Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment

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ABSTRACT

Information asymmetries are important in theory but difficult to identify in practice. We estimate the empirical importance of adverse selection and moral hazard in a consumer credit market using a new field experiment methodology derived from theoretical models. We randomized 58,000 direct mail offers issued by a major South African lender along three dimensions: 1) the initial "offer interest rate" appearing on the direct mail solicitations; 2) a "contract interest rate," equal to or less than the offer interest rate and revealed to the over 4,000 borrowers who agreed to the initial offer rate; and 3) a dynamic repayment incentive that extends preferential pricing on future loans to borrowers who remain in good standing. These three randomizations, combined with complete knowledge of the Lender's information set, permit identification of specific types of private information problems. Specifically, our setup distinguishes adverse selection from moral hazard effects on repayment, and thereby generates unique evidence on the existence and magnitudes of specific credit market failures. We find some evidence of both adverse selection and moral hazard, and the findings suggest that about 40% of default is due to asymmetric information problems. This helps explain the prevalence of credit rationing even in a market that specializes in financing high-risk borrowers at very high rates.

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I. Introduction

Information asymmetries are often believed to cause credit market failures. Stiglitz and Weiss (1981) sparked a large literature of theoretical papers on the role of asymmetric information in credit markets; this literature has influenced economic policy and practice worldwide. These theories show that information frictions can produce harmful real consequences at both the micro and the macro level, via underinvestment (Gale 1990; Hubbard 1998), overinvestment (de Meza and Webb 1987; Bernanke and Gertler 1990), or poverty traps (Mookherjee and Ray 2004).

Yet empirical evidence on the existence and importance of specific information frictions is relatively thin. Chiappori and Salanie (2003) finds this to be true for contract theory in general, and for tests of adverse selection and moral hazard in particular.[1] Distinguishing between adverse selection and moral hazard is difficult even when precise data on underwriting criteria and clean variation in contract terms are available, as a single interest rate (or insurance contract) may produce independent, conflated selection and incentive effects.[2]

More generally, theoretical and empirical work on credit constraints often lacks empirical microfoundations in specific credit market failures. Our work provides such microfoundations, and thereby complements theoretical (e.g., Wasmer and Weil (2004)) and empirical (e.g., Banerjee and Duflo (2004)) work that examines the impact and existence of reduced-form credit constraints.

We test for the presence of distinct types of hidden information problems using a new experimental methodology that disentangles selection from ex-post incentive effects on repayment. Specifically, we designed a market field experiment that was implemented by a South African firm specializing in making high-interest, unsecured term loans to poor workers. The experiment

[1] The 2001 Nobel Prize Committee's citation for pioneering work on asymmetric information did not cite any empirical work on credit markets, while citing six empirical papers on labor markets and four on insurance markets (Bank of Sweden 2001).
[2] See Ausubel (1999) and Chiappori and Salanie (2000) for related discussions of this problem in the credit and insurance market contexts, respectively.

identifies information asymmetries by randomizing loan pricing along three dimensions: first on the interest rate offered on a direct mail solicitation, second on the actual interest rate on the loan contract, and third on the interest rate offered on future loans.[3]

A stylized example, illustrated in Figure 1, captures the heart of our methodology. Potential borrowers with the same observable risk are randomly offered a high or a low interest rate on a direct-mail solicitation. Individuals then decide whether to borrow at the solicitation's "offer" rate. Of those that respond to the high rate, half are randomly given a new lower "contract" interest rate, while the remaining half continue to receive the high rate (i.e., their contract rate equals the offer rate). Any selection effect is identified by considering the sample that received the low contract rate, and comparing the repayment performance of those who responded to the *high offer* interest rate with those who responded to the *low offer* interest rate. This follows from the fact that although everyone in this hypothetical sample was randomly assigned identical contracts, they selected in at varying, randomly assigned rates, so any difference in repayment is attributable to selection on unobservables. Similarly, any effect of moral hazard (or more generally of repayment burden)[4] is identified by considering the sample that responded to the high offer interest rate, and comparing the repayment performance of those who received the *high contract* interest rate with those who received the *low contract* interest rate. These borrowers selected in identically, but ultimately received randomly different interest rates on their contract, and any difference in default is attributable to the resulting repayment burden.

[3] The Lender assumed all of the revenue and repayment risk from these pricing changes. Some implementation and operational costs were shared with the authors, e.g., training and project management. Although the Lender typically employs direct mail solicitation to market to former clients, they have not in the past included price, or any particular special promotion, in their letters.

[4] We define moral hazard as the effect of debt burden on repayment that stems from ex-post behavioral changes driven by the incentives of the contract. Repayment burden also includes a mechanical wealth or income effect: those with positive (negative) shocks to wealth or income will be more (less) able to repay higher interest debt. Section IV discusses this in more detail.

Our approach to estimating the extent and nature of asymmetric information is thus most similar in intent to Edelberg (2004), and in methodology to Ausubel (1999).[5] Edelberg estimates a structural model to disentangle the effects of adverse selection and one type of moral hazard (in effort) in collateralized consumer credit markets in the United States. She finds evidence consistent with both phenomena. Ausubel uses market experiments conducted by a large American credit card lender to estimate the extent and nature of adverse selection. He does not attempt to account for moral hazard separately, arguing that any such effect must be trivially small over the range of interest rates (800 basis points) contracted on in his data.

We find some evidence of moral hazard among male borrowers and adverse selection among female borrowers. The magnitudes of these information problems appear to decrease with the length of the prior lending relationship with the Lender. Where statistically significant, the effects of private information are economically important, and overall our results indicate that adverse selection and moral hazard explain about 40% of default in our sample. Information asymmetries thus help explain the prevalence of rationing even in a market that specializes in financing high-risk borrowers at very high rates.

The paper proceeds as follows. Section II provides background on South African consumer credit markets and our cooperating Lender. Section III lays out the experimental design and implementation. Section IV details how specific theoretical models motivate the design. Section V maps the experimental design and related theory into our empirical strategy. Section VI presents the empirical results. Section VII concludes with a brief discussion of some implications, unresolved questions, and future work.

[5] At least two other papers endeavor to disentangle adverse selection from moral hazard in credit market in developing countries. Karlan (2004) finds evidence of social capital mitigating moral hazard effects. Klonner and Rai (2004) uses institutional features of rotating credit associations in India, and finds evidence for adverse selection. Other papers estimating the prevalence of private information in credit markets include Calem and Mester (1995), Crook (2002), Drake and Holmes (1995), and Cressy and Toivanen (2001).

II. Market and Lender Overview

Our cooperating Lender competes in a "cash loan" industry segment that offers small, high-interest, short-term credit with fixed repayment schedules to a "working poor" population. Table 1b shows that the sample in our study are fairly representative of the South African population according to the World Bank Living Standards Measurement Study 1998 data. Cash loan borrowers generally lack the credit history and/or collateralizable wealth needed to borrow from traditional institutional sources such as commercial banks. Cash lenders arose to substitute for traditional "informal sector" moneylenders following deregulation of the usury ceiling in 1992, and they are regulated by the Micro Finance Regulatory Council (MFRC). Aggregate outstanding loans equal 38% of non-mortgage consumer credit (Department of Trade and Industry South Africa 2003).[6]

Cash loan sizes tend to be small relative to the fixed costs of underwriting and monitoring them, but substantial relative to borrower income. For example, the Lender's median loan size of R1000 ($150) is 32% of its median borrower's gross monthly income. Cash lenders focusing on the observably highest-risk market segment typically make one month term loans at 30% interest *per month*. Lenders targeting observably lower risk segments charge as little as 3% per month.[7] Rationing is prevalent even at these high rates: the Lender rejects 50% of new loan applicants.

The Lender has been in business over 20 years and is one of the largest micro-lenders in South Africa, with over 100 branches throughout the country. Our experiment took place in a mix of 86 urban and rural branches throughout the provinces of Kwazulu-Natal, Eastern Cape, Western Cape, and Gauteng. All loan underwriting and transactions are conducted face-to-face in the branch network, with the risk assessment technology combining centralized credit scoring with

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[6] The prevalence of for-profit institutional players makes the consumer credit market in South Africa distinct from most other developing countries (Porteous 2003).

[7] 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.

decentralized loan officer discretion. The Lender's product offerings are somewhat differentiated from competitors. Unlike many cash lenders, it does not pursue collection or collateralization strategies such as direct debit from paychecks, or physically keeping bank books and ATM cards of clients. Its pricing is transparent and linear, with no surcharges, application fees, or insurance premiums added to the cost of the loan. The Lender also has a "medium-term" product niche, with a 90% concentration of 4-month loans (Table 1a). Most other cash lenders focus on 1-month or 12+-month loans.[8] The Lender's standard 4-month rates, absent this experiment, range from 7.75% to 11.75% per month depending on observable risk, with 75% of clients in the high risk (11.75%) category.

Borrowers face several incentives to repay these high-interest loans. Carrots include decreasing prices and increasing future loan sizes following good repayment behavior. Sticks include reporting to credit bureaus, frequent phone calls from collection agents, court summons, and wage garnishments.

III. Experimental Design and Implementation

We identify specific types of asymmetric information by integrating the random assignment of interest rates into the day-to-day operations of a consumer lender. This section outlines the experimental design and implementation, describes related data collection, and validates the integrity of the random assignments using several statistical tests. The methodology is implemented in a consumer credit market, but is applicable to other market settings as well.

The experiment was pilot tested in July 2003, and then fully executed in two additional waves launched in September and October 2003. We begin with a brief overview of the experiment, and then describe each step in detail below.

[8] The Lender also has 1, 6, 12, and 18 month products, with the longer terms offered at lower rates and restricted to the most observably creditworthy customers.

A. Design Overview

First the Lender randomized interest rates attached to "pre-approved," limited-time offers that were mailed to 57,533 former clients with good repayment histories.[9] Two rates were assigned to each client: an "offer rate" (r^o) included in the direct mail solicitation, and 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. Clients did not know beforehand that the contract rate may be smaller than the offer rate. For 59% of the clients, the contract rate was identical to the offer rate. Final credit approval (i.e., the Lender's decision on whether to offer a loan after updating the client's information) and the loan size and term offered to the client were orthogonal to the experimental interest rates by construction. Therefore the two interest rate randomizations enable us to cleanly distinguish selection effects from moral hazard effects since some clients will select on different interest rates *ex-ante*, but then have identical repayment burdens *ex-post*, while other clients will select on the same rate *ex-ante*, but have different repayment burdens *ex-post.*[10]

We also randomly assigned differential dynamic repayment incentives (D), with some clients eligible to receive r^c on all future loans taken within the next year (D=1), conditional on repayment performance, and others obtaining r^c for just the first loan (D=0). Since r^c was less than the Lender's standard rate in 98% of the cases, this dynamic repayment incentive (D) enables us to test whether access to future financing at preferable rates reduces any moral hazard found in this market. Clients were informed of this dynamic repayment incentive by the branch manager, after all paperwork had been completed and all other terms of the loan were finalized. Figure 2 shows the experimental operations, step-by-step. Figure 3 shows a scatter plot of the offer rate against the contract rate for all individuals (41% of sample) who were assigned $r^c < r^o$.

[9] Private information may be less prevalent among past clients than new clients if hidden information is revealed through the lending relationship (Elyasiani and Goldberg 2004). We return to this issue in Section VI.
[10] As detailed in Section IV, we define "repayment burden" as the reduced-form combination of several underlying moral hazard parameters and a wealth effect.

B. Sample Frame

The sample frame consisted of all individuals from 86 branches who had borrowed from the Lender within the past 24 months and were in good standing, but who did not have a loan outstanding in the thirty days prior to the mailer. Tables 1a and 1b present summary statistics on the sample frame and the sub-sample of clients who obtained a loan at r^c by applying before the deadline on their mailer. Most notably, clients differ in observable risk as assessed by the Lender. The Lender assigns prior borrowers into "low", "medium", and "high" risk categories, and this determines the borrower's loan pricing and term options under normal operations. The Lender does not typically ask clients why they seek a loan, but the experimental protocol included a survey that indicates the following self-reported uses: education (19%), housing renovations (11%), payoff other debt (11%), household consumption and/or family event (13%), funeral and medical (4%) and miscellaneous/unreported (32%).

C. The Randomizations

Each client was assigned three random variables: an offer interest rate (r^o), a contract interest rate (r^c), and a binary variable for whether the contract rate would be valid for up to one year (D=1) or one loan (D=0). Rates varied from 3.25 percent per *month* to 11.75 percent per month.[11] 41% of the sample was chosen randomly and unconditionally to receive $r^c<r^o$ (Table 1a). 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 shows that the randomizations were

[11] Appendix Table 1 shows the resulting r^o and r^c distributions conditional on the three observable risk categories. Note these are "add-on" rates, where interest is charged upfront over the original principal balance, rather than over the declining balance. We adopt the cash loan market's convention of presenting rates in add-on, monthly form.

successful, *ex-ante*, in this fashion, i.e., conditional on the observable risk category, r^o and r^c were uncorrelated with other observable characteristics[12].

Lastly, each individual was assigned to receive r^c either for one full year (D=1) or for only the first loan (D=0). In the pilot and the second wave of the experiment, this randomization was conducted at the branch level, such that 14 branches were assigned to a "one loan" r^c window, and 10 branches were assigned to a "one year" r^c window. In the third wave, this randomization was done at the individual level.[13]

D. The Offer and Loan Application Process

The Lender mailed solicitations featuring the offer rate to 57,533 "pre-approved" former clients. Each letter had a deadline by which the individual had to respond in order to obtain r^o. The deadline ranged from 2 weeks to 6 weeks, and is discussed in related research (Bertrand, Karlan, Mullainathan, Shafir and Zinman 2004).[14] The Lender routinely mails teasers to former borrowers but had never promoted specific interest rate offers before this experiment.

