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Liquidity defaults and progressive lending in microfinance: A lab-in-the field experiment in Bolivia

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Abstract

Many microfinance institutions (MFIs) use dynamic incentives in combination with progressive lending schemes to reduce defaults. However, the specific role of progressive lending has never been tested empirically, while observational evidence in other contexts points to potentially adverse effects. Using an experimental approach, we study the impact of progressive lending on overborrowing, attending to the possibility that progressive lending may actually increase liquidity defaults. We organize a framed field experiment in the municipality of Coroico, Bolivia, inviting 271 members of an MFI to participate in an experimental game. In Bolivia, the penetration rates of microfinance are among the highest in the world, progressive lending systems are a common practice, and the concept and practices of microfinance are well known among most people. We find that participants who borrowed over multiple rounds with progressively increasing borrowing caps showed increased liquidity defaults once the caps became unconstraining compared to those without progressive lending. We speculate that this result stems from anchoring borrowing loan requests on the credit limit set by the lender and formalize this rationale in a model for credit demand and naive borrowers.

MFIs should consider the potential perverse anchoring effects of progressive lending when designing policies aimed at reducing overborrowing.

KEYWORDS
lab-in-the-field experiment, microfinance, progressive lending

JEL CLASSIFICATION
G2; G21

1 | INTRODUCTION

Progressive lending systems—in which credit limits increase over time conditional on full repayment of previous loans—are one of the most popular instruments that microfinance institutions (MFIs) currently use to get around enforcement problems (Herring & Musshoff, 2017). Also known as "stepped" lending, this system often functions in combination with dynamic incentives, in the form of threats not to refinance defaulting borrowers. The growing popularity of progressive lending systems among MFIs is based on theoretical analyses, suggesting that progressive lending may help to reduce *strategic* defaults if the threat of no further financing is credible (Armendáriz & Morduch, 2000, 2010; Diagne et al., 2000; Egli, 2004; Ghosh & Ray, 2001). However, whereas these theoretical models suggest the positive effects of progressive lending systems, empirical evidence confirmed that a "stepped" lending system does indeed reduce defaults, which is very scant.[1] In other contexts, such as that of credit cards and consumer borrowing, the potential adverse effect of anchoring to borrowing and repayment limits on indebtedness has instead been widely shown (e.g., Gross & Souleles, 2002; Keys & Wang, 2019; Soman & Cheema, 2002; Stewart, 2009). If microfinance borrowers anchor to progressively increasing lending limits, the effect on overborrowing (and thus involuntary liquidity defaults) may at some point trump the expected beneficial effect on strategic defaults.

This paper contributes to the microfinance literature by presenting the first *experimental* analysis to probe the impact of progressive lending on defaults. In particular, we organized a lab-in-the-field experiment in Bolivia to gauge the effects of progressive lending in a microfinance context, inviting 271 members of a microfinance organization across 12 rural communities in the Coroico municipality to participate. As an experimental setting, Bolivia is ideal, because the country features some of the highest microfinance penetration rates in the world (Schipani, 2012), with progressive lending systems as common practice, and widespread familiarity with the concept and practices of microfinance among its population, including the participants in our games. Nonperforming loans in the Bolivian microfinance sector hover between 1% and 4% of the total loan portfolio (Heng, 2015), but no information is available to determine which portion of those is due to strategic decisions by the borrower and what instead was caused by overborrowing or unanticipated negative economic shocks.

Our analysis reveals that progressive lending may indeed increase *liquidity* defaults. Interestingly, our results also suggest that progressive lending, with stepwise increasing credit limits, is inferior to a system with constant, high, credit limits. We further present a formal model arguing that progressive lending will increase liquidity defaults if the increasing credit limit set by the MFI in different loan cycles is not in line with actual future repayment possibilities of the borrower, but the borrower's current demand for microcredit is partially determined by it (i.e., anchoring). This is especially problematic if the borrower gains increasing confidence in the credit limits set by MFIs as a predictor of his or her future repayment possibilities. Overall, this evidence suggests that if MFIs are concerned about defaults, it may be better to rely on a simpler dynamic incentive system without stepwise credit limits.

Section 2 details the experimental design and sampling. Section 3 explains the empirical strategy. Section 4 presents the main results, and Section 5 develops a model that provides a simple mechanism to formalize the main outcomes of our experimental analysis. Section 6 concludes.

2 | THE EXPERIMENT

The lab-in-the-field experiment was conducted in December 2015 in Coroico, a municipality in the region of Yungas in Bolivia. In this region, five MFIs are active. We invited 271 people from 12 communities to participate in a behavioral game and then organized two daily sessions at central locations in each community (one in the morning and one in the evening). Selected participants were notified a day in advance by a community head.

