Credit Elasticities in Less-Developed Economies:
Implications for Microfinance*

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Policymakers often prescribe that microfinance institutions increase interest rates to eliminate reliance on subsidies. This strategy makes sense if the poor are rate insensitive: then microlenders increase profitability (or achieve sustainability) without reducing the poor's access to credit. We test the assumption of price inelastic demand using randomized trials conducted by a consumer lender in South Africa. The demand curves are downward-sloping, and steep for price increases relative to the lender's standard rates. We also find that loan size is far more responsive to changes in loan maturity than to changes in interest rates, which is consistent with binding liquidity constraints.

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Preface

One important theme in the work of the Center for Global Development is the search for ways to make foreign aid agencies more effective. It is a tough problem because aid agencies are not accountable to the people they aim to serve in aid-receiving countries. One symptom of this lack of accountability, noted by CGD's Evaluation Gap Working Group, is that donors too rarely commission rigorous, independent studies of how the programs they back affect clients. This leaves donors vulnerable to development fads and waste.

CGD non-resident fellow Dean Karlan and his co-authors are exemplars of a growing movement within academia to change that. This paper comes out of a program of work that strives to bring the highest scientific standards to the study of microfinance, an area in which public and private donors are heavily involved. Understanding how microfinance affects clients is not straightforward because there are several possible explanations for why, say, a borrower is doing well compared to her non-borrowing peers. The credit may be helping—or perhaps she only borrowed because she was already well-off. This, and other papers in the series, elucidates cause and effect by performing controlled experiments, in which a few parameters are randomly varied and the effects measured. The result is sharper answers, in specific contexts, to questions such as: How sensitive are potential borrowers to high interest rates? At the margin, does access to credit increase their incomes? Does it empower women? In the solidarity group lending method made famous by the Grameen Bank, wherein small groups of borrowers guarantee each other's loans, is that mutual guarantee the essential glue that holds the system together?

This paper contributes both by giving donors insight into the programs they fund, and, more generally, by demonstrating the value of rigorous impact evaluation.

I. Introduction

Microcredit fights poverty by expanding access to credit. Some microfinance institutions (MFIs) focus on maximizing profits, and do so while lending to the poor. Others seek to maximize access for the poor subject to a budget constraint. Regardless, nearly all MFIs face tightening pressure from policymakers, donors, and investors to eliminate reliance on subsidies.

Loan pricing is central to economic modeling, policy, and practice in credit markets. Yet existing research offers little evidence on interest rate sensitivities in MFI target market(s), and little methodological guidance on how to derive optimal rates (Morduch 2000; Armendariz de Aghion and Morduch 2005). Instead MFIs and policymakers rely heavily on descriptive evidence and intuition. Policymakers often presume that the poor are largely insensitive to interest rates, and then prescribe that MFIs should increase rates without fear of reducing access.[1] Thus the assumption of price inelastic demand for credit by microcredit clients has fueled support for strategies where MFIs attempt to wean off subsidies by increasing interest rates.

Here we test hypotheses of inelastic demand for microcredit using data from a field experiment in South Africa. A for-profit South African lender in a high-risk consumer loan market worked with us to randomize individual interest rate direct mail offers to over

[1] A common argument is that many poor individuals borrow from moneylenders at very high rates and thus must not be too price sensitive. There are several problems with this argument, discussed in detail in Morduch (2000). Individuals may be sensitive on the intensive margin, with respect to loan size. Individuals may be sensitive on the extensive margin, with respect to the willingness to incur the additional transaction costs associated with borrowing from an MFI, and with respect to the frequency of borrowing. Many individuals targeted by MFIs do *not* borrow from moneylenders, or do so infrequently (hence their marginal cost of moneylender borrowing is high, but the total cost is low). And increasing numbers of MFIs face some competition from other institutions offering rates substantially below the moneylenders. See also Christen (1997) and Rosenberg (2002) for more details.

50,000 former clients, conditional on the client's prior rate. The Lender then tracked gross revenue and repayment. This enables us to calculate the profit-maximizing pricing strategy, and to identify the effects of price changes on the number and characteristics of clients served (i.e., the effects on the targeted access margin that interests policymakers and many practitioners).

Using randomized trials to optimize pricing strategy is a novel approach in the MFI world.[2] More generally there is little scientific evidence of any kind to guide MFI pricing strategies. The most comparable study is Dehejia, Montgomery and Morduch (2005), which exploits quasi-experimental variation from a pricing policy change by a Bangladeshi non-profit MFI, and finds full-sample elasticities ranging from -0.73 to unity.[3]

MFIs that do attempt to estimate elasticities directly analyze behavior before and after an institution-wide change, or use data on the behavior of past borrowers who were assigned interest rates endogenously. These typical approaches are imprecise, and prone to omitted variable bias. In contrast randomized trials can deliver more precise and reliable evidence on how MFIs can use interest rates to achieve their objectives.

We also worked with the Lender to explore a margin of loan contracting that has been largely ignored by academics, policymakers, and practitioners: loan maturity. An exception is Attanasio, Goldberg, and Kyriazidou (2005), which shows formally that

[2] Randomized controlled trials are standard practice among many U.S. credit card companies, but the results of these experiments are rarely made public (Day 2003). Ausubel (1999) is the only exception we know of, and it focuses largely on repayment effects, not on net profits and optimal pricing implications.

[3] There has been similarly little work on estimating the price elasticity of demand for credit in developed countries. Exceptions include Alessie, Hochguertel, and Weber (2005) on consumer loan borrowers in Italy; Gross and Souleles (2002) on credit card holders in the U.S; and Attanasio, Goldberg, and Kyriazidou (2005) on car loan borrowers in the U.S. Each of these studies exploits quasi-experimental variation from government or business policy rules.

liquidity constrained consumers may borrow more when offered longer maturities.[4] We worked with the Lender to engineer exogenous variation in maturities by displaying a randomly assigned, non-binding maturity suggestion (in the form of a four-, six- or twelve-month "example" loan) on the direct mailer sent to the subset of borrowers eligible for longer maturities. The example maturity powerfully predicts the actual maturity chosen, and hence provides us with an instrumental variable for maturity that we use to identify maturity elasticities for the subsample of eligible borrowers.

We identify demand curves with respect to price that indicate the Lender was profit maximizing at its standard (non-experimental) interest rates. Demand was downward sloping but relatively flat throughout a wide range of rates falling below the Lender's standard ones. So the revenue gains from cutting rates-- attracting additional clients, increased loan size, and improved repayments-- was not enough to offset the revenue losses on inframarginal borrowing. We also find that price sensitivity increased sharply when individuals were offered a rate *above* their prior loan's rate and discuss several interpretations of this kink in the demand curve at standard rates. The practical implication is that increasing rates was a clearly dominated strategy in this market, given that information asymmetries decreased repayments as prices rose, reinforcing the negative gross revenue effects created by highly elastic demand with respect to price increases.[5]

We also estimate that loan size was far more responsive to changes in loan maturity than to changes in interest rate. We estimate that increasing maturity by a month (i.e., by

[4] The empirical evidence in Attanasio et al suggests that U.S. car loan borrowers were an order of magnitude more sensitive to maturity than to price during 1984-1995. See also Juster and Shay (1964).

20 percent) raised demand by 16 percent. Our point estimates on the sub-sample of borrowers we can use to estimate maturity elasticities suggests that the monthly interest rate would need to fall 436 basis points (68 percent) to have the same effect.

We also find some evidence that maturity elasticities are more heterogeneous with respect to income than price elasticities are. A practical implication is that some MFIs should consider using maturity rather than (or in addition to) price to balance profitability and targeting goals. But much work remains to be done: we do not have the sample size to estimate the impacts of extending maturities on repayment (and hence on profits), and more generally of course it is not clear whether our parameter estimates apply to other populations and markets of interest.

In particular, our experimental design, its implementation using direct mail, and the market setting raise several important external validity questions. Do our results apply to non-borrowers? We present some results suggesting that they do, *within sample*, but our sample of prior borrowers sheds little direct light on the elasticities of the truly marginal (first-time) borrowers who are often the targets of MFI efforts to expand access. Secondly, do elasticities to direct mail solicitations apply to other loan offer technologies? Not necessarily. But our data and results suggest that most clients did read the letter, and that readers and non-readers have similar elasticities. Lastly, do results from a market served by for-profit firms offering individual liability consumer loans apply to more "traditional" microcredit settings where NGOs target female microentrepreneurs with joint liability loans? Not necessarily, although it bears mentioning that our setting is becoming

[5] We do not have sufficient sample size to estimate the repayment effects directly in the sample of borrowers at higher than standard rates, but our estimates on the much larger sample of borrowers at weakly less than

increasingly representative: many for-profit lenders are entering MFI markets with consumer products, adding to the growing number of MFIs that do not target on demographics or use of funds.[6]

In the end, of course, our results are more provocative than definitive. Our primary contribution is methodological. Randomized-controlled trials can and should be used to help MFIs pin down their optimal contracting strategies. The findings and methods in this paper highlight some specific directions for future research, policy, and practice.

The paper proceeds as follows. Section II describes the Lender and its market. Section III details our experimental design and implementation. Section IV maps the experiment into our empirical strategy. Section V presents our main results on price elasticities. Section VI calculates the Lender's profit-maximizing pricing strategy and illustrates how pricing could be used to expand and target access. Section VII presents our estimates of maturity elasticities. Section VIII concludes with some directions for related research that would further inform credit market practice and policy in developing countries.

II. Market and Lender Overview

Our cooperating Lender operated for over 20 years as one of the largest, most profitable micro-lenders in South Africa.[7] It did not have an objective of expanding access or targeting *per se* but did have a client base that was almost entirely working poor. The

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standard rates suggests that information asymmetries do reduce repayment as rates rise.

[6] This shift away from targeting is motivated in part by evidence that many households use "entrepreneurial" credit for consumption purposes (Menon 2003).

[7] The Lender was merged into a bank holding company in 2005 and no longer exists as a distinct entity.

Lender competed in a "cash loan" industry segment that offers small, high-interest, short-term, uncollateralized credit with fixed monthly repayment schedules to the working poor population. Aggregate outstanding loans in the cash loan market segment equal about 38 percent of non-mortgage consumer debt.[8] Estimates of the proportion of working-age population currently borrowing in the cash loan market range from below 5 percent to around 10 percent.[9]

Cash loan borrowers generally lack the credit history and/or collateralizable wealth needed to borrow from traditional institutional sources such as commercial banks. Data on how borrowers use the loans is scarce, since lenders usually follow the "no questions asked" policy common to consumption loan markets. The available data suggest a range of consumption smoothing and investment uses, including food, clothing, transport, education, housing, and paying off other debt.[10]

Policymakers and regulators have encouraged the development of the cash loan market as a less expensive substitute for traditional "informal sector" moneylenders. Since deregulation of the usury ceiling in 1992 cash lenders have been regulated by the Micro Finance Regulatory Council (MFRC). Cash loan sizes tend to be small relative to the fixed costs of underwriting and monitoring them, but substantial relative to a typical borrower's income. For example, the Lender's median loan size of 1000 Rand ($150) was 32 percent

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[8] Cash loan disbursements totaled approximately 2.6% of all household consumption and 4% of all household debt outstanding in 2005. (Sources: reports by the Department of Trade and Industry, Micro Finance Regulatory Council, and South African Reserve Bank).

