Progress Report for the Project:
Fingerprinting to Reduce Risky Borrowing: A Randomized Evaluation in Malawi

Grant No. AID-OAA-F-13-00032

Principal investigators: Jessica Goldberg (U. Maryland), Xavier Gine (World Bank), and Dean Yang (University of Michigan)

Milestone 1 (June 21, 2013)

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Part 1: Implementation Plan
Part 2: Evaluation Strategy
Part 3: List of Key Indicators

Part 1: Implementation Plan

Fingerprint identification of borrowers will be embedded in the normal loan application process and credit bureau reporting procedures of the microfinance institutions that are members of the Malawi Microfinance Network (MAMN). Thus, the implementation process will be carefully coordinated with the roll-out of the new credit bureau, and designed to permit evaluation of the effect of fingerprint identification on borrowing and repaying.

The first phase of the implementation is stakeholder engagement, which began with a series of meetings with MAMN officials and representatives of the credit bureau and Reserve Bank in July and August 2012. Stakeholder engagement is planned to continue in July 2013 with the visit to Malawi of co-PI Jessica Goldberg to have the first meetings with MAMN, credit bureau, and Reserve Bank officials during the active (post-approval) phase of this DIV project. These meetings will be particularly important because of the unexpected death in May of Stewart Kondowe, the Executive Director of MAMN (and our key collaborator there).

We anticipate providing training to loan officers on fingerprint collection through regional capacity-building workshops starting in the beginning of 2014. Loan officers in geographic areas that are chosen for early implementation of fingerprinting will begin collecting fingerprint data when clients apply for new loans in the latter half of 2014. They will use equipment financed by the grant to collect and store these fingerprints, and will follow the protocol agreed to in the stakeholder meetings and institutionalized in the credit bureau guidelines to share the fingerprint data and other information about borrowers with the credit bureau.

The research team's role in this phase will be to coordinate activities, monitor adherence to protocols for collecting and sharing fingerprint data, and help troubleshoot procedural obstacles. At this stage, two project team members will support the implementation process on the ground. In this regard their main responsibility will be to detect and communicate problems to all stakeholders. Furthermore, they will ensure that responses to any upcoming problem will be implemented across branches as soon as possible.

Outside consultants will provide technological assistance as necessary. Note that while the research team will work closely with MAMN and microfinance agencies to facilitate collection of fingerprint data, the data will actually be collected, stored, and used by the MFIs and the credit bureau. The research team will provide monthly status reports to MAMN summarizing information about the number of customers fingerprinted for the first time, the number of "matches" identified by the fingerprint database, and notes on common technological problems experienced by loan officers. MAMN will, in turn, make suggestions to or requests of individual lenders to bring them into compliance with the guidelines for collecting and sharing data.

In parallel, we will also implement an extensive data collection operation. We will begin with a baseline survey of 7,000 randomly-chosen households in treatment and control localities. This survey, which will be conducted in mid-2014, will measure farm production decisions, use of inputs, profits, household well-being measures such as

schooling and health outcomes, and the household's banking and financial portfolio. Summary statistics from baseline survey data will be shared with MFIs, to provide an overview of their current and potential clients.

To carry out the computer-based data collection, IPA will hire12 teams of surveyors. Each team will consist of four surveyors, who will track respondents and conduct the interviews, and one supervisor, who manages the team and conducts spot check so of interviews. Data collection staff will be supported by a support team of back checkers, who will conduct the ex-post quality checks of interviews previously taken, and 3 drivers who will operate the field cars. Altogether 69 field staff will be employed to carry both rounds of data collection. It is anticipated that each surveyor can complete around 3 60-page questionnaires per day. Given these productivity levels, it is anticipated that each survey round will be completed within 63 days. The survey duration also includes 14 days of training (i.e. number of field work days is 49). Field Drivers will be employed just for 49 days since they do not have to attend the survey trainings.

To assess the impact of fingerprinting in the short run, two intermediate assessments will use administrative data from individual MFIs and from the credit bureau itself. These assessments will compare repayment rates and on-time repayments in treatment and control localities. One assessment will take place in mid- 2015, and another at the end of 2015.

An endline survey will be conducted in mid-2016. This will mirror the baseline survey, and data from the baseline, endline, and administrative data will be used to prepare final policy reports and an academic paper. Thirty-six months after grant approval, fingerprinting will be fully rolled out, including to the delayed "control" localities. At this point, fingerprint identification and screening of borrowers will be a fully-integrated part of Malawi's credit reference bureau. The research team and stakeholders will document lessons learned for use in the future in Malawi, as well as to provide guidance to other countries interested in incorporating biometric identification in their credit bureaus.

This implementation plan builds upon the research team's experience of conducting fingerprint identification of new borrowers with a single Malawian MFI in 2007. Fingerprints were collected from 3,206 customers of the Malawi Rural Finance Company. We will use the same protocol and equipment in this expanded project as we used in the small-scale project in 2007. There, the equipment performed well; in particular, we were able to conduct convincing demonstrations to the borrowers that they could be identified and their records retrieved based on fingerprint alone. Moreover, we were able to improve repayment rates by increasing the cost of default – denial of future credit. Fingerprinting led to dramatic increases in repayment for the riskiest borrowers, and led these borrowers to voluntarily take smaller loans and use those loans on productive inputs. The fingerprinting intervention had a very favorable benefit-cost ratio of 2.34 to the lender (excluding the value of higher profits to the borrower). Those promising results are likely a lower-bound on the potential impact of a national-level project that includes multiple lenders and is a permanent feature of the borrowing landscape rather than a time-limited pilot.

Part 2: Evaluation Strategy

Identification strategy

Impact evaluation will be conducted as a randomized control trial, the gold standard in evaluation methodology. 175 rural localities in central Malawi will be randomly assigned to a treatment group and a control group. In treatment locations, all borrowers will be fingerprinted in the process of loan application. In the control group, no fingerprinting will be conducted. Due to random assignment, comparisons between treatment and control groups will reveal the causal impact of fingerprinting on the outcomes of interest.

Note: we use the term "locality" to refer to traditional authorities (TAs) or subchiefs (SCs), of which there are 207 in across Malawi. 175 will be chosen at random to be included in the study. This choice not to visit all 207 localities in Malawi is done for cost reasons, as some localities are quite remote. The fact that the 175 localities are chosen at random will assure national-representativeness of the findings.

In the terminology of Harrison and List (2004), this study will be a "natural field experiment." It is a natural field experiment for analysis of outcomes in locality-level administrative data (loan disbursements, repayment rates), since locality populations as a whole will not know they are in an experiment and simply will or will not encounter fingerprinting as part of the application process for any loans they apply for. Individuals to whom we administer the baseline survey will know they are in a study and will be followed over time through the follow-up surveys, but will not know that the impact of fingerprinting is the focus of the study, so their behavior and responses should not be influenced by their fingerprinting treatment assignment.

Implementation of the randomized control trial

Central Malawian localities will be randomly assigned to a treatment or a control group. In control group localities, no intervention will be implemented beyond data collection.

Treatment localities will receive the fingerprinting intervention. All individuals applying for new loans will be required to be fingerprinted. Loan officers will explain to loan applicants how their fingerprints uniquely identify them for credit reporting to lenders, and that future lenders will be able to access the applicant's credit history simply by checking a fingerprint.

Loan applicants in treatment localities will have the image of their right thumbprint captured by an optical scanner attached to a computer using commercially-available software. The fingerprint image will then be added to the credit bureau database. Lenders will be able to use the fingerprint-enabled credit history data for later screening of borrowers.

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Spillovers

Spillovers across treatment and control groups would take the form of individuals in the treatment localities seeking to take out loans in control localities (where they would not be fingerprinted). For several reasons, we expect our evaluation design to generate little to no spillover. First, the state of transportation infrastructure in rural Malawi is quite poor, so the costs of traveling to seek out loans in another locality will be high for most individuals. Second, individuals in a treatment locality who happen to be just on the border with a control locality would also face nonzero costs of taking out a loan in a control locality, since they would have to falsely claim that they live in a control locality. Rural loans given out in our study area will mostly be group liability, so such an individual would have to find a borrowing group in a control locality that would agree to coordinate and falsely claim that the individual lived in the control locality. Finally, in our previous study (Gine, Goldberg, and Yang 2012), we randomized fingerprinting across borrowing clubs within localities, so treatment and control groups were actually geographically quite close to one another, and found no evidence of information spillovers or of treated individuals seeking to avoid the fingerprinting by borrowing outside their club.

Data collection methods and instruments

Several of the key outcomes of interest will come from administrative records of lenders. These include individual-level data on characteristics of borrowers and loan repayment; and locality-level data on total loans disbursed, total borrowers, and repayment rates.

Loan officer activities and time allocations to borrowers will be measured using lenders' administrative records alongside surveys of the loan officers themselves. All loan officers in treatment and control localities will be surveyed and will be used to calculate average time allocation per loan, by activity (screening, processing, monitoring, enforcement), for treatment and control groups. Loan officer survey instruments used in the Gine, Goldberg, and Yang (2012) study will be used for this proposed study as well.

We will also field our own baseline and follow-up household surveys. These will be important to provide insight into particular borrower behaviors that may be affected by the treatment but are not available in administrative data. Surveys will cover both household- and individual-level variables, with specific questions for the individual most likely to contract a loan in the next season (if any). Survey instruments will be modeled after surveys successfully field-tested and implemented in our previous study (Gine, Goldberg and Yang 2012). Key outcomes of interest include farm production decisions (land allocation, input use, family labor allocation, hired labor), farm production and net income, and other indicators of household well-being such as schooling and health outcomes. So that short- and long-run effects can be compared, impacts will be assessed annually over a three-year time frame. This will require fielding of three post-treatment surveys, once at the end of each of the three years of the project.

Survey samples will be drawn so as to be population-representative at the locality level, but will overweight "potential borrowing households" (those that expect to apply

for a loan with a formal lender in the coming season). Analysis of the subsample of potential borrowing households will help increase our power to detect impacts; such households will be the most likely to be affected by the fingerprinting treatment. Locally-population-representative estimates of treatment effects can be obtained by reweighting regressions with the full sample of households appropriately.

Because the treatment may affect selection into borrowing, we will conduct intent-to-treat (ITT) analysis comparing all households in treatment and control groups, irrespective of their post-intervention borrowing status. Separately, we will examine the important question of whether selection into borrowing is affected by the fingerprinting treatment. In the event that the treatment does not affect selection into borrowing (as was found over one loan cycle in Gine, Goldberg, and Yang 2012), we will also estimate treatment effects on household outcomes for the sample of borrowers alone.

We will also estimate population-representative impacts on key outcomes across treatment and control localities using the panel sample from the Malawi Integrated Household Survey (IHS), an LSMS-type survey administered by the government of Malawi. (The 2011 and 2013 rounds of the IHS will serve as a baseline.) In addition, locality-level data on credit access reported by households in the IHS will be useful as a check on the administrative data on credit supply provided by lenders.

The data collection and analysis described above will provide estimates, separately for treated and control localities, of 1) program impacts on households, 2) program impacts on financial outcomes of lenders, and 3) the costs of program implementation. These elements will be combined into a credible estimate of the program's benefit-cost ratio for lenders alone as well as for society as a whole (considering lender profits plus benefits for households).

Attrition

An attractive aspect of our study design is that several key outcome variables are at the locality level and are measured using administrative data (e.g., loans disbursed, repayment rates), so attrition from the sample is not an issue. It is also worth noting that while we will be collecting data on loan officer activity per loan, these loan officer activity outcomes are actually not affected by attrition; the variables are total loan officer time allocation, and can ignore individual identities by pooling time across multiple officers that might have worked in the same locality over time.

For the follow-up surveys that we implement ourselves, attrition between the baseline and follow-up survey is a first-order concern. Follow-up tracking methods will exploit the past experience of the PIs in conducting panel surveys of households in rural Malawi. In addition, we will implement randomized intensity of follow-up (as in Katz, Kling, and Liebman, 2001 and Kling, Ludwig, and Katz, 2005). Two-thirds of respondents (randomly selected) will receive a limited number of follow-up visits, while the remaining one-third of respondents will be assigned to intensive follow-up (additional follow-up visits). This allows assessment of the existence and extent of attrition bias (DiNardo, McCrary and Sanbonmatsu 2006).

Impact heterogeneity and diversity across subgroups

In addition to measuring average treatment effects, we also seek to reveal the extent to which treatment effects differ by the riskiness of lending at baseline (which was also done in Gine, Goldberg, and Yang 2012). As emphasized by Deaton (2010), investigation of heterogeneity of treatment effects is most credible along dimensions that were part of the study's original treatment stratification scheme. Localities will therefore be stratified on the baseline loan repayment rate (calculated across all lenders) prior to the study. Localities will be sorted on this baseline variable, and then adjacent pairs of localities in the list will be randomly assigned to treatment and control. This will ensure balance across treatment and control groups in this key baseline variable, and set the stage for valid comparison of treatment effect heterogeneity with respect to baseline repayment rates. (Stratification also helps ensure balance on this baseline characteristic across the experimental conditions.)

We will also measure treatment effect heterogeneity along individual-level baseline variables. The most important baseline variable is an individual-level measure of borrower riskiness, along the lines of the one used in Gine, Goldberg, and Yang (2012) (and for which there was substantial treatment effect heterogeneity in that study). This involves running an individual-level regression of loan repayment on borrowers' pre-borrowing characteristics in a sample of loans prior to the experiment, and then predicting loan repayment for the entire study sample. This essentially creates a "credit score" for each individual based on their pre-intervention characteristics.

