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Does the Classic Microfinance Model Discourage Entrepreneurship Among the Poor? Experimental Evidence from India†

By ERICA FIELD, ROHINI PANDE, JOHN PAPP, AND NATALIA RIGOL*

Do the repayment requirements of the classic microfinance contract inhibit investment in high-return but illiquid business opportunities among the poor? Using a field experiment, we compare the classic contract which requires that repayment begin immediately after loan disbursement to a contract that includes a two-month grace period. The provision of a grace period increased short-run business investment and long-run profits but also default rates. The results, thus, indicate that debt contracts that require early repayment discourage illiquid risky investment and thereby limit the potential impact of microfinance on microenterprise growth and household poverty. (*JEL* A21, G32, I32, L25, L26, O15, O16)

Lending to entrepreneurs is a risky proposition in the best of cases. In developing countries, where borrowers often do not have collateral to seize in the event of a default, this risk is even higher. Somehow microfinance, which has expanded rapidly from its roots in Bangladesh in the late 1970s (Daley-Harris 2006), has structured debt contracts so as to limit the risk of lending to poor entrepreneurs and for that reason is considered an important tool for helping the poor.[1] Early initiation of repayment is widely considered an important means by which the classic "Grameen model" limits lending risk.[2] Yet there is growing evidence that microfinance, despite its success in achieving high repayment rates, has had little impact on microenterprise growth and poverty (Banerjee et al. 2009; Karlan and Zinman 2011; Kaboski and Townsend 2011). This is particularly surprising given substantial evidence that

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[1] The importance of microfinance as a tool for helping the poor was recognized in 2006 when Muhammad Yunus and the Grameen Bank were awarded the Nobel Peace Price.

[2] In 2008, microfinance institutions had an estimated 130–190 million borrowers worldwide and outstanding loans exceeded $43 billion (Gonzalez 2010).

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credit constraints inhibit small business expansion (Evans and Jovanovic 1989; Banerjee and Duflo 2012) and that returns to capital in this sector are high (de Mel, McKenzie, and Woodruff 2008, 2012).

This paper examines whether the immediate repayment obligations of the classic microfinance contract inhibit entrepreneurship, and therefore blunt the potential impact of microfinance, by making high-return but illiquid investments too risky for poor borrowers. To shed light on this question, we conducted a field experiment with poor urban borrowers in India that evaluates the short- and long-run effect of relaxing the liquidity demands early in the loan cycle. We randomly assigned 169 loan groups of five clients to one of two debt contracts: Clients assigned to the control group received the classic contract that required them to initiate repayment two weeks after receiving their loan, as is standard practice in microfinance (hereafter, regular contract). Clients assigned to the treatment group received a two-month grace period before repayment began (hereafter, grace period contract). All loans were individual liability contracts, and once repayment began, clients repaid at an identical frequency.

Survey data on loan use and long-run business profit showed that the introduction of a grace period led to a significant change in economic activity: Microenterprise investment was approximately 6.0 percent higher and the likelihood of starting a new business was more than twice as high among clients who received the grace period contract relative to those on the regular contract. Furthermore, nearly three years after receiving the loan, weekly business profits and monthly household income for grace period clients were, on average, 41.0 and 19.5 percent higher and these clients reported roughly 80 percent more business capital. Taken together, the profit and capital increases correspond to a monthly return of capital of 11.0 percent.[3]

These large effects of debt structure on investment behavior cannot be reconciled with perfect credit markets. Rather, they suggest an environment where clients face borrowing constraints and where illiquid investments yield higher returns, an interpretation that is supported by case study evidence. In the presence of borrowing constraints, illiquid investments are likely to be riskier since they reduce clients' ability to deal with shocks.

Consistent with this interpretation, we find evidence of heightened risk-taking among grace period clients. In the short run, they were more than three times as likely to default than regular clients. In the long run (three years after they received their loans) they reported riskier business practices which reflect a greater willingness to reduce their access to liquid funds and experiment with product and client diversification: relative to regular clients, they were more likely to extend credit to customers through loans and pre-orders and to offer a wider array of goods and services.

Thus, by limiting illiquid investment choices, the immediate repayment obligations of the classic microfinance lending model may simultaneously limit default

[3] All estimates refer to the top coded sample. A simple accounting exercise verifies that these differences, though large, are consistent with a return differential of 2 percent per month (6 percent for grace period clients and 4 percent for regular clients) generated by the initial difference in investment behavior followed by compounding of these returns over the next three years.

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and income growth. A heterogeneity analysis shows that more risk-averse clients and those with fewer means of dealing with short-term liquidity needs benefit more from a grace period contract. These results help reconcile experimental estimates of high returns to capital among micro-entrepreneurs in developing countries with the low estimated impact of microfinance on business growth of the poor. Our results indicate that, while access to credit places a binding constraint on microenterprise activity, successfully relaxing those constraints remains sensitive to the mode of credit access.

Given the higher business profits among grace period clients, it is natural to ask why most microfinance institutions (MFIs) do not offer a grace period contract at a higher interest rate as part of their loan portfolio. Indeed, survey data indicate a high willingness to pay for a grace period among a substantial portion of our study clients. To shed light on this question, we calibrate a simple model of MFI profits when it offers both a regular and a grace period contract and clients self-select across contracts. Our calibration utilizes survey data on client preferences and experimental data on their default risk. The calibration suggests that asymmetric information in credit markets is an important reason for the absence of grace period contracts: in the absence of moral hazard MFIs can break even when they offer existing clients the choice between the regular contract at 17.5 percent interest and a grace period contract at 37 percent. However, no such zero profit separating equilibrium exists if, in addition, study clients exhibit a modest amount of moral hazard and/or there is adverse selection into the grace period contract by new clients (from outside the study client pool). Thus, consistent with a large literature on asymmetric information in credit markets, it appears that the contract that maximizes MFI profits also creates inefficiencies via underinvestment.

To the best of our knowledge, this is the first paper to demonstrate how early initiation of repayment for microfinance loans may prevent high return investment by poor entrepreneurs. A small and predominantly theoretical literature examines the role of repayment frequency in reducing default in MFIs, but focuses on channels other than investment choice.[4]

In contrast, the idea that the structure of debt contracts influences entrepreneurial risk-taking and investment exists in many corporate finance models. One line of reasoning argues that longer term debt reduces risk-taking because lenders capture part of the returns of new growth opportunities (Myers 1977). On the other hand, if shareholders use risky investments as a way to capture debt-holder wealth (Jensen and Meckling 1976; Tirole 2005), shorter term debt can reduce entrepreneurial risk-taking (Barnea, Haugen, and Senbet 1980; Leland and Toft 1996). The empirical literature presents support for both mechanisms (Barclay and Smith 1995;

[4]Fischer and Ghatak (2010) show with present biased borrowers, the optimal contract (in terms of loan size) requires frequent small repayments. Fischer (2013) identifies peer monitoring as an alternative reason for low risk-taking by microfinance clients. On the empirical front, observational studies of how greater repayment flexibility affects default report mixed findings (possibly reflecting selection bias): Armendáriz and Morduch (2005) reports that more flexible repayment is associated with higher default in Bangladesh, while McIntosh (2008) finds that Ugandan MFI clients who choose more flexible repayment schedules are less delinquent. A few recent papers circumvent the selection issue by providing experimental evidence on the effect of changing repayment frequency. More frequent meeting improved new clients' informal risk-sharing arrangements and, therefore, ability to repay moderately sized loans (Feigenberg, Field, and Pande 2012). However, no change in default was observed when either loan amounts were very small (Field and Pande 2008) or group members were well-acquainted (Field et al. 2012).

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Brockman, Martin, and Unlu 2010). Consistent with our findings, these papers, and the corporate finance literature more broadly, emphasize the role of informational asymmetries in determining the optimal debt contract.

Section I describes the experimental intervention and predicted effect of a grace period contract on client investment behavior. Section II describes the data, client characteristics, and empirical strategy. Section III reports our experimental findings and compares the long-run increases in profit and returns to capital implied by our model with the existing literature. Section IV examines the viability of MFIs offering grace period contracts, and Section V concludes.

I. Background

With perfect credit markets, introducing a grace period contract should not alter borrowers' investment patterns. Microfinance, however, targets credit-constrained households. As background, we describe our experimental design and then, using insights from client case studies, identify the likely effect on investment of a grace period contract and determine which borrowers are most likely to be affected.

A. *Experimental Design*

Our study was conducted with Village Financial Services (VFS), an MFI that makes individual-liability loans to women in low-income neighborhoods of Kolkata. Between March and December 2007 VFS formed 169 five-member loan groups designated for inclusion in the study, giving us a study sample of 845 clients. Each client received an individual-liability loan varying in size from Rs 4,000 ($\sim$ \$90) to Rs 10,000 ($\sim$ \$225) with a modal loan amount of Rs 8,000.

After group formation and loan approval, but prior to loan disbursement, groups were randomized into one of two repayment schedules. Eighty-five groups were assigned to the regular VFS debt contract with repayment in fixed installments starting two weeks after loan disbursement, and 84 groups were assigned an analogous contract that also included a grace period of two months. Other features of the loan contract were held constant: Once repayment began, all groups were required to repay fortnightly over the course of 44 weeks. Repayment occurred in a group meeting conducted every two weeks by a loan officer in a group member's home (on group-meetings also see Feigenberg, Field, and Pande 2012). Both groups faced the same interest charges. However, longer debt maturity (55 as opposed to 44 weeks before the full loan amount was due) combined with the same total interest charges implied that grace period clients faced a slightly lower effective interest rate on the loan (on the potential income effect see Section IIID).

Treatment status was assigned within batches of 20 groups, determined by timing of group formation (the final batch was smaller with nine groups). No clients dropped out between randomization and loan disbursement.

B. *Should a Grace Period Influence Investment Behavior?*

Roughly three years after clients entered the experiment (and just prior to our final survey) we interviewed a random sample of grace period clients to better understand

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their experience. Here, we describe interviews with a sari seller and a tailor, representatives from the two largest occupations in our sample.

Both clients were second-time VFS borrowers and experienced business owners, and neither had non-VFS formal loans. Only the sari seller had a savings account. The sari seller repaid her loan on time while the tailor was delinquent and repaid the full loan only 24 weeks after the due date.

When asked directly how the grace period had influenced loan use, both said that the two-month delay had provided security to invest the entire amount into their businesses as opposed to setting aside a portion for initial repayment installments.[5] A two-month delay provided a sufficient buffer to expect a large enough return to cover the first installment. Expanding their investment, in turn, enabled economies of scale in purchasing inputs. For instance, the sari seller explained that she accessed larger wholesale discounts.

Both clients voiced concern about variability in market demand. Over half of the sari seller's clients bought on credit and repaid in small monthly installments. While on average she could sell Rs 3,000 worth of merchandise for Rs 3,800–4,500, during low seasons she earned as little as Rs 300 per month, which was insufficient to cover her monthly payment of Rs 500. She felt that the grace period combined with higher investment return reduced default risk during low months. In contrast, if she had invested her entire loan while on a regular contract then a low sales month soon after loan receipt might have required her to liquidate stock. Such liquidation would imply a loss, reduce subsequent earnings, and increase default risk. The tailor gave a similar account of the grace period reducing default risk during a low season.