[9] Sources: reports by Finscope South Africa, and the Micro Finance Regulatory Council. We were not able to find data on the income or consumption of a representative sample of cash loan borrowers. We do observe income in our sample of cash loan borrowers; if our borrowers are representative then cash loan borrowers account for about 11% of aggregate annual income in South Africa.

of its median borrower's gross monthly income (US$1 ~=7 Rand during our experiment). Cash lenders focusing on the highest-risk market segment typically make one-month maturity loans at 30 percent interest *per month*. Informal sector moneylenders charge 30-100 percent per month. Lenders targeting lower risk segments charge as little as 3 percent per month, and offer longer maturities (12+ months).[11]

Our cooperating Lender's product offerings were somewhat differentiated from competitors. It had a "medium-maturity" product niche, with a 90 percent concentration of 4-month loans (Table 1a), and longer loan terms of 6, 12 and 18 months available to long-term clients with good repayment records.[12] Most other cash lenders focus on 1-month or 12+-month loans. The Lender's standard 4-month rates, absent this experiment, ranged from 7.75 percent to 11.75 percent per *month* depending on assessed credit risk, with 75 percent of clients in the high risk (11.75 percent) category. These are "add-on" rates, where interest is charged upfront over the original principal balance, rather than over the declining balance. The implied annual percentage rate (APR) of the modal loan is 200 percent. The Lender did not pursue collection or collateralization strategies such as direct debit from paychecks, or physically keeping bank books and ATM cards of clients, as is

[10] Sources: data of questionable quality from this experiment (from a survey administered to a sample of borrowers following finalization of the loan contract); household survey data from other studies on different samples of cash loan market borrowers (FinScope 2004; Karlan and Zinman 2006a).

[11] There is essentially no difference between these nominal rates and corresponding real rates. For instance, South African inflation was 10.2% *per year* from March 2002-2003, and 0.4% per year from March 2003-March 2004.

[12] Market research conducted by the Lender, where employees or contractors posing as prospective applicants collected information from potential competitors on the range of loan terms offered, confirmed this niche. These exercises turned up only one other firm offering a "medium-maturity" at a comparable price (3-month at 10.19%), and this firm (unlike our Lender) required documentation of a bank account. ECI Africa and IRIS (2005) finds a lack of competition in the cash loan market. We have some credit bureau data on individual borrowing from other formal sector lenders (to go along with our administrative data on borrowing from the Lender) that we consider in Sections V-B and VI-A-2.

the policy of some other lenders in this market. The Lender's pricing was transparent and linear, with no surcharges, application fees, or insurance premiums.

Per standard practice in the cash loan market, the Lender's underwriting and transactions were almost always conducted in person, in one of over 100 branches. Its risk assessment technology combined centralized credit scoring with decentralized loan officer discretion. Rejection was common for new applicants (50 percent) but less so for clients who had repaid successfully in the past (14 percent). Reasons for rejection included unconfirmed employment, suspicion of fraud, poor credit rating, and excessive debt burden. Regulation required that monthly repayment could not exceed a certain proportion of monthly income, but no interest rate ceilings existed at the time of this experiment.

Borrowers had several incentives to repay despite facing high interest rates. Carrots included decreasing prices and increasing future loan sizes following good repayment behavior. Sticks included reporting to credit bureaus, frequent phone calls from collection agents, court summons, and wage garnishments. Repeat borrowers had default rates of about 15 percent, and first-time borrowers defaulted twice as often.

The cash loan market has important differences and similarities with "traditional" microcredit (e.g., the Grameen Bank, or government or non-profit lending programs). In contrast to our setting, most microcredit has been delivered by lenders with explicit social missions that target groups of female entrepreneurs, sometimes in group settings. On the other hand, the industrial organization of microcredit is trending steadily in the direction of the for-profit, more competitive delivery of individual credit that characterizes the cash loan market (Robinson 2001; Porteous 2003). This push is happening both from the bottom-up (non-profits converting to for-profits) as well as from the top-down (for-profits expanding into microcredit segments).

III. Experimental Design and Implementation

We identify demand curves for consumer credit by randomizing both the interest rate offered to each of more than 50,000 past clients on a direct mail solicitation, and the maturity of an example loan shown on the offer letter (Figure 1 shows a sample letter).[13] This section outlines the experimental design and implementation, and validates the integrity of the random assignments using several statistical tests.

A. Design Overview

First the Lender randomized the interest rate offered in "pre-qualified," limited-time offers that were mailed to 58,168 former clients with good repayment histories (III-B). Most of the offers were at relatively low rates (III-C). Clients eligible for maturities longer than four months also received a randomized example of either a four-, six- or twelve-month loan (III-D).

Clients wishing to borrow at the offer rate then went to a branch to apply, as per the Lender's standard operations (III-E). Final credit approval (i.e., the Lender's decision on whether to offer a loan after updating the client's information) and maximum loan size and maturity supplied were orthogonal to the experimental interest rate by construction. Figure 2 shows the experimental operations, step-by-step.

B. Sample Frame

The sample frame consisted of all individuals from 86 predominantly urban branches who had borrowed from the Lender within the past 24 months, were in good standing, and did not currently have a loan from the Lender as of thirty days prior to the mailer. The experiment was implemented in three "waves" of mailer/start dates that grouped branches geographically, for logistical reasons.[14] We pilot-tested in three branches during July 2003 (wave 1), and then expanded the experiment to the remaining 83 branches in two additional waves that started with mailers sent in September 2003 (wave 2) and October 2003 (wave 3).[15]

Table 1 presents summary statistics on the total sample frame (Column 1), those that applied (Column 2), those that borrowed (Column 3), and those that were eligible for the randomized maturity suggestion (Column 4).

C. Interest Rate Randomization

The offer rate randomization was stratified by the client's risk category because risk determined the loan price under standard operations. The standard schedule for four-month loans was: low-risk = 7.75 percent per *month*; medium-risk = 9.75 percent; high-risk = 11.75 percent. The randomization program established a target distribution of

[13] Thus we estimate elasticities for a particular sample (prior clients of this particular Lender), using a particular solicitation technology (direct mail). We discuss the related external validity issues in Sections VIII and VI-A-3.

[14] The sample frame includes branches and clients from four of South Africa's nine provinces: Kwazulu-Natal, Eastern Cape, Western Cape, and Gauteng.

[15] See Appendix 1 for a reconciliation of the sample frame used here and in two companion papers.

interest rates for 4-month loans in each risk category[16] and then randomly assigned each individual to a rate based on the target distribution for her category.[17] Appendix Table 2 shows the resulting distribution of rates. Rates varied from 3.25 percent per month to 14.75 percent per month. 96 percent of the offers were at lower-than-standard rates, with an average discount of 3.1 percentage points on the monthly rate (the average rate on prior loans was 11.0 percent). Slightly more than one percent of the offers were at a higher-than-standard rate (with a 1.9 percentage point increase on average), and the remaining offers were at the standard rate.

At the time of the randomization, we verified that the assigned rates were uncorrelated with other known information, such as credit report score. Table 2, Column 1 shows that the randomizations were successful, *ex-ante*, in this fashion; i.e., conditional on the risk category, the offer rate was uncorrelated with other observable characteristics.

D. Maturity Suggestion Randomization

A subset of borrowers in waves two and three received mailers containing a randomized maturity suggestion as well. The suggestion took the form of non-binding

[16] Rates on other maturities in these data were set with a fixed spread from the offer rate conditional on risk, so we focus exclusively on the 4-month rate.

[17] Actually *three* rates were assigned to each client, an "offer rate" (r) included in the direct mail solicitation and noted above, a "contract rate" (r^c) that was weakly less than the offer rate and revealed only after the borrower had accepted the solicitation and applied for a loan, and a dynamic repayment incentive (D) that extended preferential contract rates for up to one year, conditional on good repayment performance, and was revealed only after all other loan terms had been finalized. This multi-tiered interest rate randomization was designed to identify specific information asymmetries (Karlan and Zinman 2006b). 40% of clients received $r^c < r$, and 47% obtained D=1. Since D and the contract rate were surprises to the client, and hence did not affect the decision to borrow, we exclude them from most analysis in this paper and restrict the sample frame to the 31,231 clients who were assigned $r = r^c$ for expositional clarity. In principle r^c and D might affect the intensive margin of borrowing, but in practice adding these interest rates to our loan size demand specifications does not change the results. Mechanically what happened was that very few clients changed their loan amounts after learning that $r^c < r$ (Karlan and Zinman 2006b).

"example" loan showing one of the Lender's most common maturities (four, six, or twelve months), where the length of the *maturity* was randomly assigned. This randomization was orthogonal to the interest rate randomization. All letters clearly stated that other loan sizes and maturities were available. The example loan *size* presented was not randomized; it was the client's last loan size. Only low- and medium-risk borrowers were eligible to receive the suggestion randomization, since high-risk borrowers could not obtain maturities greater than four months under the Lender's standard operations. 3,096 of low- and medium-risk clients (of whom 493 borrowed) received a suggestion (51 percent four-month, 25 percent six-month, 24 percent twelve-month).

Loan officers were instructed to ignore any example loan(s) presented on the letter. In both training and ongoing monitoring, the Lender's management and the research team stressed to branch personnel that the mailers were for marketing purposes only, and should not have any impact on the loan officer's underwriting of the loan application.

E. The Offer and Loan Application Process

Each mailer contained a deadline, ranging from two to six weeks, by which the client had to respond in order to be eligible for the offer rate.[18] Table 2, Column 2 corroborates that offer rates at or below the standard ones did not influence take-up *after* the deadline, which makes sense since clients who borrowed after the deadline faced the Lender's standard rate schedule. The Lender routinely mailed teasers to former borrowers

[18] The deadlines were randomly assigned and orthogonal to the interest rate and any maturity suggestion by construction. The mailers also incorporated randomized decision frames and cues designed to test whether product presentation features found to be important psychology and marketing literatures impact loan

but had never promoted specific interest rate offers before this experiment. 1,358 mailers were returned to the Lender by the postal service and 3,000 contained atypical (i.e., non-decreasing) relationships between loan maturity and price, leaving us with a sample frame of 53,810 offers for analysis of demand elasticities.

Clients accepted the offer by entering a branch office and filling out an application in person with a loan officer. Applicants did not need to bring the mailer with them to get the offer rate, since each randomly assigned rate was hard-coded into the Lender's computer systems by client account number. Data collected by the Lender suggests that many clients read their letter, but this data must be interpreted cautiously given that letter-reading is unverifiable.[19] Strong demand responses to randomly assigned marketing treatments contained in the direct mail solicitations provides additional evidence that many did read their letter (Bertrand, Karlan, Mullainathan, Shafir and Zinman 2005).