In addition, we will measure treatment effect heterogeneity for the following subgroups: households near vs. far from a formal lending branch; female- and male-headed households; households that do and do not farm cash crops (a proxy for market integration); households above and below the median of a wealth index; households with and without past experience with formal borrowing. These subgroup analyses will be detailed in a formal pre-analysis plan to forestall concerns about data mining.

Power calculations

We assume a survey sample of 7,000 spread across 175 localities, with 50 households per locality, or on average 10 per quintile of predicted repayment. For these calculations, we conservatively assume a high attrition rate of 20%, so we will be left with 40 households per locality and 8 per quintile of predicted repayment. With these parameters, our study has sufficient power to detect effects of reasonable (and often substantial) size on the key outcomes of interest. Our power calculations are based on the assumption of a baseline survey and single follow-up. Power calculations were done using the Optimal Design program.

First, we calculate the sample size needed to detect an increase in repayment for the highest-risk quintile of borrowers, the subsample for which effects were found in the Gine, Goldberg, and Yang (2012) study. We make the following assumptions: statistical significance level 0.05; 175 clusters; intracluster correlation coefficient 0.420 (calculated from the Gine, Goldberg, and Yang 2012 survey dataset); 8 individuals per cluster in the highest-risk quintile. In the original Gine, Goldberg, and Yang (2012) study, the treatment effect on share of loan repaid on-time in the highest- risk quintile was 50.6 percentage points (1.2 standard deviations). Under these assumptions, our proposed new

study design would have power of more than 0.99 to detect an effect of this size. At power of 0.80, the minimum detectable effect size on share of loan repaid on-time would be 0.30 standard deviations, or 12.7 percentage points (which is only one-fourth of the actual effect size found in Gine, Goldberg, and Yang 2012).

To calculate our power to detect an increase in log profits in our survey sample, we make the following assumptions: statistical significance level 0.05; 175 clusters; intracluster correlation coefficient 0.126 (calculated from the Gine, Goldberg, and Yang 2012 survey dataset); 8 individuals per cluster in the highest-risk quintile. In the original Gine, Goldberg, and Yang (2012) study, the treatment effect on log profits in the highest-risk quintile was 0.434 (but was not statistically significant). Under these assumptions, our proposed new study design would have power of more than 0.99 to detect an effect of 0.434, which exceeds the typical power threshold of 0.80 by a large margin. At power of 0.80, the minimum detectable effect size on log profits would be 0.20 (less than half of the point estimate found in Gine, Goldberg, and Yang 2012).

<u>Part 3:</u> List of Key Indicators

The key outcomes of interest in this Stage 2 study are as follows:

- Individual level:
    - Household characteristics
        - Household listing (roster)
            - Age
            - Gender
            - Main activity (school, work, etc.)
            - Relation to household head
        - Asset ownership (see asset module from IHS)
        - Consumption (see consumption module from IHS)
        - Income (see module E from IHS)
    - Loan repayment
        - Indicator for on-time full repayment
        - Indicator for eventual (1 year after due date) full repayment
        - Share of loan repaid at due date
        - Share of loan repaid 1 year after due date
    - Farm and enterprise outcomes (investments, inputs, output, profits)
        - Purchase of commercial inputs (price and quantity of each)
            - Fertilizer (subsidized and unsubsidized)
            - Pesticide
        - Hired labor (days hired and total paid)
        - Other expenses
            - Transport
            - Packaging (bales for paprika, tobacco)
        - Own labor
            - Number of days weeding
            - Number of times applying manure
        - Harvest (quantity of each crop harvested)
        - Revenue
            - Quantity sold (by crop)
            - Price per kg sold
            - Total amount received for each crop
- Club level:
    - Club composition
        - Gender ratio
        - Years of membership in this club
        - Years of membership in any club
    - Loan repayment
        - Fraction of club members with full repayment at due date
        - Fraction of club members with full repayment 1 year after due date
        - Share of the total club loan repaid at due date
        - Share of the total club loan repaid 1 year after due date

- Locality-level (rural, urban, and total):
    - Number of loan applications
        - Number of first time applicants (no previous formal credit)
        - Number of repeat applicants
    - Fraction of loan applications approved
    - Number of loans disbursed
        - Number of individual loans
        - Number of group loans
        - Average group size
    - Total monetary value of loans disbursed
    - Loan repayment rate
        - By subgroup: first time borrowers vs. all borrowers, individual vs. joint liability customers
- Loan officer level:
    - Time spent per loan
        - Screening
        - Processing
        - Monitoring
        - Enforcing
    - Years of experience in current branch office
    - Total compensation
        - Base pay
        - Bonus
    - Loan officer's other income
        - Income from other work (ganyu, temporary work)
        - Agricultural investments
        - Agricultural proceeds

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Milestone 2 (July 1, 2013)

Contents:
Part 1: Implementation Plan
Part 2: Evaluation Strategy
Part 3: List of Key Indicators
Part 4: Plans to disseminate findings

<u>Part 1</u>: Implementation Plan

Fingerprint identification of borrowers will be embedded in the normal loan application process and credit bureau reporting procedures of the microfinance institutions that are members of the Malawi Microfinance Network (MAMN). Thus, the implementation process will be carefully coordinated with the roll-out of the new credit bureau, and designed to permit evaluation of the effect of fingerprint identification on borrowing and repaying.

The first phase of the implementation is stakeholder engagement, which began with a series of meetings with MAMN officials and representatives of the credit bureau and Reserve Bank in July and August 2012. Stakeholder engagement continued in July 2013: Jessica Goldberg, IPA Country Director Thomas Munthali, and Project Associate James Mwera met with MAMN leaders, and with officials at the Reserve Bank of Malawi.

The meetings at MAMN were especially critical because of a change in leadership: Mr. Stewart Kondowe, the previous Executive Director, passed away in May 2013. Mr. Mthwalo Mafuleka, the Acting Executive Director, is supportive of the plan and agreed to have the project team present to the MAMN membership in October 2013. MAMN reported that there are delays in the participation of MFIs in the fledgling credit bureau: in particular, there are uncertainties regarding the format for submitting information, and MFIs complain that fees for obtaining reports are high.

At the Reserve Bank of Malawi, we met with Mr. Daud Mthanthiko, the Principal Examiner for Microfinance and Mr. Fund B. Mzama, the Chief Examiner for Banks, and their associates. We learned of additional delays in the implementation of the credit bureau and of barriers to participation for MFIs, especially high fees for reports. However, we also learned of a promising alternative: a new credit processing hub for MFIs, which is funded by the World Bank under the Financial Sector Technical Agreement (FSTA) project for Malawi. The design of the hub has been contracted out to a consultant, and the design phase will take place from January to April, 2014. The hub is expected to be operational in May or June 2014, in advance of processing loans for the 2014-2015 growing season. The Reserve Bank is fully supportive of including fingerprinting capacity in this hub.

To that end, our team will follow up by meeting with Dr. Mwale, the coordinator for the processing hub. He also supports collaboration with this research project. He is assessing the capacity of MAMN as a host for the hub; the alternative is that the hub will be hosted by the Reserve Bank of Malawi. We are in regular contact with Dr. Mwale and Mr. Fraser Mdwazika of the Reserve Bank's National Payments Department to ensure that fingerprinting capacity is included in the hub. We have also made contact with Mr. Brian Mtonya, the World Bank technical team leader (TTL) for the FSTA.

This, we have accomplished key objectives in terms of stakeholder engagement and buy-in from regulators. Formal regulatory approval from the Reserve Bank cannot be granted until the specifications for the hub are developed; we have put in place the necessary conversations to ensure that this approval will be granted as soon as feasible.

The engagement phase will continue as follows:

1) We will work with Reserve Bank and World Bank officials to ensure that fingerprinting capacity is included as the new MFI processing hub is developed.
2) We will work with the same officials to ensure that approval for fingerprinting is granted as part of the process in which the Reserve Bank approves other loan processing procedures of the new hub.
3) We will work with MAMN officials to design protocol around fingerprint collection, under the assumption that MAMN will be the eventual host of the hub.
4) We will present the fingerprinting concept and research design to MAMN members at the Fall 2013 General Meeting. (This will be the first general meeting since the start of our project.)

We will provide training to loan officers on fingerprint collection through regional capacity-building workshops starting in May 2014, when the hub becomes operational and data sharing a reality for MFIs. Loan officers in geographic areas that are chosen for early implementation of fingerprinting will begin collecting fingerprint data when clients apply for new loans in August-November 2014. They will use equipment financed by the grant to collect and store these fingerprints, and will follow the protocol agreed to in the stakeholder meetings and institutionalized in the credit bureau guidelines to share the fingerprint data and other information about borrowers with the credit bureau.

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for a loan with a formal lender in the coming season). Analysis of the subsample of potential borrowing households will help increase our power to detect impacts; such households will be the most likely to be affected by the fingerprinting treatment. Locally-population-representative estimates of treatment effects can be obtained by reweighting regressions with the full sample of households appropriately.

Because the treatment may affect selection into borrowing, we will conduct intent-to-treat (ITT) analysis comparing all households in treatment and control groups, irrespective of their post-intervention borrowing status. Separately, we will examine the important question of whether selection into borrowing is affected by the fingerprinting treatment. In the event that the treatment does not affect selection into borrowing (as was found over one loan cycle in Gine, Goldberg, and Yang 2012), we will also estimate treatment effects on household outcomes for the sample of borrowers alone.

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An attractive aspect of our study design is that several key outcome variables are at the locality level and are measured using administrative data (e.g., loans disbursed, repayment rates), so attrition from the sample is not an issue. It is also worth noting that while we will be collecting data on loan officer activity per loan, these loan officer activity outcomes are actually not affected by attrition; the variables are total loan officer time allocation, and can ignore individual identities by pooling time across multiple officers that might have worked in the same locality over time.

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Impact heterogeneity and diversity across subgroups

In addition to measuring average treatment effects, we also seek to reveal the extent to which treatment effects differ by the riskiness of lending at baseline (which was also done in Gine, Goldberg, and Yang 2012). As emphasized by Deaton (2010), investigation of heterogeneity of treatment effects is most credible along dimensions that were part of the study's original treatment stratification scheme. Localities will therefore be stratified on the baseline loan repayment rate (calculated across all lenders) prior to the study. Localities will be sorted on this baseline variable, and then adjacent pairs of localities in the list will be randomly assigned to treatment and control. This will ensure balance across treatment and control groups in this key baseline variable, and set the stage for valid comparison of treatment effect heterogeneity with respect to baseline repayment rates. (Stratification also helps ensure balance on this baseline characteristic across the experimental conditions.)

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We assume a survey sample of 7,000 spread across 175 localities, with 50 households per locality, or on average 10 per quintile of predicted repayment. For these calculations, we conservatively assume a high attrition rate of 20%, so we will be left with 40 households per locality and 8 per quintile of predicted repayment. With these parameters, our study has sufficient power to detect effects of reasonable (and often substantial) size on the key outcomes of interest. Our power calculations are based on the assumption of a baseline survey and single follow-up. Power calculations were done using the Optimal Design program.

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study design would have power of more than 0.99 to detect an effect of this size. At power of 0.80, the minimum detectable effect size on share of loan repaid on-time would be 0.30 standard deviations, or 12.7 percentage points (which is only one-fourth of the actual effect size found in Gine, Goldberg, and Yang 2012).

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<u>Part 3:</u> List of Key Indicators

The key outcomes of interest in this Stage 2 study are as follows. Starred (*) items will be from administrative data of partnering microfinance institutions (MFIs).

- Individual level:
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    - Farm and enterprise outcomes (investments, inputs, output, profits)
        - Purchase of commercial inputs (price and quantity of each)
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            - Pesticide
        - Hired labor (days hired and total paid)
        - Other expenses
            - Transport
            - Packaging (bales for paprika, tobacco)
        - Own labor
            - Number of days weeding
            - Number of times applying manure
        - Harvest (quantity of each crop harvested)
        - Revenue
            - Quantity sold (by crop)
            - Price per kg sold
            - Total amount received for each crop
- Club level:
    - Club composition
        - * Gender ratio
        - * Years of membership in this club
        - * Years of membership in any club
    - Loan repayment
        - * Fraction of club members with full repayment at due date
        - * Fraction of club members with full repayment 1 year after due date

        - * Share of the total club loan repaid at due date
        - * Share of the total club loan repaid 1 year after due date
- Locality-level (rural, urban, and total):
    - * Number of loan applications
        - * Number of first time applicants (no previous formal credit)
        - * Number of repeat applicants
    - * Fraction of loan applications approved
    - * Number of loans disbursed
        - * Number of individual loans
        - * Number of group loans
        - * Average group size
    - * Total monetary value of loans disbursed
    - Loan repayment rate
        - * By subgroup: first time borrowers vs. all borrowers, individual vs. joint liability customers
- Loan officer level:
    - * Time spent per loan
        - * Screening
        - * Processing
        - * Monitoring
        - * Enforcing
    - * Years of experience in current branch office
    - * Total compensation
        - * Base pay
        - * Bonus
    - Loan officer's other income
        - Income from other work (ganyu, temporary work)
        - Agricultural investments
        - Agricultural proceeds

<u>Part 4:</u> Plans to disseminate findings

IPA will disseminate results of the study via knowledge-sharing events with relevant Malawian stakeholders, highlighting both private rates of return (for microfinance institutions) and social rates of return (private returns plus increased effort on the part of farmers leading to higher crop output and household income). Should we confirm in this national sample the positive rates of return found in the previous study, private adoption of fingerprinting technology by MFIs should be rapid. In addition, positive social rates of return should lead to increases in donor funding to stimulate adoption by MFIs and strengthen fingerprint-enabled national credit bureaus.

The specific results dissemination plan remains to be completed, since this must be designed in coordination with our primary partner, the Malawi Microfinance Network

(MAMN). Discussions on specific plans have been delayed by the death of MAMN's executive director and their ongoing search for a replacement. We remain committed to dissemination of research results and policy impact, so completion of this dissemination plan will be a primary objective once a new executive director is in place.

