right\}$$

The dependency of net income from borrowing v on p is made explicit. If the borrower diverts, consumption is qb because the bank cannot seize income, but if the borrower invests in paprika production, consumption only takes place when production is successful as the bank seizes all output if paprika production fails.

Now let p_D be the success probability that leaves a borrower with the larger loan size b_H indifferent between diverting the inputs or investing them in paprika production. More formally, $qb_H = p_D y_S(b_H)$ as plotted in Appendix Figure 2.

If $p < p_D$, the solution to the problem when dynamic incentives are absent is to always borrow the large amount b_H and to divert all inputs ($D = 1$). If $p \geq p_D$, the borrower also borrows the large amount b_H but does not divert and therefore repays with probability *p*. Expected net income in a period $v(p)$ is

$$v(p) = qb_H \text{ if } p < p_D \text{ and } v(p) = py_S(b_H) \text{ if } p \geq p_D. \qquad (1)$$

Borrower behavior with dynamic incentives

In this case, the lender will only provide credit in period two to borrowers that have successfully repaid in period one. Because there are only two periods, in the last period the lender cannot provide additional incentives to elicit repayment, so the optimization problem that borrowers face is the same as the period-by-period optimization when dynamic incentives were absent. Borrowers maximize their lifetime utility by solving the following problem in period one:

$$V(p) = \max_{b \in \{b_L, b_H\}} \left\{ \max_{D \in \{0,1\}} Dqb_H + (1-D)p\left[y_S(b_H) + v(p)\right], \max_{D \in \{0,1\}} Dqb_L + (1-D)py_S(b_L) + v(p) \right\}$$

where again the dependency of V and v on p is made explicit. Net income v in period two is derived in (1). If the lower amount b_L is chosen, the borrower can always repay the loan and so net income from borrowing $v(p)$ in period two is assured. If, on the other hand, the higher

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[8] Using similar notation, the previous assumption implies that when the crop fails, farm profits are larger under the smaller loan size: $y_F(b_H) < y_F(b_L)$.

amount b_H is chosen, then the borrower will obtain $v(p)$ in period two only if there is no diversion ($D=0$) and paprika production is successful in period one. Income from not borrowing is normalized to zero.

It is easy to see that with dynamic incentives, diversion of inputs in the first period is never optimal. A borrower with a high probability of success $p \geq p_D$ would not divert in the absence of penalties, so he would certainly not do it when the lender can impose penalties. More formally, because $py_S(b_H) > qb_H$ if $p \geq p_D$, it follows that $p[y_S(b_H) + v(p)] > qb_H$ since $v(p) > 0$.

When $p < p_D$, borrowers choose to divert in the absence of dynamic incentives. When dynamic incentives are in place, they can increase lifetime utility by choosing the lower amount in the first period. They then secure a loan in the second period which can then be diverted to achieve the same utility as if they had diverted in the first period. In addition, if cash crop production succeeds, then they also consume in the first period.[9]

We now study the choice of loan amount in the first period. Let p_{B0} be the probability of success that leaves a borrower with success probability $p \geq p_D$ indifferent between the two loan amounts. If success probability is such that $p_D < p < p_{B0}$, then the borrower chooses b_L to ensure loan repayment, but if the probability is high enough, so that $p_D < p_{B0} < p$ he then chooses b_H. The subscript 0 denotes the fact that in the absence of dynamic incentives the borrower would not divert because $p \geq p_D$. Probability p_{B0} can be written as

$$p_{B0} = \frac{y_S(b_L)}{y_S(b_H)}. \qquad (2)$$

Now let p_{B1} be analogous to p_{B0} for borrowers with success probability $p < p_D$. Here the subscript 1 indicates that the borrower would divert in the absence of dynamic incentives. If success probability satisfies $p < p_{B1} < p_D$, the borrower will choose the smaller loan amount b_L and if $p_{B1} < p < p_D$ the larger amount b_H. It is easy to show that p_{B1} satisfies

$$qb_H(1-p_{B1}) = p_{B1}[y_S(b_H) - y_S(b_L)] \qquad (3)$$

or, after some algebra and substitutions,

$$p_{B1} = \frac{p_D}{p_D + 1 - p_{B0}}. \qquad (4)$$

As it turns out, depending on the magnitude of $y_S(b_L)$, $y_S(b_H)$ and qb_H only $p_D > p_{B1}$ or $p_D < p_{B0}$ will hold, because $p_D > p_{B1}$ is true if and only if $p_D > p_{B0}$.[10] So either p_{B0} or p_{B1} is relevant. There are three cases, which we label (i), (ii), and (iii), distinguished by the size of the gains from input diversion (qb_H) relative to those from successful cash crop production, $y_S(b_H)$ and $y_S(b_L)$.

The first case is where (i) $qb_H > y_S(b_H)$, in which the gains from diversion are higher than the gains from cash crop production even when the high loan amount is taken and

[9] While this result is immediate without discounting, it can be obtained with discounting provided the discount rate is low enough.

[10] This is easy to see using the expression for p_{B1} derived in (4).

production is successful. In this case, $p_D > 1 > p_{B1} > p_{B0}$ and p_{B0} becomes irrelevant because $p_D < p_{B0}$ is violated. Intuitively, $p_D > 1$ means that there are no borrowers who would repay without dynamic incentives, because the gains from diversion are higher than the gains from cash crop production even for borrowers with the highest success probabilities; p_{B0} is irrelevant because there are no farmers for whom $p > p_D$. In the first period with dynamic incentives, borrowers with $p \geq p_{B1}$ take the larger loan and those for whom $p < p_{B1}$ take the smaller loan size.

The second – and probably most interesting – case is where (ii) $y_S(b_H) > qb_H > y_S(b_L)$, in which the gains from diversion (relative to cash crop production) are intermediate. In this case, in the absence of dynamic incentives, some borrowers (those with highest success probabilities, for whom $p > p_D$) will choose to produce rather than divert, while others with lower success probabilities will divert rather than produce. In this case we have $1 > p_D > p_{B1} > p_{B0}$,[11] and so p_{B0} is irrelevant (those with $p > p_D$ always choose the larger loan in the first period). In the first period with dynamic incentives, borrowers with $p \geq p_{B1}$ take the larger loan and those for whom $p < p_{B1}$ take the smaller loan size.

The third case is where (iii) $y_S(b_L) > qb_H$, in which the gains from diversion are small relative to the gains from successful cash crop production, even when the small loan size is taken. Here, $1 > p_{B0} > p_{B1} > p_D$ so that p_{B1} now becomes irrelevant (because all individuals with $p < p_D$ will take the smaller loan size in the first period with dynamic incentives). Now it is those borrowers for whom $p > p_D$ that show variation in loan size in the first period with dynamic incentives: those with $p \geq p_{B0}$ take the larger loan and those for whom $p < p_{B0}$ take the smaller loan size.

Appendix Figure 2 is drawn assuming Case (ii) holds. It plots p_{B0} and p_{B1}, and because $p_D > p_{B0}$, p_{B0} is irrelevant. Probability p_{B1} is shown as the intersection of the left hand side and right hand side of the equality in (3) above.

For each regime (with and without dynamic incentives), Appendix Figure 3 reports the first period optimal choices of loan size and whether to divert as well as repayment rate as a function of the borrowers' success probability.

Interestingly, and as mentioned in the text, dynamic incentives have different effects on the optimal choices of borrowers depending on their probability of success. For example, borrowers with relatively low probability of success are most affected by the introduction of dynamic incentives. They choose the higher loan amount and to divert it all without dynamic incentives but borrow the lower amount and invest it in cash crop production when dynamic incentives are introduced. As a result, their repayment rate changes from zero to one once incentives are introduced.

Borrowers with relatively high probability of success are the least affected, since they never divert inputs and always choose the higher loan amount, except for in Case (i) where they would divert without incentives and not divert with incentives.

[11] To see this, divide inequalities in (ii) by $y_S(b_H)$ and recall $qb_H = p_D y_S(b_H)$ and expression (4).

Borrowers with an intermediate value of the probability of success will, upon introduction of dynamic incentives, change either the diversion or the loan size decisions depending on the parameter values and functional forms. In Case (ii) they always choose the higher loan amount but move from diversion to no diversion when incentives are introduced. In Case (iii), they never divert but incentives lead them to move from the higher to the lower loan amount.