Finally both clients stated that the grace period encouraged experimentation with new business opportunities, and increased their willingness to take on entrepreneurial risk. For instance, in addition to increasing her stock of saris, the sari seller expanded the variety of saris she was offering. Prior to the second loan, the tailor had operated his business with a borrowed sewing machine or sewing by hand. He invested the VFS loan in a sewing machine as well as in raw materials that allowed him to expand into the ready-made market. This expansion also prompted him to establish business connections in Assam, a neighboring state.

A key hypothesis that emerges from these case studies is that a grace period contract allows credit-constrained clients to access high-return but lumpy and illiquid investment opportunities. More formally, consider a three-period loan contract. A client receives a loan with principal b at $t = 0$ and owes payments of amount p_1 in $t = 1$ and p_2 in $t = 2$. There are two contract types: a grace period contract with $p_1 = 0$ and $p_2 = b$ and a regular contract with $p_1 = F \in [0, b)$, $p_2 = b - f$.

Suppose the client has access to an illiquid high-return investment with minimum investment size $i_{\min}$. An investment of $i > i_{\min} \in (b - f, b)$ pays $r \times i$ in $t = 2$ with $r > 1$. Clients can save at zero interest rate and default incurs a fixed penalty $d \geq b$. Hence, default is never optimal if the client has sufficient cash on hand.[6]

[5] Both respondents affirmed that they had saved a portion of their previous VFS loan (which had no grace period) to pay their first few installments. While the sari seller had taken the loan out for her own business, the tailor's wife had borrowed for her husband's tailoring business. Hence, for the tailor, household responses about loan use and business activity were given by the husband.

[6] We implicitly assume that outside income is unavailable or will be needed for purposes other than paying the loan in $t = 1$. Put differently, consistent with recent evidence (Dupas and Robinson 2013), we assume that the

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In this setup, only the grace period client can invest in the high-return asset. Hence, the grace period client makes positive profits (of $r \times b - b$) while the regular client makes zero profits. Moreover, the profit difference is independent of loan size.[7] While a larger loan size also allows a regular client to invest in the high-return project, at any loan size the grace period client invests more.

Which borrowers are most likely to change investment decisions when provided a grace period contract? We consider two categories of factors that are frequently discussed in the entrepreneurship literature (Hurst and Lusardi 2004). First, if high-return investments are illiquid and risky (as suggested by our case studies), then the effect of a grace period should be more pronounced among the more risk-averse and those who lack alternative income-smoothing mechanisms to buffer against short-run income shocks (such as a savings account).[8] Second, the effect of the grace period should be lower for clients that lack the skills and access to complementary markets required to succeed in entrepreneurial activities.[9] Proxies for this include business ownership at baseline and household specialization in business activity. Similarly, grace period contracts may be poorly utilized by present-biased clients (Fischer and Ghatak 2010). In our data, we unfortunately do not measure present bias and will, therefore, restrict attention to client discount rates.

To summarize, this framework raises three empirical questions. First, do poor credit-constrained entrepreneurs have access to high-return but illiquid and lumpy projects, such that a grace period changes their investment choices and profit? If yes, then does the effect of a grace period vary with observable project and client characteristics? Finally, does the introduction of such a contract increase risk for the MFI? Below, we use data from our field experiment to investigate these questions.

II. Data and Empirical Strategy

As a precursor to the empirical analysis, we describe the data sources and relevant characteristics of our sample, and provide a randomization balance check.

A. *Data*

We tracked clients for roughly three years from when they entered the study. We gathered information on household business activities, socioeconomic status, and demographic characteristics at three points in time: shortly after they entered the study (Survey 1), when they completed the experimental loan cycle (Survey 2), and two years after the experiment ended (Survey 3).

regular contract leads clients to invest some loan money in short-term informal savings that provide negligible or even negative returns.

[7] To see this, suppose loan size b is increased with p_1, p_2 scaling proportionally until $b - f > i_{\min}$. Regular clients can now invest $b - f$ in the illiquid investment for a profit of $(b - f)r - (b - f)$, but this is still below grace period clients' profit of $r \times b - b$.

[8] Suppose the illiquid investment is risky and succeeds with probability $1 - p$, reflecting either project failure or greater uncertainty as to the timing of returns. Grace period clients get a payoff of $prb - pb - (1 - p)d$ if they make the illiquid investment or a payoff of 0 if they make the liquid investment. They invest in the illiquid investment if and only if the return is high enough such that $d < \frac{p}{1-p}(rb - b)$, in which case they have higher profits and also default more often. Note that risk attitudes and income-smoothing mechanisms are likely to be correlated. Madajewicz (2011), for example, argues that client project choice and attitude to risk will vary with wealth.

[9] In our model, this translates to only a fraction of clients who have access to a high-return investment.

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We use Survey 1, which was conducted an average of eight weeks after loan disbursement, to check the balance between treatment and control groups along time-invariant characteristics and to measure the fraction of clients who invest their loans into new businesses. This survey also provides data on client characteristics that we use in the heterogeneity analysis. The loan use module in Survey 2, which was completed roughly one year after loan disbursement by 93 percent of clients, is used to study differences in short-run investment behavior. Clients reported loan allocation across the following categories: business, human capital (health and school), housing repair, food expenditure, savings, relending, and other. Finally, Survey 3 administered in 2010 (almost three years after loan disbursement) to 91 percent of clients provides long-run data on household income and microenterprise profits and assets for up to five household businesses. It also includes information on client business practices.[10]

To study delinquency and default, we tracked client repayment behavior using VFS administrative data in which repayment date and amount paid were recorded by loan officers in client passbooks and then compiled into a centralized database. Data are available through January 2010, by which date at least 52 weeks had passed since the loan due date for all groups.

As a check on VFS administrative data, we also collected repayment data from a separate logbook on meeting activities maintained by loan officers for the purpose of our experiment. The logbook recorded date of meeting, number of clients present, and names of clients who repaid at the meeting. We find similar default rates across this measure and VFS administrative data (4.9 percent compared with 5.4 percent).

B. *Client Characteristics*

The majority (75 percent) of our sample are second-time VFS borrowers and the remainder are first-time borrowers. Since VFS clients rarely drop out between the first two loan cycles, the two groups have similar demographic characteristics.[11]

A key baseline variable of interest is business ownership. A large fraction of India's urban poor rely on (informal) household enterprises. The nationally representative 2009–2010 Employment and Unemployment Survey (National Sample Survey Office 2011) reports business ownership among urban households with a female aged 20 to 60 as 57.6 percent and 60.7 percent for the poorest and second poorest quartiles respectively (the subpopulation most closely corresponding to the MFI client population). In urban Hyderabad, Banerjee et al. (2009) report that roughly 50 percent of MFI borrowers had businesses of some kind. We construct a baseline measure of microenterprise activity ("Has business") using Survey 1 data on the duration of existing household business activities to exclude businesses that were formed after loan receipt. When asked without probing, slightly more than

[10] Survey 2 was completed between January and November 2008; average time between Surveys 1 and 2 was 12 months. For Survey 3, the first wave (of 88 percent) clients were surveyed between April and July 2010, and the second wave (which tracked temporarily out-of-town clients) was completed between October and November 2010.

[11] Feigenberg, Field, and Pande (2012) find no VFS client dropout between the first two loan cycles, and that VFS client demographics, such as income, home ownership, and home size, are comparable to those of clients with similar MFIs operating in other Indian cities (Spandana in urban Hyderabad and SEWA in urban Ahmedabad). However, consistent with cross-city differences in MFI penetration, VFS clients report relatively lower rates of borrowing outside of the MFI (online Appendix Table 1, Feigenberg, Field, and Pande 2012).

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three-quarters of households reported some kind of microenterprise at the time they entered the study. When business activities were probed more extensively in Survey 3, virtually all households (97 percent) reported being engaged in some type of business activity around the time they entered the experiment ("Has Business (broad measure)").[12]

The lower rate (78 percent) is most likely to correspond to business activity elicited in other surveys. Still, business ownership in the VFS population is relatively high, which likely reflects the fact that VFS, more than many MFIs, targets entrepreneurial households.[13] In this respect, our study results most readily apply to the large subset of MFIs that screen clients on loan purpose or client occupation.

In terms of employment diversification, roughly half the households report at least one wage earner. The households also face significant risk: over the last month 62 percent report a shock to household income and 16 percent report having missed days of work due to a household shock (birth, death, or exposure to heavy rain or flood). Levels of chronic sickness—defined as having at least one household member with an illness that lasted more than three months in the previous year—are relatively high at 19 percent.

At the same time, access to savings and informal sources of credit or insurance to finance shocks is relatively limited. Only 19 percent of households have a formal savings account. Household ability to smooth shocks by liquidating assets is similarly limited. The long-run survey probed respondents on liquidation costs of selling business stock. On average households said that they could only retrieve 37 percent of their inventory's original value if they had to sell their stock in a one-day period. Paralleling this, clients report a high rate of business closure: over 35 percent of businesses that were active at baseline are reported as shut down three years later. Roughly a third of these (11.5 percent of businesses) were closed due to household member illness.

Our baseline survey provides two psychological measures relevant to entrepreneurial decision-making: risk attitudes and discount factors. Discount factor is measured from client responses to a lottery game in which she was given a choice between receiving 200 rupees now or receiving between 210 and 250 rupees in a month. The average rupee amount between the point at which the client prefers the money up front and the point at which she prefers to delay consumption is used to calculate her discount rate. The mean discount rate is 18.9 percent. A client with discount rate above the median is defined as impatient. Risk index is constructed from client responses to eight questions regarding client willingness to choose a lottery over a safe return under different levels of expected returns to the lottery. A client with risk index above the median is defined as risk-loving.

[12] The difference in reported rates of business activity across the baseline and follow-up surveys is due to additional effort we put into capturing microenterprise ventures and self-employment in the follow-up, which we believe was underestimated at baseline. We observe very significant female participation in household business—roughly 80 percent of business owners report that the female client closely manages and can answer detailed questions about at least one household business.

[13] VFS rules require that loans be used for business, and loan officers ask for business descriptions when evaluating potential clients. Such targeting is reasonably widespread among South Asian MFIs.

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C. *Randomization Check*

Online Appendix Table 1 reports a randomization balance check using Survey 1 data. In panel A, which considers only time-invariant client characteristics, treatment and control groups are imbalanced in only one out of 11 baseline characteristics (married), and a joint test of significance (χ^2) of mean differences demonstrates overall balance. Balance checks (available from authors) show that Survey 2 and 3 data remain balanced on all covariates other than marriage.

Panel B reports client characteristics that were either potentially influenced by treatment assignment or were only collected for a subset of clients due to change in survey format. Only one panel B variable—risk-aversion—is imbalanced across treatment arms. This variable is not included in the set of controls, but is used in the heterogeneity analysis. We have, therefore, verified that adding risk-aversion to the set of controls does not alter the magnitude or significance of our results and that all empirical results are robust to excluding the one randomization strata with imbalanced risk attitudes (results available from authors).

III. The Effect of a Grace Period on Business Activity

We start by describing our specification and then report average treatment effects for short-run investment decisions and long-run profits. Next, we use administrative data on client default and survey data on client business behavior to examine investment risk and long-run business practices. Finally, we examine heterogeneous treatment effects and compute returns to capital.