Progress Report for the Project:
Fingerprinting to Reduce Risky Borrowing: A Randomized Evaluation in Malawi

Grant No. AID-OAA-F-13-00032

Principal investigators: Jessica Goldberg (U. Maryland), Xavier Gine (World Bank), and Dean Yang (University of Michigan)

Milestone 3 (December 31, 2013)

Contents:
Part 1: Implementation Plan
Part 2: Evaluation Strategy
Part 3: List of Key Indicators
Part 4: Plans to disseminate findings

Part 1: Implementation Plan

Fingerprint identification of borrowers will be embedded in the normal loan application process and credit bureau reporting procedures of the microfinance institutions that are members of the Malawi Microfinance Network (MAMN). Thus, the implementation process will be carefully coordinated with the roll-out of the new credit bureau, and designed to permit evaluation of the effect of fingerprint identification on borrowing and repaying.

The first phase of the implementation is stakeholder engagement, which began with a series of meetings with MAMN officials and representatives of the credit bureau and Reserve Bank in July and August 2012. Stakeholder engagement continued in trips in July and October and at an event in September 2013.

At the last general annual meeting of the MAMN held in September 2013, Thom Munthali (IPA Country Director) and James Mwera (IPA, Field coordinator for this project) presented an overview of the project on behalf of the research team to MAMN members to elicit interest in participating in the project. A participating institution would agree to fingerprint its borrowers during loan application and to transfer credit and fingerprinting data to a central database. The grant would cover the software and hardware to enable the collection of fingerprint data and the transfer of data to the central database.

The week of October 14th-18th, 2013 the research team (Xavier Giné, Jessica Goldberg, Dean Yang along with Thom Munthali and James Mwera) met with 4 of the 5 largest microfinance institutions (including CUMO, FINCA, OIBM and Vision Fund) that had expressed an interest in participating during MAMN annual meeting. In these meetings, all MFIs restated their interested in participating in the fingerprinting project. Although the research team has so far reached out to the microfinance sector, it is also willing to partner well with the banking sector that engages in micro-lending.

During the same week, the research team met with the senior management of Credit Data and Credit Reference Bureau (CRB) Africa. Both institutions are currently not functioning due to regulatory and legal issues that will hopefully be resolved by early 2014. CRB Africa is the subsidiary of Trans-Union in Malawi, while Credit Data is fully owned by Malawians. Since credit bureau run by the subsidiary of Trans-Union in Kenya is fingerprint-based, we expect that CRB Africa will assist the project team with technical expertise on how to best incorporate biometric identification technologies into the generation of credit references and perhaps identifying a well-trained IT specialist on management information systems (MIS) who will help MFIs introduce fingerprinting into their day-to-day lending operations.

The project will therefore hire an IT specialist to assess the MIS of partner organizations, redesign and make appropriate adjustment and solution so as to enable all participating lenders to employ biometric identification technologies. Both the lenders and the credit bureaus will be involved in the process to establish the specialist's terms of reference, which will ensure the specialist's consultancy is most attuned to the requirements of all partnering organizations.

Once the technology has been procured, we will provide training to loan officers on fingerprint collection through regional capacity-building workshops starting in May 2014, when the hub becomes operational and data sharing a reality for MFIs. Loan officers in geographic areas that are chosen for early implementation of fingerprinting will begin collecting fingerprint data when clients apply for new loans in August-November 2014. They will use equipment financed by the grant to collect and store these fingerprints, and will follow the protocol agreed to in the stakeholder meetings and institutionalized in the credit bureau guidelines to share the fingerprint data and other information about borrowers with the credit bureau.

During the October trip, the project team also met with other stakeholders such as Malawi's Reserve Bank, the Ministry of Finance, and the World Bank co-TTL of the FSTAP financial sector support project. Because the details of which hardware and software will be used to collect fingerprint data and where the central fingerprint database will be hosted have not been finalized, the research team plans to coordinate closely with the FSTAP project to avoid duplication of efforts as the microfinance hub is designed.

The research team's role in this phase will be to coordinate activities, monitor adherence to protocols for collecting and sharing fingerprint data, and help troubleshoot procedural obstacles. At this stage, two project team members will support the implementation process on the ground. In this regard their main responsibility will be to detect and communicate problems to all stakeholders. Furthermore, they will ensure that responses to any upcoming problem will be implemented across branches as soon as possible.

Outside consultants will provide technological assistance as necessary. Note that while the research team will work closely with MAMN and microfinance agencies to facilitate collection of fingerprint data, the data will actually be collected, stored, and used by the MFIs and the credit processing hub. The research team will provide monthly status reports to MAMN summarizing information about the number of customers fingerprinted for the first time, the number of "matches" identified by the fingerprint database, and notes on common technological problems experienced by loan officers. MAMN will, in turn, make suggestions to or requests of individual lenders to bring them into compliance with the guidelines for collecting and sharing data.

In parallel, we will also implement an extensive data collection operation. We will begin with a baseline survey of 7,000 randomly-chosen households in treatment and control localities. This survey, which will be conducted in June-July 2014, will measure farm production decisions, use of inputs, profits, household well-being measures such as schooling and health outcomes, and the household's banking and financial portfolio. Summary statistics from baseline survey data will be shared with MFIs, to provide an overview of their current and potential clients.

To carry out the computer-based data collection, IPA will hire12 teams of surveyors. Each team will consist of four surveyors, who will track respondents and conduct the interviews, and one supervisor, who manages the team and conducts spot check so of interviews. Data collection staff will be supported by a support team of back checkers, who will conduct the ex-post quality checks of interviews previously taken, and 3 drivers who will operate the field cars. Altogether 69 field staff will be employed to carry both

rounds of data collection. It is anticipated that each surveyor can complete around 3 60-page questionnaires per day. Given these productivity levels, it is anticipated that each survey round will be completed within 63 days. The survey duration also includes 14 days of training (i.e. number of field work days is 49). Field Drivers will be employed just for 49 days since they do not have to attend the survey trainings.

To assess the impact of fingerprinting in the short run, two intermediate assessments will use administrative data from individual MFIs and from the credit bureau itself. These assessments will compare repayment rates and on-time repayments in treatment and control localities. One assessment will take place in June 2015, and another in December 2015.

An endline survey will be conducted in June 2016. This will mirror the baseline survey, and data from the baseline, endline, and administrative data will be used to prepare final policy reports and an academic paper. Thirty-six months after grant approval, fingerprinting will be fully rolled out, including to the delayed "control" localities. At this point, fingerprint identification and screening of borrowers will be a fully-integrated part of Malawi's credit reference bureau. The research team and stakeholders will document lessons learned for use in the future in Malawi, as well as to provide guidance to other countries interested in incorporating biometric identification in their credit bureaus.

This implementation plan builds upon the research team's experience of conducting fingerprint identification of new borrowers with a single Malawian MFI in 2007. Fingerprints were collected from 3,206 customers of the Malawi Rural Finance Company. We will use the same protocol and equipment in this expanded project as we used in the small-scale project in 2007. There, the equipment performed well; in particular, we were able to conduct convincing demonstrations to the borrowers that they could be identified and their records retrieved based on fingerprint alone. Moreover, we were able to improve repayment rates by increasing the cost of default – denial of future credit. Fingerprinting led to dramatic increases in repayment for the riskiest borrowers, and led these borrowers to voluntarily take smaller loans and use those loans on productive inputs. The fingerprinting intervention had a very favorable benefit-cost ratio of 2.34 to the lender (excluding the value of higher profits to the borrower). Those promising results are likely a lower-bound on the potential impact of a national-level project that includes multiple lenders and is a permanent feature of the borrowing landscape rather than a time-limited pilot.

Part 2: Evaluation Strategy

Identification strategy

Impact evaluation will be conducted as a randomized control trial, the gold standard in evaluation methodology. Branches of participating MFIs serving borrowers in rural localities in Malawi will be randomly assigned to a treatment group and a control group. In treatment branches, all borrowers will be fingerprinted in the process of loan application. In control branches, no fingerprinting will be conducted. Due to random assignment, comparisons between treatment and control branches will reveal the causal impact of fingerprinting on the outcomes of interest. A novel aspect of the design is we will vary the proportion of branches operating in a TA to be treated, thereby creating exogenous variation in the number of lenders that will use biometric technology in a given locality.

Note: we use the term "locality" to refer to traditional authorities (TAs) or subchiefs (SCs), of which there are 207 in across Malawi. This choice of TAs will be dictated by MFIs having a presence as some localities are quite remote and without MFI penetration.

In the terminology of Harrison and List (2004), this study will be a "natural field experiment." It is a natural field experiment for analysis of outcomes in locality-level administrative data (loan disbursements, repayment rates), since locality populations as a whole will not know they are in an experiment and simply will or will not encounter fingerprinting as part of the application process for any loans they apply for. Individuals to whom we administer the baseline survey will know they are in a study and will be followed over time through the follow-up surveys, but will not know that the impact of fingerprinting is the focus of the study, so their behavior and responses should not be influenced by their fingerprinting treatment assignment.

Implementation of the randomized control trial

Branches will be randomly assigned to a treatment or a control group. In control group branches, no intervention will be implemented beyond data collection.

Treatment branches will receive the fingerprinting intervention. All individuals applying for new loans will be required to be fingerprinted. Loan officers from those branches will explain to loan applicants how their fingerprints uniquely identify them for credit reporting to lenders, and that future lenders with the technology will be able to access the applicant's credit history simply by checking a fingerprint.

Loan applicants in treatment branches will have the image of their right thumbprint captured by an optical scanner attached to a computer using commercially-available software. The fingerprint image will then be added to the credit bureau database. Lenders that use the technology will be able to use the fingerprint-enabled credit history data for later screening of borrowers.

After fingerprints are collected, a computer-based demonstration program will be used to show participants that the computer is able to identify the applicant with only a fingerprint. The applicant will be asked to have his right thumb re-scanned, and will be

shown that the person's name and demographic information (entered earlier alongside the original scan) can be retrieved by the computer.

Spillovers

Spillovers across treatment and control branches would take the form of individuals in the treatment branches seeking to take out loans in control branches (where they would not be fingerprinted) or vice-versa. Our design allows us to measure these changes in the client base. While the choice of lenders is possible and something we are interested in, individuals from one TA seeking credit in another TA is less of a concern for several reasons. First, the state of transportation infrastructure in rural Malawi is quite poor, so the costs of traveling to seek out loans in another locality will be high for most individuals. Second, individuals in a treatment locality who happen to be just on the border with another locality would also face nonzero costs of taking out a loan in this other locality, since they would have to falsely claim that they live in that locality. Rural loans given out in our study area will mostly be group liability, so such an individual would have to find a borrowing group in a control locality that would agree to coordinate and falsely claim that the individual lived in the control locality. Finally, in our previous study (Gine, Goldberg, and Yang 2012), we randomized fingerprinting across borrowing clubs within localities, so treatment and control groups were actually geographically quite close to one another, and found no evidence of information spillovers or of treated individuals seeking to avoid the fingerprinting by borrowing outside their club.

Data collection methods and instruments

Several of the key outcomes of interest will come from administrative records of lenders. These include individual-level data on characteristics of borrowers and loan repayment; and locality-level data on total loans disbursed, total borrowers, and repayment rates.

Loan officer activities and time allocations to borrowers will be measured using lenders' administrative records alongside surveys of the loan officers themselves. All loan officers in treatment and control branches will be surveyed and will be used to calculate average time allocation per loan, by activity (screening, processing, monitoring, enforcement), for treatment and control groups. Loan officer survey instruments used in the Gine, Goldberg, and Yang (2012) study will be used for this proposed study as well.

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            - Transport
            - Packaging (bales for paprika, tobacco)
        - Own labor
            - Number of days weeding
            - Number of times applying manure
        - Harvest (quantity of each crop harvested)
        - Revenue
            - Quantity sold (by crop)
            - Price per kg sold
            - Total amount received for each crop
- Club level:
    - Club composition
        - * Gender ratio
        - * Years of membership in this club
        - * Years of membership in any club
    - Loan repayment
        - * Fraction of club members with full repayment at due date
        - * Fraction of club members with full repayment 1 year after due date

        - * Share of the total club loan repaid at due date
        - * Share of the total club loan repaid 1 year after due date
- Locality-level (rural, urban, and total):
    - * Number of loan applications
        - * Number of first time applicants (no previous formal credit)
        - * Number of repeat applicants
    - * Fraction of loan applications approved
    - * Number of loans disbursed
        - * Number of individual loans
        - * Number of group loans
        - * Average group size
    - * Total monetary value of loans disbursed
    - Loan repayment rate
        - * By subgroup: first time borrowers vs. all borrowers, individual vs. joint liability customers
- Loan officer level:
    - * Time spent per loan
        - * Screening
        - * Processing
        - * Monitoring
        - * Enforcing
    - * Years of experience in current branch office
    - * Total compensation
        - * Base pay
        - * Bonus
    - Loan officer's other income
        - Income from other work (ganyu, temporary work)
        - Agricultural investments
        - Agricultural proceeds

<u>Part 4:</u> Plans to disseminate findings

IPA will disseminate results of the study via knowledge-sharing events with relevant Malawian stakeholders, highlighting both private rates of return (for microfinance institutions) and social rates of return (private returns plus increased effort on the part of farmers leading to higher crop output and household income). Should we confirm in this national sample the positive rates of return found in the previous study, private adoption of fingerprinting technology by MFIs should be rapid. In addition, positive social rates of return should lead to increases in donor funding to stimulate adoption by MFIs and strengthen fingerprint-enabled national credit bureaus.