Discussion

If the lender sets gross interest rate R to break even, and the individual probability of success $p \in [0,1]$ is drawn from the density function $G(p)$, then R satisfies

$$ib_H = [1 - G(p_D)][E(p \mid p \geq p_D)Rb_H + (1 - E(p \mid p \geq p_D))f_F(b_H)], \qquad (5)$$

where i is the deposit rate and $E(p \mid p \geq p_D) = \int_{p_D}^{1} p dG(p)$.

Notice that the bank breaks-even whenever $p_D < 1$, otherwise all borrowers would divert and the bank would be unable to collect repayment. As a result, there is no interest rate R such that case (i) considered before is an equilibrium.

Depending on the parameters, a separating equilibrium may exist where the lender maximizes borrower welfare subject to breaking even by offering a menu of loan sizes and gross interest rates. Borrowers with low probability of success p may either borrow the large amount and default or borrow the lower amount and produce (again depending on the parameters), borrowers with intermediate probability of success will borrow the lower amount and produce and borrowers with high probability of success will borrow the large amount and produce.[12]

When dynamic incentives are introduced, the lender can follow a strategy similar to Stiglitz and Weiss (1983) or Boot and Thakor (1994). In words, the lender could lower the interest rate associated with the lower loan size b_L in the second period below the per period break even interest rate (thereby making a loss) but raise it in the first period so as to satisfy the break even constraint intertemporally. This may be optimal because in the first period the borrower has the added incentive of the promise of a loan in the future, a loan that will be ever more attractive the lower is the interest rate charged.

If collateral was available, then a menu of interest rates and collateral could always be offered in both periods (Bester, 1985). But as Boot and Thakor (1994) point out, dynamic incentives can be more efficient than static incentives like collateral. As in their model, the value of long-term contracting does not arise from the ability to learn the borrower type (in their model all agents are equal) nor from improved risk-sharing (in both models agents are risk neutral). Long term relations are valuable because the lender has the ability to punish defaulters and to reward good borrowers.

Because repayment is higher with dynamic incentives, lenders could lower the interest rate and as a result borrowers might borrow more. The lender should also be willing to extend more credit if dynamic incentives can be used. As a result, overall borrowing could increase, although borrowers with low probability of success may still borrow less to ensure future access to loans. This increase in borrowing is also predicted by the more macro literature that tries to

[12] The observation that only a unique (pooling) contract exists may be used to rule out parameter combinations where the separating equilibrium is optimal. Of course, other considerations outside the model may be responsible for only observing one contract, even if it is sub-optimal. For example, before the study MRFC gave only a few loans for paprika and so it may still be learning about the optimal contract.

explain the increase in personal bankruptcies over the last few decades as a result of improvements in information technology available to lenders for credit decisions (see for example Livshits, McGee and Tertilt, forthcoming and 2009; Narajabad, 2010 and Sanchez, 2009).

The source of heterogeneity in the model is the probability of success p. If there was heterogeneity in the discount rate, then dynamic incentives would only be relevant for agents that are patient (ie with low enough discount rate). In this alternative model, if borrowers prefer to divert in the absence of dynamic incentives, repayment would be low without fingerprinting and would only increase for agents with low discount rate when fingerprinting is introduced.

In many multi-period models of limited commitment and asymmetric information, agents are not allowed to save because they could borrow and default and subsequently live in autarky by reinvesting the savings (Bulow and Rogoff, 1989). In Boot and Thakor (1994), the agent has no incentive to save because the long-term contract provides better-than-market interest rates. In this model without dynamic incentives, agents with high probability of success will not find it profitable to default and save for period 2 either, even if a savings technology were available at rate i. But if the probability is low enough, in particular if p is such that

$$p < \frac{(i-1)qb_H}{y_S(b_L)},$$

then agents would borrow the higher amount b_H in period one, divert and hence default and save it into period 2 to earn $i > 1$. When dynamic incentives are allowed, then the same argument of Boot and Thakor (1994) applies and so agents would prefer to borrow again in the second period, even if savings technology were available.

Appendix E: Checking for loan officer responses to fingerprinting

In this appendix section we describe in further detail the findings that loan officers do not appear to have responded to whether or not a club was fingerprinted (summarized in Section 5.A. of the main text). Online Appendix Table 2 examines reports from all loan officers collected in August 2008 as well as borrower responses in the August 2008 follow-up survey. Loan officers were first asked about the specific treatment status of five clubs randomly selected from the sample of clubs for which they were responsible. They were then asked whether they knew the secretary or president of the club and finally they were asked to estimate the number of loans given out in each club. The first row of the table shows that loan officers had very little knowledge about the actual treatment status of clubs. Only 54 percent of the fingerprinted clubs are reported correctly as being fingerprinted and an even lower 22 percent of non-fingerprinted clubs are reported correctly as such. Pure guesswork would yield an accuracy rate of 50 percent. This evidence alone suggests that loan officers did not take into account treatment status in their interactions with the clubs.

Loan officers know club officers roughly half of the time, and on average misreport the number of loans disbursed to a club by 1.5 loans. More importantly, there are no statistical differences in the reporting accuracy of fingerprinted clubs compared to non-fingerprinted ones. Borrower reports in the last three rows of the table paint a similar picture. Loan officers are no more likely to visit non-fingerprinted clubs to collect repayment compared to fingerprinted clubs, and as a result, members of non-fingerprinted clubs report talking the same number of times to loan officers as do members of fingerprinted clubs. Finally, they all report finding it relatively easy to contact the loan officer.

The evidence in the table indicates that loan officers did not respond to the treatment. Therefore, we interpret impacts of the treatment as emerging solely from borrowers' responses to being fingerprinted.

Appendix F: Additional robustness checks

Impact of fingerprinting in full sample

Analyses of the full sample of farmers, without restricting the sample only to borrowers, can help address concerns about selection bias. Appendix Tables 5 and 6 present results from regressions analogous to the main Tables 4 and 5, respectively, with the difference that the regressions include *all* 1,226 individuals interviewed in the follow-up survey (borrowers plus nonborrowers).

Full-sample regression results in Appendix Tables 5 and 6 are very similar to those from the borrower-only regressions. As discussed in the main text, the general pattern is for coefficients that were significant before to remain statistically significant, but to be only around half the magnitude of the coefficients in the borrowing sample regressions. This reduction in coefficient magnitude is consistent with effect sizes in the full sample representing a weighted average of no effects for nonborrowers and nonzero effects for borrowers.

To be specific, in the land-use full-sample regressions (Appendix Table 5), fingerprinting leads farmers in quintile 1 of predicted repayment to devote 5.8 percentage points more of their land to paprika (significant at the 5% level). In the inputs regressions (Appendix Table 6, Columns 1-7), the interaction of fingerprinting with predicted repayment in Panel B is negative and significant at the 5% level in the regressions for fertilizer and all paid inputs, compared to significance at the 10% level in main Table 5. The fingerprinting * (quintile 1) interaction term is also positive and statistically significant at the 10% level or better for all input types in the table except for man-days. Results in the sales and profits regressions of Appendix Table 6, Columns 8-11 are similar to corresponding ones in main Table 5, but as before they are not statistically significantly different from zero.

Results with "simple" predicted repayment regression

We discuss here robustness of treatment effect heterogeneity results to constructing the predicted repayment variable when excluding the locality*(week of initial club visit) fixed effects. Compared with the predicted repayment regression used in the main results (column 3, Table 2), when (locality)*(week of initial club visit) fixed effects are dropped the R-squared of the regression falls from 0.48 to 0.08. These alternative specifications are reported in Appendix Table 10.

This simpler regression is then used to predict repayment for the full sample, and the predicted repayment variable is interacted with treatment to examine heterogeneity in the treatment effect. Results from this exercise are presented in Appendix Tables 7 through 9, which should be compared (respectively) to the main Tables 3 through 5.

Results are very similar when using this simpler index of predicted repayment. For example, the coefficients on the interaction between linear predicted repayment and fingerprinting in Panel B remain large in magnitude and retain statistical significance in the repayment and inputs regressions (Appendix Table 7, Columns 4-9, and Appendix Table 9, Columns 1-7, respectively). In Panel C, where fingerprinting is interacted with quintiles of predicted repayment, a slight difference vis-à-vis previous results is that typically the significant interaction term is (fingerprinting)*(quintile 2) rather than the interaction with quintile 1. In sum, the general pattern that fingerprinting has more substantial effects on repayment and activities on the farm for individuals with lower predicted repayment is robust to using this simpler predicted repayment regression.