During the game, participants had to sort four colors of pasta into cups. If correctly filled with a single color of pasta, these cups could be sold at the end of each round for 5 Bs (slightly less than 0.15 Euro). At the beginning of the experiment, each participant received a bag filled with mixed pasta, common in Bolivia, in four colors: orange, white, yellow, and green. The supply per participant was more than twice the highest amount anyone ever sorted in 4 min during a previous pilot test—thus virtually unlimited. Before they started sorting the pasta, participants had to buy empty cups, for 2 Bs each. They did not have an initial endowment, so they had to borrow from a bank, which offered short-term loans that had to be repaid at the end of each round with an interest rate of 50% (i.e., borrow 2 Bs, repay 3 Bs). The act of filling cups of only one color required participants to “sort” the right pasta and thus prevented people from filling hastily: it was not an exercise of brute force but rather one of careful selection that required relative physical capacity and mental focus. Simultaneously, it was easy enough for anybody to perform it. No savings were available; money could not be transferred from one round to the next, so in each round, participants had to rely on credit to buy the cups. If the short-term debt and interest were repaid in time, the gain per cup sorted equaled 2 Bs (5 – 2[1.5]). In the case of default, participants were not allowed to buy in the next round, mimicking a standard dynamic incentive setting.

We played four rounds, with exactly 4 min in each session. After each round, the cups with sorted pasta were emptied back into the bags of mixed pasta, and the contents of the bag were thoroughly mixed. To limit strategic behavior (and defaults), we did not inform the participants about the number of rounds in advance, though they were informed about the time per round. In several preliminary pilot tests we determined that the production capacity of participants likely would range between 6 and 10 cups per round. Given the game specifics, participants would not be able to repay the loan (liquidity default) if they overborrowed by more than 50% of the cups they actually managed to fill.[2] For the test of the impact of progressive lending on liquidity defaults, we randomly assigned participants to one of three different short-term debt contracts, as detailed in the following three treatments:

> **Treatment 1**: *progressive lending system* (*T1*). In line with common microfinance policies in Bolivia, credit limits increased gradually. In the first round, the credit limit was set at 6 Bs such that participants could borrow for only up to three cups (highly credit constrained). In the next rounds, the debt limits were set at 12, 18, and 24 Bs, respectively. The limit of the last round was deliberately set higher than the expected optimal borrowing level, based on pilot tests.

Treatment 2: *no borrowing limit (T2)*: participants could borrow whatever they want in all rounds.

Treatment 3: *high credit limit (T3)*: 24 Bs in all rounds; higher-than-expected optimal borrowing.

That is, though our main aim for this experiment is to compare the progressive lending system with a system without credit limits, as a further test of learning behavior, we also consider a treatment in which the bank always uses a nonconstraining, high credit limit of 24 Bs, equal to the credit limit in the last round of the progressive lending system. If no anchoring takes place, and the high credit limit of round 4 is indeed not constraining for anyone, we should expect borrowing and default rates in round 4 to be the same across the three treatments. Instead, if borrowers are “naive” about their credit necessities, they may anchor on credit limits. We hypothesize that in a progressive lending setting, anchoring to the credit limit persists as a naive prior gets updated by evidence that any previous round credit limit resulted in a credit constraint (less than optimal borrowing). If so, as the lending cap surpasses optimal lending, the probability of overborrowing and liquidity defaults may be higher in a progressive lending system than in a system without or with high credit limits.

In this experimental setting there is only one bank, which does not provide new loans to defaulting subjects. This is equivalent to a scenario where all banks communicate seamlessly and blacklist any defaulter instantly across the whole banking system. However, we also consider a setting that includes three separate banks: participants could borrow at the same time from all three banks; those who had not fully repaid their debt to one bank could borrow in the next round from that bank only. For this case, we set the credit limits per bank, in both the progressive lending system and the high credit limit system, to equal one-third of the credit limits set in the single bank treatments; that is, the total limits were the same. Thus, in total we considered six treatments. We randomly selected a group of four of the six treatments for each community. After determining these treatments for each community, participants in each community were randomly allocated to one of them, in a between-subject experimental design.[3]

3 | SAMPLE, BALANCE, AND SPECIFICATIONS

Table 1 presents the samples per treatment in the first and the last rounds of the experiment. As mentioned earlier, default from all banks in the system meant being excluded for the next rounds; therefore, the sample size decreased slightly over rounds.

Since the sample sizes of the different treatment groups are relatively small, the randomization may have resulted in unbalanced groups. Fortunately, balance tests indicate that the randomization

TABLE 1 Sample size per treatment group

	No limit		High limit		Progressive lending	
	Round 1	**Round 4**	**Round 1**	**Round 4**	**Round 1**	**Round 4**
One bank	45 (9)	43(9)	45 (9)	40(9)	45 (7)	43(7)
Three banks	46 (9)	46 (9)	45 (9)	45 (9)	45 (7)	43(7)

Note: Number of communities per treatment appears in parentheses.

worked well; as Table 2 shows, there are no differences per treatment group in terms of age (*Age*), sex (*Female* = 1), or years of education (*Years of Education*).

To test the impact of the progressive lending system, we conducted simple posttreatment ordinary least square regressions,[4] separately for the system with one bank and the system with three banks. The main dependent variable is overborrowing (*OB*), defined as the fraction of total loans not used productively. Our main specification is

$$OB = \alpha T1 + \beta T3 + \vartheta Age + \theta Sex + \mu EDUC + \sigma CD + \varepsilon, \tag{1}$$

such that we include *Age*, *Sex,* and *EDUC* to improve the precision of the estimates. Furthermore, *CD* is a vector of community dummies, added to control for differences in community characteristics. We estimate this equation for rounds 1 and 4 and thus can study the consequences of progressive lending when credit limits are restricting (round 1) and too high (round 4). Again, we consider both the system with one bank and the system with three banks.