Clients accepted the offer by entering a branch office and filling out an application in person with a loan officer. Loan applications were taken and assessed as per the Lender's normal 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 for which applicants qualified; and c) decided the longest loan term for which applicants qualified. Each decision was made "blind" to the experimental rates. Table 2 Column 5 verifies that the Lender's rejection decision was in fact uncorrelated with the contract interest rate and

[12] Column 3 shows that the dynamic repayment incentive was predicted by the number of months since the last loan. In the primary tables. However, including a control for this in the primary specifications do not change the estimates of the effect of the dynamic incentive on default.

[13] The dynamic repayment incentive randomization was done initially at the branch level because operations personnel at the Lender were concerned that it would be complicated to communicate D on a case-by-case basis. Once the branches were more comfortable with the experimental design, this was relaxed for the third (and largest) wave of offers.

[14] The solicitations also incorporated randomized framing manipulations (orthogonal to the manipulations we examine in this study), inspired by findings from marketing and psychology literatures, that were designed to estimate the impact of these "behavioral" effects on consumer demand.

dynamic repayment incentive. 5,028 (8.7%) clients applied for a loan under this experiment, and of those 4,348 (86.5%) were approved.

In determining maximum loan size, the Lender relies on a debt service ratio: the monthly payment of a loan can be no larger than a certain percentage of their net monthly income. A lower interest rate would thus allow for a larger loan. A larger loan might then generate a repayment burden effect, which could cause a higher default rate (and bias against finding moral hazard with respect to the interest rate). In order to mitigate this potential confound, the maximum allowable loan size was established based on the *normal*, not experimental, interest rates.

The contract rate r^c was kept secret from both the loan officer and borrower until after the officer approved the loan application and a loan amount and term were established.[15] Special operations software was developed to facilitate and control this process, and we verify that this condition held in practice in Table 2, column 4 by testing that the offer rate, and not the contract rate (once controlling for the offer rate), predict take-up of the loan. Once the loan terms were decided, the software then revealed r^c, which was weakly less than r^o. If the rates were the same, no mention was made of the second rate. If $r^c<r^o$, the loan officer told the client that the actual interest rate was in fact lower than the initial offer. Loan officers were instructed to present this as simply what the computer dictated, not as part of a special promotion or anything particular to the client.

Clients then were permitted to adjust their desired loan size L following the revelation of r^c. In theory endogenizing L in this fashion has implications for identifying moral hazard effects (since a lower r^c strengthens repayment incentives *ceterus paribus*, but might induce choice of a

[15] There are several reasons to implement the contract rate assignment "double-blind". Most importantly, we did not want the contract rate to contaminate any selection effects (by influencing either credit approval, or the applicant's decision whether to accept the loan offer). The double blind device also elicits two points on the credit demand curve for each consumer who received $r^c<r^o$ (Karlan and Zinman 2004).

higher L that weakens repayment incentives), as discussed below. But in practice only 10% of borrowers changed their loan demand after r^c was revealed (Karlan and Zinman 2004).[16]

Finally, the software informed the loan officer whether the individual's r^c was valid for one year (47%, D=1) or for one loan (53%, D=0).

E. Default Outcomes

We use three measures of default: (1) Monthly Average Proportion Past Due (the average default amount in each month divided by the total debt burden), (2) Proportion of Months in Arrears (the number of months with positive arrearage divided by the number of months in which the loan was outstanding), and (3) Account in Collection Status (typically, the Lender considers a loan in collection status if there are three or more months of payments in arrears). Table 1a presents the summary statistics on the default measures. These measures were chosen in consultation with the Lender as proxies for the credit risk, collection costs, and ultimate bad debt incurred by the firm.

IV. Theoretical Overview

We begin by discussing the specific models of private information that motivate our experimental setup, and then describe how the experimental design maps into these models. The Theory Appendix provides a more formal derivation.

We test across two models of selection on unobservables: the Stiglitz-Weiss (1981) *adverse selection* model (hereafter "SW") and the de Meza and Webb (1987; 2001) *advantageous selection* model (hereafter "DW").[17] Specifically, r^o can produce either adverse or advantageous

[16] On the other hand, project clients *did* exhibit significant interest rate elasticities with respect to r^o on both the extensive (takeup) and intensive margins (Karlan and Zinman 2004).

[17] Klonner and Rai (2004) provides a clear comparison of the Stiglitz-Weiss and de Meza-Webb models of selection.

selection, depending on the relationship between borrower risk and return. [18] If risk, defined from the Lender's perspective as the probability of default, and return are positively correlated, then SW implies that higher rates induce unobservably less risky borrowers to drop out of the applicant pool. Thus under adverse selection, repayment would decrease in r^o as we move away from the initial equilibrium. If risk and return are negatively correlated, then DW implies that higher rates induce unobservably riskier borrowers to drop out of the applicant pool. Thus under advantageous selection, repayment would increase in r^o as we move away from equilibrium.[19] In a consumer credit context, this would hold if borrowers with relatively unstable income view high interest rates as unaffordable. One limitation of our setup is that if there are heterogeneous selection effects, such that some borrowers select adversely and others advantageously, then the effect of r^o will obscure the true magnitude of selection on unobservables. We explore this in Section VI, although empirically, we cannot distinguish heterogenous intensity of adverse selection from offsetting adverse and advantageous effects.

The second randomly assigned interest rate, r^c, identifies the reduced-form impact of repayment burden via a combination of several underlying structural parameters of interest. Repayment burden incentives operate through the borrower's project management and repayment choices. Project management choices are defined as those that impact returns. Higher interest rates will produce moral hazard in *project choice* (conditional on effort) if borrowers prefer mean-preserving spreads in project returns under limited liability (Stiglitz and Weiss 1981). Similarly, higher interest rates reduce effort (conditional on project choice), by producing *debt overhang* that

[18]There is potentially a third type of selection based on private information, a "lemons" effect, which is unlikely to be important in our setting. As described in Ausubel (1991) and elsewhere, given a setting with competitive bargaining and the presence of private information generated from lending relationships, a single deviating lender would find that reducing rates attracts *ex-ante* unobservably worse repayment risks, since competing lenders will match the rate reduction only for the better risks. But survey evidence on pricing practices in the cash loan market suggests strongly that lenders as a rule do not make price concessions, even for good customers. Note that while the lemons effect is commonly described as *adverse* selection, in our setting it is analogous to *advantageous* selection in the sense that reducing interest rates decreases profitability on the margin in either case.

[19] de Meza and Webb (2000) shows that advantageous selection can persist in equilibrium if moral hazard prevents lenders from raising interest rates to clear the market.

reduces borrower returns in successful states (Ghosh, Mookherjee and Ray 2000). Repayment choice simply refers to the fact that *voluntary default* (conditional on project returns) becomes more attractive under limited enforcement as repayment burden increases (Eaton and Gersovitz 1981; Ghosh and Ray 2001). In contrast, the *income effect* of repayment burden has nothing to do with choice: it works mechanically, by simply increasing the probability that a borrower with uncertain cash flow will be unable to repay. Note that each of these hypothesized incentive and income effects works in the same direction — a higher repayment burden decreases the probability of repayment.

These four components of repayment burden all have intuitive salience in this setting, and hence our priors are agnostic regarding their relative importance. *Project choice* may be relatively limited (compared to say a pure commercial loan market), or may not — anecdotal reports suggest the possibility of "hidden" investment in entrepreneurial projects, and reveals cross-sectional variation in the deployment of funds consistent with a range of consumption smoothing and human capital investment opportunities. *Debt overhang* might also be less salient in a consumer rather than commercial credit setting, but then again the relevant effort in the consumer case might be related to maintaining one's wage employment, or to obtaining credit from the informal sector in the event of a negative outcome. *Voluntary default* might be mitigated by reputation effects (repeat contracting opportunities) and aggressive (if imperfect) enforcement, but to what extent? The size of the *income effect* depends critically on the variance of borrower cash flows, which is unknown to us.

Given that we find a significant reduced-form effect of repayment burden, distinguishing among the structural channels is important. Several approaches are feasible. First, we have collected data on utilization of loan proceeds and use this to estimate whether *project choice* varies with r^c. Second, recall that we randomly assigned repeat contracting opportunities at preferential, experimental rates, conditional on previous repayment performance. D=1 provides an additional, marginal incentive to repay, helping us to distinguish incentive from income effects. Identifying specific income and debt overhang effects would require data collection on cash flows and project outcomes.

V. Empirical Strategy

We now present the empirical strategy used to test the theoretical models and interpret the results of the experiment. Recall that we identify any selection and repayment burden effects by randomly assigning separate offer and contract interest rates to potential borrowers ("borrowers"), conditional on observable risk, and then estimating the relationship between loan repayment and these rates. We employ four approaches to analyzing the results: stylized comparison of means, a base-case OLS specification, a [pseudo]-matching non-parametric estimator, and instrumental variables.

Abstracting from functional form considerations for the moment, our basic empirical model takes the form:

(1) $\mathbf{Y_i = f(r_i^o, r_i^c, D_i, X_i)}$

where i indexes borrowers. Y is a measure of repayment; r^o is the rate offered on the "pre-qualified" mail solicitation; and $r^c \leq r^o$ is the rate actually contracted upon loan approval. D is the randomly assigned contract rate window, with D=1 if r^c is valid for up to one year (if the borrower stays current), and D=0 if r^c applies to one loan only. X always includes the Lender's summary measure of observable risk (since the interest rates were randomized conditional on this measure), and also may include other readily observable characteristics that the Lender *could* use for screening.

The Theory Appendix shows formally:

- r^o identifies the selection effect conditional on r^c -- with $dY/dr^o>0$ if there is adverse selection on net, and $dY/dr^o<0$ if there is advantageous selection on net.
- r^c identifies the repayment burden effect conditional on r^o — with $dY/dr^c>0$ if there is such an effect.

Stylized Comparison of Means: Table 3

We classify rates into "high" and "low" groups, *a la* Figure 1. This is done by setting cutoffs at the median experimental rates for each observable risk category. Table 3 presents mean comparisons using this method. The findings preview the regression results: we find occasional evidence of adverse selection and moral hazard in the full sample, but robust evidence for adverse selection among female borrowers and moral hazard among male borrowers.

OLS Specification: Tables 4 and 5

The base specification is a linear model estimated using OLS:

$$(2)\quad \mathbf{Y_i = \alpha + \beta_o r_i^o + \beta_c r_i^c + \beta_w D_i + \chi X_i + \varepsilon_{ib}}$$

i again indexes borrowers, and β_o, β_c, and β_w are the estimates of the selection effect, the repayment burden effect, and the dynamic incentive effect, respectively. X need include only the Lender's summary measure of observable risk since the randomizations conditioned only on this variable. We also include fixed effects for the month in which the offer letter was sent (June, September, or October 2003). The error term, ε_{ib}, is corrected for clustering at the branch level, *b*. The model is estimated on the takeup sample of 4,348 observations since these are the only project clients for whom we observe repayment behavior. The OLS results are robust to including loan size and term as control variables, which may be important since loan size is partly determined by the interest rate (Karlan and Zinman 2004), and could have its own independent effect on default. Results obtained with the OLS estimator are similar to the comparison of means, and are presented in Tables 4 and 5 and discussed in Section VI.

Semi-Parametric Matching Estimator: Table 6

Next we develop a semi-parametric approach which resembles a matching estimator with a continuous treatment variable. Specifications in Tables 4 and 5 may impose undesirable functional form assumptions if any of the three different random variables interact to influence default. We address this possibility by conditioning non-parametrically on all combinations of the offer interest rate (r^o), the dynamic repayment incentive (D), and risk category when examining the repayment burden effect (i.e., the contract interest rate), and all combinations of the contract interest rate (r^c), the dynamic repayment incentive (D), and risk category when examining the selection effects (i.e., the offer interest rate). Specifically, to examine the selection effect (r^o), we employ a fixed effect model in which we demean the dependent variable (default) and the random variable (offer interest rate) when grouped by all observations that match perfectly on the other random variables and the risk level. In the following formulas, the subscript "c" represents contract interest rate, "o" represents offer interest rate, "d" represents the dynamic incentive, and "r" represents the lender-defined categorical risk level (high, medium or low). The unit of observation is *i*, the individual borrower. The month of the offer letter, *M*, is a categorical variable (either July, September or October, 2003). This is effectively a matching estimator, where we match on 2 of the 3 random variables plus the risk level in order to examine the effect of the 3rd random variable. We estimate the following three specifications:

For the offer rate: (3) $Y_{icdr} - \overline{Y}_{cdr} = \beta(r^o_{icdr} - \overline{r}^o_{cdr}) + \delta M_i + \varepsilon_{icdr} - \overline{\varepsilon}_i$

For the contract rate: (4) $Y_{iodr} - \overline{Y}_{odr} = \beta(r^c_{iodr} - \overline{r}^c_{odr}) + \delta M_i + \varepsilon_{iodr} - \overline{\varepsilon}_i$

For the dynamic incentive: (5) $Y_{icor} - \overline{Y}_{cor} = \beta(W_{icor} - \overline{W}_{cor}) + \delta M_i + \varepsilon_{icor} - \overline{\varepsilon}_i$

Table 6 presents the estimate obtained using three specifications. The results are discussed in Section VI. There we also relax the linear treatment effect assumptions imposed by (4)-(8), using a graphical kernel regression approach described below.