Results where predicted repayment coefficients obtained from partition of control group

This section describes our approach to estimating predicted repayment using a partition of the control group separate from a partition used as a counterfactual for the treatment group in the main regressions. We conduct this exercise 1,000 times, where in each replication we first randomly select 50% of the control group for inclusion in the auxiliary regression to predict repayment. We then predict repayment for the other half of the control group and the full treatment group. Finally, we estimate the heterogeneous effects of treatment on repayment, land use, input use, and farm profits using equation (2) on a sample that includes the full treatment group and the half of the control group not randomly chosen for the auxiliary regression.

We report the 95 percent confidence interval for coefficients obtained from this procedure in Appendix Table 11. We focus on results for the interaction between the treatment indicator and the indicator for quintile 1 of predicted repayment.[13] Panel A of Appendix Table 11 corresponds to Table 3, Columns 4-9; Panel B corresponds to Table 4; Panel C corresponds to Table 5, Columns 1-7, and Panel D corresponds to Table 5, Columns 8-11. The coefficient and standard error reported are the original estimates and bootstrap replications using the full sample, as described previously.

In every case, the coefficient from the estimate using the full sample falls within the 95 percent confidence interval from the procedure using the partitioned sample. Furthermore, in every case where the original coefficient is significant, all coefficients in the 95 percent confidence interval of the partitioning exercise have the same sign as the coefficient in the main regressions of the paper, and the confidence interval never includes zero.

Appendix G: Details of benefit-cost calculation

The benefit-cost calculation is presented in Appendix Table 13. The uppermost section of the table is the calculation of benefits per individual fingerprinted. At the suggestion of MRFC, we assume that all new loan applicants are fingerprinted, and that 50% of applicants are approved for loans. Based on our experimental results we assume that the increase in repayment due to fingerprinting is confined to the first quintile (20% of borrowers), and that for this subgroup fingerprinting causes an increase in repayment amounting to 32.7% of the loan balance (from column 8 of Table 3). We assume that the total amount to be repaid is MK15,000 on average. Total benefit per individual fingerprinted is therefore MK490.50 (US$3.38).

The next section of the table calculates cost per individual fingerprinted. There are three general types of costs. First, equipment costs need to be amortized across farmers fingerprinted. We assume each equipment unit (a laptop computer and external fingerprint scanner) costs

[13] The confidence interval is the 2.5th to 97.5th percentile of coefficients from the 1,000 replications.

MK101,500,[14] and is amortized over three years, for annual cost of each equipment package of MK33,833. Twelve (12) of these equipment packages (two for each of six branches) will be required to fingerprint MRFC's borrowers throughout the country. With an estimated 5,000 new loan applicants per year, each of these equipment units will be used to fingerprint 417 farmers on average. The equipment cost per farmer fingerprinted is therefore MK81.20.

The second type of cost is loan officer time. We estimate that it takes 5 minutes to fingerprint a customer and enter his or her personal information into the database. At a salary of MK40,000 per month and 173.2 work hours per month, this comes out to a cost of MK19.25 per customer fingerprinted.

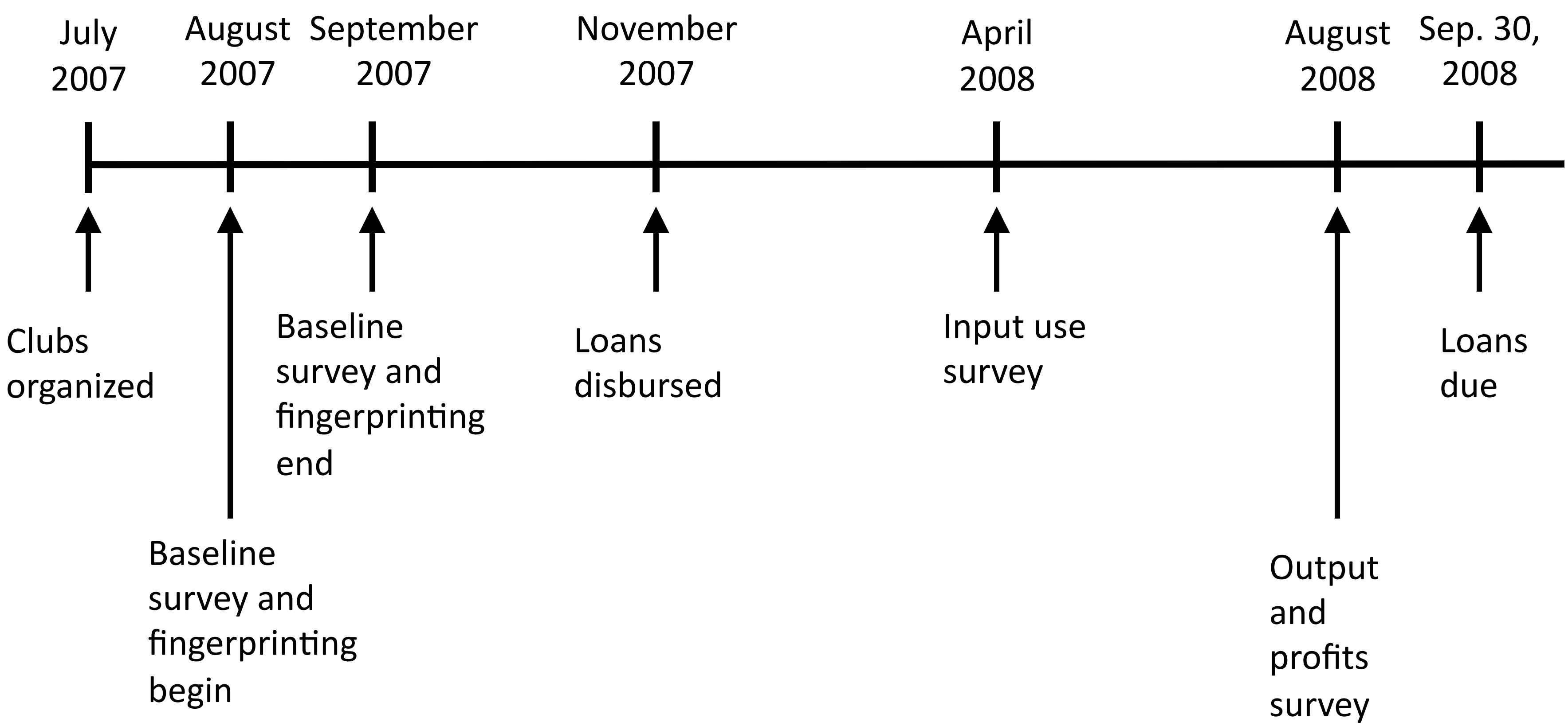
The third type of cost is the transaction cost per fingerprint checked, MK108.75 (US$0.75). We assume here that MRFC hires a private firm to provide the fingerprint identification services, in which case the fingerprint database is stored on the firm's server overseas and batches of fingerprints to be checked are sent electronically by MRFC to the firm during loan processing season. Lists of identified defaulters are sent back to MRFC with fast turnaround. In consultation with a U.S. private firm that provides such services, we were given a range of $0.03-$0.75 per fingerprint identification transaction. Per-fingerprint transaction costs are higher when the client has a relatively low number of transactions per year, and MRFC's 5,000 transactions per year is considered low, so we conservatively assume the transaction cost per fingerprint at the higher end of this range, $0.75 (MK108.75).