A. *Empirical Strategy*

Randomization of contract-type implies that differences in average outcomes across clients assigned to different contracts has a causal interpretation. Since no client dropped out after assignment, Intent To Treat estimates are the average treatment effects of being on a grace period contract. We, therefore, estimate for client i in group g:

$$y_{ig} = \beta G_g + B_g + \delta X_{ig} + \epsilon_{ig}, \tag{1}$$

where y_{ig} is the outcome of interest and G_g is an indicator variable that equals one if the group was assigned to the grace period contract. All regressions control for stratification batch (B_g) and cluster standard errors within loan groups. We report regression estimates both without and with the controls (X_{ig}) listed in panel A of online Appendix Table 1 and loan officer fixed effects.

In online Appendix Table 2 we use group-level data collated from VFS transactions records and group meeting data records (collected by loan officers) to verify compliance with experimental protocol. All clients in a loan group received their loans on the same day, at which point their first repayment meeting date is announced. Consistent with the grace period contract stipulating a period of eight weeks before the first payment, groups that received the grace period contract made

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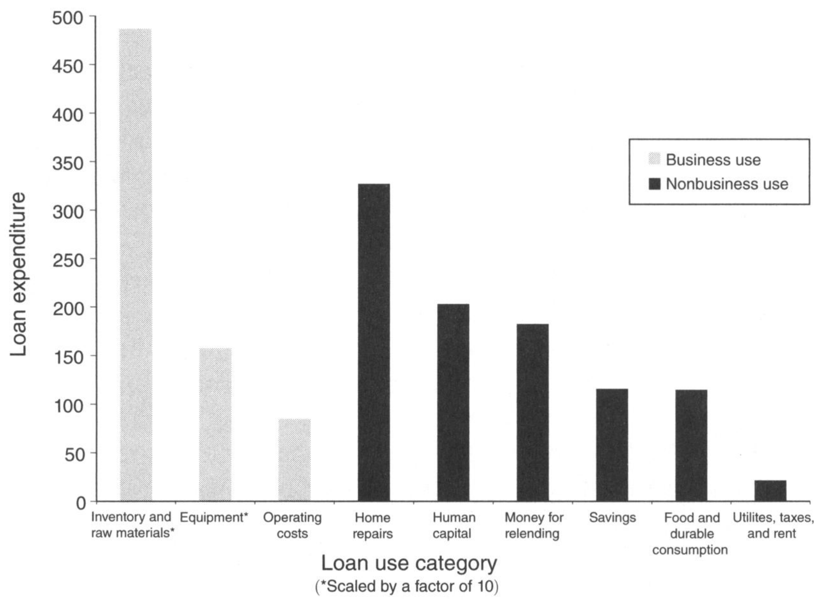

Figure 1. Category Wise Loan Use (in Rs) (*Survey* 2)

their first loan installment an average of 52 days after groups assigned to the regular contract (column 1).

Column 2 shows that, once repayment starts, the average time lapsed between two consecutive meetings is identical across the two contracts (14 days). Finally, the average repayment meeting lasted 18 minutes and was not influenced by contract type (column 3).

B. *Effects on Short-Run Investment*

Figure 1 shows category-wise spending of the VFS loan by our study clients. Over 91 percent of the clients spent at least some of their loan on business-related expenditures, and on average, a client spent 83 percent of her loan on business-related activities. Home repairs is the second largest category of loan expenditure, but only 6.2 percent of clients report spending on home repairs.

With respect to business expenditures, close to 70 percent of clients report spending on inventory and raw materials, which include the three most common expenditures: saris, wood, and sewing materials. Notably, as brought out by case studies, all of the above are relatively illiquid investments once they have been transformed. In the face of demand shocks, it may take several months to realize the returns on embroidered saris or pre-ordered goods such as tailored clothing. Consistent with this, clients who are sari sellers and tailors report that they would be able to recover an average of 34 percent and 10 percent respectively of the value of raw materials if forced to liquidate in 24 hours.

Did receipt of a grace period loan influence client expenditure decisions? Online Appendix Figure 1 plots the distribution of business spending for regular and grace

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period clients. There is more concentration of spending by grace period clients in the right tail of the business spending distribution.[14] Table 1 further investigates loan use differences by estimating equation (1).[15] The left-most column of the table shows the outcome variable of the regression. Column 1 of the table reports the mean of the outcome variable for the control group.[16] The second column of Table 1 reports the coefficient on the treatment variable in a regression without controls. The last column shows the coefficient of the treatment variable in a regression with controls.

In the first row and second column of panel A we observe that, relative to regular clients, the average grace period client invests roughly 6.0 percent (Rs 364.9) more of her loan in her business. In rows 2 through 4 we divide total business spending into inventory and raw materials, business equipment, and operating costs. While the estimates are noisy, grace period clients predominantly shift loan use toward inventory and raw materials.

Our expectation is that grace period clients finance additional investment out of money that would otherwise be set aside for initial loan payments. In row 5 we observe a significant decline in reported nonbusiness spending by grace period clients, with the decline driven by a reduction in spending on house repairs (which accounts for 58.6 percent of the difference in nonbusiness spending, row 6) and not savings (row 10). However, in-depth interviews with a random sample of six VFS clients on saving practices suggest that purchasing construction materials is actually a form of informal savings that is considered safer than keeping cash on hand. The majority (five) of clients reported incremental purchase of housing materials (including bricks and bags of concrete) which they stored for up to a month prior to construction.[17] Housing materials were preferred to cash on hand both because they are harder to steal, and because liquidation for personal consumption imposes transactions costs on household members (or clients with self-control problems). Meanwhile, compared to other investments, housing materials are very liquid (clients reported that unused materials could be readily liquidated) and highly divisible (bags of concrete vary in size and bricks are sold individually). The spending patterns are consistent with regular clients investing more of their loan in a zero-interest safe asset.

In row 12 we examine grace period effects on business formation within six months of loan receipt. New business formation is low: only 2.0 percent of regular contract clients start new businesses within the six-month period surrounding loan disbursal. However, the likelihood of starting a new business is almost thrice as

[14] A Kolmogorov-Smirnov Test shows that we can reject equality of distributions at the 0.002 level.

[15] The regressions include loan size controls (to account for loan amount) in panel A and the full set of controls in panel B. When we estimate these specifications without loan size controls, standard errors for estimated coefficients increase. The business spending measures increase in size and significance, while home repairs falls in absolute size and become insignificant.

[16] This means that the regular contract clients spent on average Rs 6,142.4 on business expenditures.

[17] Our research manager conducted these interviews in July 2012. Clients were asked whether they purchase materials for home repair incrementally and in advance of using them. If they answered yes, they were asked why they preferred this to saving money and making a bulk purchase at the time of construction. All clients reported long-term home improvement plans and all but one said that they purchase building materials incrementally as money becomes available. No households had access to a formal savings account (other than a cooperative savings account).

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Table 1—Impact of Grace Period on Loan Use and Business Formation

		Coefficient on grace period dummy (SE)	
	Control group mean (SD) (1)	OLS (no controls) (2)	OLS (with controls) (3)
Panel A. Total business spending	6,142.4	364.9**	383.9**
	(162.4)	(180.1)	(185.2)
Component-wise business spending			
Inventory and raw materials	4,521.4	337.1	367.6
	(226.3)	(279.9)	(272.8)
Business equipment	1,536.5	8.786	−14.4
	(172.4)	(234.1)	(227.1)
Operating costs	84.46	19.01	30.75
	(36.91)	(48.37)	(49.38)
Panel B. Total nonbusiness spending	1,149.1	−356.1**	−371.6**
	(149.1)	(172.4)	(178.7)
Component-wise nonbusiness spending			
Home repairs	557.2	−208.8**	−222.1**
	(116)	(105.1)	(110.4)
Utilites, taxes, and rent	25.95	−8.214	−9.657
	(15.66)	(19.9)	(20.66)
Human capital	237.9	−34.97	−33.06
	(76.88)	(90.26)	(91.99)
Money for relending	197.6	−27.42	−30.13
	(56.74)	(70.61)	(69.51)
Savings	131.6	−15.02	−10.75
	(35.97)	(47.12)	(47.48)
Food and durable consumption	151	−91.79	−94.73
	(76.21)	(94.11)	(97.86)
Panel C. New business	0.02	0.0268**	0.0258*
	(0.00648)	(0.0135)	(0.0139)

Notes: The cells in columns 2 and 3 of the table present the coefficient estimate of OLS regressions which regress loan use and business creation variables on the grace period coefficient, estimated without and with controls respectively. All regressions include stratification fixed effects and loan size, and standard errors are clustered by loan group. Column 3 regressions include all controls reported in panel A of online Appendix Table 1 and loan officer fixed effects. Missing controls are set to zero and a dummy variable included for whether the variable is missing. The dependent variables in reported regressions differ by row and are as follows: the rows under panel A include: all business expenditures and then its components (inventory and raw materials; business equipment; and operating costs). Panel B rows include all non-business expenditures and then its components (home repairs; utilities, taxes, and rent; human capital; money for relending; savings; food and durable consumption).The dependent variable in panel C is an indicator variable which equals one if the household reported having started a business up to 30 days before or up to 180 days after loan disbursal. Data in panels A and B comes from Survey 2. The Loan Use module of the survey was completed by all clients, hence the number of observations in all regressions is 845. Panel C data come from Surveys 1 and 3, and the number of observations is also 845 (see the online Appendix for variable construction details).

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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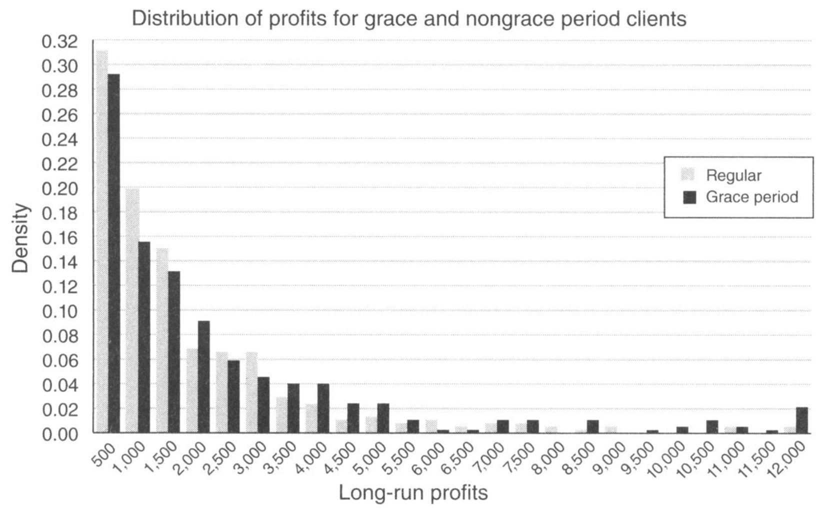

FIGURE 2. DISTRIBUTION OF LONG-RUN PROFITS DIVIDED INTO RS 500 BINS

Notes: Profits are top coded at Rs 12,000. Data come from Survey 3.

high among grace period clients.[18] These differences in business formation demonstrate treatment effects not only in the quantity of business expenditures but also on the nature of business investment since new ventures presumably entail greater risk. They also serve as a consistency check on the business spending results: since business creation was measured independently of how a client reported loan expenditures, it avoids the concern that receiving a grace period contract may influence mental accounting regarding loan use but not actual expenditures.