Instrumental Variables Estimator: Table 7

Lastly, we consider the case where debt burden is defined as total interest due on the loan, not merely the marginal cost of debt (the interest rate). Total interest due includes an *endogenous* component (loan size) multiplied by a random variable (the interest rate), so we employ an instrumental variables approach to identify the effect of loan pricing on default. Specifically, we use the random variables to instrument for endogeneous variable of interest, debt burden. The instrumental variable specification is:

(6) $Y_i = \alpha + \beta_0 \hat{I}_i^o + \beta_c \hat{I}_i^c + \delta X_i + \varepsilon_i$

where I^0 and I^C are the endogenous variables, total interest due under the offer and contract rates, respectively. The first stage specification is:

(7) $I_i^o = \alpha + \beta_o r_i^o + \beta_c r_i^c + \chi X_i + \upsilon_i$

and

(8) $I_i^c = \alpha + \beta_o r_i^o + \beta_c r_i^c + \chi X_i + \upsilon_i$

With r_i^o and r_i^c serving as instrumental variables.

These results are presented in Table 7 and discussed in the next section.

VI. Empirical Results

A. Overview of Base Specification

Our primary analysis estimates equation (2) using ordinary least squares, tobit, or probit on the "full" sample containing all three observable risk categories (Table 4).[20] The dependent variables are the three repayment measures described above. In all specifications, the interest rate units are in monthly percentage points (e.g., 7.50 for 7.50% per month), and we report marginal effects where applicable. Results on interest rate variables therefore capture the effect of a one percentage point (100 basis point) increase in the monthly rate. We find evidence of moral hazard through the dynamic pricing incentive D, but little suggestion of any selection on unobservables in the full sample.

B. Primary Results with the Base Specfication

Row 1 of Table 4 presents estimates of β_o, the response of repayment behavior to the offer rate. This coefficient identifies any net selection on unobservables, with $\beta_o>0$ indicating adverse selection, and $\beta_o<0$ indicating advantageous selection. We find no robust evidence in either direction on the full sample.[21]

Row 2 of Table 4 presents estimates of β_c, the response of repayment behavior to the contract rate. This coefficient identifies any effect of repayment burden, with $\beta_c>0$ indicating some combination of moral hazard and wealth effects. Similar to the adverse selection results, we find consistently positive effects that are typically insignificant statistically. The one marginally

[20] Results are robust to including the log of loan size, and loan term, to address the possibility of endogenous loan size. An alternative, instrumental variables approach is presented in Table 7. This too yields qualitatively similar results. Nor do results change if we include branch fixed effects to control for any differences in experimental implementation and/or the mechanical influence of varying mailer dates (staggered by groups of branches) on repayment measures. Pooling the risk categories implies that the full sample model lacks a common support for interest rates exceeding 7.75 (since, e.g., low risk borrowers are never offered a rate above 7.75). We re-estimate our base specifications over a common support and report qualitatively similar results in Appendix Table 2, although much power is lost on the smaller sample size.

[21] Recall from Section IV that the offer rate coefficient will understate the true extent of private information problems if there are concurrent adverse and advantegeous selection effects in the sample. This would manifest as parameter heterogeneity; e.g., if part of the sample has $\beta_o<0$, and part of the sample has $\beta_o>0$. We explored this possibility by interacting the offer rate variable with various demographics (see, e.g., Table 7), and found some evidence that adverse selection was decreasing in income. Splitting the sample into income quintiles or at the median (not reported), we found that only one of the six offer rate coefficients had the negative sign consistent with advantageous selection, and that this coefficient was not statistically significant (t-stat = 0.6).

significant result (column 2) implies that a 400 basis point cut would reduce the average number of months in arrears by 13%.[22]

Results on D, the contract rate window variable, deliver robust evidence of moral hazard (Table 4, row 3). Recall that clients with D=1 face a marginal *incentive* to repay — if they maintain good standing with the Lender they are eligible to borrow at r^c for up to a year. D consequently has no effect on the debt burden of the current loan, but does increase the benefit of maintaining a good relationship with the lender by reducing the interest rate on future loans. D therefore is free of the noise (bad shocks) and confound (endogenous loan size) that might bias estimates of the reduced-form repayment burden effect toward zero. D thus identifies pure *moral hazard* that is alleviated by the provision of a marginal, dynamic repayment incentive. D's effect is large and significant, with the incentive producing decreases in the various default measures ranging from 1.1 to 1.9 percentage points in the OLS specifications on the full sample. These magnitudes imply that D=1 clients defaulted 7 to 16 percent less often than the mean borrower. Table 4 Columns 2, 4 & 6 show that this effect is increasing in and driven by the size of the discount on future loans, as each 100 basis point decrease in the price of future loans reduces default by 4% in the full sample.

Table 5 shows the primary results from Table 4, but by gender. We find significant and robust evidence of moral hazard (but not adverse selection) for males, and adverse selection (but not moral hazard) for females. The issue of differential response to interest rates by gender is of particular interest to development economists and microfinance practitioners, given that microcredit initiatives often target women, in part because females are considered more likely to repay loans and/or less able to obtain formal sector credit.[23]

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[22] Coefficient * 4 / mean outcome = 0.007 * 4 / 0.219 = 13%

[23] Although the reasons for this are unclear, the anecdotal evidence suggests that women are weakly more likely to repay microcredit loans. Studies of consumer choice in other financial markets have found gender differences. Barber and Odean (2001) finds that males are more likley to trade excessively in public equities. Pitt and Khandker (1998) finds that impacts of participation in a mircofinance program differ by gender.

Table 5, Columns 1 through 6 show the results for male borrowers. We find evidence of moral hazard but no selection on unobservables. Both experimental instruments for moral hazard, the contract rate and the contract rate window length (D), are large and generally significant determinants of default. The coefficient on the offer rate effect is essentially zero (signed negatively, consistent with advantageous selction, but not significant statistically).

Table 5, Columns 7 through 12 show a different pattern for female borrowers. We find evidence of adverse selection but no repayment burden or moral hazard effects. The offer rate coefficient is always large and positive for females, and statistically significant in 5 of the 6 regressions reported, indicating adverse selection. On the other hand, the contract rate coefficient is now wrong-signed (and significant in one case). The contract rate window results are insignificant, but signed negatively (evidence for moral hazard) and often large economically. On balance then there is no statistically significant evidence for repayment burden or moral hazard influencing the repayment behavior of female borrowers.

In specifications not shown, we test whether the gender effects are significantly different from each other by including gender interaction terms in the Table 4 specifications. The interaction term is significant statistically for both the offer and contract interest rates, but not for the contract rate window variable. This is not surprising, since the coefficient on the contract rate window for women is negative and similar (slightly smaller) to that for men, just not significant statistically.

C. Primary Results with Matching Estimator and IV Specification

Table 6 presents the results of the semi-parametric matching estimator specified in equations (6)-(8). The point estimates remain largely the same as in the OLS results shown in

Table 5, but the standard errors are slightly larger due to the loss of hundreds of degrees of freedom.

Table 7 presents the results of the IV estimator outlined in equations (9)-(11). These follow a similar pattern to the results obtained from the base specification, with a few notable exceptions. First, we now find more weakly significant evidence for adverse selection (although as before these effects appear to be driven by females). Second, the evidence for a repayment burden is actually *weakened* (contrary to our intution that endogenous loan size would bias *against* finding a repayment burden effect).

Figures 4-12 show smoothed plots of coefficients from a non-parametric estimator that relaxes the linear treatement effect assumption maintained in all of our regression specifications. Each plot has one random variable of interest; e.g., in Figure 4 this variable is the offer rate. The estimates of interest are the coefficients on the each individual offer rate (e.g., one cell for 7.25, another for 7.5). The specifications include controls (again, non-parametric) for the contract interest rate, risk category and month of the offer. The plots reproduce the qualitative patterns (sign and magnitudes) found in our regressions, but are not conclusive in the sense that the confidence intervals leave open the possibility of nontrivial nonlinearities.[24]

D. Gender Analysis

Next, we explore whether the gender effects are actually driven by systematic variation in household demographics rather than something unobservable and/or fundamental to gender *per se*. The Lender collects extensive demographic information, and Tables 1a and 1b show that there are minimal compositional differences across gender. The question is whether these differences interact with interest rates to generate default and thereby confound the interpretation of gender differences in selection and moral hazard.

[24] The confidence bands on these plots were created by bootstrapping with 500 replications.

A parsimonious test for compositional confounds is to add interactions between the interest rate variables and observable characteristics to our base specification, the results of which we report in Table 8. The significant interaction terms between gender and the rate variables, *conditional on other demographics* (and their interactions with rates and/or gender), suggest that the gender differences are not merely driven by mechanical composition effects. We continue to find strong repayment burden effects among males, and strong adverse selection effects among females. None of the demographic interaction effects are significant, nor detract from the simple gender interaction effect. If, for instance, the gender effect was masking a "married" effect, then we would observe the interaction term of "married and offer rate" significant and the gender interaction term would go to zero.

A related check is to predict default using observable demographic information, and then test whether observable selection on the interest rate differs across males and females. Table 9 shows that it does; specifically, the effect of the interaction between observable risk and the offer rate on the decision to apply is significant and positive for women, but not for men. This means that the price elasticity of the application decision is decreasing in observable risk for women but not for men, and provides further confirmation of a gender difference that is not driven purely by other observable characteristics. Had the gender effect been driven by an observable sample composition, the results in Columns 6 and 7 should have been consistent across genders. This finding also should not be surprising, in that if unobservably riskier women are more likely to borrow at high interest rates, one should also find that observable riskier women are also more likely to borrow at high interest rates.

Of course we do not observe all of the observable characteristics of interest; e.g., we do not have independent measures of education and occupation, nor do we observe health status, or unmarried co-habitation. Hence the above tests do not completely rule out the possibility that relatively mechanical demographic differences generate the observed gender pattern.

In all, the evidence suggests that male and female borrowers pose different types of private information problems for the Lender, with strong evidence that females select adversely and evidence that male repayment is sensitive to repayment burden. The question of what drives that pattern (e.g., demographics, outside options, social norms or hard-wiring) by gender in South Africa merits further, moresystematic, exploration.

E. Observable Determinants of Default and Selection on Observables

The significant interactions between interest rates and observable characteristics beg the related question of how efficiently the Lender assesses risk. We begin by exploring whether observable characteristics help predict default, *conditional on the Lender's summary statistic for risk*. Now we report results obtained from adding several additional observables to equation (2). Table 10 shows that the Lender's summary statistic for observable risk does not in fact completely summarize the role of observables, at least over the range of interest rates used in our experiment. Each specification includes an indicator variable for the sufficient statistic the lender uses (one of 11 categories) in their risk assessment. Regardless of specification, several readily observed variables help predict default, including credit scores and the number of prior transactions with the Lender. However, adding observables beyond the summary statistic generates little or no improvements in the overall explanatory power of the models (as measured by the adjusted R-squareds in Tables 4 and 10).

F. External Validity and the Power of Repeated Transactions

We may find little evidence of adverse selection in the full sample because our borrowers have already revealed their types to the Lender, i.e., in the process of transacting, private information becomes public.[25] We explore this possibility indirectly, and within-sample, by exploring whether the offer rate effect varies with the number of prior loans the borrower has taken from the Lender. Table 11 shows that this is indeed the case: adding a prior loans main effect and interaction with r^o to equation (2) produces a negative and significant interaction term. The interaction effect is large; e.g., it eliminates 43% of adverse selection at the mean number of prior loans (4.3) in the full sample. Thus selection is indeed relatively more adverse for those borrowers with whom the Lender is least familiar. The repayment burden effect (through the contract interest rate) appears to decrease with prior transaction frequency as well. The moral hazard effect (through the dynamic repayment incentive), on the other hand, abates only a little.

G. Magnitude Calculations Comparing Observables and Unobservable Effects

We now conduct a rough calculation designed to estimate the relative importance of private vs. public information in determining default. Recall that the Lender uses the three-tiered risk category to determine interest rates. On average, the high risk clients have 10.0 percentage points less default (account in collection status) than the low risk clients (Table 1a). The moral hazard effect, over the 400 basis point spread between the normal rates provided to high versus low risk clients, predicts a 4.0 percentage point decrease in default rates for men (Table 5, Column 3). For women, the adverse selection effect also predicts a 5.2 percentage point reduction in default rate (Table 5 Column 9). Hence, perhaps 29% (4.0%/14.0%)[26] and 54% (5.2%/9.7%) of the reduction in default rates from high to low risk clients for males and females, respectively, can be explained not by the observable difference in risk, but rather by the lower interest rate mitigating

[25] We sought to include clients with no prior relationship with the Lender by extending 3,000 offers to names obtained from a mailing list; unfortunately, the list results in one borrower. A pilot follow-up list of 5,000 offers (without randomization of interest rates) yielded two borrowers. Hence, in order to conduct this experiment on "new" clients, we need to find an alternative channel for identifying the sample frame and contact information.

[26] 14.0%, from Table 1a, is the percentage of loans in collection for males, and 9.7% is the percentage for females.

the information asymmetry problem.

VII. Conclusion

We develop a new market field experiment methodology that disentangles adverse selection from moral hazard effects. The experiment is implemented in a South African consumer credit market, and yields evidence of moral hazard among males and adverse selection among females. We also find that asymmetric information problems appear to be mitigated by the lending relationship (as measured by the number of prior loans). Overall the findings provide unusually clean empirical evidence of significant, specific information asymmetries in a consumer credit market.