The specific results dissemination plan remains to be completed, since this must be designed in coordination with our primary partner, the Malawi Microfinance Network

(MAMN). Discussions on specific plans have been delayed by the death of MAMN's executive director and their ongoing search for a replacement. We remain committed to dissemination of research results and policy impact, so completion of this dissemination plan will be a primary objective once a new executive director is in place.

Progress Report for the Project:
Fingerprinting to Reduce Risky Borrowing: A Randomized Evaluation in Malawi

Grant No. AID-OAA-F-13-00032

Principal investigators: Jessica Goldberg (U. Maryland), Xavier Gine (World Bank), and Dean Yang (University of Michigan)

Milestone 4 (July 30, 2014)

Contents:
Part 1: Implementation Plan
Part 2: Evaluation Strategy
Part 3: List of Key Indicators
Part 4: Plans to disseminate findings
Part 5: Fingerprinting Protocol and Technical Requirements
Part 6: Baseline Survey

Part 1: Implementation Plan

Fingerprint identification of borrowers will be embedded in the normal loan application process and credit bureau reporting procedures of the microfinance institutions that are members of the Malawi Microfinance Network (MAMN). Thus, the implementation process will be carefully coordinated with the roll-out of the new credit bureau, and designed to permit evaluation of the effect of fingerprint identification on borrowing and repaying.

The first phase of the implementation is stakeholder engagement, which began with a series of meetings with MAMN officials and representatives of the credit bureau and Reserve Bank in July and August 2012. Stakeholder engagement continued in trips in July and October and at an event in September 2013.

At the last general annual meeting of the MAMN held in September 2013, Thom Munthali (IPA Country Director) and James Mwera (IPA, Field coordinator for this project) presented an overview of the project on behalf of the research team to MAMN members to elicit interest in participating in the project. A participating institution would agree to fingerprint its borrowers during loan application and to transfer credit and fingerprinting data to a central database. The grant would cover the software and hardware to enable the collection of fingerprint data and the transfer of data to the central database.

The week of October 14th-18th, 2013 the research team (Xavier Giné, Jessica Goldberg, Dean Yang along with Thom Munthali and James Mwera met with several of the MFIs that had expressed an interest in participating during MAMN annual meeting. In these meetings, all MFIs restated their interested in participating in the fingerprinting project. Since that time 3 of Malawi's largest micro lenders have agreed to participate in the project. They are CUMO, MEDF and Microloan and cumulatively they serve 300,000 borrowers, capturing over 50% of Malawi's micro-lending market. Four MFIs (OBM, Vision Fund, FINCA and Green Root) have agreed to serve as inactive partners, providing geographical data on their loan officer and customer base to enable to project to do market analysis.

During the same week, the research team met with the senior management of Credit Data and Credit Reference Bureau (CRB) Africa. Both institutions are currently not functioning due to regulatory and legal issues that are set to go to Parliament in September 2014. CRB Africa is the subsidiary of Trans-Union in Malawi, while Credit Data is fully owned by Malawians. Since credit bureau run by the subsidiary of Trans-Union in Kenya is fingerprint-based, CRB Africa has assisted the project team with technical expertise on how to best incorporate biometric identification technologies into the generation of credit references through engaging with our technology provider.

In February of 2014 the project issued a request for proposals for a technology provider to supply a biometric solution for fingerprint capture. Eleven companies submitted proposals and four (Craft Silicon, Techno Brain Ltd, Ideco and Globe Computer Systems Limited) were short listed for interviews. Techno Brain Ltd was issued a contract based on their high experience and recommendations of working with biometrics in Malawi.

A steering committee was convened in May 2014 and was comprised of members from all active partner MFIs, the two credit bureaus, and MAMN for the purpose of providing input into the biometric technology development and solution. Techno Brain engaged each acting partner through June 2014 and developed a feasible solution for hardware and software development as well as a data flow plan that was agreed upon by all parties (see **Part 5: Fingerprinting Protocol and Technical Requirements**). MAMN has been given permission by the Reserve Bank of Malawi to house and service the servers carrying fingerprint registration data. MAMN is also a strong candidate for the hosting of the microfinance hub, currently under discussion as part of the World Bank's FSTAP program.

Currently Techno Brain is undergoing software development. User acceptance tests and piloting is set for late August, 2014. At that time we will host a training-of-the-trainers workshop in Lilongwe for identified loan officer trainers from the participating MFIs. These trainers will then train selected loan officers at their institutions in early September 2014. Loan officers selected for treatment will begin collecting fingerprint data in mid-September 2014. They will use equipment financed by the grant to collect and store these fingerprints, and will follow the protocol agreed to in the stakeholder meetings and institutionalized in the credit bureau guidelines to share the fingerprint data and other information about borrowers with the credit bureaus.

The local staff team has continued to follow up on meeting made by the project team last October with other stakeholders such as Malawi's Reserve Bank, the Ministry of Finance, and the World Bank co-TTL of the FSTAP financial sector support project. Since the details of the hardware and software to collect and store fingerprint data have already been finalized, the research team continues to coordinate closely with the FSTAP project to avoid duplication of efforts as the microfinance hub is designed.

In this phase, the research team will coordinate activities, monitor adherence to protocols for collecting and sharing fingerprint data, and help troubleshoot procedural obstacles with the support of two project team members. Their main responsibilities will be to detect and communicate problems to all stakeholders and ensure that responses to any upcoming problem will be implemented across branches as soon as possible.

Outside consultants will provide technological assistance when necessary. While fingerprint data will actually be collected and used by the MFIs and the credit bureaus, MAMN will play an important role as the database host and custodian. The research team will engage regularly with MAMN summarizing information about the number of customers fingerprinted for the first time, the number of "matches" identified by the fingerprint database, and notes on common technological problems experienced by loan officers. MAMN will, in turn, make suggestions to or requests of individual lenders to bring them into compliance with the guidelines for collecting and sharing data.

In parallel, we will also implement an extensive data collection operation. We will begin with a baseline survey of 1000 randomly-chosen borrowing groups under treatment and control loan officers. This survey, which will be conducted in August 2014, will measure farm production decisions, use of inputs, profits, household well-being measures such as schooling and health outcomes, and the household's banking and financial

portfolio. Summary statistics from baseline survey data will be shared with MFIs, to provide an overview of their current and potential clients.

To carry out the computer-based data collection, IPA will hire 10 teams of surveyors. Each team will consist of four surveyors, who will track respondents and conduct the interviews, and one supervisor, who manages the team and conducts spot check so of interviews. Data collection staff will be supported by a support team of back checkers, who will conduct the ex-post quality checks of interviews previously taken, and 3 drivers who will operate the field cars. Altogether 57 field staff will be employed to carry both rounds of data collection. It is anticipated that each team of 4 surveyors can survey approximately 3.5 borrowing groups per day, approximately 15 borrowers per group. Given these productivity levels, it is anticipated that each survey round will be completed within 43 days. The survey duration also includes 14 days of training (i.e. number of field work days is 29). Field Drivers will be employed just for 29 days since they do not have to attend the survey trainings.

To assess the impact of fingerprinting in the short run, two intermediate assessments will use administrative data from individual MFIs and from the credit bureau itself. These assessments will compare repayment rates and on-time repayments in treatment and control localities. One assessment will take place in June 2015, and another in December 2015.

Two follow-up surveys in June 2015 and June 2016 and an endline survey will be conducted. They will mirror the baseline survey, and data from the baseline, follow-ups, endline, and administrative data will be used to prepare final policy reports and an academic paper. Thirty-six months after grant approval, fingerprinting will be fully rolled out, including to the delayed "control" localities. At this point, fingerprint identification and screening of borrowers will be a fully-integrated part of Malawi's credit reference bureau. The research team and stakeholders will document lessons learned for use in the future in Malawi, as well as to provide guidance to other countries interested in incorporating biometric identification in their credit bureaus.

This implementation plan builds upon the research team's experience of conducting fingerprint identification of new borrowers with a single Malawian MFI in 2007. Fingerprints were collected from 3,206 customers of the Malawi Rural Finance Company. We will use a similar protocol and equipment in this expanded project as we used in the small-scale project in 2007. There, the equipment performed well; in particular, we were able to conduct convincing demonstrations to the borrowers that they could be identified and their records retrieved based on fingerprint alone. Moreover, we were able to improve repayment rates by increasing the cost of default – denial of future credit. Fingerprinting led to dramatic increases in repayment for the riskiest borrowers, and led these borrowers to voluntarily take smaller loans and use those loans on productive inputs. The fingerprinting intervention had a very favorable benefit-cost ratio of 2.34 to the lender (excluding the value of higher profits to the borrower). Those promising results are likely a lower-bound on the potential impact of a national-level project that includes multiple lenders and is a permanent feature of the borrowing landscape rather than a time-limited pilot.

Part 2: Evaluation Strategy[CF1]

Identification strategy

Impact evaluation will be conducted as a randomized control trial, the gold standard in evaluation methodology. Loan officers of participating MFIs serving borrowers in rural localities in Malawi will be randomly assigned to a treatment group and a control group. For treatment loan officers, all borrowers will be fingerprinted in the process of loan application. For control loan officers, no fingerprinting will be conducted. Due to random assignment, comparisons between treatment and control loan officer borrowing groups will reveal the causal impact of fingerprinting on the outcomes of interest. Random assignment in this case causes natural variation in the number of lenders, and thus the proportion of borrowers being treated in each locality.

Note: we use the term "locality" to refer to traditional authorities (TAs) or subchiefs (SCs), of which there are 207 in across Malawi. This choice of TAs will be dictated by MFIs having a presence as some localities are quite remote and without MFI penetration.

In the terminology of Harrison and List (2004), this study will be a "natural field experiment." It is a natural field experiment for analysis of outcomes in locality-level administrative data (loan disbursements, repayment rates), since locality populations as a whole will not know they are in an experiment and simply will or will not encounter fingerprinting as part of the application process for any loans they apply for. Individuals to whom we administer the baseline survey will know they are in a study and will be followed over time through the follow-up surveys, but will not know that the impact of fingerprinting is the focus of the study, so their behavior and responses should not be influenced by their fingerprinting treatment assignment.

Implementation of the randomized control trial

Loan officers will be randomly assigned to a treatment or a control group. Loan officers in the control group will be trained to convey to their clients the importance of maintaining a good credit record, how their fingerprints uniquely identify them for credit reporting to lenders, and that future lenders with the technology will be able to access the applicant's credit history simply by checking a fingerprint.

Treatment loan officers will receive the fingerprinting intervention. All clients of treatment loan officers will be fingerprinted as soon as possible thus creating variation as to when in the loan cycle clients are fingerprinted. All new applicants will also be fingerprinted. Treated loan officers will receive the same training as control loan officers and will provide to their clients the same information.

Loan applicants in the treatment group will have the image of their fingerprints captured on a tablet device with an optical scanner. The fingerprint images will then be added to the server database, go through a de-duplication process and be assigned a

unique ID number. Lenders that use the technology will be able to use the unique ID number generated by the system to exchange credit history information.

After fingerprints are collected, a tablet-based demonstration program will be used to show participants that the tablet is able to identify the applicant with only a fingerprint. The applicant will be asked to have his fingerprint re-scanned, and will be shown that the person's name and demographic information (entered earlier alongside the original scan) can be retrieved by the tablet from the central servers.

Spillovers

Spillovers across treatment and control borrowing groups would take the form of individuals in the treatment groups seeking to take out loans in control groups (where they would not be fingerprinted) or vice-versa. Our design allows us to measure these changes in the client base due to the varying density of fingerprinted groups per locality. For example, administrative data will allow us to capture the number of individuals exiting treatment groups and entering control groups (and vice versa). Seeing a large movement of borrowers between groups in low density localities, where it is presumably easier to find a control group to join, will provide insight into the effects of a partial implementation of fingerprinting technology. Additionally, within participating MFIs roughly 50% of the localities are served by only one loan officers making it difficult to move between treatment and control groups within the same MFI. Finally, in our previous study (Gine, Goldberg, and Yang 2012), we randomized fingerprinting across borrowing clubs within localities, so treatment and control groups were actually geographically quite close to one another, and found no evidence of information spillovers or of treated individuals seeking to avoid the fingerprinting by borrowing outside their club.

Data collection methods and instruments

Several of the key outcomes of interest will come from administrative records of lenders. These include individual-level data on characteristics of borrowers; and locality-level data on total loans disbursed, total borrowers, and repayment rates.

Loan officer activities and time allocations to borrowers will be measured using lenders' administrative records alongside surveys of the loan officers themselves. All loan officers will be surveyed and will be used to calculate average time allocation per loan, by activity (screening, processing, monitoring, enforcement), for treatment and control groups. Loan officer survey instruments used in the Gine, Goldberg, and Yang (2012) study will be used for this proposed study as well.

We will also field our own baseline and follow-up household surveys. These will be important to provide insight into particular borrower behaviors that may be affected by the treatment but are not available in administrative data. Surveys will cover both household- and individual-level variables, with specific questions for the individual most likely to contract a loan in the next season (if any), identified as the member of the borrowing group. Survey instruments will be modeled after surveys successfully field-tested and implemented in our previous study (Gine, Goldberg and Yang 2012). Key outcomes of interest include farm production decisions (land allocation, input use, family

labor allocation, hired labor), farm production and net income, and other indicators of household well-being such as schooling and health outcomes. So that short- and long-run effects can be compared, impacts will be assessed annually over a three-year time frame. This will require fielding of three post-treatment surveys, once at the end of each of the three years of the project. Survey samples will be drawn from new and existing borrowing groups at participating MFIs.