C. *Long-Run Effects*

Microenterprise Growth.—Does this change in investment influence microenterprise activity in the long run? We measure long-run business profits in Survey 3 by asking about both business outcomes and household income with single survey questions: "Can you please tell us the average weekly profit you have now or when your business was last operational?" and "During the past 30 days, how much total income did your household earn?"[19]

Figure 2 graphs the profit distribution for the two client groups. Relative to regular clients, those on a grace period contract are less likely to report very low (or zero) profits and more likely to report high profits.[20] In Table 2 we examine this difference

[18] For clients administered Survey 1 more than one month after loan disbursal but before the loan cycle ended, this variable is measured close to business formation. For those administered Survey 1 less than four weeks after loan disbursal, we also use retrospective data on business formation collected in Survey 3, making the indicator more noisy. Note that Survey 1 timing is balanced across treatment arms, and our result is robust to excluding clients surveyed fewer than four weeks after loan disbursal. The online Appendix describes variable construction, and online Appendix Figure 2 shows that new business formation reflects an increase in vendor business.

[19] de Mel, McKenzie, and Woodruff (2009) provide evidence that simply asking about profits provides a more accurate measure of small entrepreneur profits than detailed questions on revenues and expenses.

[20] A Kolmogorov-Smirnov Test rejects equality at the 0.077 level.

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TABLE 2—IMPACT OF GRACE PERIOD ON LONG-RUN PROFIT, INCOME, AND CAPITAL

	Average weekly profits		log of monthly HH income		Capital	
	OLS (no controls) (1)	OLS (with controls) (2)	OLS (no controls) (3)	OLS (with controls) (4)	OLS (no controls) (5)	OLS (with controls) (6)
Panel A. Full sample						
Grace period	906.6**	902.9**	0.195**	0.199**	28,770.2**	35,733.1***
	(373.8)	(370.2)	(0.0805)	(0.0782)	(11,291.0)	(13,020.6)
Observations	752	752	749	749	766	766
Control mean	1,586.8	1,586.8	20,172.71	20,172.71	35,730.2	35,730.2
	(121.8)	(121.8)	(55,972.25)	(55,972.25)	(5,056.0)	(5,056.0)
Panel B. Top coded sample						
Grace period	645.0***	640.9***	0.195**	0.202**	23,594.1***	29,068.9***
	(214.6)	(208.1)	(0.0801)	(0.0778)	(8,849.6)	(9,432.4)
Observations	752	752	749	749	766	766
Control mean	1,579.3	1,579.3	18,110.65	18,110.65	35,535.9	35,535.9
	(117.9)	(117.9)	(26,962.41)	(26,962.41)	(4,951.8)	(4,951.8)
Panel C. Top coded sample and trimmed at 1 percent						
Grace period	503.8***	486.5***	0.190**	0.199**	15,266.2**	19,010.0***
	(182.8)	(176.8)	(0.0798)	(0.0770)	(6,825.5)	(7,067.9)
Observations	748	748	744	744	761	761
Control mean	1,514.7	1,514.7	17,160.57	17,160.57	33,030.8	33,030.8
	(102.7)	(102.7)	(23,571.94)	(23,571.94)	(4,238.4)	(4,238.4)
Panel D. Top coded sample and trimmed at 5 percent						
Grace period	440.5**	452.6**	0.198**	0.207***	15,266.2**	19,010.0***
	(175.9)	(175.3)	(0.0795)	(0.0768)	(6,825.5)	(7,067.9)
Observations	747	747	743	743	761	761
Control mean	1,514.7	1,514.7	16,692.76	16,692.76	33,030.8	33,030.8
	(102.7)	(102.7)	(21,739.62)	(21,739.62)	(4,238.4)	(4,238.4)

Notes: The outcome variables are "Can you please tell us the average weekly profit you have now or when your business was last operational?" (columns 1 and 2); "During the past 30 days, how much total income did your household earn?" (columns 3 and 4). Columns 5 and 6 report the value (Rs) of raw materials and inventory plus equipment across all businesses in operation at the time of the survey. All data comes from Survey 3. Variation in number of observations for a given sample reflects missing data. The panel-wise sample is as follows: Panel A uses the full sample. In panel B the the top 0.5 percent of the cumulative distribution of the dependent variable is top coded to the 99.5th percentile value. Panels C and D use the top coded sample and exclude the top 1 percent and 5 percent of dependent variable respectively. We report OLS regressions which include stratification fixed effects and standard errors are clustered by loan group. Regressions reported in even number columns include controls presented in panel A of online Appendix Table 1 and loan officer fixed effects. If a control variable is missing, its value is set to zero and a dummy is included for whether the variable is missing.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

in profit outcomes in a regression framework. To address the concern of noise in survey responses to questions that require a high level of aggregation, we also examine top coded and trimmed specifications. In columns 1 and 2 of panel A we see that grace period clients report 57.1 percent higher weekly profits and the difference is statistically significant. In panels B through D we present additional specifications to test the sensitivity of this result to outliers. We first top code the top 0.5 percent of the cumulative distribution of profits to the value at the 99.5th percentile (panel B). Next, we trim the top coded sample to drop the top 1 percent and 5 percent of values

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of the household profits distribution (panels C and D). While the estimates retain significance, since much of the gain in profits for grace period clients occurs in the right tail, the magnitude of the estimate falls as we trim (to 29.1 percent at 5 percent trimming).

An alternative measure of business profitability is total household income, which may be measured with less noise. Consistent with the profit distributions, online Appendix Figure 3 shows a rightward shift of income among grace period clients.[21] Columns 3 and 4 of Table 2 report the difference in a regression framework (again, with the same top coding and trimming rules as with the profits variable). In column 3 we see that household income is an estimated 19.5 percent higher for grace period clients three years after loan disbursement ($\sim$ two years after the loan was due). The income results are highly robust across alternative specifications. Reassuringly, the magnitudes of the income and profit estimates are consistent, with our weekly profit estimate accounting for 92.2 percent of the estimated increase in monthly household income.[22]

Finally, we examine an important measure of business size: business capital, defined as the sum of raw materials and inventory and assets. The value of raw materials and inventory is computed from survey questions on the value of materials clients currently stock and which are used for production. We compute the value of equipment from clients' valuation of their durable assets that are used in business. Online Appendix Figure 4 shows the distribution of business capital—once again, we see a rightward shift in the distribution for grace period clients (relative to regular clients). Columns 5 and 6 of Table 2 test the significance of this difference in a regression framework. The column 5 estimate for the full sample suggests that microenterprises in grace period households are 81.0 percent larger in terms of assets and inventory and raw materials. The effect on business capital falls to 46.2 percent in the top coded and trimmed sample (panel D).[23]

Entrepreneurial Risk-Taking.—Three years after entering the experiment, grace period clients have larger and more profitable businesses. Next, we examine whether default outcomes and reported business practices suggest that higher profits entailed greater risk-taking.

The most direct measure of differences in investment risk is default rates, which reflect income realizations in Year 1 of clients' loan investment. Figure 3 graphs the fraction of clients who had not repaid in full relative to the date of first installment. The vertical bars indicate the loan due date and eight weeks after the loan was due. Relative to regular contract clients a substantially lower fraction of grace period clients had repaid in full two months after the due date.

[21] A Kolmogorov-Smirnov Test rejects equality of distributions at the 0.034 level.

[22] To calculate the increase in profits as a fraction of the increase in income, observe that column 3 shows the control mean income is 20,172.71. The treatment effect is therefore $20{,}172.71 \times 0.195 = 3{,}933.67$. In column 1, the treatment effect on monthly profits is $906.6 \times 4 = 3{,}626.4$. Thus the increase in profits accounts for $3{,}626.4/3{,}933.67 = 92.2$ percent.

[23] Grace period households also report more workers relative to regular contract households (2.89 versus 2.53 workers), though the difference is statistically insignificant. The fact that scale of business operations adjusts more rapidly than size of the microenterprise workforce is consistent with imperfect substitutability between outside and in-family labor.

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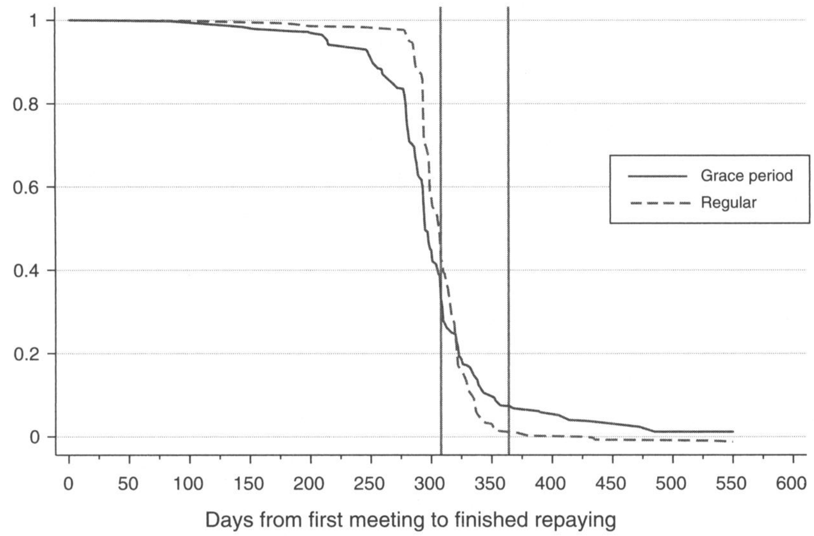

Figure 3. Fraction of Clients Who Have Not Repaid in Full Relative to the Date of First Installment

Notes: The vertical bars indicate the loan due date and eight weeks after the loan was due. The figure is constructed using administrative data and loan officer data collected at group meetings.

Table 3 examines the statistical significance of these patterns. We consider client default at three time intervals: 8, 24, and 52 weeks after loan due date (defined as the date when the final installment was due). Throughout, we observe a robust difference in default patterns between regular and grace period clients. Grace period clients are, on average, six to nine percentage points more likely to default than regular clients. Twenty-four weeks after the loan was due, 2 percent of the regular clients and 9 percent of the grace period clients have failed to repay (column 2). Even after one year, the experimental difference is roughly the same (column 3). Column 4 shows that, on average, grace period clients have roughly three times (Rs 220 versus 70) higher fraction of unpaid debt 52 weeks after their loan was due.