We are building on this work in several respects. The gender results motivate additional experiments, in the lab and in the field, to test their robustness across different settings and unravel any underlying drivers of the observed differences. The presence of significant information problems provides a microfoundation for credit rationing, but not a sufficient condition for welfare-enhancing interventions (no matter how well-run), as efficiency depends critically on borrower returns. This helps motivate our ongoing experiment, also in South Africa, with relaxing credit constraints, whereby lenders randomly assign credit to marginal rejected borrowers, and we follow-up with household surveys documenting loan uses and a broad range of outcomes. This is another step in identifying the existence, causes, and consequences of specific market failures via field experiment methodologies that can be replicated, refined, and implemented in different countries and product markets.

Theory Appendix

Here is a more formal derivation of how our research design maps into theoretical models of private information, and thereby permits identification of unobservable selection and moral hazard effects.

Assume a Lender implementing our experiment is faced with loan applicants who have identical observable characteristics but may be heterogeneous with respect to unobservable information. These characteristics *q* are not observable to the Lender, but are known to the applicant. Let *q* ("riskiness") be continuous, and bounded below by zero: $Q = \{q, q \in [0, \infty)\}$, where a higher *q* negatively impacts but does not wholly determine the "success" of the borrower's project, which is defined discretely. The success/fail framework is most intuitive in a pure commercial credit market, but also applies to a consumer credit setting. Here we can think of "success" as having sufficient funds to repay the consumer cloan, whether these funds are from entrepreneurial activity, wage income, or other financing sources, and we can think of *q* as about the inherent riskiness, unobservable to the lender, of the consumer having such funds available to them ex-post to repay the loan. Borrowers succeed with probability *p*(q, e) and fail with probability 1-*p(q,e)*, where *e* is effort exerted by the agent. We allow effort to be continuous, $e \in [0,1]$, and assume it imposes a linear cost.

We assume that *p* is twice continuously differentiable in effort, and differentiable with respect to the common shock and the unobservable risk *q*. Next we impose the following standard assumptions on the probability structure:

Assumption 1. $$\frac{\partial p(q,e)}{\partial q} < 0, \frac{\partial p(q,e)}{\partial e} > 0, \frac{\partial^2 p(q,e)}{\partial e^2} < 0, \frac{\partial^2 p(q,e)}{\partial e \partial q} < 0.$$
$$Inada\ conditions: \frac{\partial p(q,0)}{\partial e} \to \infty, \frac{\partial p(q,1)}{\partial e} = 0.$$

i.e., the probability of success decreases with riskiness, q; the probability of success increases with borrower's effort, e; and, the probability of success with respect to effort, e, decreases with riskiness, q (and vica versa).

Next assume for simplicity that the return to the borrower is *R(q)* in the event of success and zero in the event of failure. We assume for the moment that returns are observable and verifiable, thereby abstracting from the possibility of *voluntary default* (Eaton and Gersovitz 1981; Ghosh and Ray 2001). Then default occurs if and only if the project doesn't succeed under the additional simplifying assumption that:

Assumption 2. $\forall q \in Q: \quad R(q) > (1 + r^c)B.$

Where B is the loan principal amount demanded and r^c is the interest rate on the loan contract. So a borrower repays in full if her project succeeds and repays nothing if her project fails.

We now show that the assumption on the relationship between risk (to the Lender) and returns (to the borrowers) is critical to identifying any selection effects of interest rates. Stiglitz and Weiss (1981) shows that *adverse selection* results if this relationship is positive. Formally,

Assumption 3a ("SW"). $\forall q, q' \in Q: \quad p(q,e)R(q) = p(q',e)R(q') = C(e).$

Where C is a constant. The equation states that expected returns to the borrower are constant—projects that yield high returns in the successful state have low probabilities of success. We show below that this condition will indeed produce adverse selection in our setting.

De Meza and Webb (1987) shows that *advantageous selection* results if risk and returns are negatively correlated. Formally:

Assumption 3b ("DW"). $\forall q, q' \in Q: \quad q > q' \Leftrightarrow p(q,e)R(q) < p(q',e)R(q')$.

This will hold, e.g., if borrowers differ only in the probability of project success, but not in project payoff conditional on success. We show below that in our setting 3b implies that raising the interest rate discourages *low* quality borrowers on the margin, thereby improving the average composition of the borrower pool via *advantageous selection*.

We solve for selection and moral hazard effects by focusing on the borrower's problem. Define the borrower's expected return (after the effort choice is made) as:

(1) $E(\pi) = p(q,e)[R(q) - (1 + r^c)B] - e$

Where we assume that borrowers are price takers. We ignore the Lender's problem since in our setting the interest rate is not a choice variable, and the variables the Lender does control (loan supply on the extensive and intensive margins) are orthogonal to the rate by construction. Therefore we can assume (without loss of generality) that applicants are approved by the Lender.[29]

Accordingly we return to the borrower's problem and begin by solving the model through backwards induction; i.e., conditional on the borrower deciding to apply, she decides upon the repayment effort after learning the contract interest rate, r^c. Note the interest rate that the agent takes into account is the contract rate, not the offer rate (in the case where they differ). Therefore, holding riskiness, q, fixed, the agent solves

$$(2)\ \max_{e} \quad p(q,e)[R(q)-(1+r^c)B]-e$$

Given our set of assumptions, the optimization program yields a unique interior solution for each value of q (and υ) and is characterized by the following first-order condition:

$$(3)\ \tilde{e}=e(q,r^c): \quad \frac{\partial p(q,\tilde{e})}{\partial e}=\frac{1}{R(q)-(1+r^c)B}.$$

Proposition 1. The level of effort chosen is inferior to the first-best value (that is, when effort is observable and verifiable). Moreover, note that $\partial\tilde{e}/\partial r^c<0$. This is the *debt overhang* version of moral hazard effect -- the higher the interest rate, the less the optimal effort since the agent only receives a positive return in case of success (i.e., the return function is convex). Proof is at the end of this Appendix. In this setup, a *voluntary default* model would yield qualitatively identical results regarding the relationship between repayment and r^c (Eaton and Gersovitz (1981) or Ghosh, Mookherjee et al (2000)).

The next step in solving the borrower's problem is to examine the decision to apply for the loan, which is made using the offer rate, r^o. (Recall from Section III that borrowers are not aware that

[29] In practice, 84% of applicants were approved in the experiment. More generally, one can think of any rejected borrowers as being *observably* differentiated— and this model conditions on observable information.

there might be a distinct contract rate, r^c, when they are deciding whether to apply for the loan.) Define the marginal applicant as the one who has expected returns of exactly zero. That is,

$$(4)\ \hat{q}: \quad p(\hat{q}, e(r^o))[R(\hat{q}) - (1 + r^o)B] - e(r^o) = 0.$$

Proposition 2. If the SW assumption (3a) holds, the agent applies for a loan if $q \geq \hat{q}$. Moreover, an infinitesimal increase in r^o increases the marginal borrower's *q*, $\partial\hat{q}/\partial r^o > 0$. (There is no effect through effort since it is endogenous, and the marginal effect is zero by the envelope theorem). Therefore when the offer rate increases the marginal applicant is riskier; i.e., the safer borrowers choose not to apply, creating a pool that is riskier on average. This is the classic adverse selection effect *a la* SW. If instead the DW assumption (3b) holds, the agent applies if $q \leq \tilde{q}$. In this case $\partial\tilde{q}/\partial r^o < 0,$; i.e., increasing the offer rate decreases the marginal applicant's riskiness, *q*, and the applicant pool becomes less risky on average. This is advantageous selection *a la* DW. (See the end of this Appendix for proofs.)

We can now tie our propositions regarding the selection effects of the offer interest rate, r^o, and the moral hazard effect of the contract interest rate, r^c, directly to an empirical outcome of interest, the probability of default. According to the model, the expected probability of default, once r^c is known and effort is chosen, can be expressed as:

$$(5)\ E(\text{probabiliy of default}) = \int_{\hat{q}}^{\infty} [1 - p(q, \tilde{e})] \frac{f(q)dq}{1 - F(\hat{q})}.$$

Proposition 3. The marginal effect of r^o on the default probability captures the effect of selection. If the SW assumption holds, then:

$$(6)\quad \frac{\partial E(\text{probability of default})}{\partial r^o} = \frac{\partial \hat{q}}{\partial r^o}\frac{f(q)}{1-F(q)}\int_{\hat{q}}^{\infty}[1-p(q,e)]\frac{f(q)dq}{1-F(\hat{q})} - \frac{\partial \hat{q}}{\partial r^o}\frac{f(q)}{1-F(q)}[1-p(\hat{q},e)] > 0.$$

The proof is a direct application of proposition 2. If instead the DW assumption holds then the effect of a marginal change in the offer rate on the estimated probability of default has a negative sign.

On the other hand the marginal effect of r^c will capture the moral hazard effect,

$$(7)\quad \frac{\partial E(\text{probability of default})}{\partial r^c} = -\int_{\hat{q}}^{\infty}\frac{\partial p(q,\tilde{e})}{\partial e}\frac{\partial \tilde{e}}{\partial r^c}\frac{f(q)dq}{1-F(\hat{q})} > 0.$$

The result is again immediate since, by proposition 1, $\partial\tilde{e}/\partial r^c < 0$.

Incorporating the dynamic repayment incentive (D=1) is no different substantively than increasing the benefits of repayment, holding the costs constant. This additional repayment incentive may inspire more effort to ensure a successful outcome (*debt overhang)* or simply more incentive to choose to repay the first loan (*voluntary default.* Incorporating this into the above, we add D to formula 2 as a benefit which accrues to the borrower if they repay the first loan:

$$(8)\quad \max_e \quad p(q,e)[R(q)+D-(1+r^c)B]-e$$

$$(9)\quad \tilde{e} = e(q,D,r^c): \quad \frac{\partial p(q,\tilde{e})}{\partial e} = \frac{1}{R(q)+D-(1+r^c)B}.$$

$$(10)\quad \partial\tilde{e}/\partial D > 0.$$

Although not explicitly shown in the model, D is not merely binary, but rather is larger the lower r^c relative to the normal lender rate. The empirical strategy will analyze the incentive both as a binary and as a continuous variable.

Proof of Proposition 1.

To show that the effort level is lower than the first-best level of effort, begin by noting that in a first-best setting where effort is observable and verifiable to all parties the first-order condition reads:

$$\frac{\partial p(q,e^*)}{\partial e} = \frac{1}{R(q)}$$

The right-hand side of this first-order condition is smaller than the one for which effort is unobservable, making the optimal effort level larger due to decreasing returns in effort.

To show the moral hazard effect, $d\tilde{e}/dr^c < 0,$ totally differentiate the first-order condition to obtain

$$\frac{d\tilde{e}}{dr^c} = \frac{B}{\frac{\partial^2 p}{\partial e^2}\left[R-(1+r^c)B\right]^2} < 0,$$

since the returns to effort are decreasing. *Q.E.D.*

Proof of Proposition 2.

Assume the SW assumption (3a) holds. Recall that the marginal borrower's return once the offer rate is announced is by definition. Since the expected returns are increasing in *q* only applicants with q*'s* higher than marginal borrower's $\hat{q}$ are going to have nonnegative expected returns. Accordingly these borrowers with $q > \hat{q}$ form the pool of applicants.

Totally differentiating the marginal applicant condition yields:

$$\frac{d\hat{q}}{dr^o} = \frac{pB}{-(1+r^o)B\dfrac{\partial p(\upsilon, \hat{q}, \tilde{e})}{\partial q}} > 0,$$

since p is decreasing in unobservable risk q. If instead the DW assumption (3b) holds the steps are the same but the signs are the opposite. In particular expected returns are decreasing in q and so only safer projects than the marginal q apply. In this case the total differentiation produces:

$$\frac{d\tilde{q}}{dr^o} = \frac{pB}{\left[R-(1+r^o)B\right]\dfrac{\partial p(\tilde{q}, \tilde{e})}{\partial q}} < 0. \textit{ Q.E.D.}$$