4 | EXPERIMENTAL RESULTS

Table 3 presents the average profits per round for each of the treatments, in Bolivianos. It is self-evident how progressive lending curbs profits for participants in the early rounds, as a result of its higher credit constraints. At later rounds, with nonbinding credit constraints for all treatments, profits are instead similar across all treatments.

Figure 1 shows the share of participants overborrowing in each of the rounds, across treatments. Here and later we define overborrowing as a dummy for participants who borrowed to purchase more cups than they could sort within the 4-min period in each round and thus did not yield returns (cups

TABLE 2 Treatment groups

	N	Age	Female (%)	Years of education
No limit—one bank	45	42.07 (17.80)	0.55 (0.50)	7.98 (3.92)
High limit—one bank	45	40.81 (16.74)	0.58 (0.50)	5.45 (3.90)
Progressive lending—one bank	45	46 (16.05)	0.62 (0.49)	5.82 (3.94)
No limit—three banks	46	40.66 (16.15)	0.54 (0.50)	7.98 (4.75)
High limit—three banks	45	44.62 (17.39)	0.58 (0.50)	7.76 (5.06)
Progressive lending—three banks	45	46.43 (16.39)	0.56 (0.50)	7.43 (4.46)
Total	271	43.53 (16.76)	0.57 (0.50)	7.105 (4.46)
F-test		1.01 (0.4133)	0.14 (0.9820)	5.36 (0.374)

Notes: Standard errors are in parentheses for the mean; *p*-values are in parentheses for *F*-test.

TABLE 3 Profits

	No limit		High limit		Progressive lending	
	One bank	**Three banks**	**One bank**	**Three banks**	**One bank**	**Three banks**
Round 1	7.3	7.9	6.7	9.5	5.0	6.7
Round 2	9.3	11.8	9.3	10.7	8.4	8.7
Round 3	9.4	14.0	11.0	9.9	10.6	10.4
Round 4	9.5	10.7	11.5	11.5	9.3	13.1
Overall mean	8.9	11.1	9.7	10.4	8.3	9.8

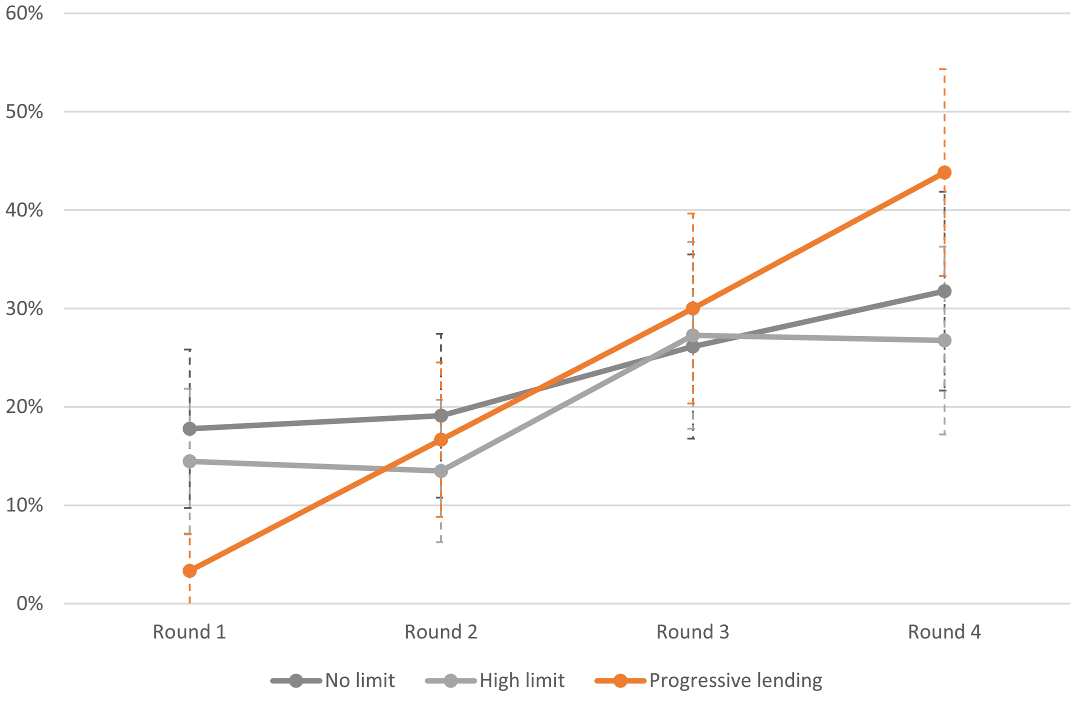

FIGURE 1 Overborrowing. Error bars indicate 95% confidence intervals

not completely sorted could not be sold at a profit). Obviously, in round 1 progressive lending participants had a much lower likelihood of overborrowing, as most of them were severely credit constrained (could borrow only up to three cups). Instead, as the lending cap is relaxed over the rounds, the progressive lending treatment seems to show a larger share of participants' overborrowing. As already mentioned, we are most interested in the outcomes of round 4, as this is the first round in which borrowing conditions between progressive lending borrowers and high-limit borrowers were identical (and thus all differences should stem from the different caps they experienced in previous rounds). Next, we will test this overborrowing difference parametrically.