Summing up these three types of costs, total cost per individual fingerprinted is MK209.20. The net benefit per individual fingerprinted is therefore MK281.30 (US$1.94), and the benefit-cost ratio is an attractive 2.34. [15]

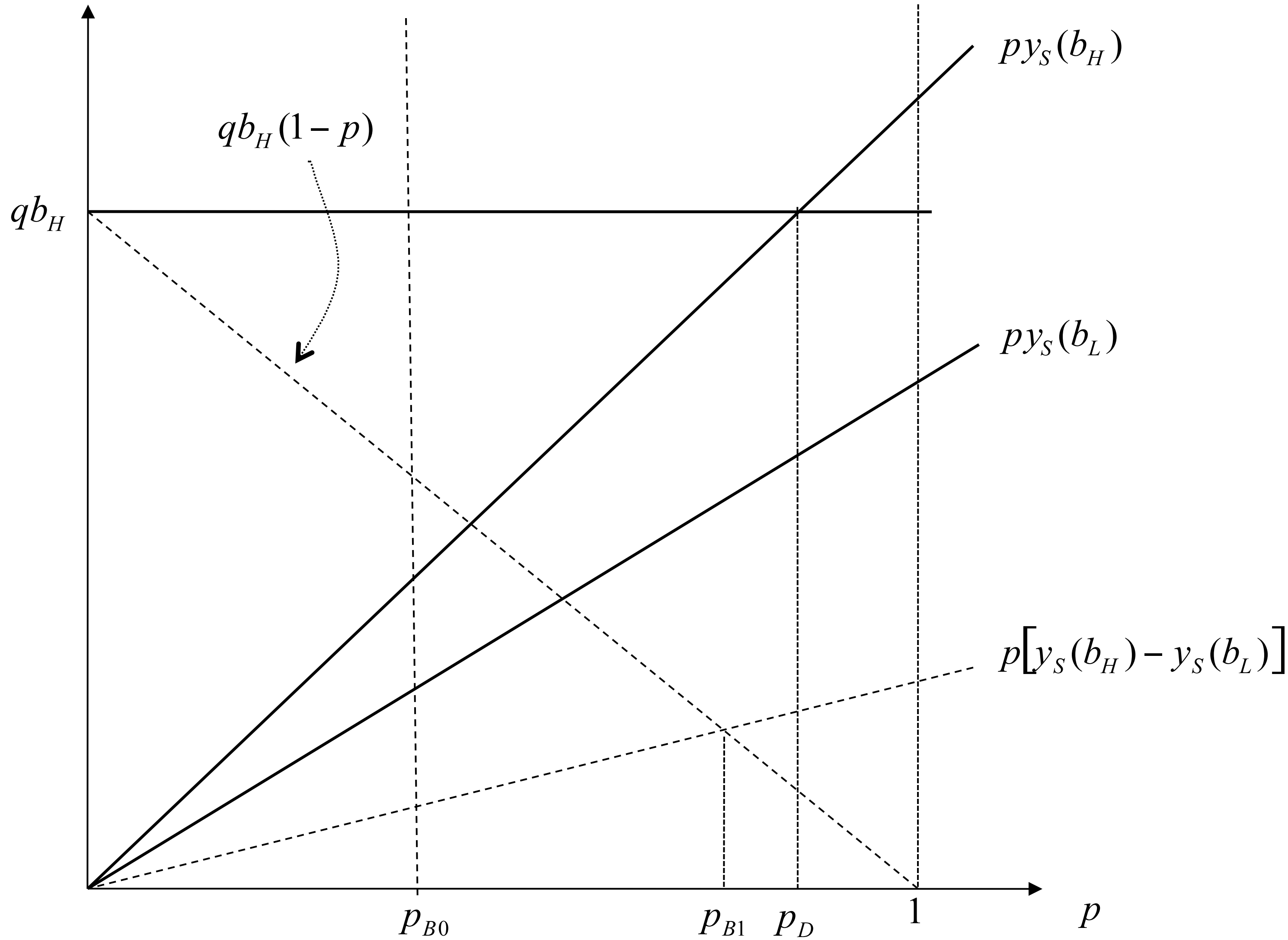
[14] This is the actual cost of each equipment unit we purchased for the project, which included a laptop computer ($480), an extra laptop battery ($120), a laptop carrying case ($20), and an external fingerprint scanner ($80).

[15] An alternative is for a lending institution to purchase its own fingerprint matching software and do fingerprint identification in-house instead of subcontracting this function to an outside firm. This would eliminate the $0.75 (MK108.75) transaction cost per fingerprint checked. According to a U.S. fingerprint identification services firm we consulted, the initial fixed cost of installing an off-the-shelf fingerprint matching software system is in the range of $15,000 to $50,000 (depending on specifications), with an annual maintenance cost of 10-20% of the initial fixed cost. In addition, there would be personnel costs for staff to operate the system. Assuming an initial fixed cost of $15,000, maintenance cost of 10% of the original fixed cost, and an additional full-time staff member to run the system costing the same as a current MRFC loan officer, NPV is lower when fingerprint identification is done in-house than when this function is contracted out (which is why Appendix Table 13's calculation assumes contracting out). But with a high enough annual volume of transactions (perhaps in the context of a credit bureau in which many or all of Malawi's lenders participate), in-house fingerprint identification could make economic sense.

Appendix Figure 1: Experimental Timeline



<u>Appendix Figure 2</u>: Optimal behavior as a function of p



Appendix Figure 3: Borrower behavior under various theoretical cases, with and without dynamic incentives

	Without Dynamic Incentives			With Dynamic Incentives		
Case (i): $qb_H > y_S(b_H)$						
	$p < P_{B1}$	$p \geq P_{B1}$		$p < P_{B1}$	$p \geq P_{B1}$	
Loan size b	b_H	b_H		b_L	b_H	
Diversion D	1	1		0	0	
Repayment Rate	0	0		1	p	
Case (ii): $y_S(b_H) > qb_H > y_S\,(b_L)$						
	$p < P_{B1}$	$P_{B1} \leq p < P_D$	$p \geq P_D$	$p < P_{B1}$	$P_{B1} \leq p < P_D$	$p \geq P_D$
Loan size b	b_H	b_H	b_H	b_L	b_H	b_H
Diversion D	1	1	0	0	0	0
Repayment Rate	0	0	p	1	p	p
Case (iii): $y_S(b_L) > qb_H$						
	$p < P_D$	$P_D \leq p < P_{B0}$	$p \geq P_{B0}$	$p < P_D$	$P_D \leq p < P_{B0}$	$p \geq P_{B0}$
Loan size b	b_H	b_H	b_H	b_L	b_L	b_H
Diversion D	1	0	0	0	0	0
Repayment Rate	0	p	p	1	1	p

Appendix Table 1: Tests of balance in baseline characteristics between treatment and control group
(For online appendix; not for publication)

	Full baseline sample		Loan recipient sample	
Variable:	Mean in control group	Difference in treatment (fingerprinted) group	Mean in control group	Difference in treatment (fingerprinted) group
Male	0.81	-0.036 (0.022)	0.80	-0.066* (0.037)
Married	0.92	-0.004 (0.011)	0.94	0.003 (0.016)
Age	39.50	0.019 (0.674)	39.96	-0.088 (1.171)
Years of education	5.27	-0.046 (0.175)	5.35	-0.124 (0.272)
Risk taker	0.57	-0.033 (0.032)	0.56	0.013 (0.051)
Days of hunger in previous season	6.41	-0.647 (0.832)	6.05	-0.292 (1.329)
Late paying previous loan	0.14	0.005 (0.023)	0.13	0.030 (0.032)
Standard deviation of past income	25110.62	1289.190 (1756.184)	27568.34	-1158.511 (2730.939)
Years of experience growing paprika	2.10	0.096 (0.142)	2.22	0.299 (0.223)
Previous default	0.03	-0.002 (0.010)	0.02	0.008 (0.010)
No previous loan	0.74	-0.006 (0.027)	0.74	-0.020 (0.041)
P-value for test of joint significance	0.91		0.66	
Observations	3206		1147	

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.
Notes: Each row presents mean of a variable in the baseline (September 2008) survey in the control group, and the difference between the treatment group mean and the control group mean of that variable (standard error in parentheses). Differences and standard errors calculated via a regression of the baseline variable on the treatment group indicator; standard errors are clustered at the club level.

Appendix Table 2: Impact of fingerprinting on loan officer knowledge and behavior
(For online appendix; not for publication)

	Means				
	All	Treatment	Control	P-value of T-test of (2)=(3)	Num. of obs.
	(1)	(2)	(3)	(4)	(5)
Loan officer reports					
Knows treatment status of club (1=yes)	0.37	0.54	0.22	0.16	51
Knows identity of club officers (1=Yes)	0.47	0.46	0.48	0.88	51
Abs. diff. between actual and officer report of number of loans	1.6	1.3	1.9	0.47	50
Borrower reports					
Number of times loan officer visited club to request loan repayment	0.35	0.41	0.27	0.41	396
Number of times borrower spoke to loan officer since April 2008	2.62	2.57	2.68	0.74	450
Difficulty in locating loan officer (1=easy 2=moderate 3=difficult)	1.2	1.17	1.24	0.32	453

Notes: The first three rows present loan officer reports about knowledge of clubs and treatment status collected in August 2008. The last three rows present borrower reports about interactions with the loan officer collected in the follow-up survey of August 2008.