Figure 1: Stylized Depiction of Experimental Design

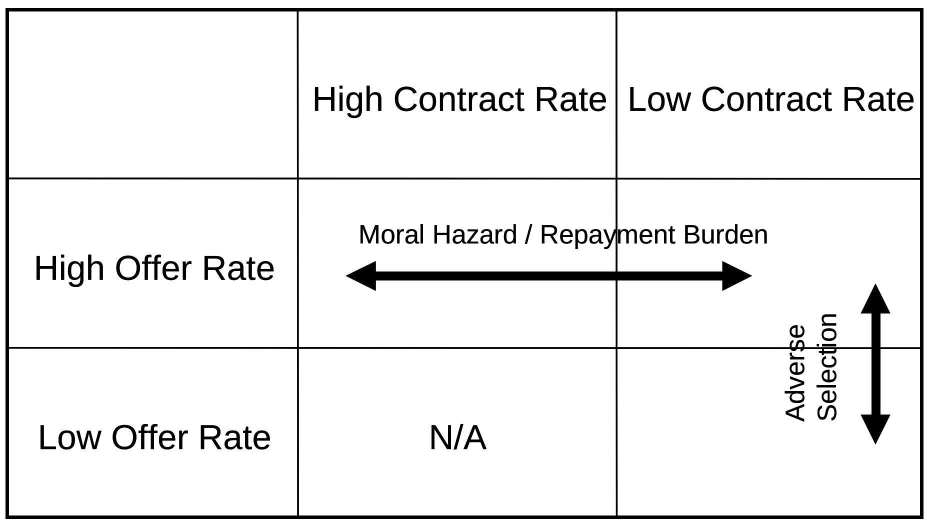


Figure 2: Operational Steps of Experiment

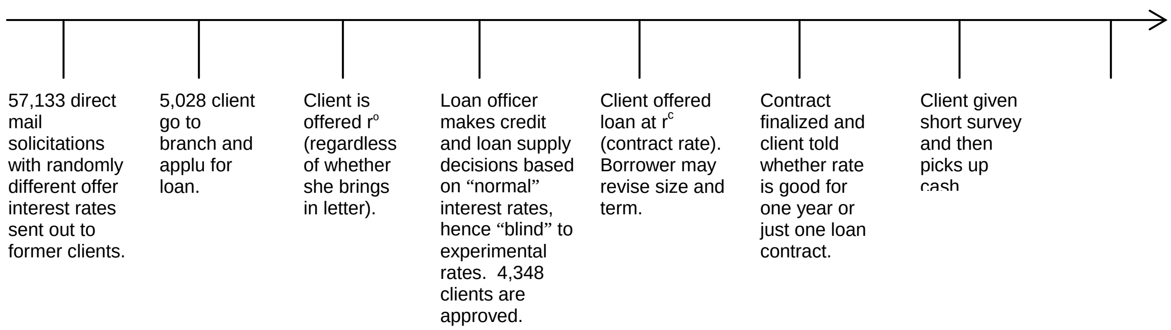
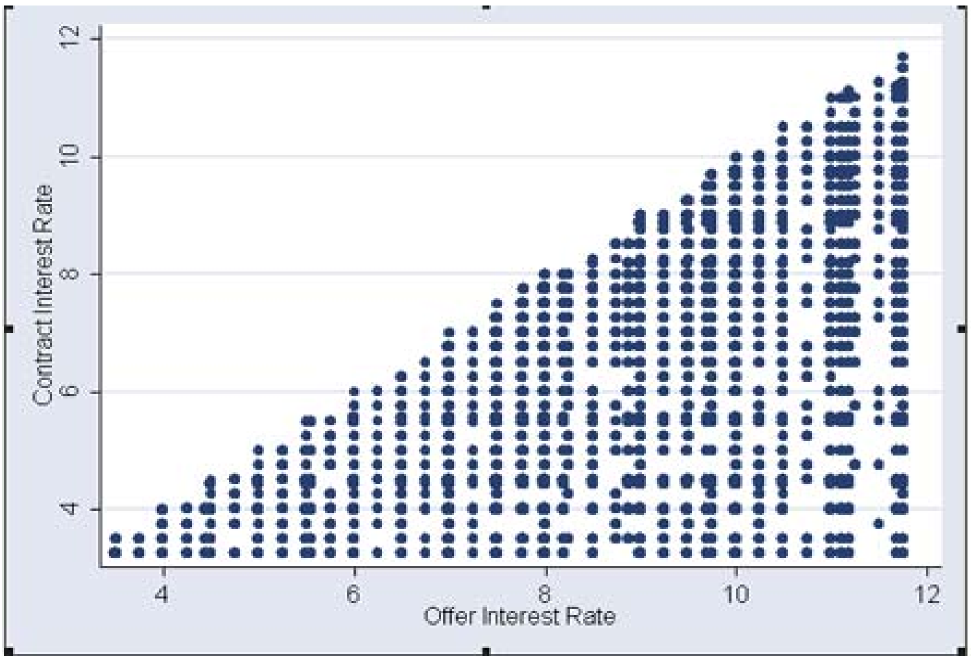
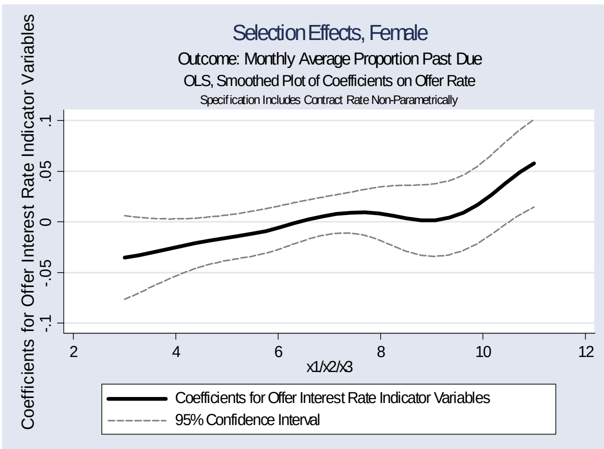
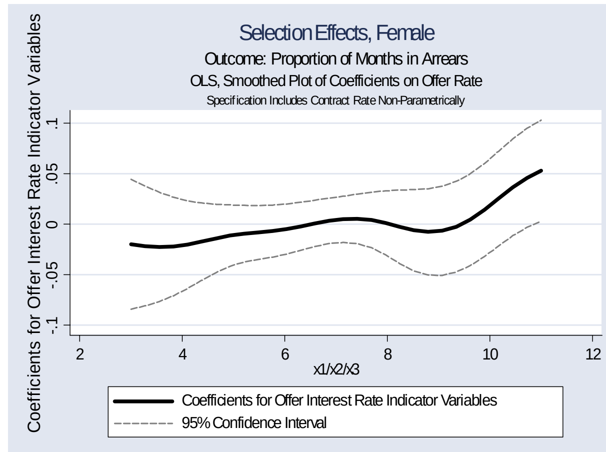


Figure 3: Scatter plot of Contract versus Offer Interest Rates on 4 Month Loans

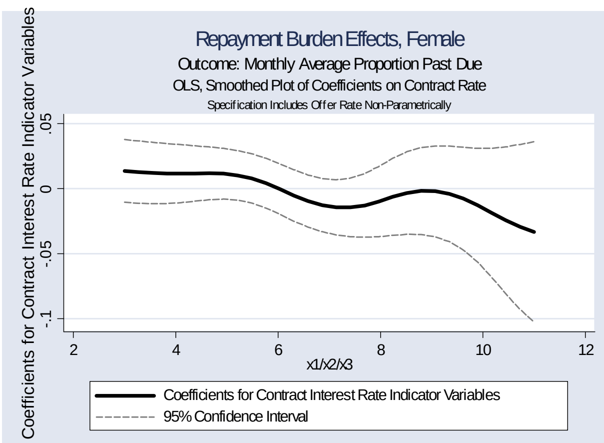


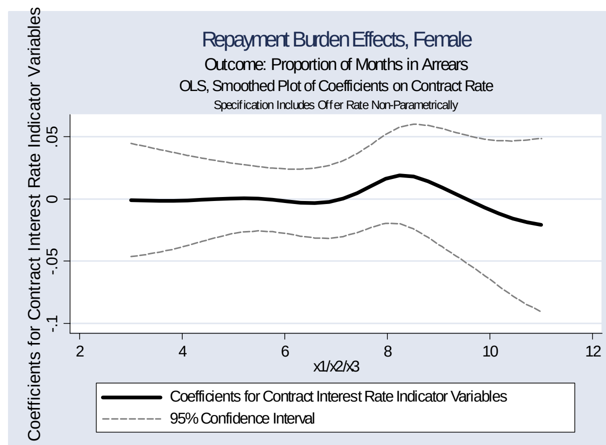
Figures 4-7





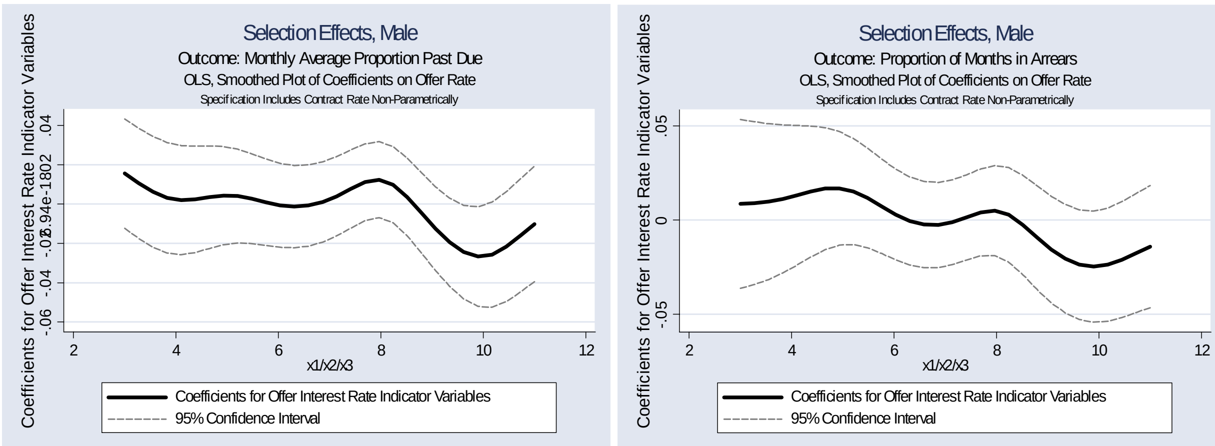
These are a smoothed plot of the coefficients on the offer rate indicator variables (y-axis), for each individual offer rate (x-axis), for females. The dependent variable is default, measured as the average past due amount as a proportion of original principal (on the left graph) and as the proportion of months in arrears (on the right graph). Other independent variables include indicator variables for each contract rate, the lender-defined risk level, and the month of the offer. This graph effectively presents the results of Table 5, Column 4, except with the offer rate specified non-parametrically rather than linearly. The upward slope is indicative of adverse selection with respect to the interest rate.



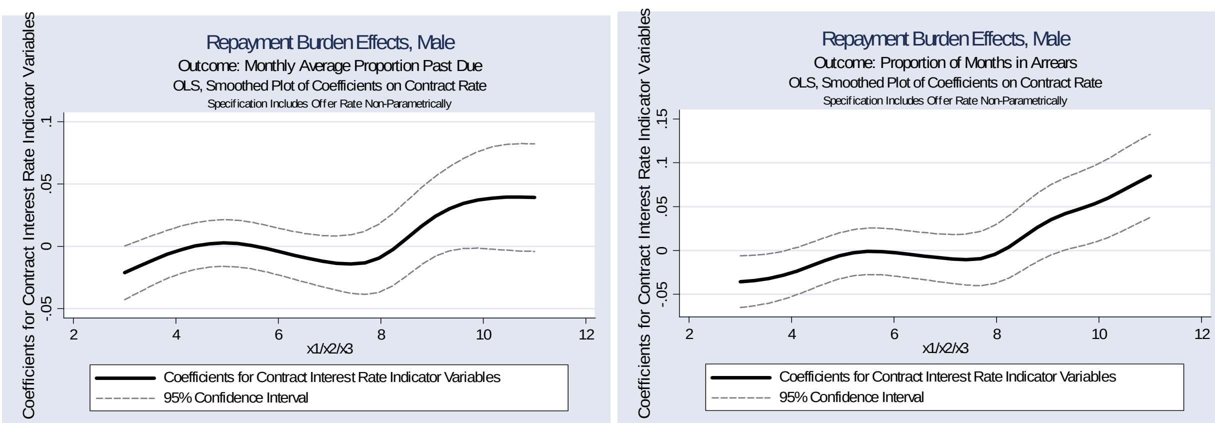


These are a smoothed plot of the coefficients on the contract rate indicator variables (y-axis), for each individual contract rate (x-axis), for females. The dependent variable is default, measured as the average past due amount as a proportion of original principal (on the left graph) and as the proportion of months in arrears (on the right graph). Other independent variables include indicator variables for each offer rate, the lender-defined risk level, and the month of the offer. This graph effectively presents the results of Table 5, Column 4, except with the contract rate specified non-parametrically rather than linearly. The flat slope is indicative of a lack of repayment burden effects with respect to the interest rate.

Figures 8-11



These are a smoothed plot of the coefficients on the offer rate indicator variables (y-axis), for each individual offer rate (x-axis), for males. The dependent variable is default, measured as the average past due amount as a proportion of original principal (on the left graph) and as the proportion of months in arrears (on the right graph). Other independent variables include indicator variables for each contract rate, the lender-defined risk level, and the month of the offer. This graph effectively presents the results of Table 5, Column 4, except with the offer rate specified non-parametrically rather than linearly. The flat slope is indicative of no selection effects with respect to the interest rate.



These are a smoothed plot of the coefficients on the contract rate indicator variables (y-axis), for each individual contract rate (x-axis), for males. The dependent variable is default, measured as the average past due amount as a proportion of original principal (on the left graph) and as the proportion of months in arrears (on the right graph). Other independent variables include indicator variables for each offer rate, the lender-defined risk level, and the month of the offer. This graph effectively presents the results of Table 5, Column 8, except with the contract rate specified non-parametrically rather than linearly. The upward slope is indicative of a repayment burden effect with respect to the interest rate.