These patterns are consistent with differences in client investments causing grace period clients to experience a higher fraction of low business income months during the loan cycle which, in turn, increased default. A slightly different explanation that is also consistent with our conceptual framework is that, independent of income realizations, grace period clients had less incentive to liquidate assets in the event of a low profit realization in order to repay the loan because doing so entailed higher losses (both in terms of lower resale value and higher expected future returns on their assets). Unfortunately, in the absence of monthly profit data during the experimental loan cycle, we cannot directly tease these two stories apart. However, we gain some insight into this from examining patterns of business activity reported in Survey 3. As reported in column 1 of Table 4, grace period clients are less likely to report a business closure between loan disbursal and the three-year follow-up: 38.6 percent of the regular clients but only 31.4 percent of grace period clients report

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TABLE 3—IMPACT OF GRACE PERIOD ON DEFAULT

	Full loan not repaid				Repayment history		
	Within 8 weeks of due date (1)	Within 24 weeks of due date (2)	Within 52 weeks of due date (3)	Amount outstanding within 52 weeks of due date (4)	Repaid at least 50 percent of the loan (5)	Made first half of loan repayments on time (6)	Made first payment (7)
Panel A. (No controls)							
Grace period	0.0901**	0.0696**	0.0614**	148.7*	−0.0137	−0.00842	0.0288
	(0.0349)	(0.0280)	(0.0251)	(83.61)	(0.0151)	(0.0613)	(0.0261)
Panel B. (With controls)							
Grace period	0.0845**	0.0642**	0.0609**	149.0*	−0.0156	−0.0246	0.0244
	(0.0333)	(0.0262)	(0.0249)	(83.55)	(0.0159)	(0.0534)	(0.0240)
Observations	845	845	845	845	845	845	845
Control mean	0.0424	0.0212	0.0165	69.65	0.988	0.501	0.953
	(0.0142)	(0.0101)	(0.00899)	(40.15)	(0.00774)	(0.0427)	(0.0231)

Notes: The outcome variables are default rates measured at increasing number of weeks after due date (columns 1–3); the outstanding balance on the loan by clients who had not repaid within 52 weeks of the due date (column 4). The outstanding amount is defined as the loan amount plus the interest minus the 10 percent security deposit given by clients prior to loan disbursal. Columns 5 and 6 report whether clients paid at least 50 percent of their loan balance and paid the first half of their payments on time (updated as recently as January 2010) and whether they were able to make their first loan payment on time (column 7). Data from columns 1–7 comes from VFS administrative data and from data collected at group meetings by loan officers. We report OLS regressions with stratification fixed effects and standard errors are clustered by loan group. Panel B regressions include all controls presented in panel A of online Appendix Table 1 and loan officer fixed effects. If a control variable is missing, its value is set to zero and a dummy is included for whether the variable is missing.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

a business closure.[24] They also experience higher within-business variance of profits (column 2), defined as the difference in reported profits in months of high and low profits (averaged across all household businesses). Relative to regular clients, the average difference in profits between high and low months is over Rs 600 higher for grace period clients. This combination of results suggests that grace period clients were less inclined to shut down businesses when short-run profits were low or negative, either because this occurred during the grace period or because liquidation is costlier due to either the nature of assets they hold or their expectations for long-run returns. Consistent with this, grace period clients are also less likely to report having ever sold goods or services at a discount in order to meet loan repayment obligations (column 3), though the result is sensitive to the inclusion of controls.

An alternative explanation for the default result is habit formation: a grace period may prevent clients from acquiring regular payment habits or, by leading them to believe that prompt payment has fewer consequences, it may increase strategic default. However, differences in habit-formation would presumably be starkest at the onset of regular repayment when grace period clients have just had two months

[24] We constructed an alternative measure of business closure from an open-ended survey question that asked households to report changes in each business they had operated since loan disbursement. We constructed a dummy variable indicating whether a household reported having closed its business. This measure of business closure yields a similar effect (−0.04) which is significant at the 5 percent level.

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Table 4—Impact of Grace Period on Business Size and Business Behavior

	Business closure (1)	Average difference in profits between high- and low-profit months (2)	Sold goods or services at a discount to make loan payment (3)	Customers buy on credit (4)	Customers pre-order goods or service (5)	Number of goods and services provided (6)
Panel A. (No controls)						
Grace period	−0.0718**	686.6*	−0.0232*	0.0972**	0.0989***	5.543**
	(0.0324)	(375.7)	(0.0128)	(0.0373)	(0.0356)	(2.467)
Panel B. (With controls)						
Grace period	−0.0669**	713.9*	−0.0166	0.113***	0.107***	6.051**
	(0.0334)	(396.6)	(0.0122)	(0.0371)	(0.0358)	(2.566)
Observations	766	751	764	769	769	769
Control mean	0.386	2,361.6	0.0468	0.432	0.395	5.607
	(0.0243)	(242.0)	(0.0112)	(0.0270)	(0.0236)	(0.475)

Notes: The outcome variables are: whether a client reported having closed a household business that was operating at the time of loan disbursement (column 1); whether clients reported having sold their goods or services at a discount to make a loan payment (column 2); the averaged difference in profits between high- and low-profit months across all household businesses (we counted a seasonal business as a business currently in operation) (column 3); whether clients report that they had customers who bought from them on credit (column 4) ; whether clients report that they had customers who pre-ordered goods or services from them (column 5); and the number of types of goods or services clients offered to their customers (column 6). Data in columns 1–6 come from Survey 3. Variation in the number of observations reflects missing outcome data. We report OLS regressions which include stratification fixed effects and standard errors are clustered by loan group. Panel B regressions include all controls presented in panel A of online Appendix Table 1 and loan officer fixed effects. If a control variable is missing, its value is set to zero and a dummy is included for whether the variable is missing.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

off. Likewise, strategic default should be concentrated early on in the loan cycle when benefit of defaulting is highest. In contrast, columns 5–7 of Table 3 indicate that grace period and regular clients were equally likely to make their first payment and just as likely to repay at least half of the loan.[25]

Corroborating evidence on entrepreneurial risk comes from Survey 3, in which clients were asked about three types of risky business practices.[26] First, clients were asked whether they sold to clients on credit, a practice which increases business scale but without enforceable contracts. As is evident in Table 4, over 43 percent of regular clients reported in the affirmative, and this number is nine percentage points higher among grace period clients (column 4). Another risky practice that arguably makes a business more vulnerable to hold-up is allowing clients to pre-order items. Roughly 40 percent

[25] The grace period could also restrict social networking among group members and thereby increase default by lowering informal insurance. However, a group-level index of network ties between group members (constructed using survey 2 data on social and financial interactions) shows no difference across contract types. Another concern is that a grace period prevents monitoring of client activities by loan officers' ability early on in the loan cycle. However, we do not consider this to be an important channel since loan officers did not undertake monitoring activities during loan meetings or discuss clients' business activities. It is also unlikely that the difference reflects loan officer effects: Each loan officer serviced groups on both the regular and grace period contract (throughout, panel B regressions include loan officer fixed effects).

[26] Due to the occupation-specific nature of risk-taking, there were very few risk measures general enough to apply to all or most businesses. Hence these were the only direct measures of risk that were included in Survey 3.

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of regular clients allow pre-ordering, and again we see a significant increase of approximately 10 percentage points among grace period clients (column 5). Finally, in column 6 we observe that grace period clients offer a wider array of business goods and services, indicating that they are both expanding and diversifying business operations.

While these findings are consistent with the idea that grace period client businesses continued to include more illiquid investments, there is at least one other possible explanation. Since the outcomes were measured three years after the loan, we cannot identify whether risky business behavior in the long run is a direct consequence of having a grace period or an indirect consequence of grace period clients having larger and more profitable businesses in the long run. Likewise, while business income is more variable for grace period clients in the long run, this may be due to the level shift in business income, and does not necessarily mean that grace period clients experience a higher incidence of critically low-income months.[27] Importantly, this finding also suggests that a full welfare calculation for clients would require knowledge of client ability to smooth consumption.[28]

Heterogeneity Analysis.—In Section I, we identified testable hypotheses regarding which types of clients will be more likely to respond to a grace period contract by increasing their investment in high-return but illiquid investments.

In Table 5 we examine these predictions. First, we hypothesized that there should be larger treatment effects for clients for whom the risk reduction provided by a grace period is particularly valuable, including those who are relatively risk averse and those without a savings account. We see that while, on average, risk-loving clients have higher profits, they do not benefit from a grace period contract (column 1). In other words, consistent with the idea that the grace period reduces the risk associated with illiquid investments, the grace period contract benefits relatively risk-averse clients. Similarly, clients who have a savings account and therefore an alternative means for addressing short-term liquidity shocks should benefit less from access to a grace period contract. Consistent with this, we see that these clients have higher profits but no marginal gain from access to a grace period contract (column 2), although the difference between clients with and without savings accounts is large but not statistically significant.

Second, clients with short-term liquidity needs (proxied as having a chronically sick household member) and impatient clients should benefit less since their likelihood of responding to investment opportunities is lower. Columns 3 and 4 show evidence consistent with this prediction, although the effect on impatient clients is

[27] In terms of long-run profits, grace period defaulters look somewhat worse off after three years relative to non-defaulters, with 14.6 percent lower profits. However, it is hard to infer much since we lack clear predictions regarding the relationship between Year 1 default and profits in Year 3.

[28] The lack of consumption and savings data precludes a full analysis of this issue. We have examined two partial measures of consumption smoothing. First, as a summary measure of consumption the client survey conducted by loan officers during loan repayment meetings asked if the client ate fish or meat in the previous day. We see no significant difference across treatment and control clients. A second medium-term measure comes from a daily consumption survey administered for seven weeks to a random subsample (134) of the clients who took out a subsequent loan. Clients were surveyed every 48 hours on their income and expenditures (the surveying occurred roughly 15 months after they entered the experimental loan cycle). We see treatment effects on business expenditures and continue to see a decline in spending on house repairs. While the treatment group does report more savings, these estimates are very noisy and we see no significant difference in the coefficient of variation in savings. Thus, taken together, these data are consistent with treatment and control households facing similar consumption and savings volatility.

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Table 5—Heterogenous Profits