Because the treatment may affect selection into borrowing, we will conduct intent-to-treat (ITT) analysis comparing all households in treatment and control groups, irrespective of their post-intervention borrowing status. Separately, we will examine the important question of whether selection into borrowing is affected by the fingerprinting treatment. In the event that the treatment does not affect selection into borrowing (as was found over one loan cycle in Gine, Goldberg, and Yang 2012), we will also estimate treatment effects on household outcomes for the sample of borrowers alone.

We will also estimate population-representative impacts on key outcomes across treatment and control localities using the panel sample from the Malawi Integrated Household Survey (IHS), an LSMS-type survey administered by the government of Malawi. (The 2011 and 2013 rounds of the IHS will serve as a baseline.) In addition, locality-level data on credit access reported by households in the IHS will be useful as a check on the administrative data on credit supply provided by lenders.

The data collection and analysis described above will provide estimates, separately for treated and control groups, of 1) program impacts on households, 2) program impacts on financial outcomes of lenders, and 3) the costs of program implementation. These elements will be combined into a credible estimate of the program's benefit-cost ratio for lenders alone as well as for society as a whole (considering lender profits plus benefits for households).

Attrition

An attractive aspect of our study design is that several key outcome variables are at the locality level and are measured using administrative data (e.g., loans disbursed, repayment rates), so attrition from the sample is not an issue. It is also worth noting that while we will be collecting data on loan officer activity per loan, these loan officer activity outcomes are actually not affected by attrition; the variables are total loan officer time allocation, and can ignore individual identities by pooling time across multiple officers that might have worked in the same locality over time.

For the follow-up surveys that we implement ourselves, attrition between the baseline and follow-up survey is a first-order concern. Follow-up tracking methods will exploit the past experience of the PIs in conducting panel surveys of households in rural Malawi. In addition, we will implement randomized intensity of follow-up (as in Katz, Kling, and Liebman, 2001 and Kling, Ludwig, and Katz, 2005). Two-thirds of respondents (randomly selected) will receive a limited number of follow-up visits, while the remaining one-third of respondents will be assigned to intensive follow-up (additional follow-up visits). This allows assessment of the existence and extent of attrition bias (DiNardo, McCrary and Sanbonmatsu 2006).

Impact heterogeneity and diversity across subgroups

In addition to measuring average treatment effects, we also seek to reveal the extent to which treatment effects differ by the riskiness of lending at baseline (which was also done in Gine, Goldberg, and Yang 2012). As emphasized by Deaton (2010), investigation of heterogeneity of treatment effects is most credible along dimensions that were part of the study's original treatment stratification scheme. Loan officers will therefore be stratified on the baseline loan recovery rate prior to the study. Loan officers will be sorted on this baseline variable, and then adjacent pairs of officers in the list will be randomly assigned to treatment and control. This will ensure balance across treatment and control groups in this key baseline variable, and set the stage for valid comparison of treatment effect heterogeneity with respect to baseline repayment rates. (Stratification also helps ensure balance on this baseline characteristic across the experimental conditions.)

We will also measure treatment effect heterogeneity along individual-level baseline variables. The most important baseline variable is an group-level measure of borrower riskiness, along the lines of the one used in Gine, Goldberg, and Yang (2012) (and for which there was substantial treatment effect heterogeneity in that study). This involves running an group-level regression of loan repayment on borrowers' pre-borrowing characteristics in a sample of loans prior to the experiment, and then predicting loan repayment for the entire study sample. This essentially creates a "credit score" for each borrowing group based on their pre-intervention characteristics.

In addition, we will measure treatment effect heterogeneity for the following subgroups: households near vs. far from a formal lending branch; female- and male-headed households; households that do and do not farm cash crops (a proxy for market integration); households above and below the median of a wealth index; households with and without past experience with formal borrowing. These subgroup analyses will be detailed in a formal pre-analysis plan to forestall concerns about data mining.

Power calculations

We assume a survey sample of 7,000 spread across 175 localities, with 50 households per locality, or on average 10 per quintile of predicted repayment. For these calculations, we conservatively assume a high attrition rate of 20%, so we will be left with 40 households per locality and 8 per quintile of predicted repayment. With these parameters, our study has sufficient power to detect effects of reasonable (and often substantial) size on the key outcomes of interest. Our power calculations are based on the assumption of a baseline survey and single follow-up. Power calculations were done using the Optimal Design program.

First, we calculate the sample size needed to detect an increase in repayment for the highest-risk quintile of borrowers, the subsample for which effects were found in the Gine, Goldberg, and Yang (2012) study. We make the following assumptions: statistical significance level 0.05; 175 clusters; intracluster correlation coefficient 0.420 (calculated from the Gine, Goldberg, and Yang 2012 survey dataset); 8 individuals per cluster in the highest-risk quintile. In the original Gine, Goldberg, and Yang (2012) study, the treatment effect on share of loan repaid on-time in the highest- risk quintile was 50.6 percentage points (1.2 standard deviations). Under these assumptions, our proposed new

study design would have power of more than 0.99 to detect an effect of this size. At power of 0.80, the minimum detectable effect size on share of loan repaid on-time would be 0.30 standard deviations, or 12.7 percentage points (which is only one-fourth of the actual effect size found in Gine, Goldberg, and Yang 2012).

To calculate our power to detect an increase in log profits in our survey sample, we make the following assumptions: statistical significance level 0.05; 175 clusters; intracluster correlation coefficient 0.126 (calculated from the Gine, Goldberg, and Yang 2012 survey dataset); 8 individuals per cluster in the highest-risk quintile. In the original Gine, Goldberg, and Yang (2012) study, the treatment effect on log profits in the highest-risk quintile was 0.434 (but was not statistically significant). Under these assumptions, our proposed new study design would have power of more than 0.99 to detect an effect of 0.434, which exceeds the typical power threshold of 0.80 by a large margin. At power of 0.80, the minimum detectable effect size on log profits would be 0.20 (less than half of the point estimate found in Gine, Goldberg, and Yang 2012).

<u>Part 3:</u> List of Key Indicators

The key outcomes of interest in this Stage 2 study are as follows. Starred (*) items will be from administrative data of partnering microfinance institutions (MFIs).

- Individual level:
    - Household characteristics
        - Household listing (roster)
            - Age
            - Gender
            - Main activity (school, work, etc.)
            - Relation to household head
        - Asset ownership (see asset module from IHS)
        - Consumption (see consumption module from IHS)
        - Income (see module E from IHS)
    - Loan repayment
        - * Indicator for on-time full repayment
        - * Indicator for eventual (1 year after due date) full repayment
        - * Share of loan repaid at due date
        - * Share of loan repaid 1 year after due date
    - Farm and enterprise outcomes (investments, inputs, output, profits)
        - Purchase of commercial inputs (price and quantity of each)
            - Fertilizer (subsidized and unsubsidized)
            - Pesticide
        - Hired labor (days hired and total paid)
        - Other expenses
            - Transport
            - Packaging (bales for paprika, tobacco)
        - Own labor
            - Number of days weeding
            - Number of times applying manure

        - Harvest (quantity of each crop harvested)
        - Revenue
            - Quantity sold (by crop)
            - Price per kg sold
            - Total amount received for each crop
- Club level:
    - Club composition
        - * Gender ratio
        - * Years of membership in this club
        - * Years of membership in any club
    - Loan repayment
        - * Fraction of club members with full repayment at due date
        - * Fraction of club members with full repayment 1 year after due date
        - * Share of the total club loan repaid at due date
        - * Share of the total club loan repaid 1 year after due date
- Locality-level (rural, urban, and total):
    - * Number of loan applications
        - * Number of first time applicants (no previous formal credit)
        - * Number of repeat applicants
    - * Fraction of loan applications approved
    - * Number of loans disbursed
        - * Number of individual loans
        - * Number of group loans
        - * Average group size
    - * Total monetary value of loans disbursed
    - Loan repayment rate
        - * By subgroup: first time borrowers vs. all borrowers, individual vs. joint liability customers
- Loan officer level:
    - * Time spent per loan
        - * Screening
        - * Processing
        - * Monitoring
        - * Enforcing
    - * Years of experience in current branch office
    - * Total compensation
        - * Base pay
        - * Bonus
    - Loan officer's other income
        - Income from other work (ganyu, temporary work)
        - Agricultural investments
        - Agricultural proceeds

Part 4: Plans to disseminate findings

IPA will disseminate results of the study via knowledge-sharing events with relevant Malawian stakeholders, highlighting both private rates of return (for microfinance institutions) and social rates of return (private returns plus increased effort on the part of farmers leading to higher crop output and household income). Should we confirm in this national sample the positive rates of return found in the previous study, private adoption of fingerprinting technology by MFIs should be rapid. In addition, positive social rates of return should lead to increases in donor funding to stimulate adoption by MFIs and strengthen fingerprint-enabled national credit bureaus.

The specific results dissemination plan remains to be completed, since this must be designed in coordination with our primary partner, the Malawi Microfinance Network (MAMN). Our team has begun working with the new CEO of MAMN who was appointed in January, 2014. In partnership with JPal and IPA participating members of the project, including the CEO and Operations Manager of MAMN, attended a two-day RCT training workshop in Lilongwe on July 16th and 17th. The workshop was an opportunity to emphasize to our partners the importance of strong evaluation and dissemination of results. We will continue to work closely with MAMN over the course of the project to prepare for preliminary and endline dissemination of our findings.

Part 5: Fingerprinting Protocol and Technical Requirements

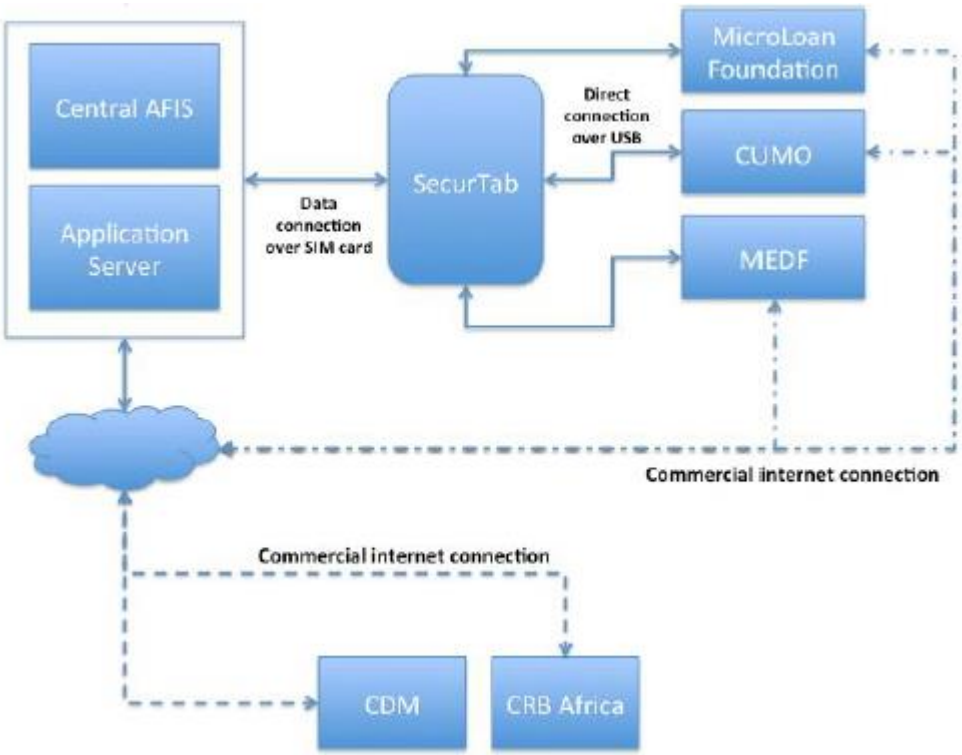
Fingerprinting will be randomized at the loan officer level. Loan officers randomly selected for treatment will be provided with an Android tablet with a build-in fingerprint scanning device to capture the fingerprints of their customers. Loan officers assigned to the control group will not receive any equipment and their loan processes will continue as normal. For further detail see **Section 2: Evaluation Strategy** (*Implementation of the randomized control trial).*

Our technology provider, Techno Brain Ltd., has proposed a solution to the capture and integration of fingerprinting into MFI and credit bureau operations.

The system will run under three different platforms with the workflow design as follows:

- **Android platform**: The custom developed android application will run on a SecureTAB for enrolling borrowers by loan officers on the field and the same application will be used by officers to establish the bona-fides of an applicant during Loan Origination process.
- **Central Web Application:** The server side application will run under .net framework 4.0 which collects and consolidates data received from the field for reporting

- **Web Service:** Developed and published for future access by authorized third-parties (Credit Reference Bureaus) to search for information stored on the central system



The following factors were taken into consideration when designing the service.

- the number of fingerprint templates being referenced (in our project this is estimated to be 1,500,000 – corresponding to 150,000 individual records)
- the acceptable time for processing an identification request (in our project this is less than 2 seconds processing time)
- the peak number of identification requests expected per hour (in our project this is estimated this to be 1,500 requests per hour)
- the target population; if the target population comprises mainly of elderly people, then the quality of fingerprint template capture may be affected
- the quality of the fingerprint scanner used to capture live-fingerprints; if a non-standard non-compliant scanner is deployed for live-print capture, the resultant template may be sub-standard – resulting in "false matching" or "false rejection" scenarios

With these considerations and through our partnership with Techno Brain we have worked to avoid common pitfalls in biometric services by ensuring the following:

- That the biometric service being procured is not based on a proprietary algorithm and format, but based on internationally accepted and compliant standards. This will ensure that independent of the contracted biometric service provider, the procuring entity will be able to use the biometric data collected in other applications, and more importantly, third-party applications will be able to query and use the stored templates
- That the quality of the end hardware device (used to capture the fingerprints of the applicants) is of proper standars. For example, it is important to ensure that the quality of fingerprints captured are at an optimum resolution for future use.
- That any image compression techniques employed are as per WSQ (Wavelet Scalar Quantization) formats as defined by the FBI.