Table 4 presents the results of our regression analysis, in which we cluster standard errors at the community level (12) and correct the standard errors for the small number of clusters (Cameron et al., 2008). The significance of high limits and progressive lending reflects whether there is a difference in overborrowing relative to the system without credit limits (given by the constant). Columns

TABLE 4 Impact progressive lending on overborrowing

Variables	(1) One bank: Round 1	(2) One bank: Round 4	(3) Three banks: Round 1	(4) Three banks: Round 4	(5) Pooled: Round 1	(6) Pooled: Round 4
Progressive lending	0.00	0.09^{***}	-0.06^{**}	0.04	–0.03	0.06^{**}
	(0.025)	(0.029)	(0.025)	(0.028)	(0.021)	(0.023)
High limit	0.03	0.02	–0.04	-0.06^{***}	–0.00	–0.02
	(0.045)	(0.032)	(0.036)	(0.019)	(0.033)	(0.018)
Age	0.00	0.00	0.00	-0.00^{*}	0.00	–0.00
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sex	–0.00	–0.03	0.02	–0.01	–0.01	–0.03
	(0.026)	(0.032)	(0.021)	(0.022)	(0.018)	(0.018)
Education	–0.00	0.00	0.00	–0.00	0.00	–0.00
	(0.004)	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)
Three banks					–0.02	–0.00
					(0.021)	(0.019)
Constant	–0.02	–0.01	–0.05	0.22^{***}	0.01	0.14^{**}
	(0.062)	(0.082)	(0.091)	(0.080)	(0.051)	(0.054)
No limit mean	0.068	0.051	0.052	0.066	0.059	0.059
Observations	122	114	132	130	254	244
R^2	0.435	0.253	0.110	0.278	0.199	0.163
p-Value Wald test high limit = progressive lending	0.041	0.07	0.56	0.004	0.26	0.004

Notes: Cluster robust standard errors estimated using the wild cluster bootstrap method (with the community as the cluster) are in parentheses. Community dummies are added to all equations.

*** $p < .01$; ** $p < .05$, and; * $p < .1$.

TABLE 5 Impact progressive lending on liquidity defaults

Variables	(1) One bank: Round 1	(2) One bank: Round 4	(3) Three banks: Round 1	(4) Three banks: Round 4	(5) Pooled: Round 1	(6) Pooled: Round 4
Progressive lending	–0.00	0.07**	–0.03	0.05*	–0.02	0.06***
	(0.007)	(0.029)	(0.025)	(0.025)	(0.016)	(0.021)
High limit	0.01	0.02	0.00	0.00	0.006	–0.00
	(0.011)	(0.019)	(0.021)	(0.011)	(0.021)	(0.012)
Age	0.00	0.00	0.00	–0.00	0.00*	0.00
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sex	–0.01	–0.06**	0.01	–0.01	–0.01	–0.03*
	(0.012)	(0.031)	(0.018)	(0.021)	(0.011)	(0.018)
Education	–0.00	0.00	0.00	–0.00	0.00	–0.00
	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Three banks					–0.01	–0.01
					(0.012)	(0.015)
Constant	–0.03	–0.04	–0.10	0.06	–0.07	0.00
	(0.050)	(0.044)	(0.084)	(0.070)	(0.05)	(0.037)
No limit mean	0.022	0.000	0.020	0.000	0.021	0.000
Observations	122	122	133	133	255	255
R^2	0.229	0.135	0.092	0.136	0.081	0.084
p-Value Wald test high limit = progressive lending	0.27	0.10	0.16	0.05	0.14	0.009

Notes: Cluster robust standard errors estimated using the wild cluster bootstrap method (with the community as the cluster) are in parentheses. Community dummies are added to all equations.

*** p <.01; ** p <.05, and; * p <.1.

1, 3, and 5 show overborrowing for high and progressive lending limits compared to a base scenario without borrowing limits (control). Progressive lending reveals significantly lower overborrowing in round 1 only in the case of multiple banks, but pooling the results yields insignificant differences compared to the no-limit treatment. Similarly, a Wald test comparing the coefficients for high limit versus progressive lending in round 1 cannot reject the null of no difference in overborrowing between these treatments in the pooled sample (p =.26). In other words, while progressive lending obviously limits the borrowing amount and thus overborrowing in round 1, in the other two treatments with nonbinding limits, participants seem to do no worse. This result could be explained by initial cautious approaches to borrowing by participants, in line with risk-averse investment strategies.

The most interesting outcomes appear in round 4 (columns 2, 4, and 6): a progressive lending system leads to more overborrowing once the credit limit is not restrictive anymore. This result is strongest under the one-bank scenario (column 2) and is confirmed statistically significant over the pooled sample (column 6). Compared to the control group mean of around 6% of participants overborrowing, progressive lending leads to an additional 6%—statistically significant at the conventional 5% level. Furthermore, progressive lending performs significantly worse than high constant lending limits[5]: comparing the coefficients for high limit versus progressive lending in round 4 rejects the null of no difference in overborrowing for one bank, three banks, and the pooled sample (columns 2, 4, and 6).