	Monthly profit (in Rs)						
Characteristic	Risk loving (1)	Savings account (2)	Household member chronically ill (3)	Impatient (4)	No household business (5)	Wage earner (6)	Heterogeneity index (7)
Panel A. Full sample; OLS (no controls)							
Grace period	1,733.1**	1,097.1**	579.9*	1,547.5**	906.2**	1,428.5**	2,984.6**
	(710.9)	(518.2)	(317.5)	(718.8)	(375.4)	(647.7)	(1,395.1)
Characteristic × grace period	−1,557.9*	−1,420.3	−1,004.3*	−1,208.8	−1,187.4**	−1,243.2*	−1,350.7*
	(795.4)	(1,071.5)	(512.9)	(794.4)	(568.9)	(743.5)	(715.2)
Characteristic	660.5**	1,247.6*	34.13	103.4	−1,366.1***	−543.5**	213.9
	(284.1)	(633.1)	(384.7)	(247.9)	(284.6)	(236.8)	(213.4)
Treatment effect evaluated at characteristic = 1 SE	175.2	−323.3	−424.3	338.6	−281.2	185.3	1,633.9
	(304.8)	(822.6)	(384.4)	(286.9)	(427.9)	(1,633.9)	(331.6)
Panel B. Full sample; OLS (with controls)							
Grace period	1,543.6**	1,075.8*	531.5*	1,512.2**	900.6**	1,399.0**	2,913.6**
	(623.8)	(552.9)	(295.8)	(665.4)	(373.4)	(622.0)	(1,293.9)
							0
Characteristic × grace period	−1,243.5*	−1,518.6	−831.1	−1,193.6*	−1,195.8	−1,203.0*	−1,310.5**
	(654.6)	(1,184.5)	(516.2)	(700.0)	(914.5)	(702.8)	(652.5)
							0
Characteristic	512.0*	1,138.2*	−134.7	−128.1	−472.9	−512.6*	124.5
	(287.8)	(634.0)	(403.8)	(354.1)	(674.7)	(275.4)	(231.3)
Treatment effect evaluated at characteristic = 1 SE	300.1	−442.8	−299.6	318.6	−295.2	196.0	1,603.1
	(311.5)	(867.4)	(420.1)	(281.0)	(989.0)	(331.6)	663.4
Observations	713	683	489	721	752	751	752
Panel C. Top coded sample; OLS (no controls)							
Grace period	1,207.7***	690.3***	589.3*	1,008.9***	643.6***	970.8***	1,903.4***
	(351.7)	(252.4)	(314.7)	(346.0)	(215.1)	(304.6)	(583.6)
Characteristic × grace period	−1,034.5**	−815.5	−1,015.8**	−649.7	−926.4*	−806.6*	−810.3**
	(478.6)	(796.8)	(509.2)	(433.3)	(484.6)	(428.3)	(318.0)
Characteristic	539.8**	1,269.5**	47.92	87.33	−1,495.9***	−554.6**	180.7
	(245.6)	(567.4)	(379.4)	(236.9)	(238.9)	(222.9)	(196.5)
Treatment effect evaluated at characteristic = 1 SE	173.1	−125.2	−426.5	359.2	−282.8	164.3	1,093.0
	(291.3)	(718.7)	(383.1)	(263.9)	(433.7)	(296.0)	(306.0)
Panel D. Top coded sample; OLS (with controls)							
Grace period	1,096.4***	625.9**	534.9*	1,020.9***	633.9***	967.1***	1,919.5***
	(339.8)	(248.4)	(294.9)	(334.2)	(209.1)	(297.8)	(564.1)
		0	0	0	0	0	0
Characteristic × grace period	−880.6*	−754.3	−839.0	−736.1*	−1,476.1*	−833.2*	−827.6***
	(464.2)	(823.4)	(513.7)	(429.8)	(789.3)	(438.0)	(306.2)
	0	0	0	0	0	0	0
Characteristic	489.1*	1,140.8**	−125.5	32.31	−646.9	−507.4**	160.5
	(257.1)	(568.7)	(400.8)	(255.0)	(551.1)	(252.9)	(203.0)
Treatment effect evaluated at characteristic = 1 SE	215.8	−128.4	−304.2	284.8	−842.2	133.9	1,091.9
	(279.3)	(738.8)	(418.4)	(260.6)	(696.8)	(298.0)	(296.6)
Observations	713	683	489	721	752	751	752
Mean of characteristic	0.515	0.190	0.190	0.494	0.0221	0.482	1.632
	(0.500)	(0.393)	(0.393)	(0.500)	(0.147)	(0.500)	(0.937)

Notes: Each panel in this table reports (column-wise) the coefficients on the regression of profits on a set of characteristic (indicated in column heading), a dummy for grace period, and the interaction of grace period dummy with the characteristic. The characteristics are a dummy for above median riskiness in a risk index (see online Appendix) (column 1); whether the household has a savings account (column 2); whether any household member had been ill for over 3 months in the 12 months preceding the survey (column 3); a dummy for having a monthly discount rate above the median (column 4); a dummy for not having any household business (column 5); and whether any household member earned wages at the time of the survey (column 6). The heterogeneity index (column 7) is the total number of characteristics (from columns 1–6) that a household possesses. For example, a household in which the client was risk loving and impatient, there was at least one wage earner, and there was at least one savings account gets a value of 4 in the heterogeneity index. Panels A and B consider the full sample while panels C and D consider the top coded sample, where the top 0.5 percent of the cumulative distribution of profits is top coded to the value of profits at the 99.5th percentile. Panels A and C provide the estimates without controls and panels B and D with controls. All characteristics, except for household business (described in the online Appendix), were measured at baseline in Survey 1. The row with "Treatment Effect Evaluated at Characteristic = 1" reports the *F*-test for whether the sum of the level treatment effect and the treatment effect interacted with the characteristic differs from 0. The standard error is reported below the point estimate. The row total "Mean of characteristic": reports the mean of the characteristic presented at the top of the column. For example, 51.5 percent of the sample is classified as Risk loving (column 1). We report OLS regressions which include stratification fixed effects, and standard errors are clustered by loan group. Panel B regressions include all controls presented in panel A of online Appendix Table 1 and loan officer fixed effects. If a control variable is missing, its value is set to zero and a dummy is included for whether the variable is missing.

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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noisily estimated. Finally, clients with more business experience and skill (proxied by having a business at baseline and having no wage earners in the household) should benefit more.[29] The estimates in columns 5 and 6 support this prediction.[30] In all cases, our results are robust across the full sample and the sample where we top code profits.

Thus, while not all clients are "responders," treatment effects are distributed across a wide fraction of the population and vary in magnitude in predictable ways according to client characteristics. The largest average treatment effects we estimate are on the subpopulation of risk-averse clients, which encompasses 48.5 percent of our sample. The estimate in row 1 of column 1 implies a 92.0 percent increase in profits among clients in this group.[31] In Section IIID, we conduct a back-of the-envelope exercise using estimated returns to capital to show that it is reasonable to anticipate differences in profits of this magnitude after three years of compounding.

To summarize our heterogeneity analysis, we construct a simple index equal to the number of "non-responder" traits a client possesses, and regress profits at endline on treatment and treatment interacted with this index of responsiveness. We include all traits in columns 1 through 6 of Table 5 other than whether a household member is chronically ill since health data are only available for 60 percent of the sample. The estimates in column 7 suggest positive and significant treatment effects among as few as 47 percent to as much as 82 percent of our sample.[32] Accounting for average profits in the corresponding subsamples, our treatment effects on the treated imply an increase in profits of 20.9 percent for the 35 percent of the sample with two non-responder traits, 70.9 percent for the 36 percent of the sample with one non-responder trait, and 109.2 percent for the 10 percent of the sample with zero non-responder traits.[33]

D. *Returns to Capital*

What do these results imply about returns to capital? Following de Mel, McKenzie, and Woodruff (2008), we estimate a linear relationship between capital and profits:

$$PROFITS_i = \beta CAPITAL_i + \alpha HOURS_i + \epsilon_i. \quad (2)$$

We instrument total capital using the grace period treatment. Following de Mel, McKenzie, and Woodruff (2008), we control for labor inputs by including hours

[29] It is possible that the absence of wage earners increases responsiveness to the grace period because these households have fewer alternative sources of income to address short-term liquidity shocks. However, as business profits are significantly lower for households with wage earners, we think the absence of business expertise and interest is likely to be the most important channel.

[30] An important caveat is that only 3 percent of our clients do not have businesses.

[31] The mean weekly profits for risk averse clients on the regular contract is Rs 1,313.81.

[32] That is, the estimated treatment effect is large and highly significant for clients with an index value of 0 or 1, and reasonably large but insignificant for clients with an index value equal to 2, indicating significant treatment effects for as few as 47 percent (clients with heterogeneity index of values 0 or 1) to as much as 82 percent of our sample (clients with heterogeneity index values of 0, 1, or 2).

[33] The mean weekly profits in the control are 1,742.29 (for zero non-responder traits), 1,540.742 (for one non-responder trait), and 1,346.67 (for two non-responder traits).

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worked as a covariate.[34] Online Appendix Table 3 reports the IV estimates. The point estimates imply monthly returns of 13.0 percent for the full sample (column 2) and 11 percent for the top coded sample (column 4). These estimates (together with the corresponding 95 percent confidence interval which are 2.4–19.7 percent for the top coded estimate and between 1.0–26.0 percent for the full sample) are consistent with existing estimates in the literature. For instance, monthly returns of 5.5 percent are estimated by de Mel, McKenzie, and Woodruff (2008), while McKenzie and Woodruff (2008) estimate returns of 20–33 percent per month for Mexican enterprises (with higher returns of over 70 percent for financially constrained firms). Dupas and Robinson (2013) find implied median returns of capital of 5.9 percent per month among Kenyan micro-entrepreneurs. Udry and Anagol (2006) report average returns of 4 percent per month in the informal sector in urban Ghana and Banerjee and Duflo (2012) estimate returns to capital for small and medium enterprises in India at 89 percent per month.[35]

Our heterogeneity analysis identified the subsample of risk-averse clients as exhibiting the largest change in profits. Using the same procedure as above, the returns to capital for this group are between 12.0 percent and 15.7 percent per month.

As a consistency check, we undertake a simple accounting exercise to gauge whether the capital accumulation rates implied by observed differences in investment are reasonable. Suppose the average regular and grace period clients invest Rs 6,100 and Rs 6,500 respectively (as we observe from the control mean and row 1 coefficient estimate in column 1 of Table 1). Further, suppose that grace period clients earn a net monthly return of $(x + z)$ percent compared with a return of x percent for regular clients. If all returns are reinvested, then the differential in capital stocks at endline three years later will be $(1 + x + z)^{36}6{,}500 - (1 + x)^{36}6{,}100$. With $x = 0.017$ and $z = 0.04$, this yields a difference of Rs 23,000, which is comparable to the difference of Rs 23,600 that we estimate (column 5 of Table 2). More generally, online Appendix Figure 5 shows that the observed capital stock differential is generated by a range of (reasonable) values for x and z, where we assume the return differential persists for all three years.[36] Furthermore, the required rates of return are reasonably robust to alternative assumptions about rate of profit reinvestment. For instance, if instead of reinvesting all profits in the business clients invested only half, then the differential would have to be 3.4 percent (11.4 percent versus

[34] Since de Mel, McKenzie, and Woodruff (2008) have a panel of observations on capital, profits, and hours worked, they first estimate the coefficient on hours worked in the pre-intervention period, and then use that estimated coefficient multiplied by post-intervention hours worked as an estimate of labor's share of profits. Both their approach and the approach used here rely on cross-sectional variation in hours worked to identify the causal relationship between hours worked and profits.

[35] One caveat is that our estimate is identified off the change in capital induced by the grace period contract, and, according to our conceptual framework, marginal investments have a higher-than-average expected return. Thus, if the composition of capital difference persists three years after loan disbursement then we are estimating the return for the high-return capital (although that is also true for some of the existing estimates).

[36] This is consistent with the fact that our evidence on differential investment composition is from the long-run survey. In results not presented, we make the more conservative assumption that the return differential persists for only three months. An initial return differential of 8 percent in the first three months followed by a return of 8 percent for *both* grace period and regular clients yields a capital stock differential of Rs 26,000. Using as a benchmark the returns estimated above, the required values of x and z are well within the interval of the estimates.

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8 percent) per month for grace period clients relative to regular clients to generate the observed capital differential.[37]

Finally, the grace period contract potentially encompasses two effects: a *portfolio* effect which makes illiquid investments more viable and an *income* effect which increases total repayment time by two months, making it easier for a client to accumulate income needed for repayment. Up to now, we have solely focussed on the portfolio effect.