Part 6: Baseline Survey

The baseline survey was developed from the survey instruments previously employed by the research team in Malawi on both the previous related study and other relevant work. It is attached in a separate pdf titled "FRRB_baseline_EN."

Fingerprinting to Reduce Risk Borrowing: Loan officer randomization process
July 3rd, 2014[1]

Randomization at the loan officer (LO) level is stratified within Microfinance Institution (MFI) and by past repayment performance[2] (PAR). The randomization was done separately for those LOs with PAR information available and those who were missing PAR information.

For those with PAR information available the process was done as follow:

1. Within each MFI, LOs were sorted by PAR.
2. A random number between 0 and 1 was assigned to each LO using a uniform distribution.
3. For groups with an even number of LOs per MFIs:
    a. Every two LOs were assigned to the same pair. In that sense, LOs were assigned to pairs with similar PAR scores.

	MFI	PAR	temppair
1	CUMO	0	1
2	CUMO	0	1
3	CUMO	0	2
4	CUMO	0	2
5	CUMO	0	3
6	CUMO	0	3
7	CUMO	0	4
8	CUMO	0	4
9	CUMO	.0014386	5
10	CUMO	.00614035	5
11	CUMO	.01392857	6
12	CUMO	.01416667	6
13	CUMO	.02852459	7
14	CUMO	.0286551	7
15	CUMO	.03453847	8
16	CUMO	.04210082	8
17	CUMO	.04273687	9
18	CUMO	.04329787	9

    b. A unique identifier was assigned to each pair. The unique identifier was the code of the MFI (CUMO: 1/ Microloan: 2/ MEDF: 3) followed by pair number within MFI.

	MFI	MFIcode	PAR	temppair	pair
73	CUMO	1	.24276432	37	137
74	CUMO	1	.2512984	37	137
75	CUMO	1	.25217488	38	138
76	CUMO	1	.26413146	38	138
77	CUMO	1	.26477742	39	139
78	CUMO	1	.33077314	39	139
79	CUMO	1	.34867218	40	140
80	CUMO	1	.44951957	40	140
81	Microloan	2	0	1	21
82	Microloan	2	.00121966	1	21
83	Microloan	2	.00301657	2	22
84	Microloan	2	.0036025	2	22
85	Microloan	2	.00529076	3	23
86	Microloan	2	.0053693	3	23
87	Microloan	2	.00697823	4	24
88	Microloan	2	.00806177	4	24

    c. For each sequential pair of LOs within MFI, the LO with the highest random number was assigned to treatment and the one with the lowest was assigned to control.

---

[1] The process of randomization was done with information collected between February and June 2014.

[2] See appendix I for more information on the PAR calculation.

	MFI	PAR	pair	random	treatment
13	CUMO	.0286551	17	.0292672	0
14	CUMO	.02852459	17	.5678066	1
15	CUMO	.04210082	18	.4991379	0
16	CUMO	.03453847	18	.8359776	1
17	CUMO	.04273687	19	.7188058	1
18	CUMO	.04329787	19	.5876957	0
19	Microloan	0	21	.6800693	0
20	Microloan	.00121966	21	.7448381	1
21	Microloan	.0036025	22	.06404	0
22	Microloan	.00301657	22	.9297732	1

4. CUMO (83), MEDF (65) and Microloan (53) had an odd number of LOs with PAR information. In order to have an even number group, the process was as follow:
    a. The LO with the lowest random number was left out of the group for each MFI.
    b. For the LOs from CUMO and MEDF the MFIcode changed temporarily, as if it was part of a different MFI (MFIcode=4).
    c. For the LO from Microloan the MFIcode changed temporarily, as if it was part of a different MFI (MFIcode=5).

The previous step left five groups: One even number group for each MFI (3 in total), one temporary pair between the LOs from CUMO and MEDF and one group with one LO from Microloan.

    d. For the even number group of each MFI, the randomization was done within pairs as described in step 3.
    e. For the temporary pair, between LO of MEDF and CUMO, the LO with higher random number was assigned to treatment and the one with the lowest was assigned to control.
    f. The individual LO from Microloan was coded with a different MFIcode so it can be paired with the LO with no PAR information left out of the group.

For those LOs with no PAR information the randomization was done as follow:

5. A new random number was created only for those LOs with no PAR information.
6. MEDF had an even number of LOs without PAR information (18). Half of LOs with higher random numbers were assigned to treatment and the other half, with lowest random numbers, were assigned to control. The median of the random number for this group of LOs, was the cut point to divide the top and bottom.
7. Microloan had an odd number of LOs without PAR info (15). The LO with the lowest random number was left out of the group. The MFIcode of this observation was temporarily changed as if it was part of a different MFI. (MFIcode=5).
8. Step 6 was repeated for the even number of LOs of Microloan.

Additional pair: One LO officer with PAR information and one without

9. Both LOs from Microloan that were left out from their odd number groups (MFIcode=5), were paired. Notice that for this pair both are LO from Microloan but one has PAR info and the other doesn't.
10. A new random number was created for this new pair.
11. The LO with higher random number was assigned to treatment and the one with the lowest was assigned to control.

In addition to the randomization, demographic variables – gender, marital status, education, type of loan - were coded as categorical variables as follow:

- male: 1 male, 0 female
- married: 1 married, 0 never married
- educ -years of education-:
  - 10: Junior certificate
  - 12: MSCE
  - 13: Certificate
  - 14: Teaching certificate
  - 15: Diploma
  - 17: Diploma + Teaching certificate
- loantype_both: 1 If the loan officer has individual and group clients, 0 otherwise
- loantype_group: 1 If the loan officer has only clients in groups, 0 otherwise
  Note: Any of the LOs has exclusively individual clients. CUMO and Microloan only have clients in groups. MEDF has both, group and individual clients.

Additional variables were created to include them in the balance test of the randomization:

- rule1: 1 if LO was left out from odd group, had PAR info, was paired with other LO with PAR info and max random number was treatment, 0 otherwise.
- rule2: 1 if LO was left out from odd group, only one LO in the pair has PAR info and max random number was treatment, 0 otherwise.
- NOPAR: 1 If there is no available information on loan officer performance.
  Note:
  - Microloan LOs with no PAR information are new loan officers.
  - LOs with no figures in MEDF are due to three factors:
    - MEDF didn't report any information for them on performance: (11 records)
    - They are new loan officers: (6 records)
    - A supervisor assumed the role of a loan officer: (1 record: Sathawa Chifundo)

From a total of 234 Loan Officer, 117 were assigned to treatment and 117 to control. The distribution of treatment and control per MFI is as follow:

MFI	Treatment	Control	Total
CUMO	41	42	**83**
MEDF	42	41	**83**
Microloan	34	34	**68**
Total	**117**	**117**	**234**

Balance test

The following are the result of the main two regressions to check for the balance of the randomization[3]. In every case, the control variables were non-significant.

1. Treatment on NOPAR

```
Linear regression                                      Number of obs =     234
                                                       F(  1,   232) =    0.04
                                                       Prob > F      =  0.8518
                                                       R-squared     =  0.0002
                                                       Root MSE      =  .50211

------------------------------------------------------------------------------
             |               Robust
   treatment |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       NOPAR |  -.0176391    .094279    -0.19   0.852    -.2033914    .1681133
       _cons |   .5024876   .0354185    14.19   0.000     .4327045    .5722706
------------------------------------------------------------------------------
```

2. Treatment on NOPAR age educ duration customer TA new rule1 rule2 male married loantype_both

```
Linear regression                                      Number of obs =     233
                                                       F( 12,   220) =    0.38
                                                       Prob > F      =  0.9691
                                                       R-squared     =  0.0188
                                                       Root MSE      =  .50969

-------------------------------------------------------------------------------
              |               Robust
    treatment |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
        NOPAR |  -.0910102   .1403221    -0.65   0.517    -.3675578    .1855373
          age |    .008721   .0069842     1.25   0.213    -.0050435    .0224854
         educ |   .0028194   .0276973     0.10   0.919    -.0517665    .0574053
     duration |  -.0019218   .0015354    -1.25   0.212    -.0049477    .0011042
     customer |  -2.35e-06   .0000187    -0.13   0.900    -.0000391    .0000344
           TA |   .0185704   .0240021     0.77   0.440    -.0287331    .0658739
          new |   .0717551   .1676767     0.43   0.669    -.2587032    .4022133
        rule1 |  -.0995336    .417175    -0.24   0.812    -.9217044    .7226371
        rule2 |  -.0200765   .3388334    -0.06   0.953    -.6878514    .6476983
         male |  -.0919362   .0766983    -1.20   0.232    -.2430935    .0592212
      married |  -.0410234   .0770134    -0.53   0.595    -.1928018     .110755
loantype_both |  -.0499903    .104322    -0.48   0.632    -.2555886    .1556081
        _cons |   .3129077   .4382724     0.71   0.476    -.5508421    1.176657
-------------------------------------------------------------------------------
```

[3] To see the regressions of treatment on each individual control variable check: July3rd2014_balancetest.smcl

APPENDIX: Loan Performance Data

Microloan Foundation

Microloan Foundation provided us in May 2014 loan performance data by officer and district for the 12 months of 2013. We were directed to the Performance Sheet and the PAR score. In Stata we included the PAR by month, the total PAR, and then the average PAR (taking the total PAR and dividing by the number of months for which there was customer data available). Microloan's explanation for PAR is as follows:

Portfolio at Risk (PAR) is a standard international measure of portfolio quality that measures the portion of a portfolio which is deemed at risk when payments are overdue.

This is calculated in percentages for example Loan Officer B has an outstanding portfolio of K1,000,000 (Principal pus Interest) but the expected repayment amounting to K100, 000 was not collected at the end of month. PAR focuses only on the amount of money which was not paid or which is in arrears. It will be:

100,000/1,000,000 x 100% = 10%

Meaning 10% of the portfolio is at risk because the money is not yet recovered as expected.

Note:
- For MLF Loan officer with no PAR information are new loan officers.
- Avg_PAR will be the performance measure used on the randomization data set.

MEDF

MEDF provided us in June 2014 loan performance data by officer for 10 months from July 2013 to April 2014. Data was based on MEDF group loans. Each loan officer was provided with a monthly target based upon their *individual* outstanding loan portfolio. Each month provided list the amount of loan recovered for that month. In Stata a total PAR (portfolio-at-risk) has been calculated by taking a loan officer's projected target (monthly target times 10 months) minus the amount collected, divided by the projected target. Example:

Monthly target= 100,000MK
Total Collected over 10 months= 650,000
PAR= ((100,000*10)-650,000)/(100,000*10) = .35

Average PAR was calculated by taking the a loan officer's projected target (monthly target time active months for which data is provided) minus the amount collected divided by the projected target. Example:

Monthly target= 100,000MK
Active months (where data is provided) = 5
Total Collected over 10 months= 350,000
PAR= ((100,000*5)-350,000)/(100,000*5) = .3

Note:

- Avg_PAR will be the performance measure use on the randomization process.
- Loan officers with no figures (missing data for 10 months) are due to three factors:
    - MEDF didn't report any information for them on performance: (10 records)
    - They are new loan officers: (6 records)
    - A supervisor assumed the role of a loan officer: (1 record :Sathawa Chifundo)

<u>CUMO</u>

CUMO provided us with loan officer performance data in June 2014 of current outstanding loans per loan officer. This contained the initial amount disbursed, the outstanding balance (both what was currently due and what was not yet due) and the overdue principle (amount that is due but not yet paid).
The calculation was done as follow:

PAR= total (OverduePrincipal)/total(ActualDisb)
Note:
CUMO doesn't have missing values for the PAR variable. Initially those Loan officers that didn't have performance data were those who didn't have any portfolio at risk (Best performance/ PAR=0).

Additional explanations:

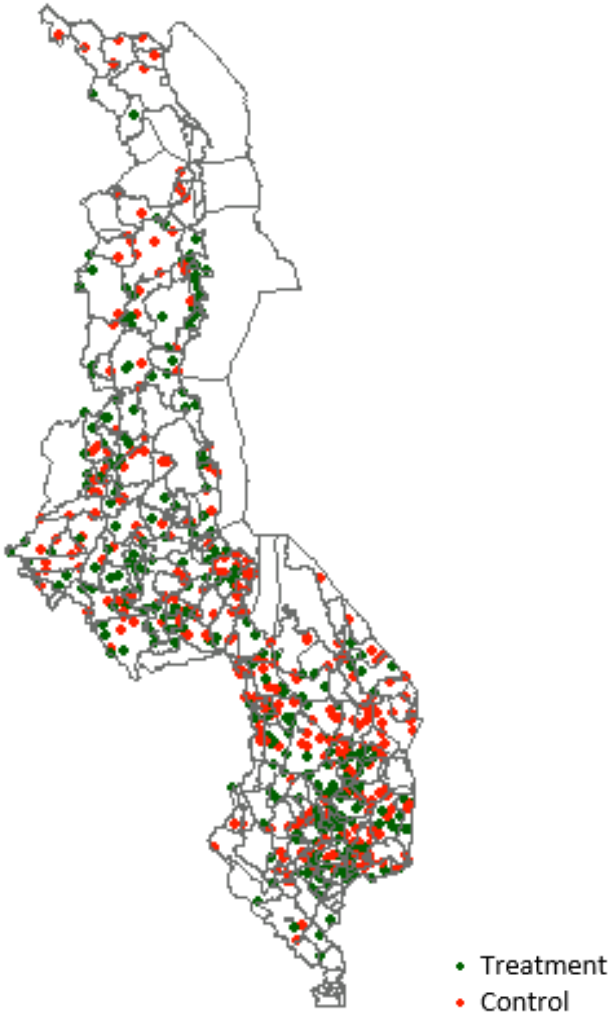
- In every case having a higher PAR is worse.
- The new loan officer variable is 1 for Loan Officer with a duration <= 3 months.