Loan applications were taken and assessed as per the Lender's standard underwriting procedures. Specifically, loan officers (a) updated observable information and decided whether to offer *any* loan based on their updated risk assessment; (b) decided the maximum loan size to offer the accepted applicants; and (c) decided the longest loan maturity to offer the accepted applicants. Each decision was made "blind" to the experimental rates, with strict operational controls (including software developed in consultation with the research team) ensuring that loan officers instead used the Lender's

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demand (Bertrand, Karlan, Mullainathan, Shafir and Zinman 2005). These treatments were also orthogonal to the interest rate and maturity suggestion.

[19] The data on letter reading has sampling issues as well. One set of observations was collected as part of a follow-up phone call before the offer expiry deadline. The Lender called a non-random sample of 500 clients, of whom 35% were reached. Approximately 50% of the respondents reported reading the letter. The other set of observations comes from a short survey, administered by branch managers to a non-random

standard rates in any debt service calculations. This rule was designed to prevent loan supply from adjusting endogenously to a lower rate (due to debt service ratios) and thereby complicating estimation of loan size demand elasticities. Table 2, Column 3 corroborates that rejection decisions were uncorrelated with the offer rate, conditional on credit risk. 4,540 clients (out of 53,810) in our sample frame applied for a loan at the offered interest rate (i.e., before the deadline on the letter), an 8.4 percent application rate. Of these, 86 percent, or 3,887, were approved for a loan.

Following the loan officer's assessment approved clients chose an allowable loan size and maturity. All clients who were approved ended up taking a loan. This is not surprising that given that the typical application process takes only 45 minutes and everyone in our sample had borrowed from the Lender before.

IV. Empirical Strategy

Now we map our experiment into testable predictions and identification of demand elasticities with respect to price and maturity. We specify models to produce unbiased estimates *within* our sample of prior borrowers from a particular Lender, using direct mail. We postpone discussion of how our results might apply to other solicitation technologies and settings until Sections VI-A-3 and VIII.

Our basic model for estimating the response of loan demand to changes in price and maturity is:

(1) $y_i = f(C_i, X_i)$

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sample, following completion of the loan contract. 75% of applicants reported *receiving* a letter; we did not include a separate question on *reading* the letter.

where i indexes potential borrowers in our sample frame; y is a measure of extensive (take-up) or intensive (loan size) demand for debt from the Lender (we consider balance-shifting and overall demand in Sections V-B and VI-A-2); C_i is a vector of loan contract terms, including the offer rate (r_i) and/or the maturity (m_i); and X_i includes the two variables that we used to stratify the random assignment of r_i: the Lender's summary statistic for credit risk (low/medium/high), and the mailer wave (July, September, or October). The standard errors always allow for clustering within branches.

The standard identification problem in estimating loan demand elasticities is that the loan contract terms of interest may be correlated with unobserved investment opportunities, financing alternatives, or supply decisions that are not actually functions of the interest rate or maturity *per se*. In the case of interest rate sensitivity, we address the identification problem by using interest rate variation created by the Lender's random assignment. The randomly assigned interest rate enables us to observe the counterfactual of interest: what happens to a consumer's borrowing behavior if we exogenously change her interest rate?

Our identification is cleanest for the price sensitivity of loan takeup; i.e., for the extensive margin of price sensitivity (see Section V-A for results and discussion). Here we estimate linear probability (or probit) models of the form:

(2) $a_i = \alpha + \beta r_i + \delta X_i + \varepsilon_{ib}$,

Here a=1 if the client applied for a loan. The offer rate r is orthogonal to ε by construction and hence β is an unbiased estimate of the price sensitivity of loan takeup from direct mail solicitation.[20] We also allow for nonlinearities in some specifications, since there may be kinks in the demand curve at prices where clients have outside options.[21]

Almost any model of consumer intertemporal choice predicts that demand will be downward sloping with respect to price; i.e., that $\beta < 0$ (Becker 1962). The degree of sensitivity may depend on outside options/liquidity constraints and returns to borrowing. The available evidence from microcredit markets suggests that liquidity constraints bind, returns to investment and consumption smoothing are high, and that constraints and returns are heterogeneous.[22] In particular, as we discussed above, many MFIs target relatively poor and female borrowers on the premises that: a) liquidity constraints are relatively severe and returns are relatively high for these individuals; b) price sensitivities are relatively low among these individuals. Consequently we estimate (2), and some of our other models, separately for different gender and income groups (see Section VI-B for results and discussion).

Of course we are also interested in the price sensitivity of loan size demand (see Sections V-C and V-D for results and discussion). We estimate the intensive margin by changing a_i in (2) to a function of loan size (l_i). Here identification is complicated a bit by

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[20] In principle β could be downward-biased, and/or representative of creditworthy applicants only, if the solicited clients tried to infer a signal of their application acceptance probability from the offer rate. But this is unlikely in practice since our entire sample had borrowed from the Lender in the past, and the basic creditworthiness criteria (steady job, contactability by phone, no serious delinquencies observable in credit bureau reports) is common knowledge in the cash loan market. Moreover the nontrivial rejection rate (14%), and the fact that rejection was not correlated with the offer rate (Table 2, Column 3), suggests that applicants with some uncertainty about their creditworthiness did not try to use the offer rate as a signal.

[21] To see the microfoundation for potential nonlinearities, note that in a perfectly competitive market with no supply constraints and multiple lenders, the price elasticity will be negative infinity for any interest rate that exceeds the equilibrium risk-based rate. A client offered a rate by the Lender that exceeds her best outside option (the market rate for her risk category) will not borrow from the Lender.

[22] See Banerjee and Duflo (2004), de Mel, McKenzie and Woodruff (2006), Emran and Stiglitz (2006), Karlan and Zinman (2006a), McKenzie and Woodruff (2006), and Udry and Anagol (2006).

the fact that, if the β in (2) is indeed nonzero and heterogeneous, then there is selection on r_i. Specifically, the loan size and maturity demanded may be correlated with applicant characteristics other than X_i if those who choose to apply at a given r_i are different (e.g., in terms of preferences, or opportunity sets) than those who choose not to apply. In this sense the most straightforward interpretation of our loan size elasticity results is that they hold only for the sample of borrowers; i.e., β is unbiased only for the sample where takeup = a_i = 1. We also estimate loan size specifications with an additional vector of controls for demographics and credit risk characteristics. If β is unchanged after adding these controls this provides indirect evidence that our results apply to non-borrowers as well as borrowers in our sample.

Estimating the elasticity of loan size with respect to maturity presents many of the same issues, since we only observe maturity for those who borrow. Recall that our setup has the additional feature that we instrument for maturity with a randomly assigned example maturity shown to a subset of eligible applicants. Given the need for detailed consideration of the suggestion-eligible subsample, and the first-stage results, we postpone discussion of our estimating equations for maturity elasticities until Section VII.

V. Price Elasticity Results

A. Extensive Margin, Initial Borrowing from Lender

We begin by estimating the extensive price elasticity of loan demand for pre-deadline borrowing from the Lender. As detailed above our measure of demand is binary: whether the client responded to the Lender's solicitation by applying for a loan before her deadline for the randomly assigned interest rate elapsed. Under this definition takeup = a_i = 1 for both clients who obtained a loan, and for the 14% of applicants that the Lender rejected. Our results are robust to defining takeup as obtaining a loan.

We start with the 99 percent of the sample frame that received offers at or below the standard rate for their risk category. Table 3, Column 1 presents the probit marginal effects for this sample: a 100 basis point increase in the monthly interest rate reduces take-up by 3/10 of a percentage point.[23] This is a precisely estimated but rather small effect, given that average take-up is 8.5 percent. Thus a price decrease from the maximum (11.75 percent) to the minimum (3.25 percent) rates offered in this sample would only increase take-up by 2.6 percentage points, or 31 percent of the baseline take-up rate. Another way to scale the estimated magnitude is to calculate the take-up elasticity (i.e., multiplying the marginal effect by the ratio of the mean offer rate to mean takeup), which is -0.28.

B. Asymmetric Elasticities for Prices Increases versus Reductions

Next we estimate whether the average price sensitivity changed when the Lender offered rates that were greater than its standard ones.[24] The Lender primarily was interested in testing sensitivity at lower rates, and consequently only made 632 offers at higher rates. Column 2 shows that high rates depressed the *level* of takeup: clients randomly assigned a higher-than-standard offer rate for their risk category were 3 percentage points (36 percent) less likely to apply. Column 3 shows that the *slope* of the

[23] Results are robust to using OLS rather than probit, and to controlling for the contract experimental rates (see footnote 17), borrower characteristics besides risk category, and/or branch fixed effects.

demand curve steepened in the region of higher rates: here take-up falls 1.7 percentage points for each 100 basis point increase in the interest rate, on an average take-up rate of 6.6 percent. Thus the point estimates show that the price sensitivity of takeup was 6 times greater at higher-than-standard rates.[25] This kink in the demand curve, which we show graphically in Figure 3, is consistent with several underlying (and potentially complementary) explanations.

One explanation for the kink is selection based on discounting or rates of return. Since our sample consists only of prior borrowers, it could be that everyone in the experiment has a discount or return rate equal to the Lender's standard rates. Then lowering the interest rate would affect the intensive, but not extensive margin. On the other hand, raising the interest rate would affect the extensive margin as well (unfortunately our small sample of rate increases does not permit estimating the intensive margin separately.) However, circumstantial evidence casts doubt on this interpretation. We do find some sensitivity on the extensive margin to rate cuts (Table 3). Also recall that the Lender has *several* standard rates that vary with risk level, and any individual borrower can obtain progressively lower rates through time with good repayment performance. Thus for selection to explain the kink, borrowers would need to have *time-varying* discount or return rates, or be willing and able to borrow at a loss for an extended period in order to obtain future credit at lower rates.

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[24] "Standard" equals the rate the client would have been charged had the experiment not taken place, which in almost all cases is the rate on the client's last loan. Our results are robust to defining the reference/kink point as either the standard rate or the rate on the last loan .

[25] The *elasticity* here is 12 times greater: -.017*(12.8/.066) = -3.3, where 12.8 is the mean offer rate and .066 is the mean takeup rate. Gross and Souleles (2002) find the reverse asymmetry; in their data, the price elasticity is somewhat greater in absolute value for price *decreases.* This suggests that ex-ante indebtedness

A second potential explanation for the kink is that consumers receiving high-rate offers borrowed elsewhere. However, recall from Section II that competition in the Lender's niche appeared to be thin, with a dearth of close substitutes. To test this the Lender obtained credit bureau data for our sample period. Table 3, Columns 4-6 show that high offer rates from the Lender did not induce significantly more borrowing from other financial institutions. The point estimates are positive, but the confidence intervals rule out economically large substitution (e.g., we estimate that offering a higher rate increased outside takeup by no more than 1.5 percentage points, which is only 7 percent of the mean). Note however that the credit bureau only measures borrowing from financial institutions. Hence we can not rule out substitution to informal sources (friends, family, and moneylenders).