Next, we test whether progressive lending increases the probability of liquidity defaults. We define liquidity defaults by a dummy, equal to 1 if the borrower had no other option than to default on the loan because of a lack of liquidity. Table 5 presents the results of a series of posttreatment linear probability regressions. Defaults are very rare in our experiment, around 2% across all treatments and rounds (columns 1, 3, and 5), in line with the low default rate (1%–4%) of Bolivian MFIs (Heng, 2015). By round 4 instead, there are significantly more liquidity defaults under a progressive lending system than in a dynamic incentive system without stepped lending with either one or three banks (see columns 2 and 4). Pooling the bank scenarios in round 4 (column 6)—when progressive lending caps are identical to the high limit—produces around 6% defaults for progressive lending, significant at the 1% level, against nihil for the treatment without limit. Similarly, progressive lending leads to greater defaults than the equivalently capped treatment 3 (high limit), with the same borrowing cap but a different lending cap history: a Wald test comparing these coefficients in round 4 is significant at the 1% level.[6] Rather than incentivizing virtuous borrowing, progressive lending seems to drive greater overborrowing and more frequent liquidity defaults. In the next section we try to provide a formal model to explain this outcome pointing to a possibly counterproductive microfinance practice.

5 | A THEORETICAL MODEL

In this section, we construct a simple model to help explain the main result of our experimental analyses. Note that our aim is not to capture all channels by which a progressive lending system might affect defaults in one encompassing model; rather, we aim at presenting a theoretical model that can identify an important condition that might cause progressive lending systems to enhance defaults in the short run, in line with our experimental results. Traditional arguments state that a progressive lending system may reduce *strategic* defaults, which can be explained by the following simple model. Assume a setting with two periods, an investor/borrower and an MFI. The investor wants to run an investment project, which provides a return of $y > 1$. However, the investor has no possessions and needs to borrow 1 from the MFI to conduct the project. The loan needs to be repaid in the second period, including some interest. There is asymmetric information between the investor and the MFI, and therefore a possibility of strategic defaults, which may set a maximum limit on the lending rate

R (including repayment) that the MFI can charge from the borrower. Assume that the probability of being refinanced by the MFI in case of a default equals v. The expected payoff of the investor if he or she defaults equals $y + vy$, abstracting for simplicity from discounting. If the investor repays, his or her expected payoff will be $y - R + y$. The investor will repay only if $y - R + y > y + vy$ or if $R < y(1 - v)$. It is immediate that fully denying access to future funds (dynamic incentive), which corresponds to $v = 0$, will provide the maximum threat and reduce *strategic* defaulting as much as possible. It is easy to show that the threat of nonrefinancing becomes even bigger with a progressive lending system with increasing credit limits. However, it is also clear that competition between MFIs will undermine the threat of nonrefinancing, as there will be outside options to refinance, which will increase the value of v.

If we accept the fact that dynamic incentives help to reduce *strategic* defaults and that MFIs for this reason use progressive lending, as this makes the threat of nonrefinancing ever stronger, how can we explain the result of our experiment? Our experiment clearly shows that when banks do not provide new loans after a default, defaults still occur and that these defaults are even higher if the dynamic incentive is combined with a progressive lending system. However, note that our experiment does not actually suggest that progressive lending leads to more strategic defaults; the experiment suggests that progressive lending leads to more overborrowing, so if anything, progressive lending leads to more *liquidity* defaults. Therefore, we argue that even if progressive lending may help to reduce *strategic* defaults, it may increase *liquidity* defaults. The following model suggests a mechanism that can explain why progressive lending systems may indeed increase liquidity defaults.

Assume that there are risk-neutral smallholders and an MFI. Farmers use inputs (e.g., fertilizer, farm chemicals, machinery, and/or seeds) for the production of consumer goods (Y). At the beginning of each period, the farmers buy a certain amount of inputs. Because they do not possess wealth, the funds needed to buy these inputs must be borrowed. The MFI offers two nearly identical dynamic incentive loan contracts that exclude defaulting farmers from future loans; the only difference between the type 1 and type 2 debt contracts is that type 2 contracts contain a progressive lending clause (in line with our experiment discussed earlier).

We assume that the dynamic incentives used by the MFI, for both loan contracts, are “strong” enough to preclude strategic defaults. Thus, for simplicity, we abstract from modeling strategic defaults explicitly. We also assume that there are no outside options, so that defaulting farmers have no options to borrow from other banks. This is, of course, not fully in line with reality, but it enables to concentrate on the main mechanism we want to explore.