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Table 1a: Summary Statistics

	All	Borrowed	Female Borrowed	Male Borrowed	Did Not Borrow	Lender-Defined Risk Category: High Risk	Medium Risk	Low Risk
A. Full Sample								
# of months since last loan	10.3	5.9	6.0	5.8	10.6	12.7	2.8	2.8
	(6.9)	(5.8)	(5.8)	(5.8)	(6.8)	(6.1)	(1.7)	(1.6)
Size of last loan prior to project (Rand)	1116.4	1156.0	1161.4	1150.9	1113.1	1086.4	1176.5	1229.7
	(829.9)	(825.7)	(798.2)	(851.6)	(830.2)	(785.2)	(878.4)	(994.5)
# of prior loans with the lender	4.3	4.9	4.8	4.9	4.2	3.6	5.7	6.6
	(3.9)	(4.2)	(4.2)	(4.2)	(3.8)	(3.5)	(4.2)	(4.3)
Term of last loan prior to project								
1 or 2 months	1,656	132	54	78	1,524	1,407	93	156
	2.88%	3.04%	2.53%	3.52%	2.87%	3.26%	1.50%	1.92%
4 months	53,296	3,939	1,926	2,013	49,357	40,687	5,658	6,951
	92.64%	90.59%	90.30%	90.88%	92.80%	94.18%	91.17%	85.54%
6 months	2,030	223	123	100	1,807	887	369	774
	3.53%	5.13%	5.77%	4.51%	3.40%	2.05%	5.95%	9.52%
12 months	551	54	30	24	497	220	86	245
	0.96%	1.24%	1.41%	1.08%	0.93%	0.51%	1.39%	3.02%
Number of Observations	57,533	4,348	2,133	2,215	53,185	43,201	6,206	8,126
B. Randomized Variables								
Offer Interest Rate	7.88	7.18	7.16	7.22	7.94	8.10	7.20	5.73
	(2.42)	(2.30)	(2.32)	(2.29)	(2.42)	(2.48)	(1.85)	(1.36)
Contract Interest Rate	7.08	6.53	6.46	6.58	7.12	7.29	6.56	5.28
	(2.42)	(2.26)	(2.25)	(2.27)	(2.42)	(2.52)	(1.87)	(1.34)
Proportion Receiving Rate for One year (vs. one loan)	0.43	0.47	0.47	0.47	0.43	0.46	0.47	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)
Proportion Receiving a Contract Rate < Offer Rate	0.41	0.40	0.40	0.40	0.41	0.41	0.39	0.39
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
C. Default Measure								
Monthly Average Past Due Amount		152.56	131.10	173.21		180.13	224.49	57.40
		(359.28)	(337.39)	(378.09)		(404.86)	(408.52)	(181.67)
Monthly Avg Past Due Amount, Proportion of Principal		0.09	0.08	0.11		0.12	0.13	0.03
		(0.21)	(0.19)	(0.23)		(0.24)	(0.24)	(0.11)
Proportion of Months With Some Arrearage		0.22	0.20	0.24		0.25	0.32	0.10
		(0.29)	(0.28)	(0.30)		(0.31)	(0.31)	(0.19)
Account is in Collection (3+ months arrears)		0.12	0.10	0.14		0.14	0.17	0.04
		(0.32)	(0.30)	(0.33)		(0.35)	(0.38)	(0.19)
Number of Observations	57,533	4,348	2,133	2,215	53,185	2,090	941	1,317

Standard deviations are in parentheses
~7.5 Rand = US $1 at the time of the experiment.

Table 1b: Summary Statistics

	Full Sample	Female	Male	Female Borrowed	Male Borrowed	1998 LSMS 25th Percentile	1998 LSMS Median	1998 LSMS 75th Percentile	1998 LSMS Mean
A. Client Characteristics									
Female, proportion	0.48	1	0	1	0				x
	(0.50)	(0)	(0)	(0)	(0)				
Married, proportion	0.44	0.37	0.50	0.39	0.52				x
	(0.50)	(0.48)	(0.50)	(0.49)	(0.50)				
# of dependants	1.59	1.53	1.64	1.82	1.97	x	x	x	x
	(1.74)	(1.62)	(1.85)	(1.61)	(1.87)				
Age	41.25	42.03	40.55	41.74	40.10	x	x	x	x
	(11.53)	(11.89)	(11.14)	(11.38)	(10.82)				
Education (# of years, estimated from occupation)	6.78	7.23	6.36	7.45	6.53	x	x	x	x
	(3.32)	(3.45)	(3.14)	(3.51)	(3.19)				
Monthly gross income at last loan (000's Rand)*	3.42	3.26	3.56	3.39	3.45	x	x	x	x
	(19.66)	(2.63)	(27.05)	(2.19)	(2.07)				
Home bond, proportion	0.07	0.07	0.06	0.08	0.06	x	x	x	x
	(0.25)	(0.25)	(0.24)	(0.26)	(0.24)				
External credit score	551.35	544.23	557.82	547.77	571.69				
	(215.64)	(210.22)	(220.27)	(203.20)	(204.22)				
No external credit score, proportion	0.12	0.11	0.12	0.11	0.10				
	(0.32)	(0.32)	(0.33)	(0.31)	(0.30)				
Months at Employer	93.82	90.42	96.92	93.34	96.86				
	(88.01)	(82.55)	(92.59)	(82.33)	(88.53)				
# of Observations	57533	27387	30146	2133	2215				
B. Loan Characteristics									
Amount of last loan prior to experiment	1116.36	1122.87	1110.44	1161.37	1150.86				
	(829.90)	(844.42)	(816.46)	(798.21)	(851.56)				
Term of last loan prior to experiment	4.06	4.09	4.03	4.15	4.07				
	(1.00)	(1.01)	(1.00)	(1.16)	(1.09)				
# of prior loans with the lender	4.26	4.22	4.29	4.83	4.90				
	(3.86)	(3.82)	(3.90)	(4.20)	(4.26)				
# of months since the last loan	10.26	10.21	10.31	5.98	5.82				
	(6.88)	(6.84)	(6.92)	(5.78)	(5.82)				
Internal credit score when new borrower	29.66	32.59	26.99	32.97	27.40				
	(8.75)	(8.53)	(8.06)	(8.38)	(8.22)				
# of Observations	57533	27387	30146	2133	2215				
C. Self-Reported Loan Usage									
School				24.2%	13.6%				
Housing (mostly renovations)				12.6%	9.8%				
Payoff other debt				10.9%	11.1%				
Family/Event				5.7%	8.1%				
Consumption				5.6%	7.1%				
Transport				4.1%	7.6%				
Funeral/Medical				3.8%	4.4%				
Durable				2.3%	1.0%				
Business/Other Investment				2.3%	2.7%				
Misc/unreported				28.7%	34.6%				
# of Observations				690	775				

* Standard deviations are in parentheses. Gross income at time of last loan is missing for participants from pilot phase. Age, gender and other demographic information also missing for <10 observations. Number of observations reported is the total number, irrespective of missing data. Usage sample size is low relative to takeup due to reluctance of loan officers to administer survey (the Lender does not typically ask applicants about intended usage, and if anything emphasizes that it does not ask such questions). Reported "Consumption" uses are primarily food (39%) and clothing (23%); "Family/Events" are largely Christmas (45%) expenses; "School" is largely the fees required for children to attend; "Misc" is largely borrowers declining to specify (88%).

Table 2: Experimental Integrity Checks

OLS

					Sample Restricted to Applied = 1
Dependent variable:	Contract Rate	Offer Rate	Rate Valid for One Year (versus One Loan)	Applied=1	Rejected = 1
	(1)	(2)	(3)	(4)	(5)
Female	0.009	0.028	-0.002		
	(0.022)	(0.021)	(0.004)		
Married	0.017	0.022	0.004		
	(0.022)	(0.021)	(0.004)		
External credit score	-0.000	-0.000	0.000		
	(0.000)	(0.000)	(0.000)		
No External credit score	-0.017	-0.006	0.016		
	(0.093)	(0.091)	(0.016)		
Internal credit score	-0.001	-0.002	0.000		
	(0.001)	(0.001)	(0.000)		
Log (Size of last loan prior to project)	-0.017	-0.003	-0.004		
	(0.017)	(0.017)	(0.003)		
Term of last loan prior to project	-0.010	-0.011	-0.001		
	(0.011)	(0.010)	(0.002)		
# of prior loans with the lender	0.003	0.003	0.001**		
	(0.003)	(0.003)	(0.001)		
Gross income	-0.001	-0.000	0.000		
	(0.001)	(0.000)	(0.000)		
Years at Employer	0.000	0.001	-0.000		
	(0.002)	(0.002)	(0.000)		
Mean education	0.002	-0.002	-0.000		
	(0.003)	(0.003)	(0.001)		
# of dependants	0.002	-0.005	0.000		
	(0.007)	(0.006)	(0.001)		
Age	-0.000	-0.001	-0.000*		
	(0.001)	(0.001)	(0.000)		
Home bond	0.053	0.028	0.011		
	(0.041)	(0.040)	(0.007)		
# of months since the last loan	-0.001	-0.001	-0.001***		
	(0.002)	(0.002)	(0.000)		
Offer Interest Rate				-0.003***	
				(0.001)	
Contract Interest Rate				0.000	-0.001
				(0.001)	(0.002)
Rate valid for one year, Indicator Variable					-0.014
					(0.012)
Constant	7.700***	8.369***	0.228***	0.081***	0.334***
	(0.297)	(0.292)	(0.051)	(0.005)	(0.075)
Observations	57339	57339	57339	57533	5028
Joint F-Test	0.87	0.96	0.01		
R-squared	0.10	0.14	0.37	0.04	0.09

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses. Columns 1 through 3 test whether the randomized variables are correlated with information observable before the experiment launch. For column 3, if the dormancy variable were omitted the F-test is 0.21. Column 4 shows that the decision to borrow by the client was affected by the Offer Interest Rate, but not the Contract Interest Rate, hence verifying the internal controls of the experimental protocol. Column 5 shows that the decision by the branch manager to reject applicants was not predicted by the contract interest rate or the year long versus one-loan length of the special rate. The regression is conditional on "Applied"=1. Includes controls for lender-defined risk category, month of offe letter and branch.

Table 3: Disentangling Selection on Unobservables from Debt Burden Effects: Comparison of Means

		Moral Hazard / Repayment Burden Effects			Selection Effects		
		High Offer, High Contract	High Offer, Low Contract	t-stat: diff≠0	High Offer, Low Contract	Low Offer, Low Contract	t-stat: diff≠0
Full Sample							
	Average Monthly Proportion Past Due	0.105	0.102	0.23	0.102	0.082	1.90*
		(0.006)	(0.009)		(0.009)	(0.004)	
	Proportion of Months in Arrears	0.244	0.211	2.38**	0.211	0.202	0.72
		(0.008)	(0.011)		(0.011)	(0.006)	
	Account in Collection Status	0.139	0.123	0.99	0.123	0.101	1.50
		(0.009)	(0.013)		(0.013)	(0.007)	
	# of observations	1636	625		625	2087	
Female							
	Average Monthly Proportion Past Due	0.089	0.101	-0.85	0.101	0.067	2.42**
		(0.007)	(0.013)		(0.013)	(0.005)	
	Proportion of Months in Arrears	0.221	0.209	0.64	0.209	0.181	1.55
		(0.011)	(0.02)		(0.02)	(0.008)	
	Account in Collection Status	0.107	0.121	-0.65	0.121	0.082	1.88*
		(0.121)	(0.019)		(0.019)	(0.008)	
	# of observations	779	307		307	1047	
Male							
	Average Monthly Proportion Past Due	0.120	0.103	1.05	0.103	0.099	0.30
		(0.008)	(0.013)		(0.013)	(0.007)	
	Proportion of Months in Arrears	0.264	0.213	2.60***	0.213	0.223	-0.51
		(0.011)	(0.016)		(0.016)	(0.009)	
	Account in Collection Status	0.168	0.126	1.87*	0.126	0.120	0.26
		(0.013)	(0.019)		(0.019)	(0.010)	
	# of observations	857	318		318	1040	

In this stylized demonstration of the results, "high" is defined as above the median offer rate for that risk category. This is equal to 7.77% for high risk clients, 7.50% for medium risk clients and 6.00% for low risk clients. T-tests assume unequal variances across columns.

Table 4: Full Sample Results: Disentangling Selection on Unobservables from Moral Hazard

	OLS						Tobit		Probit
Dependent Variable:	*Monthly Average Proportion Past Due*		*Proportion of Months in Arrears*		*Account in Collection Status*		*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Offer Rate (AS)	0.004	0.004	0.002	0.002	0.007	0.007	0.004	0.002	0.007
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.004)
Contract Rate (MH)	-0.000	-0.002	0.007*	0.003	0.001	-0.001	0.002	0.010	0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)
Rate valid for one year, Indicator Variable	-0.011*	0.003	-0.016**	0.013	-0.019**	0.000	-0.021**	-0.032**	-0.019**
	(0.005)	(0.011)	(0.008)	(0.018)	(0.009)	(0.019)	(0.009)	(0.016)	(0.008)
Rate valid for one year * # of points below normal rate		-0.004		-0.008**		-0.005			
		(0.003)		(0.004)		(0.004)			
Constant	0.079***	0.094***	0.139***	0.171***	0.069***	0.090***	-0.065**	-0.081	
	(0.014)	(0.019)	(0.025)	(0.027)	(0.024)	(0.028)	(0.028)	(0.052)	
Observations	4348	4348	4348	4,348	4348	4348	4348	4348	4348
Adjusted R-squared	0.04	0.04	0.11	0.11	0.03	0.03			
Mean of dependent variable	0.09	0.09	0.22	0.22	0.12	0.12	0.09	0.22	0.12
Prob(both "rate valid for one year variables" = 0)		0.08*		0.01***		0.05**			

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. "Offer Rate" and "Contract Rate" are in monthly percentage point units (7.00% interest per month is coded as 7.00). "Rate Valid for One Year" is an indicator variable equal to one if the contract interest rate is valid for one year (rather than one loan) before reverting back to the normal (higher) interest rates. "Rate Valid for One Year * # of points below normal rate" interacts the above indicator variable with the difference between the Lender's normal rate to that individual's risk category and the experimentally assigned contract interest rate. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results. A positive coefficient on the Offer Rate variable indicates adverse selection, a positive coefficient on the Contract Rate variable indicates a reduced-form repayment burden effect, and a negative coefficent on Rate Valid for One Year indicates moral hazard that is alleviated by the dynamic pricing incentive.