Third, clients receiving high rates could wait for their deadlines to expire (two to six weeks hence) and then borrow at standard rates. This is testable by examining post-deadline borrowing from the Lender: if high-rate consumers wait then they should be more likely to borrow after the high-rate offer expires. In fact we find the opposite-- high-rate offers produce *lower* post-deadline borrowing (Table 3, Column 8), and the likelihood of post-deadline borrowing decreases with the rate (Column 9). Thus, as with pre-deadline borrowing, high rates had strong negative effects on both the level of post-deadline takeup, and on the slope of post-deadline takeup with respect to price. This is consistent with switching costs; e.g., clients substituted to other (informal) lenders pre-deadline and then found it costly to switch back to the Lender post-deadline.

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may be a key margin: many in the Gross and Souleles sample had debt outstanding at the time of rate changes, while essentially no one in our sample did.

Our pattern of results is also consistent with two types of behavioral models. Prospect theory generates relatively strong sensitivity to price increases because consumers evaluate prices relative to their prior experience and weight losses (price increases) more heavily than gains (Kahneman and Tversky 1979).[26] Models that allow for transaction utility also generate particular aversion to high-than-standard prices if consumer perceive the price increase as unfair (Thaler 1985; Thaler 1999).[27]

In all, our results on nonlinearities in price sensitivity seem to be most consistent with behavioral explanations and/or the presence of viable outside options in informal markets with switching costs.

C. Unconditional Loan Size, Initial Borrowing from the Lender

Table 4, Column 1 presents our main OLS estimate of the price sensitivity of the amount borrowed, unconditional on borrowing (this is the outcome featured in both Gross and Souleles (2002) and Dehejia, Montgomery and Morduch (2005)). The dependent variable here includes pre-deadline borrowing only, and we condition only on risk and mailer wave. As described in Section III, we limit the sample to clients who were randomly assigned equal offer and contract rates (see footnote 17) that were at or below the Lender's standard rate for each individual. The precisely estimated coefficient shows a R4.4 decrease for each 100 basis point increase the interest rate. Given the mean unconditional loan size of 106 and mean offered interest rate of 7.8, this implies an

[26] See also Hardie, Johnson, and Fader (1993).
[27] See Anderson and Simester (2006) for some related empirical evidence. A "price point", as discussed in Kashyap (1995), seems an unlikely explanation for our kink since the Lender's standard prices do not match competitors or feature common price-endings.

elasticity of -0.32. This is small relative to the estimates in Gross and Souleles and Dehejia et al.

As discussed in Section IV, the interpretation of this result is complicated a bit by the fact that, if price sensitivity is nonzero and heterogeneous on the extensive margin, then there is selection on the offer rate r_i. Specifically, the loan size demanded may be correlated with applicant characteristics other than credit risk if someone who applies at a given r_i is different (e.g., in terms of preferences, or opportunity sets) than someone who does not apply. In this sense the most straightforward interpretation of our loan size elasticity results is that they hold only for the sub-sample that borrow (and see the next sub-section for estimates on this sub-sample).

We explore whether our unconditional loan size price sensitivity estimate might hold for the sample of non-borrowers as well by re-estimating the model with an additional vector of controls for demographics, credit risk characteristics, and branch fixed effects. The result does not change (Table 4, Column 2), which is consistent with non-borrowers having the same intensive margin price sensitivity as borrowers.

D. Conditional Loan Size

Columns 3 and 6 of Table 4 present our main estimates of loan size price sensitivity conditional on borrowing. OLS estimates that loan size decreases R26 for each 100 basis point increase in the interest rate. The implied elasticity here is -0.13. The log-log specification (Column 6) yields an elasticity of -0.11. Columns 4 and 7 add our set of additional controls for selection; these increase the elasticity estimates to -0.17 and -0.14.

Columns 5 and 8 presents tobit estimates addressing the fact that loan size demand may be censored by supply constraints; many borrowers take the maximum amount offered by the loan officer. The results do not change. Figure 4 depicts the conditional loan size demand curve graphically.

In all, we again find elasticities of loan size demand that are quite low relative to comparable recent estimates obtained in other settings.

VI. Pricing Strategy for Profitability and (Targeted) Access

In this section we combine our estimates of average price elasticities of demand from Section V with additional information on revenues and repayment. This enables us to calculate the optimal pricing strategy for our Lender. We also illustrate how pricing could be used to pursue specific poverty (or other demographic) targeting objectives.

A-1 Gross Revenue and Repayment Price Sensitivities: Implications for Short-run Pricing Strategy

We estimate the price sensitivity of short-run profit components in Table 5. Column 1 shows the price sensitivity of gross revenue obtained on initial, pre-deadline borrowing. Combining this with the repayment effects will yield a measure of short-run profitability at different interest rates. Table 5, Column 1 and Figure 5 shows that Lender’s gross revenue curve is slightly upward-sloping over the range of interest rates below its standard ones (3.25 percent to 11.75 percent). Each 100 basis point drop in the monthly rate reduces gross revenue by R2.6.

Table 5, Column 2 shows that loan defaults increase as interest rates increase. This will occur if there is adverse selection, moral hazard, and/or bad shocks that are difficult for borrowers to smooth (Karlan and Zinman 2006b). The average past due amount falls by R12.2 for every 100 basis point decrease in the interest rate. Our default data is censored (some loans may have defaulted after our sample period), so we present tobit estimates as well in Column 3. These suggest a R18.1 decrease in average past due for every 100 basis point decrease in the interest rate.

Accordingly our results suggest strongly that an interest rate increase would be unprofitable for the Lender. It would produce both decreased gross revenues due to the kink in the demand curve (Table 3, Column 3) and increased loan losses (Table 5, Column 2). The question remained whether the Lender should cut rates. To estimate the Lender's optimal price we aggregate the revenue and repayment results over the entire sample frame that received rates at or below the Lender's standard ones. The gross revenue result (Table 5, Column 1) implies that a 100 basis point decrease produces R2.6 less revenue per existing client. The default result (Table 5, Column 2) implies that the same interest rate decrease will generate higher repayment (conditional on take-up) of R12.2. With a 7.4 percent average take-up rate, this implies R0.90 more revenue (repayment) per client offered the loan, for a net revenue decrease of R1.7 per offered client. (Using the tobit repayment estimate instead of OLS changes the net revenue decrease to R1.3.) Thus unless our measure of default dramatically understates the true cost of default (conversations with the Lender's senior management suggest that this is not the case),[28] our results show that the Lender had no incentive to cut rates in partial equilibrium.

A-2. Pricing Strategy with Competition

The prospect of strategic responses by competitors further discourages a price decrease. Our experiment likely identifies the upper bound on the price elasticity of (short-run) demand for the Lender's credit, since the price cuts were unprecedented and short-term. Permanent cuts and/or repeated short-term cuts would be more likely to provoke a response from competitors. This would make the general equilibrium revenue curve relatively steep if in fact some of our short-term borrowers used the partial equilibrium rate cuts to pay off other debt. Lenders can estimate balance-shifting directly using credit bureau data. Our results using credit bureau data suggest that the upper bound on the extensive margin of balance-shifting to competitor financial institutions is small (Table 3, Columns 4), although we can not rule out nontrivial balance-shifting on the intensive margin (results not reported).

[28] The measure of default used here is the average amount past due over the first seven to twelve months of the loan. This will understate the true cost of higher rates on default to the extent that it fails to capture the marginal administrative cost of defaults and/or fails to anticipate future default. It will overstate costs to the extent that some defaults are eventually (partially) cured by the borrower, or (partially) recovered via collection efforts.

A-3. Direct Mail Price Elasticities and Pricing Strategy

The analysis above focuses on the short-run pricing implications for direct mail solicitations. In the longer-run prices offered via direct mail may become common knowledge, and also be offered to walk-ins.

Consequently, when forming pricing strategy, lenders must consider what fraction of solicited clients would read the solicitation and become aware of the offered interest rate. Inattention to the letter may produce elasticities that differ from those in a steady-state where new rates were common knowledge. To see how direct mail elasticities could underestimate steady-state elasticities, consider the thought experiment where no clients read their solicitation. In that case we would find a price elasticity of zero. If 50% of clients read their solicitation (see footnote 19), then direct mail may underestimate the strength of common knowledge elasticities by as much as a factor of 2, all else equal.

But all else may not be equal: letter-readers may have different elasticities than non-readers. Thus another issue is that direct mail may under- (over-)estimate the strength of steady-state elasticities if letter-readers are less (more) price sensitive than non-readers.

We explore these issues by constructing client-level proxies for letter-reading probability, splitting the sample based on these proxies, and re-estimating our models of price sensitivity. Our proxies for letter-reading are education, recent borrowing from the Lender, and a relatively high number of past loans from the Lender. We then test whether those with presumed higher probabilities of letter-reading exhibit different price sensitivities than the rest of the sample, conditional on our full set of demographic and risk controls. As discussed above, the predicted pattern of results is ambiguous: letter-reading increases price sensitivity of course, but letter readers could have lower average price sensitivity than non-readers.

Table 6 reports our estimated unconditional loan size price sensitivities for sub-samples with presumed high probabilities of reading the letter. Column 1 reproduces Table 4, Column 2 for reference. Column 2 limits the sample to those with relatively high education levels (as predicted from occupation). Column 3 limits the sample to those who borrowed from the Lender within the last 9 months, and Column 4 limits the sample to those with at least 3 prior loans from the Lender. Our presumption on these two cuts is that more recent and frequent borrowers had stronger attachments to the Lender, and consequently would be more likely to open and read the solicitation. But none of the elasticities differ by more than |0.05| from that obtained in the full sample. Our results here are merely suggestive, but they provide little evidence that longer-run elasticities would differ from our short-run elasticities due to increased awareness of lower rates.

B. Pricing with Other Objectives in Mind: (Targeted) Access

As noted at the outset, many MFIs seek to expand access and often target specific groups; e.g., female and relatively poor borrowers. Our Lender did not have such objectives. But we use our results to illustrate how an MFI can use randomized pricing to inform strategic decisions when it has multiple objectives.

The profitability results in Section VI-A-1 imply that expanding access comes at a pecuniary cost. But in the Lender's case the cost was small; each 100 basis point rate cut retained a nontrivial number of clients (approximately 3 for every 1,000 offers), at a net profit loss of only R1.7 for each additional loan.

Some MFIs have more targeted objectives than merely expanding access to a poor population generally. They seek to expand access to targeted groups, such as females, micro-entrepreneurs, and the relatively poor. Whereas some MFIs try to screen out anyone who is not in their targeted group(s), many MFIs lend more broadly but retain some targeting objectives. Below we show how loan pricing can be used to further such objectives if targeted groups have different price sensitivities than non-targeted groups.

Table 7 provides the additional pieces of evidence needed to determine whether and how pricing could be used for targeting purposes. It suggests that two groups commonly targeted by MFIs have slightly stronger price elasticities than average in our sample. Here we take our preferred specifications for takeup (Table 3, Column 1), loan size (Table 4, Column 1), and loan size conditional on borrowing (Table 4, Column 3) and estimate them on sub-samples of female, low-income, and female low-income clients.[29] Columns 1-3 show that the takeup elasticities for these groups (-0.33, -0.32, -0.32) are slightly stronger than in full sample (-0.28). Columns 4-6 show that loan size elasticities for these groups (-0.40, -0.40, -0.51) are somewhat stronger than in the full sample (-0.32). Columns 7-9 show that loan size elasticities conditional on borrowing for these groups (-0.14, -0.21, -0.17) are again slightly larger than in the full sample (-0.13).[30]

[29] We do not include additional control variables since MFIs typically target unconditional on other characteristics.
[30] Our findings by income differ in magnitude from Dehejia et al, which finds that low-wealth MFI borrowers in Bangladesh are about three times more elastic than their higher-wealth counterparts.

