NBER WORKING PAPER SERIES

ACCESS TO DIGITAL CREDIT FOR SMALLHOLDER FARMERS: EXPERIMENTAL EVIDENCE FROM GHANA

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Working Paper 33271
http://www.nber.org/papers/w33271

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2024, revised January 2026

We thank the Digital Credit Observatory at the Center for Effective Global Action for funding. This study was pre-registered at the AEA RCT Registry (ID: 0005829) and obtained approval from the Innovations for Poverty Action Human Subjects Committee IRB # 14431. We are grateful to the field and project management team at Innovations for Poverty Action (IPA) Ghana office for survey and project management support; to Andre Nickow at the Global Poverty Research Lab for research management; and, to Farmerline, our implementing partner, for their collaboration throughout. All interpretations of the results are our own and do not reflect the views of the funders or implementing partner. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 33271
December 2024, revised January 2026
JEL No. Q14

ABSTRACT

Digital finance in agriculture is a nascent technology which could help improve rural financial inclusion. In an experimental evaluation of a digital lending product for farmers in Southern Ghana, credit increases farm investments but has few statistically significant average effects on downstream outcomes. However, logistical challenges generated imperfect compliance with the treatment assignment, with some loans delivered in a timely fashion for agricultural investments and others coming later. We cautiously exploit this unplanned non-experimental implementation heterogeneity and conclude that agriculturally-focused digital credit platforms have potential to tackle persistent rural financial market imperfections, but the timing seems critical and deserves further study.

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A data appendix is available at http://www.nber.org/data-appendix/w33271
A randomized controlled trials registry entry is available at https://www.socialscienceregistry.org/trials/5829

1. Introduction

Financial market imperfections constrain low-income farmers throughout developing countries. Farmers typically lack both scorable credit histories and collateral, confronting formal lenders with often insurmountable information asymmetries. In the absence of formal credit, farmers either underinvest in otherwise profitable opportunities or borrow informally at high interest rates (Banerjee, 2013). Furthermore, when entire communities need financing simultaneously, as with rain-fed agricultural economies, local informal networks are unable to fully satisfy farmer credit demand. Lastly, while in theory savings markets could succeed in delivering timely liquidity for farmers, savings poses its own set of market failures from social, institutional, and behavioral barriers (Karlan, Ratan, and Zinman, 2014; Afzal et. al., 2018; Kremer, Rao, and Schilbach, 2019).

Making the problem more poignant, the returns to agricultural investment can be high (Beaman et. al., 2023). In West Africa, farmers identify lack of capital as a primary reason for underinvestment and their inability to realize high returns (Fosu and Dittoh, 2011). Farmers typically face capital constraints at planting, i.e., when investment is needed yet cash is low (because the last harvest was months prior). Relaxing capital constraints by expanding the availability of formal credit could generate substantial welfare gains through agricultural investment and its ensuing income. However, such gains may depend critically on the timing and magnitude of loans (Brune et. al., 2011; Karlan, Osei. et. al., 2014; Casaburi and Willis, 2018).

We examine this by conducting a randomized evaluation in which a lender randomizes credit offers to Ghanaian smallholder farmers who applied for loans through a digitized process, thus incorporating a nascent but promising technological innovation that aims to lower transaction costs for both lenders and borrowers.

We partnered with Farmerline, a digital lender and farm input provider. Farmers applied to receive farm inputs on credit from a cellphone, and could receive technical support for the application process from a local Farmerline agent. Farmerline processed applications using a non-traditional credit-scoring algorithm designed to generate quick results; 62% of applicants were deemed eligible for a loan. We then randomly assigned the eligible applicants to either treatment or control. The remainder of the lending process, up to the delivery of the farm inputs, was also digital and no human interaction was required (farmers received notifications about the status of their loans on their phones). Prior to treatment assignment Farmerline informed farmers that, for those approved for credit, farm inputs would be delivered to their farmgate within 30 days of their application.