The income effect is driven by grace period clients having a lower net-present value of payments relative to regular clients. Assume a client receives a loan of size b with a flat interest rate of 10 percent to be repaid fortnightly over a 44-week period starting either 2 or 10 weeks following loan disbursement. The client has access to a perfectly liquid investment opportunity with monthly return on capital $1 + r_L$ in which she invests i. Each fortnight, the client pays the required loan payment and reinvests remaining profits. We set b equal to the median loan size in our sample (Rs 8,000) and set initial investment size equal to Rs 6,500 as observed in the data. We assume that the remaining Rs 1,500 (8,000 − 6,500) are set aside to pay off the first four installments. Using a return to capital of $r_L = 0.08$, even if all returns are reinvested, the endline capital stock differential will be Rs 10,000, which is roughly half of the difference observed in the data. The subsequent monthly rate of return would have to be over 10 percent to generate the observed capital differential. While such a return is potentially plausible, it is much higher than the returns required when we allowed that grace period clients have a higher return to capital. This, combined with the facts that grace period clients exhibited higher default (which would not follow from a pure income effect) and that in qualitative interviews, clients highlighted the grace period effect, lead us to emphasize the portfolio effect.

A different type of "income effect" arises from differences in default rates which imply that, on average, grace period clients had Rs 149 more income in the form of outstanding loan payments one year after the loan due date compared with regular clients. However, even if this money were invested with a monthly return of 8 percent, the resulting difference one year later would be less than 2 percent of the observed capital stock differential (Rs 373). Hence, the difference in repayment amounts can explain almost none of the observed differences in long-run profits.

IV. The Viability of Grace Period Contract

Given the combination of higher returns and increased default among grace period clients, it is natural to wonder whether a grace period contract offered at a higher interest rate is a viable loan product. Put differently, why do so few MFIs include a grace period contract as part of their loan portfolio?[38]

[37] If we only consider the sample of responders with a heterogeneity index equal to zero or one, then we need to explain a larger capital difference (36,000 versus 23,600). However, returns to capital and the differential in initial investment as computed from the loan use survey (Rs 900 using the top coded estimated) are also higher for this group. Recall that for the full sample, we need a differential of 1.7 percent (5.7 percent versus 4 percent) in per month returns to capital for grace period versus regular clients. For this responder subset we would need a differential of 2.2 percent (6.2 percent versus 4 percent).

[38] The MFI-transparency database for 2012 shows that only 18 out of 144 MFIs (in 15 countries) offered a contract with a length of greater than two months between disbursement and first repayment. The interest rate on these

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To examine whether adverse selection and moral hazard make higher interest rate grace period loans unsustainable, we calibrate a model of MFI profits. We assume clients differ in their contract preferences and risk of default, and self select across loan contracts that differ in grace period and interest rate.

A. *Model*

Consider a regular loan contract with principal b paid to a borrower at $t = 0$. Equal-sized loan payments of m_{reg} are to be made at equal intervals from $t = 1$ to $t = T$. Define the implied interest rate of this contract r_{reg} as the interest rate r that satisfies

$$b = \sum_{t=1}^{T} \frac{m_{reg}}{(1+r)^t}. \tag{3}$$

Next consider a grace period contract in which payment of a possibly different fixed amount m_{gp} starts at $t = 2$ and ends at $t = T + 1$. The implied interest rate r_{gp} is the r that satisfies

$$b = \sum_{t=2}^{T+1} \frac{m_{gp}}{(1+r)^t}. \tag{4}$$

Denote contract type as $c = gp, reg$. A one-to-one mapping exists between m_c and r_c. Assuming full timely repayment, present-value of MFI revenue from the contracts is

$$PV_{reg}(r_{reg}) \equiv \sum_{t=1}^{T} \frac{m_{reg}}{(1+r_k)^t} \quad \text{and} \tag{5}$$

$$PV_{gp}(r_{gp}) \equiv \sum_{t=2}^{T+1} \frac{m_{gp}}{(1+r_k)^t}, \tag{6}$$

where r_k is the cost of capital for the MFI. Let $f^i_{reg}(\cdot)$ map the implied interest rate of the regular contract into a fraction of total present value of loan paid by client i. For any interest rate she faces, we can compute the fraction of the loan she will repay without knowledge of loan size.[39] Formally, in terms of realized repayment stream $m_1, \ldots, \infty$,

$$f^i_{reg}(r_{reg}) \equiv \frac{\displaystyle\sum_{t=1}^{\infty} \frac{m_t}{(1+r_c)^t}}{\displaystyle\sum_{t=1}^{T} \frac{m_{reg}}{(1+r_c)^t}}.$$

grace period contracts was higher (55 percent versus 48 percent; the average APR charged for a two-month grace period (only offered by six MFIs) is 58 percent).

[39] We take the fraction of loan to be repaid as non-random, but the analysis goes through even if $f^i_{reg}(\cdot)$ is instead the expected fraction of loan conditional on all client information known by MFI.

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We define $f^{i}_{gp}(\cdot)$ analogously for the grace period contract. To incorporate the notion of moral hazard, we assume $f^{i\prime}_{c}(\cdot) \leq 0$, such that a higher interest rate reduces repayment.

Let $u^i_c(r)$ denote client utility from selecting contract c with interest rate r. Normalize the outside option to zero. Expected profit per client from offering *only* contract c is

$$\pi_c(r_c) \equiv E[f^i_c(r_c)PV_c - B \,|\, u^i_c(r_c) \geq 0],$$

where the expectation is taken over the distribution of clients.

If, instead, the MFI offers both contracts, then expected MFI profit per client is[40]

$$\begin{aligned}(7)\quad & \pi_{gp,reg}(r_{gp}, r_{reg}) \\ & \equiv E[f^i_{gp}(r_{gp})PV_{gp} - B \,|\, u^i_{gp}(r_{gp}) \geq 0 \geq u^i_{reg}(r_{reg})] \times \Pr[u^i_{gp}(r_{gp}) \geq 0 \geq u^i_{reg}(r_{reg})] \\ & + E[f^i_{gp}(r_{gp})PV_{gp} - B \,|\, u^i_{gp}(r_{gp}) \geq u^i_{reg}(r_{reg}) \geq 0] \\ & \times \Pr[u^i_{gp}(r_{gp}) \geq u^i_{reg}(r_{reg}) \geq 0] \\ & + E[f^i_{reg}(r_{reg})PV_{reg} - B \,|\, u^i_{reg}(r_{reg}) \geq u^i_{gp}(r_{gp}), 0] \times \Pr[u^i_{reg}(r_{reg}) \geq u^i_{gp}(r_{gp})].\end{aligned}$$

The first term is profits from new clients who prefer the grace period contract to no loan but will never choose the regular contract. Its value (positive or negative) depends on the repayment rate of new clients. The second term is profit from existing clients who previously selected the regular contract but now prefer the grace period contract and captures two separate effects. First, clients who select the grace period contract may repay more or less compared with other existing clients. Second if interest rates differ across contracts, then the standard adverse selection and moral hazard effects apply. (For example, a higher interest rate may select riskier clients or may cause clients to take on riskier projects.) The third term is profits from existing clients who still prefer the regular contract (and again, depending on who opted for the grace period contract, repayment rate for this pool may be higher or lower than the original regular contract client pool).

Following the standard zero MFI profit assumption we restrict $\pi_{reg} = 0$, assume a unique interest rate r^*_{reg} consistent with zero profits exists and set r_{reg} equal to r^*_{reg}. Next, we examine if there is an interest rate r_{gp} such that $\pi_{gp,reg}(r_{gp}, r^*_{reg}) \geq \pi_{reg}(r^*_{reg})$. (To minimize clutter, we drop r^*_{reg} from subsequent expressions and replace r_{gp} with r.)

The first term in equation (7) is profit from new clients who prefer the grace period contract to no loan but who would never choose the regular contract. Our experimental data cannot evaluate this expression as participation was conditional

[40] All probabilities $\Pr(\cdot)$ are conditional on $\{u^i_{gp}(r_{gp}) \geq 0 \text{ or } u^i_{reg}(r_{reg}) \geq 0\}$.

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on a willingness to accept the regular contract. Hence, we begin by setting this term to zero, and restrict our calculation to the change in profits from existing clients when a grace period contract is introduced.

We denote profits from offering both contracts conditional on clients preferring the regular contract to no loan as $\pi_{gp,reg}(r \mid u^i_{reg} \geq 0)$. In this scenario, the change in profits from adding a grace period contract is[41]

$$(8)\quad \pi_{gp,reg}(r \mid u^i_{reg} \geq 0) - \pi_{reg}(r_{reg}) = \Pr[u^i_{gp}(r) \geq u^i_{reg} \geq 0]$$
$$\times \left(E\left[f^i_{gp}(r)PV_{gp}(r) \mid u^i_{gp}(r) \geq u^i_{reg} \geq 0\right] - E\left[f^i_{reg}PV_{reg} \mid u^i_{gp}(r) \geq u^i_{reg} \geq 0\right]\right).$$

See the Appendix for details. Equation (8) shows that to compute the change in profit, we need to calculate the difference between amount repaid by grace period clients who would select the grace period contract and amount repaid by clients who prefer the grace period contract but receive the regular contract. Multiplying this by the fraction of clients who prefer the grace period contract gives the total change in profits per client.

B. *Calibration*

Our calibration examines whether, holding the regular contract interest rate fixed at 17.5 percent, there is a grace period contract interest rate that makes a zero-profit separating equilibrium viable. To identify client self-selection across contracts we utilize data on clients' contract preferences collected in Survey 3. Specifically, each client was asked whether she (hypothetically) preferred a grace period to a regular contract at progressively increasing interest rate differentials.[42] Forty percent of clients are willing to pay an interest rate of 17.5 percent or higher for the grace period (no client is willing to pay more than 59 percent).

Recall that the difference in profit between offering a grace period and regular contract compared with offering only a regular contract is given by equation (8), rewritten here:

$$(9)\quad \Pr[u^i_{gp}(r) \geq u^i_{reg} \geq 0]$$
$$\times \left(E\left[f^i_{gp} \mid u^i_{gp}(r) \geq u^i_{reg} \geq 0\right] \times PV_{gp}(r) - E\left[f^i_{reg} \mid u^i_{gp}(r) \geq u^i_{reg} \geq 0\right] \times PV_{reg}\right).$$

$\Pr\left[u^i_{gp}(r) \geq u^i_{reg} \geq 0\right]$ is the fraction of clients who prefer the grace period contract to the regular contract when grace period contract interest rate is r. We compute $E\left[f^i_{reg} \mid u^i_{gp}(r) \geq u^i_{reg} \geq 0\right]$ using the fraction of present value of loan repaid by clients who received the regular contract but report preferring the grace period contract.

[41] All probabilities $\Pr(\cdot)$ are conditional on $u^i_{reg} \geq 0$.

[42] Our protocol was as follows: if the client stated a preference for the grace period contract at 17.5 percent, we progressively increased the hypothetical interest rate on the grace period contract until she reported preferring the regular contract.