Specific cases:

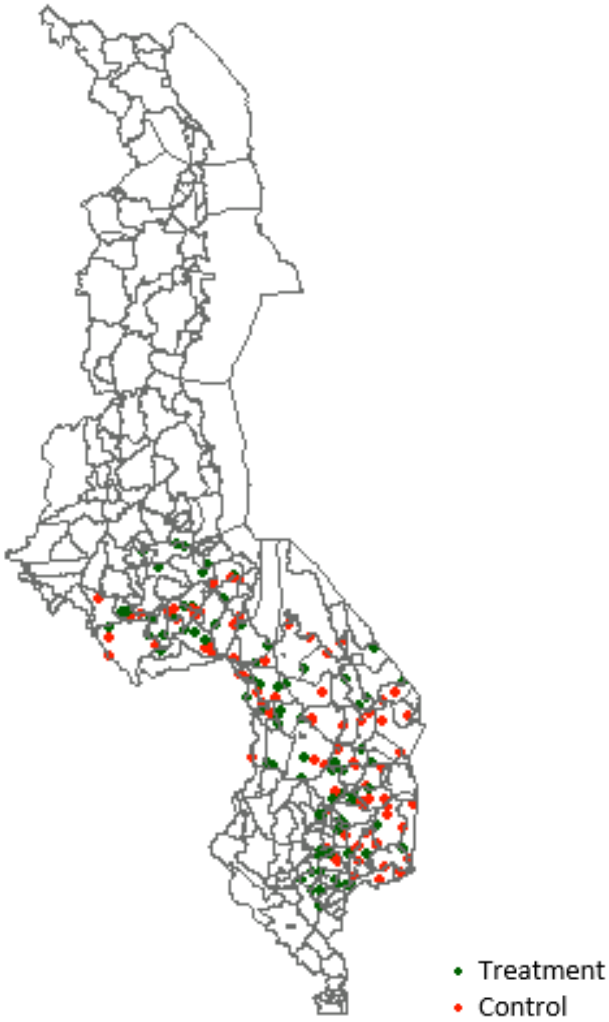
- Daudi Banda, a MLF's loan officer, he has a duration value of 46 months with no clients and performance information. In his case he recently moved from one district to other, and the PAR reported is the one in his previous district (Blantyre).
- For the MEDF office at the Neno district, LO share the same PAR information as they had reported the information as a whole so far.
- The only missing value on the #of clients and TA are for the loan officer Maurine Chimaonda (MEDF). Her supervisor doesn't have information about her and she is currently in maternal leave.

Loan Officers[1]
Dot Density Distribution
July 8, 2014

Total LO Distribution



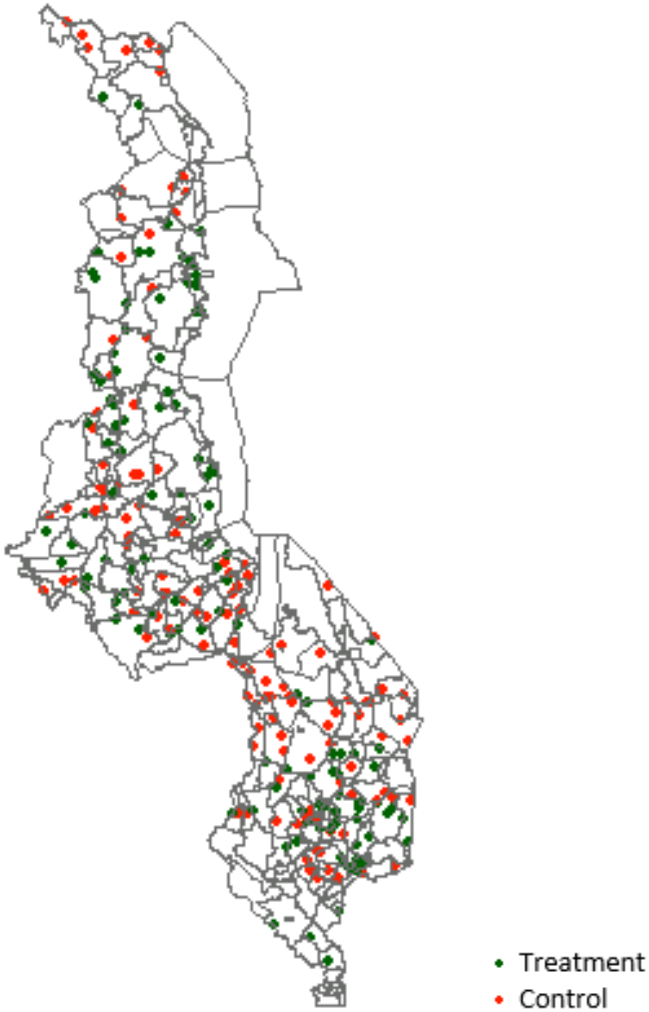
CUMO LO Distribution



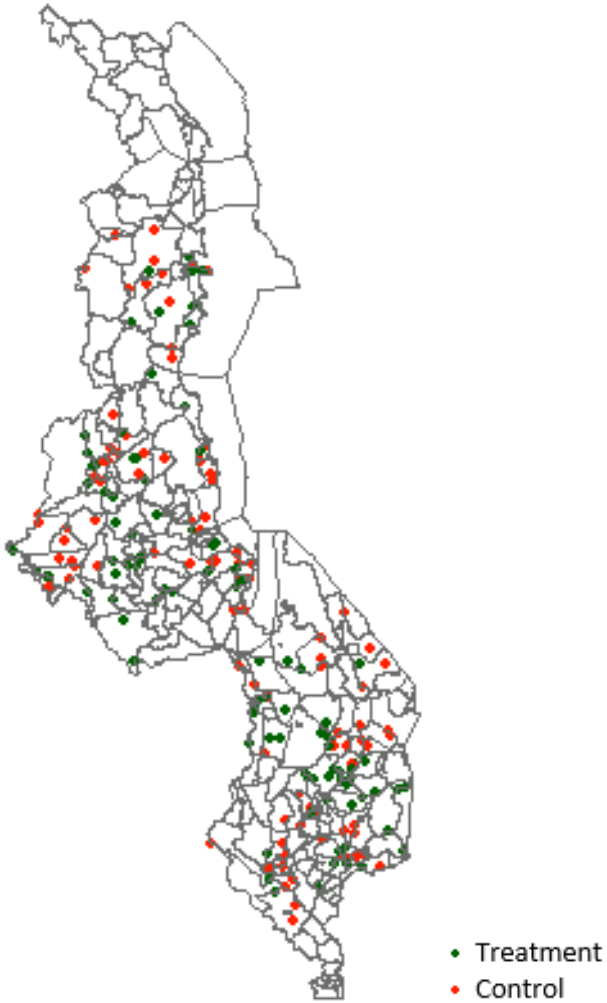
[1] Loan officers will appear, represented by a dot, in each TA in which they operate. Thus each loan officer may be represented multiple times.