Ensuring affordable access to credit for poor borrowers has long been a key financial inclusion goal (Banerjee, 2013). Yet, empirical evidence on the economic impacts of traditional microcredit programs have been mixed (Banerjee, Karlan, and Zinman, 2015; Meager, 2019). Some evidence suggests, however, that innovative lending models could be more transformative (Field et. al., 2013; Fink, Jack, and Masiye, 2020; Beaman et. al., 2023).

Aside from contributing to a broad literature on the impact of improved credit access for low income rural households, the loans tested here differ in three important dimensions with respect to much of the literature. These loans are digitally-offered, provided in-kind via agricultural inputs, and disbursed and repaid in accordance with agricultural season cashflows.

Recent research documents the promise of digital finance in promoting financial inclusion (Karlan et al., 2016), and related work has highlighted how digital credit, in particular, has significant potential over traditional models of lending to the poor (Blumenstock et al., 2017; Björkegren and Grissen, 2018; Suri, Bharadwaj, and Jack, 2021). Traditional non-digital lenders typically incur high costs, relative to the size of the loan, to reach poor borrowers. And borrowers incur time costs, with group meetings in more traditional group-based microcredit programs, or travel time to distant bank or microcredit institution branch visits in individual but non-digital based lending models. Farmerline's digital model aims to overcome these barriers. Lender costs are low as their underwriting process requires minimal official data and in-person marketing and vetting. Similarly, borrowers spend much less time or money filing paperwork, visiting branches, and participating in group meetings.

Loans are disbursed in-kind via agricultural inputs, and are thus less fungible than a cash loan. This likely leads to more expenditure on farm inputs than a traditional micro-lending product would generate. Previous research has noted that the limited observable impact of traditional microcredit on entrepreneurial outcomes could be because people borrow to increase their consumption, and not to expand their enterprises (Banerjee, 2013; Banerjee, Karlan, and Zinman, 2015; for counter-evidence, see Karlan, Osman, and Zinman, 2016).

Lastly, our loan product gives farmers a three-month period between when they receive their loans and when they start the repayment process. Classic microcredit models often involve small, frequent repayments beginning immediately after the recipient receives the loan. Such setups can limit investment in enterprises which may have high but illiquid returns. Previous work has shown how a two-month grace period before repayment increased the short-run investment and long-run profits for small firms (Field et. al., 2013). In agriculture, this may be particularly salient as farmers face liquidity constraints when they need it most during planting season and receive lumpy cash incomes only after crops are sold after harvest (Casaburi and Willis, 2018).

We have three main findings. First, using an intent-to-treat (ITT) specification, we find an average increase in farm input expenditures and amount of land dedicated to mixed-cropping. But we find no statistically significant impacts on final outcomes such as value of crops produced, sales, or profits. The point estimates are negative, and we can rule out large positive effects—e.g., a larger than 15% increase over the baseline mean in crop profits due to the treatment—on these downstream final outcomes. While several theories may explain why, a plausibly compelling argument pertains to an implementation issue: the lack of timely disbursement of the credit, as crop productivity is likely impeded by the delayed application of essential farm inputs like fertilizers and insecticides. This theory was also put forward in ex-post focus group discussions with farmers in which they specifically attributed the lack of impacts to the delayed disbursement of loans.

Our second result explores this implementation issue, although using non-experimental variation in the timeliness with which loans were disbursed. Compliance was lower than intended with respect to timing of loans (discussed more below), and this creates a window to explore, with caveats, the importance of the timing of the loan disbursal with respect to the agricultural planting season. Farmers who received a timely loan have much larger crop production and sales than the control group. These effects were large in magnitude, over 29% of the baseline mean. Farm profits also increase substantially, albeit imprecisely (p=0.20). However, while the lower bound of the 95% confidence interval allows us to rule out profit decreases greater than 17% of the baseline mean, the upper bound can only rule out profit increases larger than 79% of the baseline mean. We find no evidence of heterogeneous impact—through an ITT approach—on overall farm input expenditures or mixed-cropping acreages for farmers who received timely loans. But we find a statistically significant increase in spending on fertilizers, which is one of the key inputs provided on credit by Farmerline. Additionally, farmers who received timely loans relied less on the informal credit market. Taken together, these results suggest that the provision of inputs on credit may have had tangible, positive effects on financial outcomes, for those that received a timely delivery of the loans.