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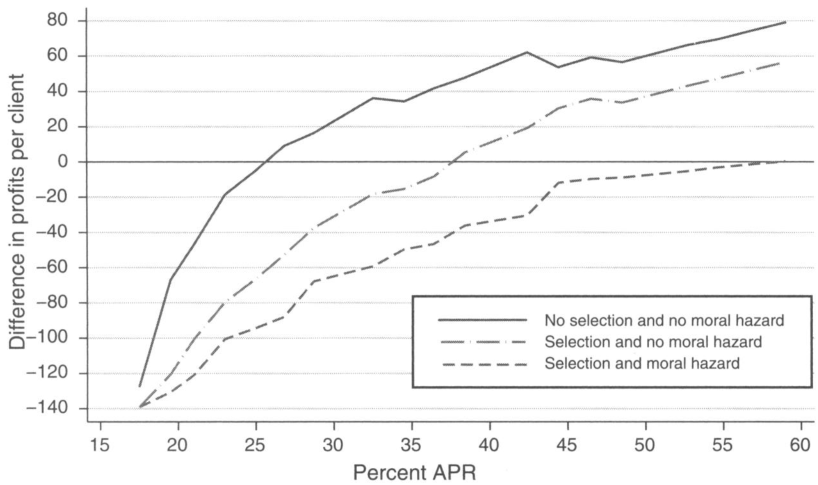

FIGURE 4. MODEL CALIBRATION RESULTS

Notes: This figure shows calibrations, under different assumptions, of the change in per client profits for an MFI which offers both a regular contract (at APR of 17.5 percent) and a grace period contract as it varies interest rates. The graph is constructed using data from Survey 3.

First, consider the case where higher interest rates introduce no additional adverse selection or moral hazard. That is, we hold fixed the repayment rates as the interest rate rises, and alter the fraction of clients who prefer the grace period contract at that interest rate using their stated willingness to pay. Hence, in equation (9) only the term $\Pr\left[u^i_{gp}(r) \geq u^i_{reg} \geq 0\right]$ varies. The solid line in Figure 4 shows that higher default by grace period clients (as documented in the experiment at 17.5 percent) along with changing client selection across contracts at higher interest rates implies that the interest rate needs to rise to at least 25 percent for the MFI to recover its losses.

Next, we allow for either adverse or advantageous selection as the interest rate rises. Specifically, at every higher interest rate we adjust both the fraction of clients choosing each contract and the fraction of present value repaid by these clients using data on their default behavior during the experiment.[43] The long dash line in Figure 4 shows that selection, on average, is adverse such that the MFI must increase the grace period contract interest rate to 38 percent. In other words, a separating equilibrium exists, though at an interest rate that is substantially higher than current rates.

Finally, we allow for moral hazard. In particular, we parameterize moral hazard using the "elasticity of the repayment rate with respect to the interest rate" (moral hazard elasticity for short) defined as the percentage fall in the repayment rate due to

[43] Note that f^i_{gp} does not change with r as we are assuming no moral hazard with respect to the interest rate—that is, a higher interest rate does not change repayment behavior. Under this assumption, we can use the repayment data for clients who received the grace period contract and report preferring the grace period contract to calculate the fraction of the present value of the loan that they repaid.

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a one-percentage-point rise in the interest rate and allow $f^i_{gp}(r)$ to vary with the interest rate of the grace period contract r. No separating equilibrium exists beyond an elasticity of 0.46, which is significantly lower than what has been estimated experimentally in other settings (Karlan and Zinman 2009).[44]

We conclude that a separating equilibrium in which both contracts are offered is unlikely to exist in many environments, both because moral hazard is likely to surpass 0.46 and because adverse selection may be exacerbated by entry of new clients who were not willing to take a regular contract but are willing to take up the grace period contract at interest rates at or above 38 percent. To gauge the response on this margin, we surveyed 13 potential clients in an existing VFS neighborhood who said that they would not take out a regular VFS loan and measured their willingness to pay for a grace period contract.[45] Four of the clients stated a willingness to pay above the MFI's break-even interest rate of 38 percent for a grace period loan. This suggests that this source of selection is likely to be important (though we cannot know ex ante whether it will be adverse or advantageous).

Finally, even if moral hazard and selection effects are moderate enough that a grace period contract is feasible, MFIs, particularly in South Asia, may find it hard to overcome regulatory and political pressures (and possibly public outcry) in order to charge an interest rate as high as 38 percent. Thus, in a wide variety of environments only offering a regular contract may be constrained efficient for an MFI.

V. Conclusion

Mirroring findings in the literature (de Mel, McKenzie, and Woodruff 2008; McKenzie and Woodruff 2008; Dupas and Robinson 2013), we identify high returns to capital for small entrepreneurs in a developing-country setting. Our evidence supports the view that liquidity constraints limit small entrepreneurs from exploiting these high returns. While much of the literature has focused on access to credit (Banerjee et al. 2009; Karlan and Zinman 2011), to our knowledge, we are the first to document experimentally the interaction between the nature of high-return investments available to the poor and microfinance contract flexibility.

[44] As a first benchmark we compute the elasticity required to make the grace period contract unprofitable when there is moral hazard but no adverse selection. At this elasticity, the additional interest payments from raising the interest rate are exactly offset by the fall in revenue from moral hazard, which occurs at an elasticity of 0.80. This elasticity provides a natural upper bound for moral hazard in existing microfinance contracts. This exercise also demonstrates the importance of adverse selection in our sample. With adverse selection, the highest the moral hazard elasticity can be without making the grace period contract unsustainable is 0.46, while without adverse selection, it is 0.80. The difference of 0.34 provides a measure of the extent of adverse selection in our sample. A second crude benchmark comes from Karlan and Zinman (2009) who find that a 1 percentage point decrease in the future interest rate decreases default by 4 percent. They do not compute repayment rates. Under the strong assumption that our estimates that defaulting decreases the rate of repayment in the treatment group by 40 percent can be extrapolated, it follows that 1 percentage point increase in the interest rate will lead to a moral hazard induced decrease in repayment of $0.40 \times 4\,percent = 1.6\,percent$. With the caveats on estimate extrapolation across contexts, our estimate of the moral hazard necessary to make the grace period contract unprofitable ($0.34 - 0.80$ depending on the level of selection) is within the bounds of the moral hazard found in Karlan and Zinman (2009).

[45] Consistent with VFS lending criteria, potential clients were screened by loan officers on age, marital status, and household income. Roughly 92 percent of respondents reported a household business. The demographic and preference results are available from authors.

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Our calibrations suggest that MFIs may not offer a higher interest rate grace period contract because of the associated adverse selection and moral hazard concerns. An open question, thus, is whether subsidizing MFIs who offer grace period contracts can encourage higher return but riskier investments among the poor. A complete answer will require knowledge of both the welfare gain to clients and the total subsidy cost to the government. Our simulation exercise provides one estimate of the second component. A subsidy of Rs 150 per client would make the MFI indifferent between only offering the regular contract and offering both the regular and grace period contracts at the baseline 17.5 percent interest rate. Calculating client welfare gains is more difficult. Ideally, we need the differential between consumption in the treatment and control groups from the beginning of the loan and a client utility function. Instead, we only observe the differential in profits at one point three years after the introduction of the loan. Under the heroic assumptions that (i) clients are risk neutral, (ii) from three years past disbursement onwards the difference in consumption is equal to the difference in profits between grace period and regular contract clients, and that (iii) prior to three years the difference in consumption is zero, the implied social rate is a return of 178 percent per year.[46]

While much more work is needed to obtain robust estimates, this back of the envelope calculation suggests that carefully targeted subsidies may well allow microfinance to alleviate credit constraints among the poor in a manner that encourages profitable investments among the poor. Related to this, we note that the typical small-business loan contract in rich countries is often significantly more flexible than a typical MFI contract and often subsidized. One such example are Small Business Administration loans in the United States which are subsidized, have relatively flexible contract terms, and default rates between 13–15 percent (compared to 2–5 percent on typical MFI loans) (Glennon and Nigro 2005).[47]

More broadly, the results in this paper suggest that evaluating the economic impact of debt contract design can provide valuable insights on entrepreneurial behavior and help identify alternative methods of reducing liquidity constraints.

[46] From Figure 4, at the baseline interest rate of 17.5 percent APR, the calibration implies that MFI profits per client drop by Rs 150 after introducing the grace period. Using the top coded client profit estimates, we perform an exercise with client profits analogous to the calibration in Section IVB comparing clients who want the grace period contract and received the grace period contract with clients who wanted the gp contract but received the regular clients. We find a difference in client profits of Rs 287. The monthly interest rate r that sets $150 = 287\left(\frac{1}{(1+r)^{36}} + \frac{1}{(1+r)^{37}} + \cdots\right) = 287\frac{1}{r(1+r)^{36}}$ is 8.9 percent which is equivalent to a return of 178 percent per year.

[47] For instance, flexible repayment options are available on Small Business Administration (SBA) loans in the United States, and typically negotiated on a loan-by-loan basis. Payments are typically via monthly installments of principal and interest. There are no balloon payments, and borrowers may delay their first payment up to three months with prior arrangement. For details, see for instance https://www.key.com/business/loans/sba-bank-loans.jsp. One reason that US lending institutions may be willing to withstand higher default rates is that SBA loans are guaranteed by the SBA. In addition, the SBA sets interest rate caps for SBA loans.

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Appendix

In this Appendix, we derive equation (9). By definition of $\pi_{gp,reg}(r_{gp}, r_{reg} \,|\, u^i_{reg} \geq 0)$ and $\pi_{reg}(r_{reg})$, we have

$$\text{(A1)}\quad \pi_{gp,reg}(r_{gp}, r_{reg} \,|\, u^i_{reg} \geq 0) - \pi_{reg}(r_{reg})$$
$$= \big(E[f^i_{gp}(r)PV_{gp}(r) \,|\, u^i_{gp}(r) \geq u^i_{reg} \geq 0] \times \Pr[u^i_{gp}(r) \geq u^i_{reg} \geq 0]$$
$$+ E[f^i_{reg}PV_{reg} \,|\, u^i_{reg} \geq u^i_{gp}(r), 0] \times \Pr[u^i_{reg} \geq u^i_{gp}(r), 0]\big)$$
$$- E[f^i_{reg}(r_{reg})PV_{reg} \,|\, u^i_{reg}(r_{reg}) \geq 0].$$

Decomposing the second term, we have

$$\text{(A2)}\quad \big(E[f^i_{gp}(r)PV_{gp}(r) \,|\, u^i_{gp}(r) \geq u^i_{reg} \geq 0] \times \Pr[u^i_{gp}(r) \geq u^i_{reg} \geq 0]$$
$$+ E[f^i_{reg}PV_{reg} \,|\, u^i_{reg} \geq u^i_{gp}(r), 0] \times \Pr[u^i_{reg} \geq u^i_{gp}(r), 0]\big)$$
$$- \big(E[f^i_{reg}PV_{reg} \,|\, u^i_{gp}(r) \geq u^i_{reg} \geq 0] \times \Pr[u^i_{gp}(r) \geq u^i_{reg} \geq 0]$$
$$+ E[f^i_{reg}PV_{reg} \,|\, u^i_{reg} \geq u^i_{gp}(r), 0] \times \Pr[u^i_{reg} \geq u^i_{gp}(r), 0]\big).$$

And finally, canceling terms yields

$$\text{(A3)}\quad \Pr[u^i_{gp}(r) \geq u^i_{reg} \geq 0]$$
$$\times \big(E[f^i_{gp}(r)PV_{gp}(r) \,|\, u^i_{gp}(r) \geq u^i_{reg} \geq 0] - E[f^i_{reg}PV_{reg} \,|\, u^i_{gp}(r) \geq u^i_{reg} \geq 0]\big).$$

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