<u>Appendix Table 3</u>: Impact of fingerprinting on attrition from sample
(For online appendix; not for publication)

<u>Dependent variable</u>: Indicator for attrition from September 2008 baseline survey to August 2009 survey

	(1)	(2)
<u>Sample</u>:	All respondents	Loan recipients
<u>Panel A</u>		
Fingerprint	-0.062*	-0.092
	(0.036)	(0.069)
<u>Panel B</u>		
Fingerprint	-0.046	-0.085
	(.096)	(.167)
Predicted repayment * fingerprint	-0.021	-0.008
	(.118)	(.192)
<u>Panel C</u>		
Fingerprint * Quintile 1	-0.032	-0.172
	(.075)	(.129)
Fingerprint * Quintile 2	-0.074	0.015
	(.073)	(.107)
Fingerprint * Quintile 3	-0.068	-0.094
	(.070)	(.107)
Fingerprint * Quintile 4	-0.089	-0.089
	(.078)	(.124)
Fingerprint * Quintile 5	-0.090	-0.137
	(.072)	(.125)
Observations	3206	1147
Mean of dependent variable	0.63	0.55
Quintile 1	0.58	0.59
Quintile 2	0.57	0.54
Quintile 3	0.63	0.58
Quintile 4	0.60	0.50
Quintile 5	0.70	0.52

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.
Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling.

Appendix Table 4: Impact of fingerprinting on loan repayment
(Only borrowers responding to follow-up survey)
(For online appendix; not for publication)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Loan recipients included in August 2009 survey	Loan recipients included in August 2009 survey	Loan recipients included in August 2009 survey	Loan recipients included in August 2009 survey	Loan recipients included in August 2009 survey	Loan recipients included in August 2009 survey
Dependent variable:	Balance, Sept. 30	Fraction Paid by Sept. 30	Fully Paid by Sept. 30	Balance, Eventual	Fraction Paid, Eventual	Fully Paid, Eventual
Panel A						
Fingerprint	-1529.644*	0.063	0.079	-875.314	0.031	0.060
	(884.322)	(0.043)	(0.069)	(670.297)	(0.032)	(0.057)
Panel B						
Fingerprint	-15727.893***	0.713***	0.794***	-8931.946*	0.362	0.390
	(3782.488)	(.196)	(.213)	(5162.708)	(.237)	(.257)
Predicted repayment * fingerprint	17587.934***	-0.805***	-0.887***	10046.221*	-0.413*	-0.411
	(4018.014)	(.206)	(.240)	(5446.717)	(.250)	(.284)
Panel C						
Fingerprint * Quintile 1	-12602.785***	0.573***	0.616***	-8016.543*	0.334*	0.373*
	(3969.935)	(.190)	(.197)	(4382.064)	(.201)	(.205)
Fingerprint * Quintile 2	1538.937	-0.094	-0.069	1799.143	-0.104	-0.090
	(2111.189)	(.110)	(.166)	(1857.158)	(.099)	(.151)
Fingerprint * Quintile 3	-364.091	0.021	0.046	-586.977	0.032	0.062
	(891.085)	(.051)	(.101)	(792.850)	(.046)	(.095)
Fingerprint * Quintile 4	560.375	-0.038	-0.085	549.532	-0.033	-0.034
	(762.879)	(.044)	(.103)	(707.901)	(.041)	(.096)
Fingerprint * Quintile 5	454.471	-0.022	0.002	289.061	-0.008	0.044
	(814.791)	(.046)	(.104)	(674.962)	(.038)	(.090)
Observations	520	520	520	520	520	520
Mean of dependent variable	2071.21	0.89	0.79	1439.16	0.92	0.83
Quintile 1	6955.67	0.62	0.52	3472.29	0.83	0.71
Quintile 2	4024.05	0.77	0.63	2610.41	0.85	0.75
Quintile 3	1571.44	0.92	0.83	476.63	0.97	0.91
Quintile 4	877.80	0.95	0.85	661.79	0.96	0.86
Quintile 5	1214.19	0.94	0.85	311.66	0.98	0.93

Stars indicate significance at 10% (*), 5% (**), and 1% (***) level

Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling. Sample limited to individuals who took out loans in 2008 and were included in follow-up survey in 2009.

Appendix Table 5: Impact of fingerprinting on land use
(Full follow-up survey sample, including non-borrowers)
(For online appendix; not for publication)

Dependent variable: Fraction of land used for...	(1) Maize	(2) Soya/Beans	(3) Groundnuts	(4) Tobacco	(5) Paprika	(6) Tomatoes	(7) Leafy Vegetables	(8) Cabbage	(9) All cash crops
Panel A									
Fingerprint	-0.014	-0.004	-0.003	-0.004	0.024**	0.001	-0.001	0.000	0.013
	(0.013)	(0.012)	(0.009)	(0.009)	(0.011)	(0.002)	(0.002)	(0.001)	(0.013)
Panel B									
Fingerprint	-0.018	-0.041	0.008	-0.008	0.052	0.005	0.004	-0.001	0.020
	(.035)	(.034)	(.026)	(.031)	(.036)	(.004)	(.007)	(.001)	(.034)
Predicted repayment * fingerprint	0.007	0.052	-0.017	0.006	-0.039	-0.006	-0.008	0.001	-0.010
	(.042)	(.040)	(.032)	(.035)	(.044)	(.005)	(.009)	(.002)	(.041)
Panel C									
Fingerprint * Quintile 1	-0.009	-0.039	-0.003	-0.010	0.058**	0.003	-0.000	-0.000	0.009
	(.029)	(.027)	(.020)	(.023)	(.024)	(.003)	(.006)	(.001)	(.029)
Fingerprint * Quintile 2	-0.033	0.019	0.030	0.001	-0.017	-0.000	-0.000	-0.000	0.033
	(.033)	(.031)	(.023)	(.023)	(.026)	(.005)	(.005)	(.001)	(.033)
Fingerprint * Quintile 3	-0.007	-0.019	-0.016	-0.010	0.051*	0.003	-0.004	0.001	0.007
	(.029)	(.028)	(.021)	(.016)	(.027)	(.005)	(.005)	(.002)	(.029)
Fingerprint * Quintile 4	-0.011	0.017	-0.017	0.002	0.011	-0.002	-0.003	0.002	0.011
	(.030)	(.030)	(.024)	(.017)	(.029)	(.006)	(.005)	(.003)	(.030)
Fingerprint * Quintile 5	-0.000	0.027	-0.024	-0.009	0.006	-0.003	-0.002	-0.001	-0.005
	(.033)	(.028)	(.023)	(.020)	(.028)	(.005)	(.004)	(.002)	(.033)
Observations	1226	1226	1226	1226	1226	1226	1226	1226	1226
Mean of dependent variable	0.46	0.16	0.12	0.09	0.15	0.01	0.01	0.00	0.54
Quintile 1	0.46	0.11	0.13	0.16	0.12	0.00	0.01	0.00	0.54
Quintile 2	0.49	0.12	0.13	0.13	0.12	0.00	0.00	0.00	0.51
Quintile 3	0.45	0.22	0.12	0.03	0.17	0.01	0.01	0.00	0.55
Quintile 4	0.44	0.21	0.12	0.04	0.19	0.01	0.01	0.00	0.56
Quintile 5	0.47	0.17	0.11	0.05	0.17	0.01	0.01	0.00	0.52

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.
Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling. Sample limited to individuals who were included in follow-up survey in 2009.