The implication is that the Lender could have used price cuts to retain more female and relatively poor borrowers in both absolute and relative (particularly debt-weighted) terms. Furthermore, the profitability calculations suggest that targeting objectives could have been achieved at very low cost in the Lender's case.

VII. Maturity Elasticities

Attanasio, Goldberg, and Kryiazidou (2005) shows that the loan demand of liquidity constrained agents may respond to loan maturity as well as loan price. The intuition for this finding is that longer maturities reduce monthly loan payments, effectively permitting more borrowing (relative to income or asset positions). Consider a client who is borrowing R1,000 to smooth consumption. With a 4-month maturity a low-risk client will face an interest rate of 7.75 percent and a monthly payment of R328. At the same interest rate and monthly payment under a 12-month maturity, she could borrow R2,036.[31] The tradeoff of course is that the longer maturity may reduce lifetime consumption, due to larger total financing costs.

In order to estimate maturity elasticities, we engineered exogenous variation in maturity choice in conjunction with the interest rate experiment. This was done via randomly-assigned maturity "suggestions" among clients eligible for longer maturities. The suggestion took the form of an example loan showing a maturity, loan size (the client's last loan size), and monthly payment. Clients assigned to the "maturity suggestion" group received a single example loan on their mailer featuring a randomly

[31] In practice, the Lender's interest rates decrease in maturities and thus amplify the extent to which longer maturities relax liquidity constraints on the margin.

chosen maturity of four, six, or twelve months. Those randomly chosen for the "no maturity suggestion" group received an analogous but larger table with several loans and maturities. The suggestion assignment was orthogonal to interest rates by construction. All example loans presented were non-binding, with the letter stating beneath the example loan(s): "Loans available in other sizes and terms" ('term' refers to 'maturity'). Loan officers were instructed to ignore the offer letter in underwriting loan applications.

Prior evidence on the psychology of consumer choice in product and financial markets motivated our suggestion design. Subtle cues have been shown to influence product choice in a durable goods market (Morwitz, Johnson and Schmittlein 1993; Fitzsimons and Shiv 2001), and defaults are very powerful drivers of savings decisions (Madrian and Shea 2001).

The example maturity did powerfully predict the actual maturity chosen. Table 8 reports estimates of this first-stage. All specifications are estimated using OLS and take the form:

(2) $m_i = \alpha + \beta S_i + \chi R_i + \delta X_i + \varepsilon_{ib}$,

where m is the maturity chosen (parameterized linearly), S is the maturity suggestion, R is a vector of the randomly assigned offer and contract interest rates, and X includes not only risk and wave (per usual) but also the loan size presented in the offer letter's example loan. We do not find a significant correlation between loan takeup and the maturity suggestion (results not shown), so we ignore the extensive margin below. We estimate (2) on a sample that includes only the following clients: the low- and medium-risks (since highrisks are ineligible for longer maturities) who received a randomized maturity suggestion *and* took a loan.[32] This reduces the sample to 493.

Table 8, Columns 1 and 4 report our estimates of suggestion effects on the sample of 493 borrowers who received a suggestion. Column 1 uses the linear parameterization of the maturity suggestion, and implies that for each additional month of maturity suggested, the actual maturity increases by 0.11 months. Column 4 reports results obtained from the categorical parameterization of the suggestion (with 4-month the omitted category). The suggestion categories are jointly significant at the 99 percent level, and it seems that the 12-month suggestion drives the linear effect; in fact, the point estimate on this variable (0.89) implies the same per-month effect (0.11) as the linear case.[33] Our estimates are highly significant (at the 99 percent level), but IV estimates may be biased towards OLS even at these significance levels (Stock, Wright and Yogo 2002). Thus our IV estimates below are more suggestive than conclusive.

Next we use the maturity suggestions to instrument for actual maturity in two-stage least squares (2SLS) versions of equation (2), in order to estimate the maturity elasticity of

[32] We drop those taking the relatively rare one- and eighteen-month maturities from the sample. This excludes 13 additional observations.

[33] We are not aware of any other "treatments" that are directly comparable to our maturity suggestion. Our maturity suggestion has the flavor of a default option but was literally only a suggestion: it did not actually shift the status quo. Actual shifts in the status quo appear to be very powerful in influencing financial decisions. A classic cite is Madrian and Shea (2001), where shifting the default from 401(k) non-enrollment to enrollment increased enrollment by an estimated 50 percentage points (a 2.4-fold increase over the baseline participation rate of 37%). To facilitate comparison we estimate two additional probits. The first implicitly assumes that the 4-month maturity is the status quo (since 91% of borrowers in our maturity elasticity sample had this as their last maturity), and estimates that borrowers who were shown a longer (6- or 12-month) maturities were 14 percentage points more likely to choose a longer term. This is a 1.5-fold increase over the baseline proportion of 0.09. The second probit estimates that borrowers who were shown a different maturity than their last loan were 15 percentage points more likely to actually choose a different maturity. Again, the 0.09 who had a long maturity on their prior loan is a natural baseline for comparison, which implies a 1.7-fold increase. So our suggestion effects are large, but smaller than the effects engineered by the actual shift in the status quo in Madrian and Shea.

demand for consumer credit. Table 9 contains related results. We report specifications using log of loan size as the outcome of interest, and our categorical suggestion instruments; results are similar for other parameterizations. Column 4 suggests that each month of additional maturity increases intensive loan demand by 15.7 percent. Interpolating, these impacts on loan demand are about twice as large as in Attanasio et al, where a one-year lengthening of maturity increases loan demand by 88.5 percent. This is consistent with credit constraints binding more tightly in the uncollateralized, high risk South African cash loan market than in the collateralized, relatively low risk U.S. auto loan market, an intuitive proposition.

Most notably our maturity effect is large relative to price sensitivity. Loan size responds negatively but insignificantly to price in our maturity-suggestion sample (Table 9, Column 4; Attanasio et al also find a insignificant price sensitivity in their full sample). The standard error does not rule out economically meaningful price sensitivity, but even if we take the largest price response contained in our 95 percent confidence interval (-.094 = -.036+(-.029*2)), a one month maturity increase has the same effect on loan size demand as a 167 basis point (.157/.094) decrease in the monthly interest rate. The interest rate point estimate implies that a one month maturity increase has the same effect as a 436 basis point decrease (.157/.036).

Following Attanasio et al, we also explore whether maturity elasticities vary with *ex-ante* liquidity constraints, as proxied by income. Table 8, Columns 2, 3, 5, and 6 show that the maturity suggestion is a large and (marginally) significant predictor for both low- and “high”-income borrowers. High-income borrowers are not wealthy in an absolute sense of course: we split the sample at median income. The first-stage point estimates are smaller for high-income borrowers but not significantly different than those for low-income borrowers.

The IV estimates in Table 9 show highly significant maturity elasticities for low-income borrowers (Column 5) but not for high-income borrowers (Column 6). The effect for high-income borrowers is imprecisely estimated: the standard errors do not rule out a large maturity elasticity. But the pattern of OLS results, where low-income and high-income borrowers have almost the same maturity sensitivity (Columns 2 and 3), suggests that the IV estimates may indeed be picking up a meaningful difference between low- and high-income borrowers.

VIII. Conclusion

We have used a randomized field experiment to estimate price and maturity elasticities of demand for consumer credit. The sample includes former borrowers from a major, for-profit, South African consumer microlender to the working poor.

We find downward-sloping but relatively flat demand with respect to price throughout a wide range of prices (50-200% APR) *at and below* the Lender's standard rates (which are the rates members of our sample received on their prior loans). In the Lender's case the cost of reducing interest rates (lost gross interest revenue on inframarginal loans) slightly exceeded the benefits (increased gross revenue from marginal borrowing, increased net revenue from higher repayment rates).

Thus our Lender, which had no social targeting objectives, had no incentive to cut rates. Many other microfinance institutions (MFIs) do have targeting objectives. So we use our results to illustrate how an MFI can use randomized experiments to evaluate the tradeoff, if any, between expanding access (reaching new poor borrowers), and profitability. In the Lender's case it could have used loan pricing to expand access cheaply: rate cuts reduced profits, but only by tiny amounts. It also could have used rate cuts to expand access in targeted fashion; e.g., its female and relatively poor borrowers were more price sensitive than average. Cutting rates increased the (debt-weighted) proportion of the Lender's book held by females and the relatively poor.

Policymakers increasingly prescribe that MFIs should *raise* rates. Our evidence shows that this would have been disastrous for our Lender. A small sample in our experiment shows that takeup elasticities of demand kinked sharply at the Lender's standard rates, rising to well above unity. Raising rates would have decreased revenue and the Lender's client base. Our results also strongly suggest that raising rates would reduce repayments as well, by exacerbating information asymmetries. In all we find that the Lender could not have increased profits by changing rates.

We also examine maturity elasticities of demand, following Attanasio et al (2005). This margin of loan contracting has been neglected by other academics, policymakers, and practitioners. We worked with the Lender to engineer exogenous variation in maturity choice by randomly assigning some nonbinding maturity suggestions (in the form of an example loan presented on a direct mailer). The suggestion strongly predicts actual maturity choice, creating an instrument that enables us to estimate maturity elasticities of demand. Our results suggest that maturity elasticities dwarf price elasticities in economic significance, *on average*. Heterogeneity may be important however. We find significant maturity elasticities only among relatively low-income borrowers, and while the confidence intervals do not rule out important maturity elasticities for relatively high-income borrowers, the pattern is consistent with liquidity constraints that decrease with income.

Our results suggest that operationally feasible increases in maturities could have large effects on aggregate credit flows in markets where liquidity constraints bind. We estimate that a one month increase in maturity increased intensive loan demand by about 15% in our sample. But our findings leave many questions unanswered, even within-sample. Does extending maturities have adverse effects on repayment? Our sample is too small to shed light. Does offering longer maturities increase demand on the extensive margin (i.e., expand access)? We do not find an effect, but this could be due to the nature of the treatment: the Lender randomized suggestions, not actual maturity offers.

The biggest unanswered question with any empirical exercise, of course, is the extent to which results apply to other settings. Preferences, outside options, returns to borrowing (broadly defined), and other elements of the intertemporal optimization problem may vary across settings, producing important variation in elasticities. Or they may not. For example, our price elasticities at relatively high rates are similar to those found (using quasi-experimental methods) for more traditional microcredit in Bangladesh (Dehejia, Montgomery and Morduch 2005), for consumer loans in Italy (Alessie, Hochguertel and Weber 2005), and for credit cards in the U.S. (Gross and Souleles 2002). Our pattern of maturity and price elasticities is remarkably similar to what Attanasio et al (2005) find for car loans in the U.S.