Table 5: Disentangling Selection on Unobservables from Moral Hazard
By Gender

	Male						Female					
	OLS			Tobit		Probit	OLS			Tobit		Probit
Dependent Variable:	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Offer Rate (AS)	-0.002	-0.004	0.001	-0.005	-0.008	0.001	0.010***	0.008*	0.013**	0.013**	0.013	0.011***
	(0.004)	(0.005)	(0.007)	(0.006)	(0.010)	(0.007)	(0.003)	(0.005)	(0.005)	(0.006)	(0.009)	(0.004)
Contract Rate (MH)	0.005	0.014***	0.010	0.010	0.021**	0.009	-0.005	-0.001	-0.009	-0.006	-0.003	-0.007*
	(0.003)	(0.005)	(0.007)	(0.006)	(0.010)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.009)	(0.004)
Rate Valid for One	-0.014	-0.025**	-0.020	-0.033**	-0.050**	-0.020	-0.007	-0.006	-0.017	-0.008	-0.009	-0.016
Year (vs one loan)	(0.009)	(0.012)	(0.015)	(0.016)	(0.023)	(0.014)	(0.008)	(0.012)	(0.012)	(0.014)	(0.025)	(0.011)
Constant	0.108***	0.178***	0.092**	-0.008	0.002		0.050***	0.097***	0.043	-0.121***	-0.176***	
	(0.025)	(0.040)	(0.043)	(0.043)	(0.072)		(0.015)	(0.026)	(0.027)	(0.029)	(0.057)	
Observations	2215	2215	2215	2215	2215	2215	2133	2133	2133	2133	2133	2133
R-squared	0.05	0.12	0.04				0.05	0.10	0.04			

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. Regressions reported here are estimated using the base specification (equation 2) on samples split by gender. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results.

Table 6: Disentangling Selection on Unobservables from Moral Hazard
OLS: Matching Specification

	Full sample			Male			Female			
Dependent Variable:	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	# of Fixed Effects for All Combinations of Other Random Variables (see notes)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Offer Rate (AS)	0.0027	0.0004	0.0046	-0.0035	-0.0064	-0.0028	0.0092**	0.0067	0.0128**	167
	(0.0026)	(0.0048)	(0.0049)	(0.0040)	(0.0062)	(0.0073)	(0.0038)	(0.0052)	(0.0062)	
Contract Rate (MH)	-0.0001	0.0062*	0.0009	0.0052	-.0128***	0.0091	-0.0056	-0.0023	-0.0090	165
	(0.0025)	(0.0034)	(0.0047)	(0.0040)	(0.0049)	(0.0075)	(0.0035)	(0.0051)	(0.0056)	
Rate Valid for One Year (vs one loan)	-.0120**	-0.019**	-0.023**	-0.013	-0.022	-0.023	-.006	-0.007	-0.018*	620
	(0.006)	(0.010)	(0.010)	(0.010)	(0.015)	(0.018)	(0.008)	(0.014)	(0.011)	
# of Observations		4348			2,215			2133		

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level.
Each cell represents a separate specification. For each cell, we report the coefficient on the indicated independent variable after including a full set of indicator variables for all possible combinations of the other independent random variables and lender-defined risk category. For example, the top left cell reports the coefficient on the Offer Rate after including fixed effects for every combination of a set of indicator variables for the Contract Rate, an indicator variavle for Rate Valid for One Year, and two indicator variables for the lender-defined risk category. All specifications include controls month of offer letter.

Table 7: Disentangling Selection on Unobservables from Moral Hazard

IV

Sample:	Full	Full	Full	Male	Male	Male	Female	Female	Female
Dependent Variable:	Average Monthly Proportion Past Due	Proportion of Months in Arrears	Account in Collection Status	Average Monthly Proportion Past Due	Proportion of Months in Arrears	Account in Collection Status	Average Monthly Proportion Past Due	Proportion of Months in Arrears	Account in Collection Status
	(2)	(3)	(4)	(6)	(7)	(8)	(10)	(11)	(12)
Panel A: IV									
Total Interest Cost, 000's Rands, at Offer Interest Rate	0.35*	0.29	0.66*	-0.03	-0.00	0.41	0.74***	0.65*	1.00**
	(0.20)	(0.28)	(0.35)	(0.29)	(0.42)	(0.51)	(0.27)	(0.35)	(0.41)
Total Interest Cost, 000's Rands, at Contract Interest Rate	-0.00	0.10*	0.01	0.07	0.19**	0.14	-0.09	-0.02	-0.14
	(0.04)	(0.06)	(0.08)	(0.05)	(0.08)	(0.11)	(0.06)	(0.09)	(0.10)
Constant	0.09***	0.19***	0.09***	0.10***	0.21***	0.09**	0.08***	0.21***	0.12***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Observations	4348	4348	4348	2215	2215	2215	2133	2133	2133
Panel B: OLS									
Total Interest Cost, 000's Rands, at Offer Interest Rate	-0.12**	0.01	-0.08	-0.15*	0.06	0.06	-0.08	-0.02	-0.19
	(0.06)	(0.10)	(0.10)	(0.08)	(0.14)	(0.14)	(0.06)	(0.12)	(0.13)
Total Interest Cost, 000's Rands, at Contract Interest Rate	-0.00	0.01	0.01	0.00	0.01	0.01	-0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Constant	0.13***	0.25***	0.15***	0.13***	0.27***	0.17***	0.12***	0.26***	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4348	4348	4348	2215	2215	2215	2133	2133	2133
	0.05	0.10	0.03	0.05	0.11	0.03	0.05	0.10	0.03

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. Two endogenous variables: (1) total debt burden, principal plus interest, on contract and (2) interest rate. Instrumental variables are (1) offer interest rate and (2) contract interest rate. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results.

Table 8: Disentangling Selection on Unobservables from Moral Hazard, by Gender & Demographics

OLS, Dependent Variable: Monthly Average Percentage Past Due

Demographic Control Variable:	*Married*		*Dependants in Household*		*Educated*		*Age*		Log(Monthly Gross Income)		Tenure at Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Experimental Variables												
Offer Rate (AS)	0.023	-0.252	0.089	0.176	0.079	-0.213	0.282	-0.341	2.700	-0.716	0.122	0.082
	(0.435)	(0.537)	(0.432)	(0.530)	(0.402)	(0.410)	(1.162)	(1.325)	(2.338)	(4.218)	(0.456)	(0.495)
Contract Rate (MH)	0.415	0.716	0.482	0.660	0.260	0.557	0.269	0.652	-0.968	1.852	0.404	0.442
	(0.393)	(0.508)	(0.446)	(0.527)	(0.414)	(0.440)	(1.098)	(1.283)	(2.707)	(4.600)	(0.465)	(0.523)
Rate Valid for One Year (vs one loan)	-1.158	-0.706	-1.098	-1.920	-0.878	-1.081	-1.280	0.934	7.378	3.457	-1.165	-0.691
	(1.160)	(1.510)	(1.237)	(1.434)	(1.028)	(1.252)	(2.678)	(4.049)	(8.692)	(12.814)	(1.145)	(1.465)
Female	-2.985	-3.095	-2.558	-1.021	-2.215	-2.652	-1.887	-5.296	-2.821	-30.918	-2.667	-2.298
	(1.939)	(2.585)	(1.980)	(3.110)	(1.886)	(2.631)	(1.914)	(7.409)	(1.926)	(28.386)	(1.875)	(3.073)
Demographic Variable (see column heading)	-1.838	-2.040	-0.036	0.427	-1.761	-2.487	-0.172	-0.223	-0.001	-2.020	-0.015	-0.013
	(1.952)	(2.854)	(0.536)	(0.741)	(2.432)	(3.909)	(0.105)	(0.157)	(1.669)	(3.019)	(0.012)	(0.018)
*Female * Experimental Variables*												
Female * Offer Rate (AS)	0.887*	1.369**	0.834*	0.637	0.902*	1.534**	0.763*	1.951	0.890**	6.945	0.807*	0.891
	(0.456)	(0.632)	(0.460)	(0.661)	(0.480)	(0.604)	(0.455)	(1.916)	(0.445)	(6.117)	(0.447)	(0.749)
Female * Contract Rate (MH)	-1.042**	-1.575**	-1.029**	-1.440**	-1.138**	-1.783***	-0.977**	-1.782	-1.040**	-6.318	-0.967**	-1.047
	(0.476)	(0.718)	(0.497)	(0.678)	(0.482)	(0.640)	(0.486)	(1.979)	(0.474)	(7.129)	(0.479)	(0.748)
Female * Rate Valid for One Year (vs one loan)	0.813	-0.037	0.896	2.732	1.077	1.554	0.701	-3.491	0.603	8.148	0.730	-0.290
	(1.350)	(2.143)	(1.343)	(2.052)	(1.351)	(1.903)	(1.336)	(5.867)	(1.353)	(14.026)	(1.328)	(2.363)
*Demographic Control Variable * Experimental Variables*												
Demographic Variable * Offer Rate (AS)	-0.135	0.415	-0.046	-0.084	-0.400	0.626	-0.008	0.008	-0.343	0.079	-0.002	-0.001
	(0.540)	(0.796)	(0.122)	(0.164)	(0.625)	(0.853)	(0.026)	(0.030)	(0.289)	(0.522)	(0.003)	(0.003)
Demographic Variable * Contract Rate (AS)	0.195	-0.397	-0.009	-0.124	0.748	-0.279	0.006	-0.003	0.183	-0.166	0.001	0.001
	(0.511)	(0.788)	(0.141)	(0.177)	(0.583)	(0.776)	(0.026)	(0.031)	(0.325)	(0.561)	(0.003)	(0.003)
Demographic Variable * Rate Valid for One Year	-0.577	-1.442	-0.224	0.162	-1.577	-1.017	-0.002	-0.056	-1.077	-0.592	-0.002	-0.007
	(1.211)	(1.897)	(0.353)	(0.431)	(1.307)	(2.104)	(0.061)	(0.092)	(1.042)	(1.530)	(0.006)	(0.009)
*Female * Demographic Control Variable*												
Female * Demographic Variable		0.305		-1.217		1.155		0.083		3.457		-0.004
		(3.234)		(1.138)		(4.167)		(0.167)		(3.460)		(0.023)
*Female * Demographic Control Variable * Experimental Variables*												
Female * Demographic Variable * Offer Rate (AS)		-1.079		0.111		-1.755		-0.029		-0.748		-0.001
		(0.951)		(0.274)		(1.080)		(0.044)		(0.758)		(0.006)
Female * Demographic Variable * Contract Rate (AS)		1.181		0.277		1.777		0.020		0.654		0.001
		(1.033)		(0.292)		(1.196)		(0.045)		(0.882)		(0.005)
Female * Demographic Variable * Rate Valid for One Year		1.797		-0.968		-1.049		0.102		-0.937		0.011
		(2.652)		(0.654)		(2.713)		(0.125)		(1.672)		(0.015)
Constant	10.161***	10.236***	8.917***	8.252***	9.608***	9.821***	14.984***	17.066**	9.240	25.704	10.281***	10.122***
	(2.476)	(2.791)	(2.542)	(2.986)	(2.240)	(2.546)	(5.136)	(7.222)	(13.856)	(25.009)	(2.642)	(3.133)
Observations	4317	4317	4317	4317	4348	4348	4348	4348	4348	4348	4348	4348
R-squared	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.05	0.05	0.06	0.06

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. Educated is a binary indicator for the top 25% in years of education, predicted by the client's occupation. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results. The dependent variable here is defined in percentage point terms, not proportion, hence equals 100x the variable used in other tables.

Table 9: Selection on Observable Information

Probit, Dependent Variable: "Applied for Loan"

Sample:	*All*	*All*	*Female*	*Male*	*All*	*Female*	*Male*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Offer Rate (AS)	-0.003***	-0.004***	-0.006***	-0.002	-0.004***	-0.006***	-0.002
	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Predicted Past Due Percentage		-158.064**	-268.010**	-17.186	-161.723**	-268.929**	-26.299
		(76.012)	(122.971)	(112.913)	(76.147)	(124.909)	(114.014)
Offer Rate* Predicted Past Due Percentage		10.071	23.443*	-4.948	10.497	23.589*	-4.234
		(8.852)	(13.105)	(13.786)	(8.780)	(13.305)	(13.916)
High Gross Income					-0.005	0.001	-0.010
					(0.008)	(0.012)	(0.011)
Offer Rate*High Gross Income					0.000	0.000	0.001
					(0.001)	(0.002)	(0.001)
Observations	48852	52985	25221	27764	52985	25221	27764

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. Predicted past due percentage is the predicted value for the default from Table 10 OLS specifications. "High Gross Income" equals to 1 if gross income above median in sample. First wave, 4339 observations, omitted because income variable missing for non-applicants. Reported coefficients are marginal effects. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results.