Then, let D be the amount borrowed, M the actual amount of inputs bought, and p_m the (fixed) price of intermediate goods such that

$$D = p_m M. \tag{2}$$

At the end of each period, the amount borrowed must be repaid (R) to the bank, including a small fixed interest (r) on the loan:

$$R = (1 + r)D. \tag{3}$$

The intermediate goods must be transformed into consumer goods before they can be sold. The maximum amount of intermediate goods that can be thus transformed depends on labor productivity, or.

$$M^* = a, \tag{4}$$

where the (fixed) labor supply, for reasons of convenience, is normalized to 1 and a denotes labor productivity as a random variable, reflecting the firm's ability to transform intermediate goods into final consumer goods. Firms are unsure about their ability a.

The amount of production that can be sold is

$$Y = Min\left[M^*, M\right]. \tag{5}$$

Assuming a fixed consumer price P, and

$$PY - P_m M^* \,(1 + r) > 0, \tag{6}$$

profit-maximizing firms try to produce as much as possible and borrow just enough to be able to buy the required amount of intermediate goods (M^*). With neither storage nor saving possibilities, in each period, farmers need to borrow again to buy the necessary inputs, so they also try to avoid overborrowing (OB) (which would lead to liquidity defaults), as denoted by

$$OB = P_m \,(M - M^*). \tag{7}$$

We next turn to the determination of the random ability variable a, which could take two values: $a = H$ with probability p and $a = L$ with probability $1 - p$. The expected value of a is

$$E(a) = pH + (1 - p)\,L. \tag{8}$$

A risk-neutral farmer confronted with a debt contract of type 1 (no progressive lending) would borrow an amount equal to $E(a)$:

$$D = pH + (1 - p)\,L. \tag{9}$$

Next, we introduce a system of progressive lending (debt contract type 2), in which the lender gradually increases the maximum amount a farmer can borrow, and compare this alternative system against a normal lending system. We assume a sequence of borrowing limits in the progressive lending system. In the first credit cycle of the stepped lending system (period 1), the MFI, in line with common practice and without access to the credit histories of the new clients, offers very small loans to "test" the creditworthiness of the agent. During this testing phase, the borrower faces a constraining credit limit, such that the amount he or she is allowed to borrow is below the optimal amount. In period 1 (which may include several initial credit cycles), the MFI sets a low credit limit. In the next period, the MFI sets a higher borrowing limit; subsequently, the credit limit might even be ignored, such that nondefaulting firms can borrow whatever they want.

We assume, again in line with the experiment, that the farmer uses the borrowing limit (B) set by the microfinance organization as a signal for what the farmer is able to produce. This assumption is in line with practice in many developing countries, where smallholders in rural areas often have imperfect knowledge about production capacities (e.g., land size is not exactly known; quality of the tree crops, such as cocoa trees, is unknown; weather predictions are uncertain). Financial intermediaries often have better information about these issues. Similar outcomes can be obtained if the borrowing limit set by the MFI provides a signal for the amount of goods a farmer could sell at the local market, and firms would use the expected demand for goods as an indicator for the amount of goods they would like to produce. Refer to Gervais et al. (2011) for a similar method of modeling information, in a different setting.

In particular, we assume that the signal B is given by

$$B = \partial a + (1 - \partial)\, e, \tag{10}$$

where $\partial = 1$ with probability $\alpha \in (0, 0.5]$ and $\partial = 0$ with probability $1 - \alpha$. Furthermore, e is a random variable, independent from a but with the same distribution function, such that with a probability p, the variable e takes a value of H, and with a probability $(1 - p)$, it takes a value of L. Because e is independent from a, the signal is assumed to be useful only if $\partial = 1$, which happens with probability α. The equation thus implies that the signal can take two values: low or high. At the beginning of each period, the borrower observes the signal (i.e., borrowing limit) and decides how much to borrow. This borrowing decision depends on the minimum of the borrowing limit or the expected (conditional) value of productivity determined at the end of the previous period, such that

$$D_{pl} = Min\, |B; E\, \langle a|B \rangle| \,. \tag{11}$$

At the end of the period, after both borrowing and production have been realized, the farmers update their beliefs regarding productivity.

We assume that the farmer overestimates the reliability of the signal set by the MFI and accordingly assigns it a probability $\alpha + h$, where $h \in (0, 0.5]$, which implies that the farmer considers that, with a probability of $(1 - \alpha - h)$, the signal has a value equal to the random variable e. Because the "signal" is set by the MFI, a positive value for the parameter h implies that the farmer overestimates the ability of MFIs to predict productivity when the signal turns out to be accurate. In this sense, h reflects "overconfidence" in the predictive ability of the MFI. We assume that borrowers gradually increase their confidence in this predictive ability, such that the parameter h increases over time. Thus, we assume that borrowers in a progressive lending system gradually increase their confidence in the predictive ability of MFIs over time.