The external validity question is best addressed with studies in the markets of interest; hence our final point is methodological. It is feasible, and in the interest of many MFIs, to use randomized-controlled trials to optimize contracting strategies with respect to profit and/or targeting objectives. Field experiments are considered best and standard practice by many leading credit card companies and other retailers. MFIs can adapt the methodology to their own marketing approaches and strategic considerations by forming partnerships with researchers.

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Figure 1: Sample Letter

the trusted way to borrow cash

30 October 2003

Shop 8
12 Market Street
Krugersdorp 1739
Tel: 011 660 2944

BUSINESS HOURS
MON - FRI 08:30 - 16:30
SAT 08:00 - 12:00

A low rate for you.

Congratulations! As a valued client, you are now eligible for a low interest rate on your next cash loan from This is a limited time offer, so please come in by 30 November 2003 to take advantage of this offer.

You can use this cash to pay for school, or for anything else you want.

Enjoy low monthly repayments with this offer! Here is one example of a loan you can get under this offer:

Interest Rate	Loan Amount	Loan Term	Monthly Repayment
10.50%	R2000.00	4 Months	R710.00

LOAN AVAILABILITY SUBJECT TO TERMS & CONDITIONS

Loans available in other amounts. There are no hidden costs. What you see is what you pay.

If you borrow elsewhere you will pay R360.00 more in total on a R2000.00, 4 month loan.

How to apply:

Bring your ID book and latest payslip to your usual branch, by **30 November 2003** and ask for **Mrs. Veno Naidoo.**

Mrs. Veno Naidoo
Area Manager

P.S. Unfortunately, if you have already taken a loan since the date this letter was issued, you do not qualify for this offer.
Comparison based on a competitor's interest rate of 15% per month.

Figure 2: Operational Steps of Experiment

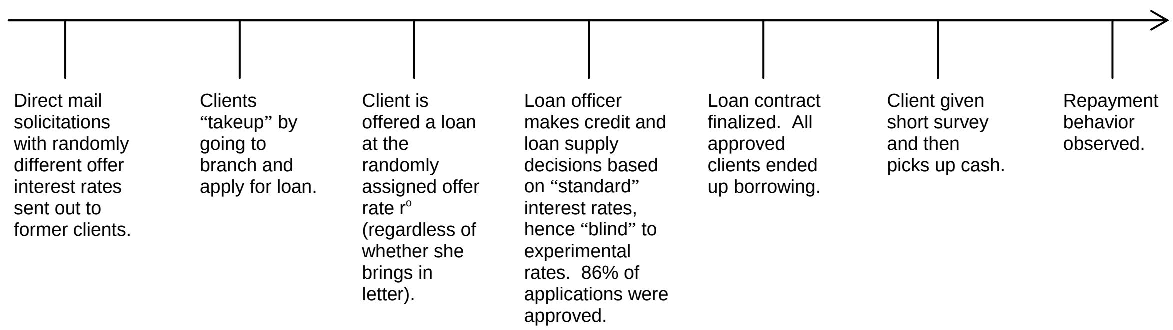
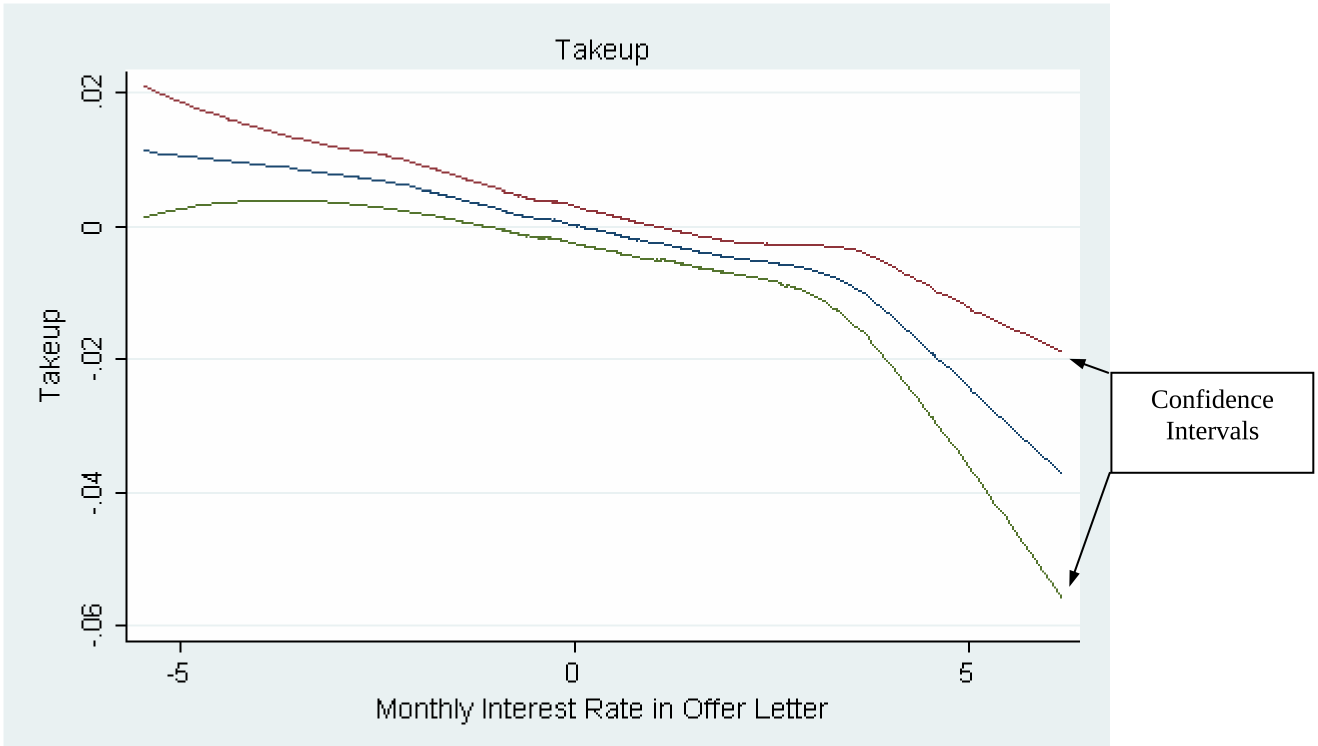


Figure 3. Regression-Adjusted Demand Curve for Takeup with Respect to Price

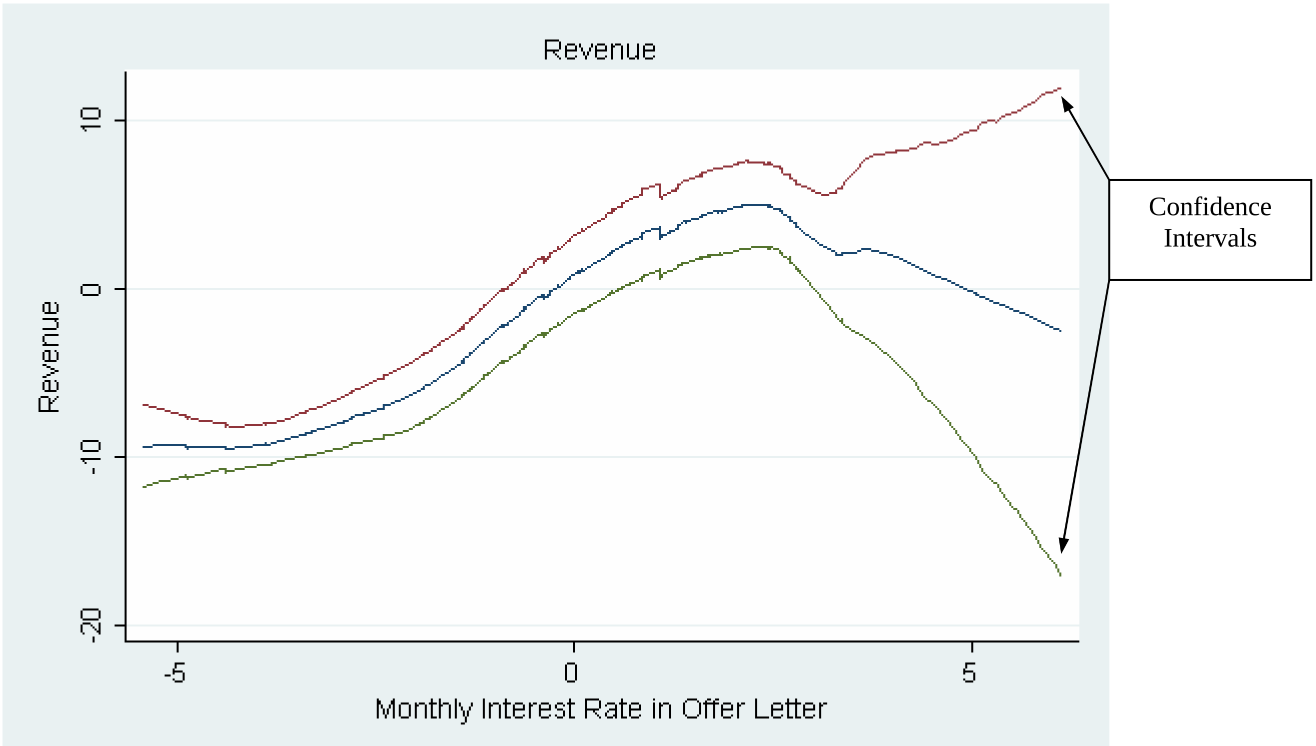


Produced with Stata 9.0 SE command lowess, locally weighted partial linear regression. The x-axis is the residual from a regression of the monthly offer interest on the conditions from the experiment (the month of the offer and the lender-defined risk level of the client prior to the experiment), and the y-axis is the residual from the regression of takeup (1 or 0) on the same conditions (month of offer and risk category of client). 95% confidence intervals were bootstrapped with 100 repetitions.

Figure 4. Regression-Adjusted Demand Curve for Loan Size, Conditional on Borrowing, with Respect to Price

Produced with Stata 9.0 SE command lowess, locally weighted partial linear regression. The x-axis is the residual from a regression of the monthly offer interest on the conditions from the experiment (the month of the offer and the lender-defined risk level of the client prior to the experiment), and the y-axis is the residual from the regression of loan size on the same conditions (month of offer and risk category of client). The sample frame includes only those who took-up (i.e., had strictly positive loan sizes). 95% confidence intervals were bootstrapped with 100 repetitions.

Figure 5. Regression-Adjusted Demand Curve for Revenue with Respect to Price



Produced with Stata 9.0 SE command lowess, locally weighted partial linear regression. The x-axis is the residual from a regression of the monthly offer interest on the conditions from the experiment (the month of the offer and the lender-defined risk level of the client prior to the experiment), and the y-axis is the residual from the regression of gross revenue for the Lender on the same conditions (month of offer and risk category of client). 95% confidence intervals were bootstrapped with 100 repetitions.