Table 10: Including Observable Determinants of Default

OLS

Dependent Variable:	*Monthly Average Proportion Past Due*		*Proportion of Months in Arrears*		*Account in Collection Status*	
	(1)	(2)	(3)	(4)	(5)	(6)
Offer Rate (AS)	-0.001		-0.003		0.003	
	(0.003)		(0.005)		(0.006)	
Contract Rate (MH)	0.005		0.014***		0.010	
	(0.003)		(0.005)		(0.007)	
Rate Valid for One Year (vs one loan)	-0.017*		-0.024**		-0.022	
	(0.010)		(0.012)		(0.016)	
Female * Offer Rate (AS)	0.007*		0.008		0.007	
	(0.004)		(0.006)		(0.007)	
Female * Contract Rate (MH)	-0.009**		-0.015**		-0.017**	
	(0.005)		(0.007)		(0.008)	
Female * Rate Valid for One Year (D=1)	0.008		0.014		0.003	
	(0.013)		(0.018)		(0.021)	
Female	-0.015	-0.021***	-0.005	-0.035***	0.033	-0.029**
	(0.019)	(0.007)	(0.026)	(0.010)	(0.027)	(0.012)
Log(loan size)	-0.026***	-0.026***	0.013*	0.013*	0.004	0.004
	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)
Age	0.000	0.000	0.002	0.001	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000	-0.000	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years at Employer	-0.001	-0.001	-0.001**	-0.001**	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gross Income	0.003	0.003	-0.007*	-0.007*	-0.006	-0.005
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Education (predicted by occupation)	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of Dependants	-0.001	-0.001	0.000	0.000	-0.006*	-0.006**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
External Credit Score	-0.000***	-0.000***	-0.000***	-0.000***	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No External Credit Score	-0.097***	-0.100***	-0.244***	-0.251***	-0.075*	-0.082*
	(0.035)	(0.034)	(0.049)	(0.049)	(0.045)	(0.044)
Internal Credit Score at First-Time Application	-0.001*	-0.001*	-0.001*	-0.001**	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Married	0.002	0.003	0.005	0.005	0.014	0.015
	(0.007)	(0.007)	(0.009)	(0.009)	(0.012)	(0.012)
Home Bond	0.010	0.009	0.014	0.012	0.041*	0.038*
	(0.014)	(0.014)	(0.021)	(0.022)	(0.023)	(0.022)
# of prior loans with the lender	-0.003***	-0.003***	-0.005***	-0.005***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of months since last loan	0.004***	0.004***	0.004**	0.004**	0.005***	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.466***	0.488***	0.412***	0.486***	0.277***	0.368***
	(0.069)	(0.068)	(0.087)	(0.080)	(0.100)	(0.089)
Observations	4348	4348	4348	4348	4348	4348
R-squared	0.0886	0.0862	0.1570	0.1520	0.0711	0.0660
Adjusted r-squared	0.0808	0.0796	0.1497	0.1459	0.0631	0.0593

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. Control dummies included for Lender's 13-category risk level.

Table 11: Do Information Asymmetries Diminish for Clients with More Frequent Borrowing History?

OLS, Dependent Varibale: Monthly Average Proportion Past Due

Sample:	*All*			*Female*			*Male*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Offer Rate (AS)	0.008**	0.004	0.004	0.014***	0.010***	0.010***	0.001	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
Contract Rate (MH)	0.000	0.004	0.000	-0.005	-0.001	-0.005	0.005	0.008*	0.005
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Rate Valid for One Year (vs one loan)	-0.011*	-0.011*	-0.013	-0.007	-0.007	-0.006	-0.015	-0.015	-0.023
	(0.006)	(0.006)	(0.010)	(0.008)	(0.008)	(0.011)	(0.010)	(0.010)	(0.017)
# of prior loans with the lender	0.001	0.000		0.003	0.001		-0.001	-0.001	
	(0.002)	(0.001)		(0.002)	(0.002)		(0.003)	(0.003)	
Offer Rate*# of prior loans	-0.001***			-0.001***			-0.001		
	(0.000)			(0.000)			(0.000)		
Contract Rate*# of prior loans		-0.001***			-0.001***			-0.001	
		(0.000)			(0.000)			(0.000)	
Rate Valid for One Year*# of prior loans			0.001			-0.000			0.002
			(0.001)			(0.001)			(0.002)
Constant	0.078***	0.083***	0.105***	0.040**	0.046***	0.070***	0.119***	0.121***	0.142***
	(0.018)	(0.017)	(0.014)	(0.017)	(0.016)	(0.015)	(0.034)	(0.032)	(0.025)
Observations	4317	4317	4317	2119	2119	2119	2198	2198	2198
R-squared	0.05	0.05	0.05	0.06	0.06	0.05	0.06	0.06	0.06

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results.

Appendix Table 1. Frequency of Monthly Offer and Contract Interest Rates

	Low Risk Clients				Medium Risk Clients				High Risk Clients			
	Offer Interest Rate		*Contract Interest Rate*		*Offer Interest Rate*		*Contract Interest Rate*		*Offer Interest Rate*		*Contract Interest Rate*	
	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
3.25%	144	1.77%	304	3.74%	94	1.51%	172	2.77%	586	1.36%	1,017	2.35%
3.49%	281	3.46%	347	4.27%	110	1.77%	135	2.18%	756	1.75%	934	2.16%
3.50%	267	3.29%	393	4.84%	116	1.87%	163	2.63%	540	1.25%	931	2.16%
3.75%	32	0.39%	42	0.52%	18	0.29%	26	0.42%	53	0.12%	80	0.19%
3.99%	367	4.52%	580	7.14%	104	1.68%	229	3.69%	754	1.75%	1,400	3.24%
4.00%	199	2.45%	341	4.20%	99	1.60%	144	2.32%	525	1.22%	845	1.96%
4.25%	40	0.49%	61	0.75%	22	0.35%	29	0.47%	59	0.14%	69	0.16%
4.44%	208	2.56%	380	4.68%	79	1.27%	214	3.45%	494	1.14%	1,220	2.82%
4.49%	399	4.91%	330	4.06%	139	2.24%	136	2.19%	775	1.79%	866	2.00%
4.50%	176	2.17%	288	3.54%	99	1.60%	149	2.40%	591	1.37%	826	1.91%
4.75%	45	0.55%	39	0.48%	22	0.35%	29	0.47%	60	0.14%	77	0.18%
4.99%	202	2.49%	378	4.65%	117	1.89%	211	3.40%	713	1.65%	1,347	3.12%
5.00%	283	3.48%	332	4.09%	119	1.92%	168	2.71%	550	1.27%	809	1.87%
5.25%	45	0.55%	49	0.60%	19	0.31%	26	0.42%	67	0.16%	77	0.18%
5.49%	338	4.16%	387	4.76%	149	2.40%	239	3.85%	712	1.65%	1,330	3.08%
5.50%	426	5.24%	415	5.11%	97	1.56%	144	2.32%	604	1.40%	761	1.76%
5.55%	288	3.54%	267	3.29%	81	1.31%	120	1.93%	513	1.19%	660	1.53%
5.75%	46	0.57%	56	0.69%	20	0.32%	27	0.44%	74	0.17%	92	0.21%
5.99%	495	6.09%	409	5.03%	213	3.43%	259	4.17%	712	1.65%	1,175	2.72%
6.00%	402	4.95%	315	3.88%	118	1.90%	141	2.27%	586	1.36%	766	1.77%
6.25%	49	0.60%	51	0.63%	24	0.39%	25	0.40%	74	0.17%	80	0.19%
6.50%	388	4.77%	377	4.64%	125	2.01%	201	3.24%	611	1.41%	1,286	2.98%
6.75%	422	5.19%	335	4.12%	148	2.38%	198	3.19%	569	1.32%	903	2.09%
6.99%	464	5.71%	308	3.79%	231	3.72%	192	3.09%	775	1.79%	903	2.09%
7.00%	435	5.35%	292	3.59%	201	3.24%	194	3.13%	855	1.98%	881	2.04%
7.25%	399	4.91%	273	3.36%	200	3.22%	205	3.30%	834	1.93%	1,028	2.38%
7.49%	575	7.08%	347	4.27%	260	4.19%	212	3.42%	1,015	2.35%	977	2.26%
7.50%	357	4.39%	229	2.82%	195	3.14%	166	2.67%	849	1.97%	825	1.91%
7.75%	354	4.36%	201	2.47%	181	2.92%	162	2.61%	909	2.10%	1,033	2.39%
7.77%	-	-	-	-	200	3.22%	138	2.22%	825	1.91%	719	1.66%
7.99%	-	-	-	-	224	3.61%	159	2.56%	1,029	2.38%	933	2.16%
8.00%	-	-	-	-	168	2.71%	160	2.58%	891	2.06%	830	1.92%
8.19%	-	-	-	-	235	3.79%	167	2.69%	1,024	2.37%	829	1.92%
8.25%	-	-	-	-	25	0.40%	28	0.45%	74	0.17%	79	0.18%
8.50%	-	-	-	-	215	3.46%	164	2.64%	830	1.92%	984	2.28%
8.75%	-	-	-	-	35	0.56%	23	0.37%	82	0.19%	77	0.18%
8.88%	-	-	-	-	221	3.56%	153	2.47%	805	1.86%	851	1.97%
8.99%	-	-	-	-	263	4.24%	174	2.80%	1,044	2.42%	814	1.88%
9.00%	-	-	-	-	214	3.45%	128	2.06%	877	2.03%	756	1.75%
9.25%	-	-	-	-	218	3.51%	145	2.34%	890	2.06%	867	2.01%
9.49%	-	-	-	-	300	4.83%	170	2.74%	1,162	2.69%	879	2.03%
9.50%	-	-	-	-	37	0.60%	28	0.45%	89	0.21%	82	0.19%
9.69%	-	-	-	-	234	3.77%	137	2.21%	1,201	2.78%	892	2.06%
9.75%	-	-	-	-	217	3.50%	116	1.87%	889	2.06%	727	1.68%
9.99%	-	-	-	-	-	-	-	-	1,242	2.87%	887	2.05%
10.00%	-	-	-	-	-	-	-	-	1,253	2.90%	876	2.03%
10.25%	-	-	-	-	-	-	-	-	1,276	2.95%	892	2.06%
10.49%	-	-	-	-	-	-	-	-	1,494	3.46%	964	2.23%
10.50%	-	-	-	-	-	-	-	-	1,282	2.97%	833	1.93%
10.75%	-	-	-	-	-	-	-	-	93	0.22%	73	0.17%
10.99%	-	-	-	-	-	-	-	-	1,390	3.22%	899	2.08%
11.00%	-	-	-	-	-	-	-	-	1,385	3.21%	857	1.98%
11.11%	-	-	-	-	-	-	-	-	1,345	3.11%	800	1.85%
11.19%	-	-	-	-	-	-	-	-	1,498	3.47%	867	2.01%
11.25%	-	-	-	-	-	-	-	-	104	0.24%	77	0.18%
11.50%	-	-	-	-	-	-	-	-	99	0.23%	72	0.17%
11.69%	-	-	-	-	-	-	-	-	1,431	3.31%	834	1.93%
11.75%	-	-	-	-	-	-	-	-	1,382	3.20%	753	1.74%
Total	8,126	100%	8,126	100%	6,206	100%	6,206	100%	43,201	100%	43,201	100%

Appendix Table 2. Primary Results: Disentangling Selection on Unobservables from Moral Hazard

Sample Restricted to Those Offered ≤ 7.75%, the Ceiling for Low Risk Clients

	OLS			Tobit		Probit
Dependent Variable:	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*
	(1)	(2)	(3)	(4)	(5)	(6)
Offer Rate (AS)	0.007	0.005	0.012	0.007	0.004	0.009
	(0.005)	(0.006)	(0.008)	(0.009)	(0.014)	(0.012)
Contract Rate (MH)	-0.006	0.001	-0.003	-0.006	0.002	0.002
	(0.005)	(0.006)	(0.008)	(0.009)	(0.014)	(0.006)
Rate Valid for One	-0.010*	-0.021**	-0.017**	-0.023**	-0.040**	-0.020
Year (vs one loan)	(0.005)	(0.009)	(0.007)	(0.011)	(0.020)	(0.017)
Constant	0.087***	0.149***	0.067***	-0.035	-0.058	
	(0.016)	(0.029)	(0.023)	(0.033)	(0.064)	
Observations	2715	2715	2715	2715	2715	1762
R-squared	0.06	0.12	0.04			

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results.

Appendix Table 3. Primary Analysis with Offer Rate Alone (No Contract Rate)

Dependent Variable: Monthly Average Proportion Past Due

Sample:	*All*	*All*	*Female*	*Male*
	Full Sample	Offer Rate = Contract Rate	Offer Rate = Contract Rate	Offer Rate = Contract Rate
	(1)	(2)	(3)	(4)
Offer Interest Rate	0.004**	0.004**	0.004*	0.004
	(0.002)	(0.002)	(0.002)	(0.003)
Rate valid for one year (Indicator Variable)	-0.011*	-0.005	-0.010	-0.001
	(0.005)	(0.007)	(0.009)	(0.010)
Constant	0.079***	0.074***	0.042**	0.104***
	(0.014)	(0.018)	(0.018)	(0.030)
Observations	4348	2619	1280	1339
R-squared	0.04	0.05	0.05	0.05

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses, and corrected for clustering at the branch level. This table repeats the primary specification, but ignores the contract rate. Hence, the offer rates results presented here do not disentangle selection effects from repayment burden effects as before, but rather present a reduced-form combination of the two effects. Includes controls for lender-defined risk category and month of offer letter. Including controls for loan size and term do not effect results.