If an MFI using a progressive lending systems sets the borrowing limit in the first period at a low level, equal to the low level of the random productivity $a = L$ to ensure that nobody overborrows, then the borrowing limit restricts borrowing to the low level of L. Again, the borrowing decision depends on the minimum of the borrowing limit or the expected productivity of the previous period, which in this case is given by the *unconditional* expected value given by Equation 11, so the borrowing limit ultimately determines how much is borrowed. Thus,

$$D_{pl,1} = B_1. \tag{12}$$

However, as borrowers continue to use the borrowing limits as signals of the capacity of the output market, they will adjust their beliefs about a, given the signal, at the end of the period. If the borrower has received a low signal, $B = L$, their posterior beliefs about a become

$$\Pr(a = H|B = L) = \frac{\Pr(B = L|a = H)\Pr(a = H)}{\Pr(B = L|a = H)\Pr(a = H) + \Pr(B = L|a = L)\Pr(a = L)}. \tag{13}$$

The a priori (unconditional) probabilities are

$$\Pr(a = H) = p; \Pr(a = L) = 1 - p. \tag{14}$$

If $a = H$, the probability that the signal is L is

$$\Pr(B = L|a = H) = \left(1 - \alpha - h_1\right)(1 - p). \tag{15}$$

In this case, the signals can be low only if the value of e is low, which happens with a probability of $(1 - p)$, and $\delta = 0$, which results with overconfident borrowers with a probability of $\left(1 - \alpha - h_1\right)$, where the subscript 1 denotes the first period. In turn,

$$\Pr(B = L|a = L) = \alpha + h_1 + \left(1 - \alpha - h_1\right)(1 - p). \tag{16}$$

Substituting Equations 14–16 into Equation 13 produces

$$\Pr(a = H|B = L) = \left(1 - \alpha - h_1\right)p, \tag{17}$$

and it follows that

$$\Pr(a = L|B = L) = 1 - \left(1 - \alpha - h_1\right)p. \tag{18}$$

Due to the borrowing limit, the borrower thus adjusts the probability of their high productivity downward and the probability of their low productivity upward.

In the next period, the MFI using a progressive lending system sets the borrowing limit at a high level H. Borrowers again determine their loan decision by taking the minimum of the borrowing limit and the last-period expected value of a, determined by using Equations 17 and 18. Because the borrowing limit is high, the loan decision now is based on the expected (conditional) value of a, which is

$$D_{pl,2} = E(a|B = L) = \left(1 - \alpha - h_1\right)pH + \left(1 - \left(1 - \alpha - h_1\right)p\right)L. \tag{19}$$

At the end of the period, the borrower again updates their beliefs. After receiving the high signal, $B = H$, their posterior beliefs about a, taking into account the update that occurred at the end of the first period, are

$$\Pr(a = H|B = H) = \frac{\Pr(B = H|a = H)\Pr(a = H|B = L)}{\Pr(B = H|a = H)\Pr(a = H|B = L) + \Pr(B = H|a = L)\Pr(a = L|B = L)}. \tag{20}$$

In turn, we can easily calculate

$$\Pr(B = H|a = H) = \alpha + h_2 + \left(1 - \alpha - h_2\right)p \tag{21}$$

and

$$\Pr(B = H|a = L) = \left(1 - \alpha - h_2\right)p. \tag{22}$$

We add the term h_2 to indicate that the firm overestimates the reliability of the signal in the second period. Substituting Equations 17, 18, 21, and 22 into Equation 20 yields

$$\Pr(a = H|B = H) = \frac{\left(\alpha + h_2\right)\left(1 - \alpha - h_1\right) + \left(1 - \alpha - h_1\right)\left(1 - \alpha - h_2\right)p}{1 - \left(\alpha + h_2\right)\left(\alpha + h_1\right)}, \tag{23}$$

and loan demand becomes

$$D_{pl,3} = E(a|B = H) = \Pr(a = H|B = H)H + (1 - \Pr(a = H|B = H))L. \tag{24}$$

We also seek to compare the loan demand created in a progressive lending system against the demand implied by a normal lending system. To do so, we compare Equations 24 and 19 (loan demand under the progressive loan system) against Equation 9 (loan demand under a normal system). It is immediately evident that the progressive lending system reduces borrowing in period 1 (due to the binding credit limit) but also in period 2 (Equations 19 versus. 9), due to the downward adjustments of high-productivity beliefs. Only if the borrowing limit signal is not informative at all ($\alpha = 0$) and there is no borrower overconfidence in the ability of MFIs to predict its abilities ($h = 0$) would borrowing in period 2 be the same in both systems.

An interesting comparison also results in relation to the loan demand implied by the progressive lending system after the MFI has abolished the credit limit (Equation 24) with the loan demand in normal cases (Equation 9). It is no longer clear-cut which loan system leads to the highest loan demand (and thus the highest probabilities of overborrowing). A simple comparison of the conditional probability implied by Equation 23 with the unconditional probability p identifies the conditions in which the progressive loan system will lead to higher loan demands. That is, if $\Pr(a = H|B = H) > p$, then the progressive lending system will induce higher loan demand. By rewriting Equation 23, we can show that for

$$p < \frac{\left(\alpha + h_2\right)\left(1 - \alpha - h_1\right)}{2\left(\alpha + h_2\right)\left(1 - \alpha - h_1\right) - \left(h_2 - h_1\right)} \tag{25}$$

the condition $\Pr(a = H|B = H) > p$ holds, and thus the progressive lending system leads to higher loan demand after abolishing the loan limit. From Equation 25, we also derive the following conditions:

1. If, $h_1 = h_2$ the condition becomes very simple: $p < 5$. Thus, a progressive lending system will lead to higher borrowing for $0 < p < 5$ but lower loan demand for $0.5 < p < 1$. If $p = 5$, both systems produce similar loan demands.
2. If $h_1 < h_2$, as is the case when borrowers exhibit greater confidence in the MFI's ability to predict their productivity, the condition for p relaxes. The greater the difference between h_1 and h_2, the higher the threshold value of p below which a progressive lending system leads to higher loan demand.