Table 1. Summary Statistics

Sample:	All	Applied	Borrowed	Eligible for Maturity Suggestion Randomization
	(1)	(2)	(3)	(4)
Panel A: Experimental variables				
Interest rate	8.029	7.410	7.345	6.440
	(2.472)	(2.371)	(2.354)	(1.721)
Dynamic repayment incentive: Rate valid for one year	0.425	0.466	0.470	0.440
	(0.494)	(0.499)	(0.499)	(0.496)
Example loan term = 4 months	0.506	0.520	0.522	0.506
	(0.500)	(0.500)	(0.500)	(0.500)
Example loan term = 6 months	0.254	0.239	0.233	0.254
	(0.435)	(0.427)	(0.423)	(0.435)
Example loan term = 12 months	0.241	0.241	0.245	0.241
	(0.428)	(0.428)	(0.431)	(0.428)
Borrowed	0.072	0.856	1.000	0.163
	(0.259)	(0.351)	-	(0.370)
Applied	0.084	1.000	1.000	0.176
	(0.278)	-	-	(0.381)
Loan size	103.351	1224.956	1430.744	269.025
	(506.430)	(1290.813)	(1285.177)	(880.112)
Panel B: Demographic Characteristics				
Female	0.476	0.487	0.487	0.809
	(0.499)	(0.500)	(0.500)	(0.997)
Married	0.439	0.450	0.457	0.471
	(0.496)	(0.498)	(0.498)	(0.500)
Age	41.174	40.819	40.843	42.206
	(11.594)	(11.235)	(11.260)	(10.966)
More educated	0.388	0.409	0.416	0.401
	(0.487)	(0.492)	(0.493)	(0.490)
Rural	0.158	0.152	0.149	0.194
	(0.365)	(0.359)	(0.356)	(0.396)
Number of dependants	1.547	1.835	1.866	2.220
	(1.732)	(1.742)	(1.739)	(1.748)
Gross monthly income	3.410	3.372	3.405	3.549
	(20.496)	(2.115)	(2.164)	(4.709)
Number of loans with the lender	4.200	4.820	4.790	5.960
	(3.850)	(4.233)	(4.231)	(4.184)
Number of months since last loan with Lender	10.640	6.720	6.305	2.911
	(6.823)	(6.177)	(5.980)	(1.578)
Low risk	0.119	0.252	0.273	0.559
	(0.324)	(0.434)	(0.445)	(0.497)
Medium risk	0.091	0.188	0.192	0.441
	(0.288)	(0.391)	(0.394)	(0.497)
High risk	0.790	0.560	0.535	
	(0.408)	(0.497)	(0.500)	
Number of observations	53,810	4,540	3,887	3,096

Standard deviations reported in parentheses. More educated equals one if the number of years of education is in highest 40th percentile. Gross monthly income was reported by the client at time of last loan. Sample size varies slightly (between 52594 and 53180) for demographic variables based on availability.

Table 2. Experimental Validation Regressions

Estimator:	OLS	Probit	Probit
Dependent Variable:	Interest Rate (00s of basis points)	1= Borrowed after deadline, and not before deadline	1= Rejected
Mean(dependent variable):	8.03	0.15	0.14
	(1)	(2)	(3)
Monthly interest in percentage points (e.g., 8.2)		-0.0001	0.002
		(0.0007)	(0.002)
Number of months since last loan with lender	0.001		
	(0.003)		
Number of prior loans with lender, log	0.00		
	(0.01)		
Female	0.02		
	(0.02)		
Number of dependants	0.00		
	(0.01)		
Married	0.02		
	(0.02)		
Age, log	-0.00		
	(0.05)		
Rural	0.02		
	(0.03)		
More educated	-0.01		
	(0.02)		
External credit bureau score, log	0.01		
	(0.01)		
Record exists in external credit bureau	0.04		
	(0.10)		
Internal credit score, log	-0.06		
	(0.13)		
(Pseudo-) R-squared	0.11	0.05	0.05
Sample:	All with nonmissing	All	Applicants
Number of observations	53,554	53,810	4,540

* significant at 10%; ** significant at 5%; *** significant at 1%.

Probit results are marginal effects. Robust standard errors reported in parentheses are clustered within branch where the loan was processed. Interest rate coefficients show the change in proportion from a 100 basis point increase in the monthly interest rate. ‘More educated’ equals one if the number of years of predicted education is in highest 40th percentile. All specifications include controls (not shown) for the client’s credit risk category and mailer wave.

Table 3. The Extensive Margin: Price Sensitivities of Loan Takeup

Dependent variable:	1= Applied			1=(Takeup with outside lender, not with our Lender)			1= (Takeup with Lender after deadline, not before deadline)		
Mean(dependent variable)	0.08	0.08	0.07	0.22	0.22	0.28	0.15	0.15	0.18
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Interest Rate in pp terms (e.g., 8.2)	-0.00289***		-0.01723***	0.00106		-0.00958	0.00042		-0.01239**
	(0.00047)		(0.00160)	(0.00083)		(0.00660)	(0.00064)		(0.00622)
1 = (rate > standard for client's risk category)		-0.02996***			0.00539			-0.03630***	
		(0.00398)			(0.00512)			(0.00869)	
Pseudo R-squared	0.045	0.044	0.055	0.002	0.002	0.003	0.048	0.049	0.056
Sample:	Offer4 <= standard	Full	Offer4 > standard	Offer4 <= standard	Full	Offer4 > standard	Offer4 <= standard	Full	Offer4 > standard
Number of observations	53,178	53,810	632	53,178	53,810	632	53,178	53,810	632

* significant at 10%; ** significant at 5%; *** significant at 1%.

Each column presents marginal effects from a single probit of a measure of loan takeup on the interest rate offered to the client, and risk category and mailer wave (not shown in table). Robust standard errors reported in parentheses and are clustered within branch. Interest rate coefficients show the change in the proportion taking up from a 100 basis point increase in the monthly interest rate.

Table 4. Price Sensitivities of Loan Size

Estimator:	OLS	OLS	OLS	OLS	Tobit	OLS	OLS	Tobit
Dependent variable:			Loan Size				Log(Loan Size)	
Mean(dependent variable):	106	104	1,428	1,428	1,428			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interest Rate in pp terms (e.g., 8.2)	-4.368***	-4.394***	-25.876**	-33.715***	-32.812***			
	(1.093)	(1.146)	(12.994)	(11.392)	(11.366)			
Log(Interest Rate)						-0.113**	-0.143***	-0.141***
						(0.049)	(0.041)	(0.041)
(Pseudo) R-squared	0.03	0.06	0.07	0.29	0.02	0.06	0.34	0.15
Additional controls for demos and credit risk?	No	Yes	No	Yes	Yes	No	Yes	Yes
Branch fixed effects?	No	Yes	No	Yes	No	No	Yes	No
Conditional on borrowing?	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	31,231	28,197	2,325	2,304	2,304	2,325	2,304	2,304

* significant at 10%; ** significant at 5%; *** significant at 1%.

Loan size in Rand; 7 Rand ~= US$1 at the time of the experiment. Robust standard errors clustered on branch in all but tobit specifications. All specifications include controls for risk category and mailer. Additional controls added to unconditional specifications include: quadratics in internal credit score, external credit score, and gross income at time of pre-approval (but not net income at time of pre-approval, since this is only available for wave 3 individuals), months since last loan with Lender, number of prior loans with Lender, gender, number of dependents, marital status, quadratic in age, rural residence, education, and province. Controls for conditional specifications use income measured at the time of loan approval, and include net income at the time of loan approval as well. Sample size falls for loan size demand models, relative to takeup models (Table 3), because with loan size we only include applicants that were not randomly assigned a surprise rate reduction upon applying for a loan—see footnote 17 for details.

Table 5: Gross Revenue and Repayment Sensitivities to Interest Rates

Estimator:	OLS	OLS	Tobit
Dependent Variable:	Gross Interest Revenue	Average Past Due	Average Past Due
	(1)	(2)	(2)
Interest rate in pp terms (e.g., 8.2)	2.553***	12.161***	18.064***
	(0.438)	(3.523)	(5.934)
Additional controls?	No	No	No
Conditional on borrowing	No	Yes	Yes
R-squared	0.02	0.05	0.01
Number of observations	31,231	2,325	2,325

* significant at 10%; ** significant at 5%; *** significant at 1%.

All Dependent variables in Rand; 7 Rand ~= US$1 at the time of the experiment. Robust standard errors reported in parentheses and clustered within branch for OLS specifications. Average past due over the first 7-12 months of the loan (this is all the we observe, hence the motivation for tobit). Controls included for risk category and wave of experiment.

Table 6. Price Sensitivity of Loan Size for Groups Assumed Most Likely to Read the Solicitation

Dependent variable:	Loan Size			
Mean(dependent variable):	104.11	136.36	174.65	127.58
	(1)	(2)	(3)	(4)
Offer Rate	-4.394***	-5.397**	-6.591***	-5.498**
	(1.146)	(2.296)	(2.278)	(2.140)
Implied elasticity	-0.33	-0.31	-0.28	-0.33
Additional controls?	Yes	Yes	Yes	Yes
Conditional on borrowing?	No	No	No	No
Sample:	Full	High education	Borrowed in last 9 months	Past loans > 2
Number of observations	28,197	11,275	13,201	14,806

* significant at 10%; ** significant at 5%; *** significant at 1%.

Loan size in Rand; 7 Rand ~= US$1 at the time of the experiment. OLS estimates with standard errors clustered on branch. Education is predicted from occupation. Borrowing in last 9 months and past loans >2 are defined based on client's history with the Lender (not outside lenders). Controls include: credit risk category mailer wave, quadratics in internal credit score, external credit score, and gross income at time of pre-approval (but not net income since this is only available for wave 3 individuals), months since last loan with Lender, number of prior loans with Lender, gender, number of dependents, marital status, quadratic in age, rural residence, education, and province.

Table 7. Price Sensitivities for Female and Low-Income Clients

Dependent variable:	Applied			Loan Size, Unconditional			Loan Size, Conditional		
Mean(dependent variable):	0.09	0.08	0.08	112.35	81.33	79.38	1,467.47	1,000.72	977.51
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Interest Rate	-0.00359***	-0.00320***	-0.00338**	-5.80435***	-4.00157***	-5.14672***	-29.24181	-28.60900***	-23.92335**
	(0.00077)	(0.00084)	(0.00137)	(1.74367)	(1.15427)	(1.86966)	(18.55180)	(7.46674)	(10.74653)
Implied Elasticity	-0.33	-0.32	-0.32	-0.40	-0.40	-0.51	-0.14	-0.21	-0.17
Conditional on borrowing?	No	No	No	No	No	No	Yes	Yes	Yes
Sample:	Female	Low-income	Female & low-income	Female	Low-income	Female & low-income	Female	Low-income	Female & low-income
(Pseudo) R-squared	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.11	0.12
Number of observations	25,323	24,434	11,709	14,786	14,178	6,773	1,132	1,201	615

* significant at 10%; ** significant at 5%; *** significant at 1%.