Appendix Table 6: Impact of fingerprinting on agricultural inputs and profits
(Full follow-up survey sample, including non-borrowers)
(For online appendix; not for publication)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable:	Seeds (MK)	Fertilizer (MK)	Chemicals (MK)	Man-days (MK)	All Paid Inputs (MK)	KG Manure	Times Weeding	Market sales (Self Report, MK)	Value of Unsold Harvest (Regional Prices, MK)	Profits (market sales + value of unsold harvest - cost of inputs, MK)	Ln(profits)
Panel A											
Fingerprint	60.585**	920.128	282.100**	-136.780	1126.032	11.992	0.080	4228.220	4734.442	7570.113	0.039
	(29.350)	(667.006)	(106.284)	(115.473)	(792.932)	(27.904)	(0.135)	(4962.283)	(23344.030)	(24615.887)	(0.079)
Panel B											
Fingerprint	49.011	3977.114**	296.011	272.076	4594.213**	122.326	0.365	23198.561	28031.981	43860.629	0.255
	(72.217)	(1687.829)	(220.025)	(210.036)	(1874.643)	(87.106)	(.328)	(16993.96)	(71967.95)	(76156.27)	(.215)
Predicted repayment * fingerprint	15.221	-4271.866**	-19.358	-577.541*	-4853.543**	-154.387	-0.400	-26665.392	-33873.351	-52029.370	-0.305
	(94.333)	(2099.599)	(295.322)	(305.778)	(2400.958)	(105.886)	(.439)	(20686.96)	(80794.67)	(87493.76)	(.245)
Panel C											
Fingerprint * Quintile 1	113.462***	2636.880**	264.742*	147.140	3162.224**	118.604*	0.468*	9768.595	52077.286	57907.978	0.129
	(44.024)	(1304.867)	(142.305)	(121.034)	(1415.625)	(70.055)	(.251)	(13316.04)	(74406.57)	(77360.26)	(.171)
Fingerprint * Quintile 2	50.930	1956.152	285.580	-115.827	2176.834	-49.929	-0.368	24668.058	-39885.974	-21083.297	0.197
	(59.562)	(1453.069)	(212.523)	(280.486)	(1635.342)	(69.820)	(.317)	(18019.75)	(76408.28)	(79611.89)	(.216)
Fingerprint * Quintile 3	86.537	-593.742	353.570	-237.639	-391.274	-56.392	-0.123	-20898.037	-9621.667	-25345.653	-0.193
	(67.608)	(1452.306)	(251.477)	(311.853)	(1701.534)	(73.851)	(.317)	(13647.96)	(51298.79)	(54260.54)	(.186)
Fingerprint * Quintile 4	6.885	-1049.852	250.558	-573.530	-1365.938	-32.321	-0.056	-4020.628	5859.113	5128.222	0.019
	(78.286)	(1612.908)	(273.541)	(370.818)	(2028.824)	(68.537)	(.346)	(12271.19)	(41342.84)	(44092.51)	(.190)
Fingerprint * Quintile 5	76.413	85.736	305.314	-157.983	309.481	16.648	0.352	1890.188	-5784.984	-7574.496	-0.050
	(79.747)	(1474.584)	(240.184)	(327.777)	(1796.701)	(80.069)	(.336)	(12186.01)	(56867.20)	(61201.66)	(.177)
Observations	1226	1226	1226	1226	1226	1226	1226	1226	1226	1226	1226
Mean of dependent variable	185.56	3948.93	362.92	396.56	4893.98	83.63	1.54	53965.29	86793.08	119870.13	11.28
Quintile 1	129.13	2335.99	182.64	152.25	2800.01	85.47	1.20	48912.14	103543.10	138101.00	11.23
Quintile 2	132.03	2924.01	277.92	178.55	3512.50	59.29	1.28	70582.23	60989.97	109699.20	11.33
Quintile 3	198.08	5481.54	426.67	593.28	6699.57	125.01	1.78	44931.14	86190.55	108497.00	11.27
Quintile 4	237.16	5837.92	543.52	726.95	7345.56	83.53	1.91	54127.28	98467.02	125928.20	11.34
Quintile 5	239.52	4786.95	516.97	579.91	6123.35	80.35	1.83	47991.75	84126.01	109740.80	11.26
Mean of dependent variable (US $)	1.28	27.23	2.50	2.73	33.75	n.a.	n.a.	372.17	598.57	826.69	n.a.

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.
Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling. Sample limited to individuals who were included in follow-up survey in 2009.

Appendix Table 7: Impact of fingerprinting on borrowing and repayment (simple predicted repayment regression) (For online appendix; not for publication)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample:	All Respondents	All Respondents	Loan Recipients	Loan recipients	Loan recipients	Loan recipients	Loan recipients	Loan recipient	Loan recipients
Dependent variable:	Approved	Any Loan	Total Borrowed (MK)	Balance, Sept. 30	Fraction Paid by Sept. 30	Fully Paid by Sept. 30	Balance, Eventual	Fraction Paid, Eventual	Fully Paid, Eventual
Panel A									
Fingerprint	0.045	0.056	-692.743*	-1489.945*	0.069*	0.088	-975.181	0.044	0.080
	(0.054)	(0.045)	(381.745)	(836.931)	(0.041)	(0.066)	(762.090)	(0.037)	(0.061)
Panel B									
Fingerprint	-0.064	0.012	-717.084	-11562.473***	0.570***	0.654***	-7303.437**	0.342**	0.423*
	(.151)	(.146)	(2351.208)	(3481.01)	(.168)	(.243)	(3428.208)	(.169)	(.230)
Predicted repayment * fingerprint	0.135	0.054	30.107	12415.234***	-0.618***	-0.698***	7800.066**	-0.367**	-0.423*
	(.171)	(.176)	(2656.956)	(3947.51)	(.185)	(.261)	(3817.025)	(.185)	(.246)
Panel C									
Fingerprint * Quintile 1	0.023	0.069	125.465	-2550.686*	0.138*	0.147	-1258.495	0.065	0.086
	(.073)	(.062)	(837.873)	(1494.379)	(.076)	(.101)	(1454.586)	(.074)	(.097)
Fingerprint * Quintile 2	0.036	0.041	-1193.165*	-3306.017**	0.149**	0.204**	-2516.761*	0.120*	0.178*
	(.070)	(.063)	(699.703)	(1538.999)	(.075)	(.102)	(1456.644)	(.071)	(.100)
Fingerprint * Quintile 3	0.076	0.032	-1790.115***	-1819.843	0.060	0.110	-1190.697	0.026	0.112
	(.070)	(.068)	(673.809)	(1259.105)	(.065)	(.100)	(1198.203)	(.061)	(.096)
Fingerprint * Quintile 4	0.031	0.053	-311.359	-391.905	0.026	0.003	-423.401	0.028	0.039
	(.070)	(.063)	(663.88)	(1089.182)	(.054)	(.085)	(969.012)	(.048)	(.075)
Fingerprint * Quintile 5	0.054	0.085	-263.503	337.027	-0.013	-0.010	304.142	-0.006	-0.002
	(.070)	(.068)	(590.087)	(979.543)	(.044)	(.072)	(893.653)	(.040)	(.068)
Observations	3277	3277	1147	1147	1147	1147	1147	1147	1147
Mean of dependent variable	0.63	0.35	16912.60	2912.91	0.84	0.74	2080.86	0.89	0.79
Quintile 1	0.58	0.29	17992.53	6955.67	0.62	0.52	4087.04	0.81	0.68
Quintile 2	0.64	0.36	17870.61	4024.05	0.77	0.63	3331.17	0.81	0.67
Quintile 3	0.71	0.44	16035.10	1571.44	0.92	0.83	1301.79	0.93	0.84
Quintile 4	0.70	0.47	15805.54	877.80	0.95	0.85	781.59	0.95	0.87
Quintile 5	0.59	0.30	16886.56	1214.19	0.94	0.85	950.29	0.95	0.88

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.

Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. The auxiliary regression used to calculate predicted repayment uses only baseline characteristics and no stratification cell (locality*week) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling.