The main insight of this model is that a progressive lending system, compared with a debt contract without a progressive lending clause, leads to greater loan demand and potentially more overborrowing and liquidity defaults, if borrowers use the credit limits set by MFIs as signals of their productivity and if the borrowers gradually increase their (over)confidence in the MFIs' productivity predictive ability. It should be noted that the theoretical model assumes one lender. More lenders obviously diminish the possibility that strategic defaults will be avoided by using dynamic incentives and progressive lending, as we have argued earlier. Yet, a priori there is no reason to expect that a model with more lenders would change the main insight of our theoretical model focusing on liquidity defaults. We leave it to further research to derive a multi-lenders model.

6 | DISCUSSION AND CONCLUSIONS

This study adds to the literature stream that investigates the relevance of using a system of progressive lending to reduce defaults. The standard theoretical literature argues that progressive lending may help to reduce *strategic* defaults. However, there is almost no empirical evidence on the impacts of progressive lending on defaults, and strategic defaults are only one reason behind nonperforming loans, the other being overborrowing or negative shock-driven *liquidity* defaults. To provide new evidence on the relevance of a progressive lending system for MFIs, we organized an experiment in Bolivia. This experiment suggests that it may not be advantageous to add progressive lending to a system of dynamic incentives, as progressive lending can cause overborrowing and liquidity defaults. Another interesting outcome of our experiment is the notion that progressive lending is inferior to a system with high but static credit limits.

To provide more insights into the reason why progressive lending may lead to overborrowing, we construct a theoretical model. The model shows that our experimental results can be fully explained if borrowers anchor their borrowing amounts to the credit limits set by the lender, if borrowers display overconfidence in the predictive ability of the MFI, and if this overconfidence increases over time. In this setting it may then also be the case that high credit limits might force borrowers to learn immediately about their optimal borrowing strategy, whereas progressive lending may provide incorrect signals about the optimal borrowing strategy.

Anchoring to credit and repayment limits is not an entirely new concept to financial literature and has been shown to have perverse effects in diverse settings such as credit card borrowing, mortgages, and consumer spending. Its role in overborrowing and liquidity defaults in a microfinance setting had, however, never been explored before. Our analyses strongly suggest that MFIs that do not have accurate information about future repayment possibilities of their borrowers could better refrain from progressive lending. MFIs could better rely on a simpler dynamic incentive system without any credit limits or with fixed credit limits than with increasing credit limits. By doing so, *strategic* defaults can still be avoided, and the risk of *liquidity* defaults will be much smaller.

Our results should be interpreted with care. We certainly do not mean to convey that progressive lending systems always invite liquidity defaults. Our study was conducted in a specific setting (Bolivia), with a relatively small sample size, and it relies on some far-reaching assumptions. In addition, our theoretical model makes some far-reaching assumptions about the borrowing behavior of farmers; that is, the farmer uses the borrowing limit set by the microfinance organization as a signal for what it is able to produce. While many smallholders in rural areas indeed often have imperfect knowledge about production capacities, and financial intermediaries often have better information about these issues, additional empirical testing is needed to know to what extent this also holds for the microfinance market. Yet our results have important implications for MFIs' willingness to adopt progressive lending systems to reduce default risks, and we hope they will induce further research on the workings of progressive lending. Our study at the least provides an initial indication that progressive lending systems may not have the positive effects in line with the traditional theoretical analyses.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in 4TU. ResearchData Repository at https://doi.org/10.4121/14748390.

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ENDNOTES

[1] The only exception is Herring and Musshoff (2017), who analyze a progressive lending system for farmers and non-farmers in Azerbaijan and find, in contrast to the theoretical literature, that the repeated borrowing increased defaults of both groups.

[2] To make the game incentive compatible, one randomly chosen round for each participant provided payment. The money earned in this round was added to a participation fee of 6 Bs; on average, the participants received 16.6 Bs each. All participants, including defaulters, were obliged to stay until the end of the game to collect their payoff.

[3] Participants did not arrive at the same time, and we wanted to avoid long waiting times, so for each community, we randomized the order in which the different treatments were conducted. The first participants to arrive thus played the randomly determined first treatment and so forth.

[4] We also used Tobit estimates (because the dependent variable is truncated) and household random effects. These estimates are not presented here, because the results were qualitatively the same.

[5] Column 4 reveals that "high limits" performs surprisingly better than no limit in round 4, under the three-banks scenario. This difference is not confirmed in the one-bank sample nor the pooled sample; we have no other explanation than plausible statistical occurrence in small samples. This is fundamentally different from the effects of progressive lending, which yield robustly poorer results in round 4 across specifications, samples, and outcomes.

[6] We also considered the impacts on strategic defaults, but there were only a few such defaults (most of them in round 4 for three banks), so it turned out to be an uninformative exercise.

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