Loan size in Rand; 7 Rand ~= US$1 at the time of the experiment. Probit marginal effects (applied) and OLS estimates (loan size) with robust standard errors clustered on branch. Here we estimate our preferred models of takeup and loan size sensitivity from Tables 3 and 4 on sub-samples that are motivated by the targeting practices of other MFIs. ‘Low-income’ is below median, and based on income at time of pre-approval for columns 1-6, and on income at time of application for columns 7-9.

Table 8. Maturity Elasticity 1st-Stage: The Power of Pure Suggestion

	(1)	(2)	(3)	(4)	(5)	(6)
Maturity shown (linear)	0.117***	0.134**	0.096*			
	(0.036)	(0.054)	(0.049)			
Maturity shown = 6-month				-0.041	-0.215	0.024
4-month is omitted category				(0.234)	(0.350)	(0.373)
Maturity shown= 12-month				0.917***	1.032**	0.759*
				(0.289)	(0.427)	(0.395)
Interest Rate, in pp (e.g., 8.2)	-0.118	-0.201	-0.007	-0.128	-0.235	-0.008
	(0.120)	(0.158)	(0.169)	(0.121)	(0.170)	(0.170)
Log(loan amount shown)	0.505**	0.772**	0.357	0.528**	0.835**	0.367
	(0.208)	(0.337)	(0.319)	(0.209)	(0.348)	(0.318)
R-squared	0.07	0.09	0.07	0.07	0.09	0.07
Income split?	No	Low income	High income	No	Low income	High income
Number of observations	493	239	254	493	239	254

* significant at 10%; ** significant at 5%; *** significant at 1%.

OLS estimates with a linear measure of maturity as the dependent variable, and robust standard errors clustered on branch. The sample frame includes those who received a suggestion (i.e, an example loan featuring a 4-, 6-, or 12-month maturity) and tookup a loan with a standard maturity (so thirteen loans with 1- and 18-month maturities are dropped). The “loan amount shown” was in all cases the client’s loan size on their most recent prior loan. All specifications also include controls for risk category, mailer wave, the contract interest rate and whether it was valid for one year. High- and low-income are split on median gross income at time of loan approval.

Table 9. Maturity Elasticities of Loan Demand: OLS and IV Estimates

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Maturity (linear)	0.161***	0.168***	0.155***	0.157**	0.214***	0.050
	(0.011)	(0.009)	(0.018)	(0.062)	(0.072)	(0.126)
Interest Rate	-0.035	-0.053**	0.011	-0.036	-0.041	0.011
	(0.027)	(0.026)	(0.038)	(0.029)	(0.038)	(0.038)
Log(Loan Amount Shown)	0.443***	0.390***	0.369***	0.445***	0.356***	0.408***
	(0.047)	(0.056)	(0.069)	(0.061)	(0.076)	(0.113)
Income split?	No	Low income	High income	No	Low income	High income
R-squared	0.52	0.59	0.45	0.52	0.56	0.32
Number of observations	493	239	254	493	239	254

* significant at 10%; ** significant at 5%; *** significant at 1%.

Robust standard errors clustered on branch. Log(loan size) is the dependent variable; results are similar for level loan size. The sample frame includes those who received a suggestion (i.e, an example loan featuring a 4-, 6-, or 12-month maturity) and tookup a loan with a standard maturity (so thirteen loans with the relatively rare 1- and 18-month maturities are dropped). IV specifications use the categorical measures of suggested maturity as the instrument; results are similar if we use the linear instrument. The “loan amount shown” was in all cases the client’s loan size on their most recent prior loan. All specifications also include controls for risk category, mailer wave, the contract interest rate and whether it was valid for one year. High- and low-income are split on median gross income at time of loan approval.

Appendix 1: Reconciliation of Sample Frames

	Frequency	Total
Sample frame reductions for this paper:		
Total letters mailed	58,168	58,168
Flat or upward sloping yield curve between 4, 6 and 12 month loan offers	3,000	55,168
Mail returned by postal service	1,358	53,810
Offer interest rate higher rate on prior loan	632	53,178
Number of observations available for analysis		53,178
Number of loan applicants		4,540
Number of loan applicants with offer interest rate higher than rate on prior loan		42
Number of loan applicants with offer interest rate equal or lower than rate on prior loan		4,498
Number of approved loan applicants		3,887
Number of approved loan applicants with offer interest rate higher than rate on prior loan		32
Number of approved loan applicants with offer interest rate equal or lower than rate on prior loan		3,855
Number of individuals eligible for multiple terms and shown one and only one term suggestion		3,096
Number of loans made to individuals eligible for multiple terms and shown one and only one term suggestion		493
Sample frame reductions for information asymmetry paper		
Total letters mailed	58,168	58,168
Offer interest rate higher than rate on prior loan	635	57,533
Number of observations available for analysis		57,533
Sample frame reductions for psychology paper		
Total letters mailed	58,168	58,168
Pilot letters excluded (did not include psychology treatments)	4,974	53,194
Number of observations available for analysis		53,194

Sample reductions are demontrated sequentially (e.g., 1423 had mail returned by the postal service, but 65 of those were already removed due to the flat or upward sloped yield curve). Individuals with flat or upward sloping yield curves were randomly chosen, and were removed from analysis since for those who did not borrow it is impossible to infer which rate they rejected. The information asymmetry paper is "Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment" (Karlan and Zinman, 2006b). The psychology paper is "What's Psychology Worth? A Field Experiment in Consumer Credit" (Bertrand, Karlan, Mullainathan, Shafir and Zinman, 2005).

Appendix 2. Frequency of Monthly Offer Interest Rates

Rate	Low Risk		Medium Risk		High Risk		Total	
	Freq.	Perc.	Freq.	Perc.	Freq.	Perc.	Freq.	Perc.
3	119	1.85%	76	1.55%	575	1.35%	770	1.43%
3	171	2.66%	64	1.31%	738	1.74%	973	1.81%
4	220	3.42%	90	1.84%	525	1.24%	835	1.55%
4	32	0.50%	18	0.37%	53	0.12%	103	0.19%
4	224	3.49%	66	1.35%	735	1.73%	1,025	1.90%
4	166	2.58%	73	1.49%	512	1.20%	751	1.40%
4	40	0.62%	21	0.43%	59	0.14%	120	0.22%
4	162	2.52%	57	1.16%	475	1.12%	694	1.29%
4	247	3.84%	84	1.72%	752	1.77%	1,083	2.01%
5	146	2.27%	82	1.67%	578	1.36%	806	1.50%
5	45	0.70%	22	0.45%	60	0.14%	127	0.24%
5	122	1.90%	73	1.49%	691	1.63%	886	1.65%
5	234	3.64%	96	1.96%	532	1.25%	862	1.60%
5	45	0.70%	19	0.39%	67	0.16%	131	0.24%
5	206	3.21%	90	1.84%	681	1.60%	977	1.82%
6	348	5.42%	77	1.57%	587	1.38%	1,012	1.88%
6	265	4.13%	71	1.45%	497	1.17%	833	1.55%
6	46	0.72%	20	0.41%	74	0.17%	140	0.26%
6	307	4.78%	134	2.74%	689	1.62%	1,130	2.10%
6	374	5.82%	108	2.21%	577	1.36%	1,059	1.97%
6	49	0.76%	23	0.47%	74	0.17%	146	0.27%
7	325	5.06%	103	2.10%	595	1.40%	1,023	1.90%
7	353	5.50%	122	2.49%	546	1.29%	1,021	1.90%
7	294	4.58%	141	2.88%	755	1.78%	1,190	2.21%
7	405	6.30%	186	3.80%	824	1.94%	1,415	2.63%
7	325	5.06%	161	3.29%	810	1.91%	1,296	2.41%
7	357	5.56%	167	3.41%	992	2.33%	1,516	2.82%
8	337	5.25%	181	3.70%	827	1.95%	1,345	2.50%
8	349	5.43%	169	3.45%	882	2.08%	1,400	2.60%
8	0	0.00%	184	3.76%	801	1.89%	985	1.83%
8	0	0.00%	143	2.92%	1,000	2.35%	1,143	2.12%
8	4	0.06%	157	3.21%	866	2.04%	1,027	1.91%
8	0	0.00%	152	3.10%	995	2.34%	1,147	2.13%
8	6	0.09%	25	0.51%	73	0.17%	104	0.19%
9	4	0.06%	177	3.62%	808	1.90%	989	1.84%
9	13	0.20%	35	0.71%	82	0.19%	130	0.24%
9	0	0.00%	196	4.00%	787	1.85%	983	1.83%
9	0	0.00%	169	3.45%	1,010	2.38%	1,179	2.19%
9	5	0.08%	199	4.06%	848	2.00%	1,052	1.96%
9	13	0.20%	202	4.13%	868	2.04%	1,083	2.01%
9	0	0.00%	193	3.94%	1,128	2.65%	1,321	2.45%
10	5	0.08%	37	0.76%	88	0.21%	130	0.24%
10	0	0.00%	155	3.17%	1,172	2.76%	1,327	2.47%
10	9	0.14%	214	4.37%	866	2.04%	1,089	2.02%
10	0	0.00%	0	0.00%	1,217	2.86%	1,217	2.26%
10	0	0.00%	1	0.02%	1,211	2.85%	1,212	2.25%
10	8	0.12%	3	0.06%	1,239	2.92%	1,250	2.32%
10	0	0.00%	0	0.00%	1,451	3.41%	1,451	2.70%
11	4	0.06%	6	0.12%	1,242	2.92%	1,252	2.33%
11	6	0.09%	4	0.08%	93	0.22%	103	0.19%
11	0	0.00%	0	0.00%	1,364	3.21%	1,364	2.53%
11	5	0.08%	2	0.04%	1,347	3.17%	1,354	2.52%
11	0	0.00%	0	0.00%	1,308	3.08%	1,308	2.43%
11	0	0.00%	0	0.00%	1,463	3.44%	1,463	2.72%
11	10	0.16%	2	0.04%	104	0.24%	116	0.22%
12	3	0.05%	0	0.00%	99	0.23%	102	0.19%
12	0	0.00%	0	0.00%	1,392	3.28%	1,392	2.59%
12	16	0.25%	5	0.10%	1,349	3.17%	1,370	2.55%
12	0	0.00%	2	0.04%	19	0.04%	21	0.04%
12	0	0.00%	4	0.08%	65	0.15%	69	0.13%
13	0	0.00%	2	0.04%	7	0.02%	9	0.02%
13	0	0.00%	2	0.04%	52	0.12%	54	0.10%
13	0	0.00%	5	0.10%	11	0.03%	16	0.03%
13	0	0.00%	8	0.16%	65	0.15%	73	0.14%
14	0	0.00%	3	0.06%	10	0.02%	13	0.02%
13.75	0	0.00%	15	0.31%	59	0.14%	74	0.14%
14.00	0	0.00%	0	0.00%	11	0.03%	11	0.02%
14.25	0	0.00%	0	0.00%	65	0.15%	65	0.12%
14.50	0	0.00%	0	0.00%	14	0.03%	14	0.03%
14.75	0	0.00%	0	0.00%	79	0.19%	79	0.15%
Totals	6,424	100.00%	4,896	100.00%	42,490	100.00%	53,810	100.00%