Appendix Table 8: Impact of fingerprinting on land use (simple predicted repayment regression) (For online appendix; not for publication)

Dependent variable: Fraction of land used for…	(1) Maize	(2) Soya/Beans	(3) Groundnuts	(4) Tobacco	(5) Paprika	(6) Tomatoes	(7) Leafy Vegetables	(8) Cabbage	(9) All cash crops
Panel A									
Fingerprint	-0.003	0.015	-0.011	-0.007	0.010	-0.001	-0.002	-0.000	0.003
	(0.020)	(0.019)	(0.016)	(0.016)	(0.014)	(0.003)	(0.003)	(0.001)	(0.020)
Panel B									
Fingerprint	-0.175	-0.045	0.058	0.032	0.093	0.023	0.018	-0.005	0.175
	(.131)	(.086)	(.088)	(.068)	(.087)	(.017)	(.017)	(.006)	(.131)
Predicted repayment * fingerprint	0.210	0.072	-0.085	-0.048	-0.102	-0.029	-0.025	0.006	-0.210
	(.144)	(.096)	(.102)	(.076)	(.101)	(.020)	(.020)	(.007)	(.144)
Panel C									
Fingerprint * Quintile 1	-0.015	0.009	-0.006	-0.001	0.013	0.000	0.002	-0.003	0.015
	(.060)	(.043)	(.035)	(.032)	(.035)	(.006)	(.007)	(.003)	(.060)
Fingerprint * Quintile 2	-0.048	-0.008	-0.048	0.008	0.087***	0.010	0.001	-0.001	0.048
	(.051)	(.042)	(.035)	(.032)	(.034)	(.008)	(.007)	(.004)	(.051)
Fingerprint * Quintile 3	0.011	0.005	0.034	-0.013	-0.030	-0.004	-0.003	-0.001	-0.011
	(.046)	(.040)	(.034)	(.028)	(.039)	(.008)	(.007)	(.003)	(.046)
Fingerprint * Quintile 4	0.016	0.025	0.014	-0.029	-0.021	-0.002	-0.005	0.002	-0.016
	(.037)	(.035)	(.032)	(.022)	(.035)	(.008)	(.006)	(.002)	(.037)
Fingerprint * Quintile 5	0.019	0.029	-0.052*	0.004	0.010	-0.006	-0.004	0.000	-0.019
	(.032)	(.033)	(.031)	(.020)	(.030)	(.007)	(.005)	(.001)	(.032)
Observations	520	520	520	520	520	520	520	520	520
Mean of dependent variable	0.43	0.15	0.13	0.08	0.19	0.01	0.00	0.00	0.57
Quintile 1	0.44	0.07	0.13	0.18	0.17	0.01	0.01	0.00	0.56
Quintile 2	0.49	0.10	0.13	0.13	0.15	0.00	0.00	0.00	0.51
Quintile 3	0.42	0.21	0.12	0.03	0.20	0.01	0.00	0.00	0.58
Quintile 4	0.42	0.19	0.12	0.04	0.21	0.01	0.01	0.00	0.58
Quintile 5	0.40	0.17	0.14	0.04	0.23	0.01	0.01	0.00	0.60

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.
Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. The auxiliary regression used to calculate predicted repayment uses only baseline characteristics and no stratification cell (locality*week) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling. Sample limited to individuals who took out loans in 2008 and were included in follow-up survey in 2009.

<u>Appendix Table 9</u>: Impact of fingerprinting on agricultural inputs and profits (simple predicted repayment regression) (For online appendix; not for publication)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<u>Dependent variable</u>:	Seeds (MK)	Fertilizer (MK)	Chemicals (MK)	Man-days (MK)	All Paid Inputs (MK)	KG Manure	Times Weeding	Market sales (Self Report, MK)	Value of Unsold Harvest (Regional Prices, MK)	Profits (market sales + value of unsold harvest - cost of inputs, MK)	Ln(profits)
<u>Panel A</u>											
Fingerprint	84.536	1037.378	357.103	-408.599**	1070.419	44.863	0.048	5808.270	3571.446	11457.127	0.043
	(54.312)	(1297.753)	(219.533)	(188.581)	(1523.582)	(37.258)	(0.141)	(9376.512)	(10525.289)	(14071.809)	(0.094)
<u>Panel B</u>											
Fingerprint	282.642	14092.032**	800.605	391.334	15566.614**	101.494	0.421**	125502.791	-1179.320	96410.326	1.257**
	(253.064)	(5590.066)	(940.826)	(1444.871)	(6469.535)	(194.348)	(.878)	(62693.17)	(147854.1)	(168129.6)	(.638)
Predicted repayment * fingerprint	-241.402	-15850.798**	-537.673	-972.848	-17602.722**	-68.915	-0.455**	-145347.128	5848.375	-103103.149	-1.476**
	(320.704)	(6394.114)	(1106.397)	(1728.811)	(7558.463)	(231.059)	(1.038)	(68584.33)	(176461.3)	(199752.9)	(.751)
<u>Panel C</u>											
Fingerprint * Quintile 1	205.670**	2417.000	644.153*	-336.456	2930.366	-7.355	0.018	23135.413	-6510.534	11781.684	0.012
	(90.561)	(2457.178)	(351.481)	(449.350)	(2788.066)	(72.893)	(.341)	(24824.16)	(41730.85)	(51026.79)	(.243)
Fingerprint * Quintile 2	204.141**	6126.022**	446.949	-130.578	6646.533**	125.404	0.181	35330.984	-3565.416	22466.436	0.491*
	(103.150)	(2513.384)	(358.592)	(557.157)	(2844.721)	(85.541)	(.320)	(23834.69)	(48903.95)	(55138.88)	(.266)
Fingerprint * Quintile 3	-80.495	631.003	350.814	-666.700	234.622	50.845	0.072	-6890.835	64018.007	67407.944	0.193
	(108.814)	(2508.503)	(407.558)	(591.505)	(2912.471)	(77.011)	(.332)	(22716.73)	(55893.06)	(61100.77)	(.236)
Fingerprint * Quintile 4	6.115	-1516.096	192.879	-316.185	-1633.287	19.131	0.053	-5737.961	-70057.413	-71136.598	-0.156
	(102.324)	(2285.521)	(448.384)	(539.082)	(2722.922)	(75.269)	(.311)	(17755.40)	(66463.94)	(70012.55)	(.235)
Fingerprint * Quintile 5	114.650	-644.719	306.239	-571.535	-795.364	26.469	-0.011	-8414.109	28216.613	25251.358	-0.215
	(122.226)	(2285.481)	(407.954)	(545.700)	(2842.941)	(80.906)	(.299)	(14952.61)	(57408.41)	(61067.75)	(.208)
Observations	520	520	520	520	520	520	520	520	520	520	520
Mean of dependent variable	247.06	7499.85	671.31	665.98	9084.19	90.84	1.94	65004.30	80296.97	117779.16	11.44
Quintile 1	174.13	6721.24	401.30	143.48	7440.15	97.39	1.47	60662.57	82739.24	121222.50	11.36
Quintile 2	140.00	6080.46	620.67	238.94	7080.08	39.25	1.55	89028.25	29995.27	91652.71	11.55
Quintile 3	269.90	8927.65	674.48	836.98	10709.00	105.73	2.05	57683.74	96247.91	123242.30	11.44
Quintile 4	292.07	7649.51	715.08	936.29	9592.95	93.23	2.24	61088.27	104927.50	136467.50	11.45
Quintile 5	340.18	8078.58	892.05	1065.18	10375.99	118.13	2.28	56593.43	85817.08	115172.50	11.39
Mean of dependent variable (US $)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	464.32	573.55	841.28	n.a.

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.

Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. The auxiliary regression used to calculate predicted repayment uses only baseline characteristics and no stratification cell (locality*week) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling. Sample limited to individuals who took out loans in 2008 and were included in follow-up survey in 2009.

<u>Appendix Table 10</u>: Auxiliary regression predicting loan repayment, no fixed effects
(For online appendix; not for publication)

	(1)	(2)
<u>Dependent variable</u>:	Fraction Paid by Sept. 30	Fraction Paid by Sept. 30
Male	0.080	0.074
	(0.073)	(0.071)
Married	-0.071	-0.080
	(0.060)	(0.065)
Age	0.004	
	(0.001)***	
Years of education	-0.005	
	(0.005)	
Risk taker	-0.078	-0.072
	(0.041)*	(0.043)*
Days of Hunger in previous season	0.001	0.000
	(0.002)	(0.001)
Late paying previous loan	-0.058	-0.045
	(0.071)	(0.067)
Standard deviation of past income	-0.000	-0.000
	(0.000)	(0.000)
Years of experience growing paprika	0.005	0.004
	(0.013)	(0.012)
Previous default	0.088	0.062
	(0.163)	(0.169)
No previous loan	-0.012	-0.009
	(0.062)	(0.061)
Constant	0.729	1.006
	(0.114)***	(0.108)***
Locality * week of initial loan offer fixed effects	--	--
Dummy variables for 5-year age groups	--	Y
Dummy variables for each year of education	--	Y
Observations	563	563
R-squared	0.05	0.08

Robust standard errors in parentheses

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.
Notes: Sample is non-fingerprinted loan recipients from the September 2008 baseline survey. All standard errors are clustered at the club level.