Loan Officers
Dot Density Distribution
July 8, 2014

MEDF LO Distribution

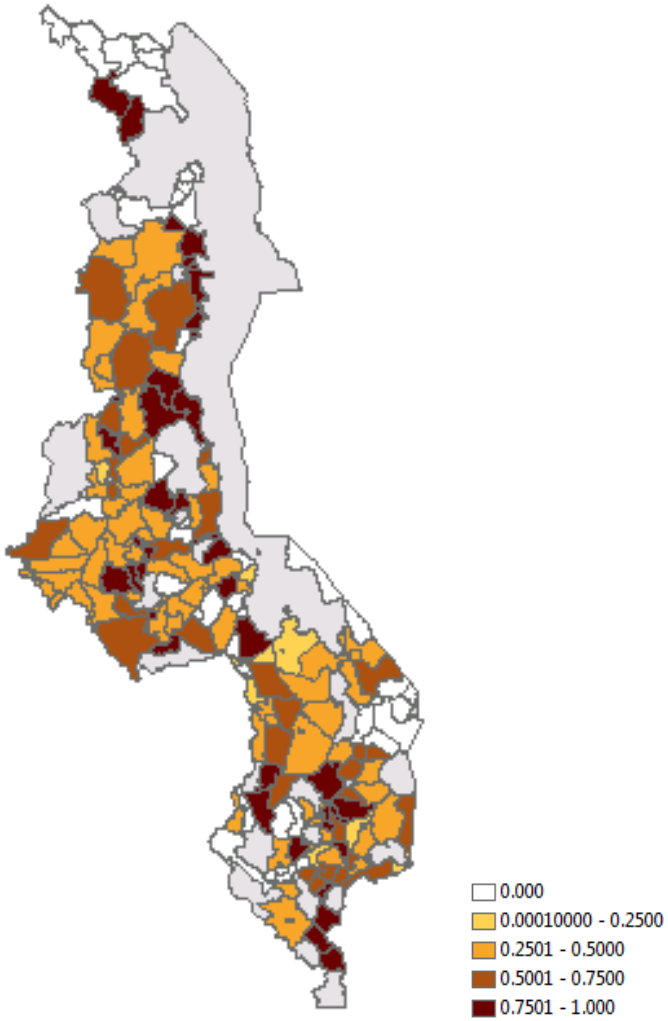


Microloan LO Distribution

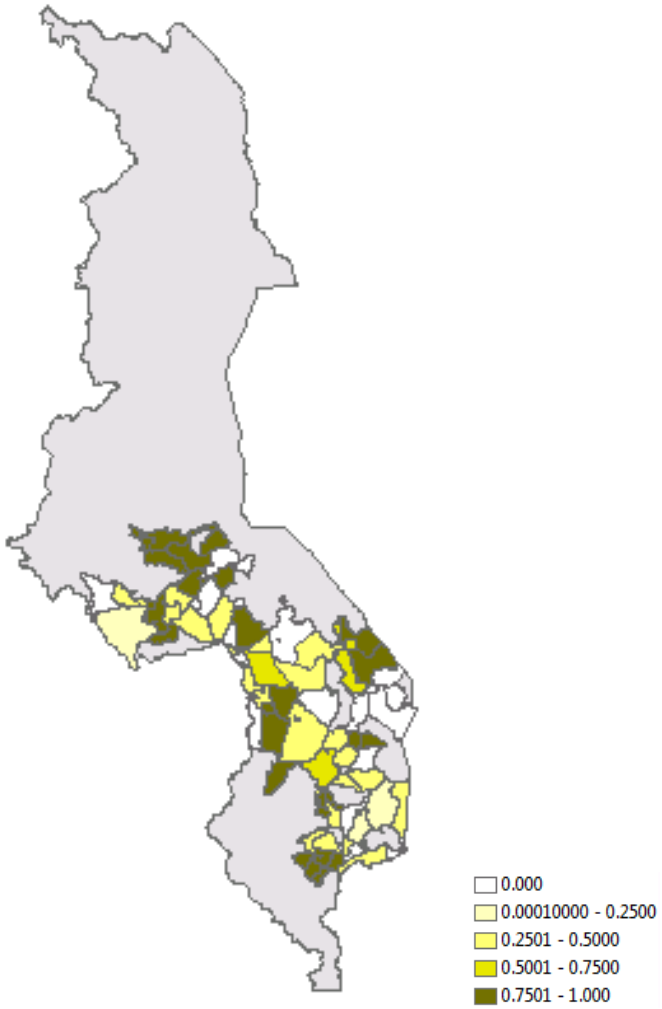


Loan Officers
Proportion of treated LO per TA
July 8, 2014

Total LO Distribution

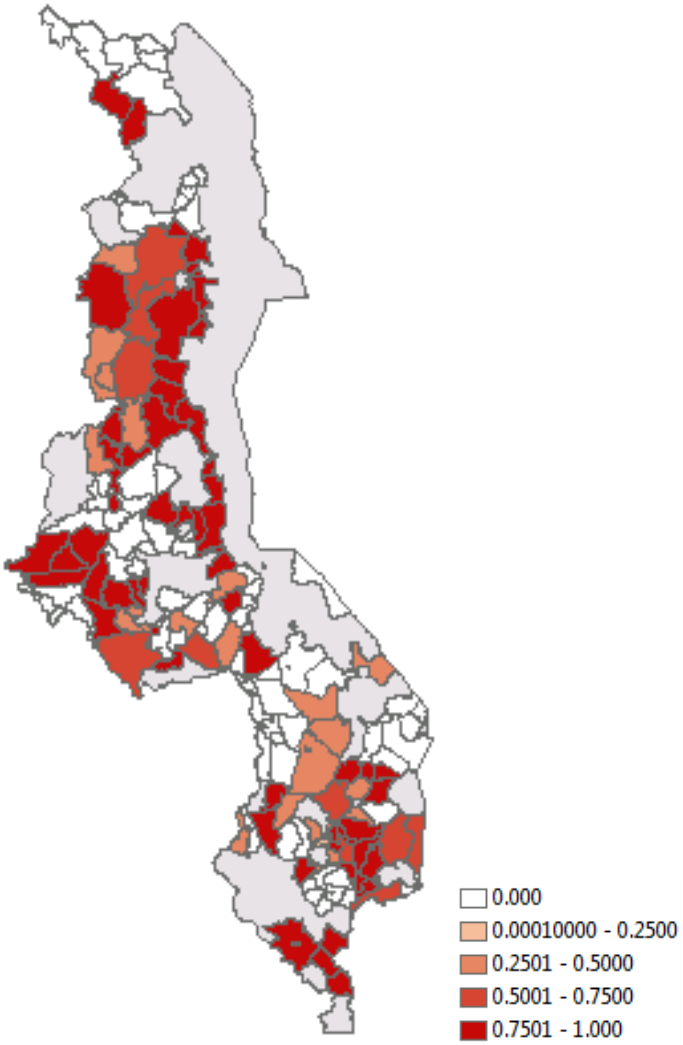


CUMO LO Distribution

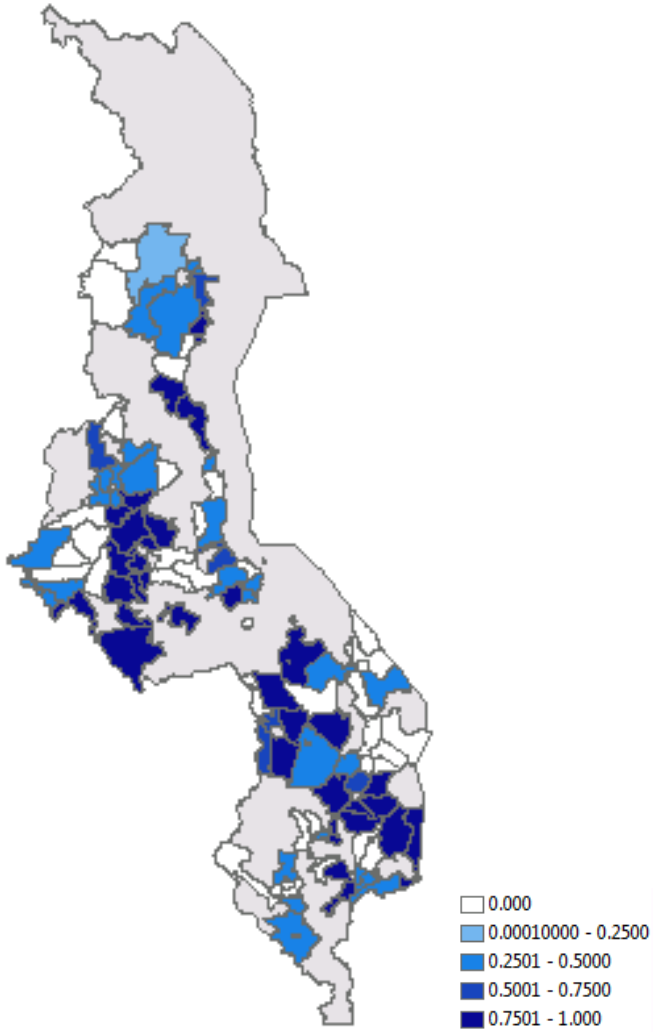


Loan Officers
Proportion of treated LO per TA
July 8, 2014

MEDF LO Distribution

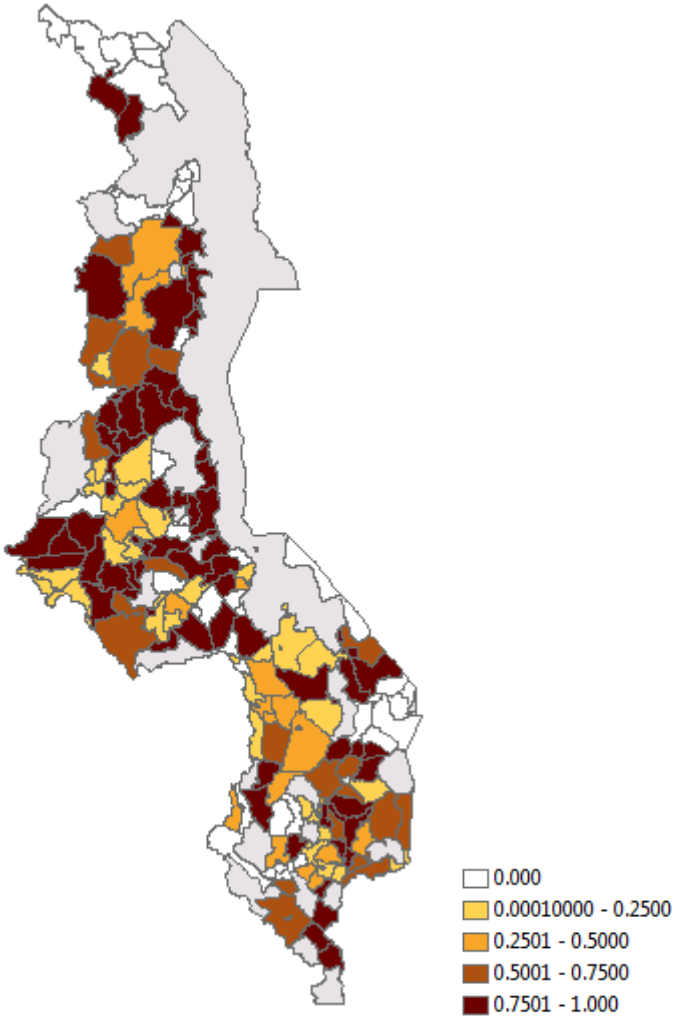


Microloan LO Distribution

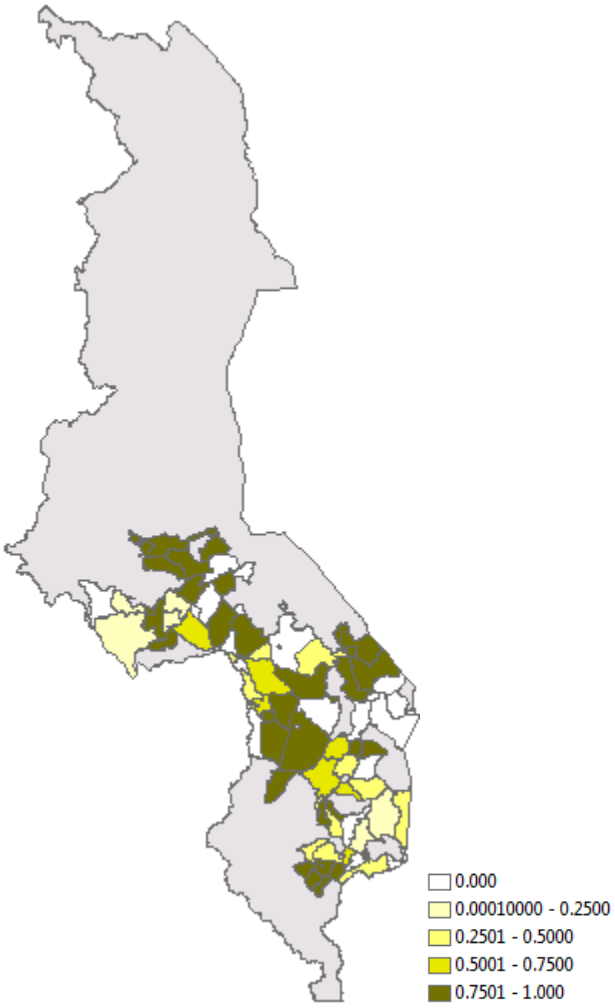


Customer
Proportion of treated customers per TA
July 8, 2014

Total Customer Distribution

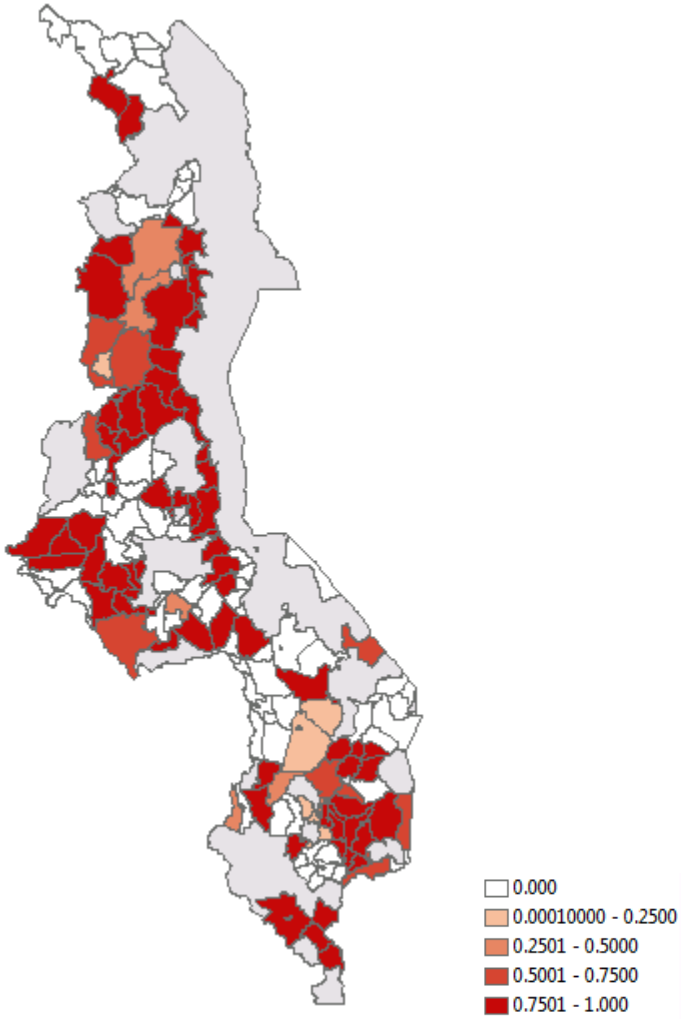


CUMO Customer Distribution

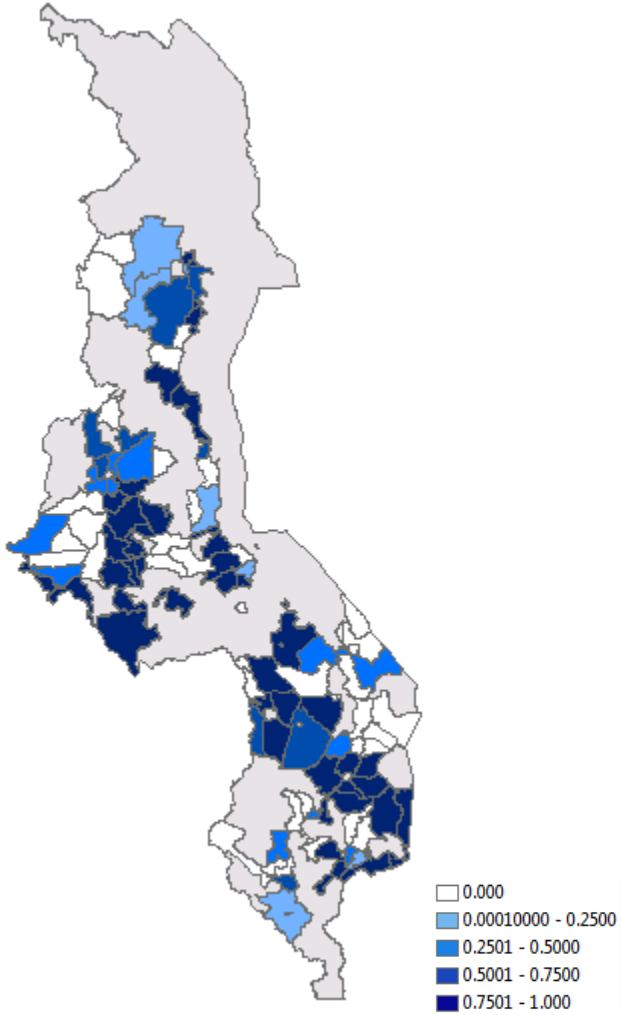


Customer
Proportion of treated customers per TA
July 8, 2014

MEDF Customer Distribution



Microloan Customer Distribution



Progress Report for the Project:
Fingerprinting to Reduce Risky Borrowing: A Randomized Evaluation in Malawi

Grant No. AID-OAA-F-13-00032

Principal investigators: Jessica Goldberg (U. Maryland), Xavier Gine (World Bank), and Dean Yang (University of Michigan)

Milestone 5 (July 30, 2014)

Contents:
Report on Randomization of Treatment and Control Groups

Report on Randomization of Treatment and Control Groups

From April to May 2014 our team collected biographical and performance data on loan officers at the participating MFIs. Since the project seeks to reveal the extent to which treatment effects differ by the riskiness of lending at baseline (which was also done in Gine, Goldberg, and Yang 2012), loan officers are therefore stratified by MFI and on the baseline loan recovery rate prior to the study as a proxy for group riskiness. Loan officers are sorted on these baseline variables, and then adjacent pairs of officers in the list are randomly assigned to treatment and control. This ensures balance across treatment and control groups in these key baseline variables, namely MFI and baseline loan recovery rate, and sets the stage for valid comparison of treatment effect heterogeneity with respect to baseline repayment rates. (Stratification also helps ensure balance on this baseline characteristic across the experimental conditions.)

From a total of 234 loan officers, 117 were assigned to treatment and 117 to control. The distribution of treatment and control per MFI are as follows:

MFI	Treatment	Control	Total
CUMO	41	42	**83**
MEDF	42	41	**83**
Microloan	34	34	**68**
Total	**117**	**117**	**234**

Each loan officer provided estimates of their customer base. In reflection of the loan officer assignment 177,326 customers have been assigned to treatment and 216,114 to control. The distribution of treatment and control per MFI are as follows:

MFI	Treatment	Control	Total
CUMO	22934	25665	**48599**
MEDF	142400	177867	**320267**
Microloan	11992	12582	**24574**
Total	**177326**	**216114**	**393440**

In addition to loan recovery performance data we gathered data on gender, age, marital status, years of education, type of loans distributed, duration of service at MFI and number of customers. Balance tests in which these variables were run against assigned treatment status revealed no statistically significant results, signaling that randomization was successful.

For further detail on how randomization was preformed, including descriptions of performance data collected, see the included pdf document titled “Randomization Explained”. We also attach a map of the location of treated and control loan officers entitled “Treatment and Control Mapping”.