Appendix Table 11: 95% confidence interval of Q1*Treatment interaction term from partitioning exercise
(For online appendix; not for publication)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Corresponds to Table 4									
Dependent variable:	Balance, Sept. 30	Fraction Paid by Sept. 30	Fully Paid by Sept. 30	Balance, Eventual	Fraction Paid, Eventual	Fully Paid, Eventual			
Coefficient: Fingerprint * Quintile 1	-10844.701***	0.506***	0.549***	-7249.271**	0.327**	0.408***			
Bootstrapped standard error	(2622.283)	(.125)	(.144)	(2918.825)	(.135)	(.156)			
95 percent confidence interval using half of control group in 1st stage	[-11284.34, -5382.259]	[.271, .527]	[.301, .623]	[-7999.921, -2937.949]	[.138, .37]	[.187, .519]			

Panel B: Corresponds to Table 5a and 5b									
Dependent variable: Fraction of land used for...	Maize	Soya/Beans	Groundnuts	Tobacco	Paprika	Tomatoes	Leafy Vegetables	Cabbage	All cash crops
Coefficient: Fingerprint * Quintile 1	-0.087	0.002	0.005	-0.007	0.077	0	0	0	0
Bootstrapped standard error	(.074)	(.058)	(.050)	(.050)	(.049)	0	0	0	0
95 percent confidence interval using half of control group in 1st stage	[-.177, .041]	[-.043, .073]	[-.056, .068]	[-.097, .06]	[-.002, .124]	[-.003, .012]	[-.015, .008]	[-.008, .001]	[-.041, .177]

Panel C: Corresponds to Table 6							
Dependent variable:	Seeds (MK)	Fertilizer (MK)	Chemicals (MK)	Man-days (MK)	All Paid Inputs (MK)	KG Manure	Times Weeding
Coefficient: Fingerprint * Quintile 1	214.555***	5852.606	384.382	114.901	6566.444	56.139	0.406
Bootstrapped standard error	(82.610)	(4058.444)	(339.435)	(207.522)	(4262.700)	(124.425)	(.329)
95 percent confidence interval using half of control group in 1st stage	[99.4, 288.319]	[1066.13, 9849.334]	[91.782, 955.366]	[-160.601, 222.7]	[1482.077, 10720.66]	[-106.88, 158.155]	[-.184, .848]

Panel D: Corresponds to Table 7				
Dependent variable:	Market sales (Self Report, MK)	Value of Unsold Harvest (Regional Prices, MK)	Profits (market sales + value of unsold harvest - cost of inputs, MK)	Ln(profits)
Coefficient: Fingerprint * Quintile 1	32123.244	168.559	25730.854	0.434
Bootstrapped standard error	(39966.77)	(33675.88)	(53903.61)	(.359)
95 percent confidence interval using half of control group in 1st stage	[3835.673, 96839.79]	[-127201.3, 46065.56]	[-91420.59, 112410.6]	[-.072, .98]

Notes: The coefficients reported in this table are for the interaction between the indicator for being in the bottom quintile of predicted repayment and being assigned to have a fingerprint collected when applying for a loan. They correspond to the coefficients for bottom quintile in Panel C of Tables 3-7. The standard errors are the bootstrapped standard errors reported in those tables. The confidence intervals are from 1000 replications of each regression where one half of the control group was randomly chosen for inclusion in the first stage regression, and the remaining half of the control group plus the full treatment group was preserved for inclusion in the second stage regression.

Appendix Table 12: Ex post moral hazard

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Balance, Sept. 30	Fraction Paid by Sept. 30	Fully Paid by Sept. 30	Balance, Eventual	Fraction Paid, Eventual	Fully Paid, Eventual
Panel A						
Fingerprint	-266.318	0.010	0.001	201.469	-0.012	-0.003
	(768.031)	(0.040)	(0.066)	(559.701)	(0.030)	(0.052)
Panel B						
Fingerprint	-9659.780*	0.422	0.412	-5190.059	0.198	0.207
	(4698.647)	(.237)	(.298)	(5140.761)	(.237)	(.280)
Predicted repayment * fingerprint	11231.990**	-0.493	-0.493	6443.577	-0.251	-0.252
	(4903.271)	(.246)	(.326)	(5378.012)	(.247)	(.308)
Panel C						
Fingerprint * Quintile 1	-8276.641*	0.372*	0.333	-5247.917	0.221	0.240
	(4308.034)	(.204)	(.246)	(4236.123)	(.189)	(.220)
Fingerprint * Quintile 2	2691.144	-0.150	-0.159	2402.793	-0.135	-0.138
	(2204.118)	(.115)	(.164)	(1919.401)	(.102)	(.148)
Fingerprint * Quintile 3	-410.867	0.031	0.042	-210.122	0.021	0.037
	(1038.583)	(.058)	(.105)	(910.565)	(.052)	(.096)
Fingerprint * Quintile 4	432.743	-0.017	-0.073	650.240	-0.026	-0.067
	(872.418)	(.050)	(0.104)	(818.118)	(.047)	(.095)
Fingerprint * Quintile 5	361.559	-0.012	-0.003	614.725	-0.021	0.015
	(1004.290)	(.055)	(.115)	(857.018)	(.046)	(.096)
Observations	520	520	520	520	520	520
Mean of dependent variable	2071.21	0.89	0.79	1439.16	0.92	0.83
Quintile 1	6955.67	0.62	0.52	3472.29	0.83	0.71
Quintile 2	4024.05	0.77	0.63	2610.41	0.85	0.75
Quintile 3	1571.44	0.92	0.83	476.63	0.97	0.91
Quintile 4	877.80	0.95	0.85	661.79	0.96	0.86
Quintile 5	1214.19	0.94	0.85	311.66	0.98	0.93
Comparison to Appendix Table 4						
Difference in Panel B interaction terms	6355.944**	-0.312**	-0.394*	4019.440	-0.197*	-0.224
	(2852.902)	(.137)	(.205)	(2485.785)	(.116)	(.183)
Difference in Quintile 1 interaction terms	-4326.144**	0.201**	0.284**	-2836.847	0.128	0.163
	(2050.553)	(.100)	(.139)	(1758.450)	(.084)	(.127)

Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.
Notes: Each column presents estimates from three separate regressions: main effect of fingerprinting in Panel A, linear interaction with predicted repayment in Panel B, and interactions with quintiles of predicted repayment in Panel C. All regressions include stratification cell (location * week of initial club visit) fixed effects. Panel B regressions include the main effect of the level of predicted repayment, and Panel C regressions include dummies for quintile of predicted repayment main effects. Standard errors on Panel A coefficients are clustered at the club level, while those in Panels B and C are bootstrapped with 200 replications and club-level resampling. Sample limited to individuals who took out loans in 2008 and who were included in follow-up survey in 2009.

<u>Appendix Table 13</u>: Benefit-cost analysis

Benefit		
(a) Increase in repayment due to fingerprinting in Quintile 1	4,905.00	Malawi kwacha
(b) Quintile 1 as share of all borrowers	20.0%	
(c) Borrowers as share of all fingerprinted	50%	
(d) Total benefit per individual fingerprinted [= (a)*(b)*(c)]	490.50	Malawi kwacha
Cost		
(e) Cost per equipment unit	101,500	Malawi kwacha
(f) Equipment amortization period	3	years
(g) Annual equipment amortization [= (e) / (f)]	33,833	
(h) Fingerprinted individuals per equipment unit	417	individuals
(i) Equipment cost per farmer [= (g) / (h)]	81.20	Malawi kwacha
(j) Loan officer time cost per farmer	19.25	Malawi kwacha
(k) Transaction cost per fingerprint checked	108.75	Malawi kwacha
(l) Total cost per individual fingerprinted [= (i) + (j) + (k)]	209.20	Malawi kwacha
(m) Net benefit per fingerprinted farmer [= (d) - (l)]	281.30	Malawi kwacha
(n) Benefit-cost ratio [= (d) / (l)]	2.34	

Assumptions:

Exchange rate:	145	MK/US$
Loan size	15,000	Malawi kwacha
Increase in share of loan repaid due to fingerprinting in Quint	32.7%	
Cost per equipment unit (laptop computer + fingerprint scanı	700	USD
Number of equipment units	12	
New loan applicants fingerprinted per year	5,000	
Fingerprinting time per individual	5	minutes
Monthly salary of MRFC loan officer	40,000	Malawi kwacha
Hours worked per month by MFRC loan officer	173.2	hours