We note that in-kind loans carry additional logistical challenges. The delays experienced are not uncommon. Simply put, lending in-kind rather than in cash (whether physical or electronic) creates additional workstreams for the lender and dependence on supply chains external to the lender. Each of those may create delays and problems. Delays in input delivery, in turn, can threaten the synchronization between rainfall patterns and farm operations required in rainfed agriculture and dramatically reduce productivity (Xu et. al., 2009; Ashraf et. al., 2009). However, in-kind delays can be avoided with the right planning and management. One Acre Fund, as an example, provides in-kind loans for agriculture and has executed successfully (Deutschmann et. al., 2025).

Third, focusing on gender differences (one of the two dimensions of heterogeneity registered in our pre-analysis plan)[1], female farmers in the treatment group spent less on farm inputs than control, whereas male farmers spent substantially more than control. While treatment induced male farmers to increase the amount of crops they grow, female farmers instead reduced crop diversification. Consistent with this gender differential, treatment also reduced the non-farm business income of male farmers, while treatment led female farmers to invest more and earn more in non-farm

[1] The other is farming experience, and we find little evidence of heterogeneity (Appendix Tables A1.1–A1.3).

enterprises. In net, treatment led male farmers to invest more in farms, but led female farmers to divest from farms and invest more in non-farm enterprises.

2. Background of Our Experiment

2A. Contextual Details

Our research takes place in Ghana's Ashanti region. Like many other low-income countries, a relatively high share of Ghana's labor force – about 52% – work in farms. 85% of farms are smaller than five hectares. The Ashanti region is a major producer of cocoa—Ghana is the world's second largest producer (FAO, 2017)—as well as rice and vegetables.

Despite the large population involved in agriculture, farmers in remote regions of Ghana face imperfect financial markets. Only about 40% of adults in Ghana have a bank account (World Bank, 2022). Moreover, while microcredit providers have not expanded across West Africa as much as elsewhere, mobile phone usage in Ghana has rapidly grown, with at least 84% of the population owning a mobile phone, and up to 120 mobile phone subscriptions per 100 (World Bank, 2022). Ghana's low bank branch penetration (6.1 per 100,000 adults) along with the rapid growth of mobile suggests a ripe frontier for digital finance operations.

2B. The Experimental Intervention and the Credit Product

Our partner, Farmerline, is a social enterprise that operates in 13 African countries to support small-scale farmers. Their platform, *Mergdata,* is a web and mobile application which contains several software modules for services such as weather forecasts, market prices, and farming tips. Mergdata also allows farmers to apply for a loan to be disbursed in-kind as farm inputs. Agents from Farmerline visited communities to market Farmerline services, including the loans. Farmers were told that should they apply and be approved for a loan, they should receive inputs within 30 days of their application. Interested farmers were directed to apply for a loan on the Mergdata platform. Agents also, in the marketing process, explained that the credit decision was based on an assessment of their creditworthiness and also luck via a computer-driven randomization process (qualitative focus groups and semi-structured interviews conducted at the end of the intervention confirmed participants were aware of both.) The application was completed digitally and did not require farmers to travel to bank branches or participate in group meetings.[2] Farmerline's proprietary credit scoring algorithm calculated farmers' creditworthiness using non-traditional data including farm characteristics, production history, and crop sales.[3] Of those determined to be eligible, Farmerline passed names to IPA to randomize to treatment and control. Farmerline informed all farmers of their loan decision typically 2-3 days after the loan application.

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[2] Farmerline also appoints and trains local agents to provide technical advice.

[3] Additionally, most farmers avail of Farmerline's services repeatedly over successive seasons, allowing Farmerline to improve its underwriting.

Intake to the experiment was conducted on a rolling basis, due to the nature of the marketing and loan application process. Treatment farmers could choose to receive a variety of farm inputs, including inorganic fertilizers, insecticides, and herbicides, as the credit product. Farmers could receive loans worth up to GHS 350 (about $75). The average loan size was GHS 189 (about $40) and median GHS 208 ($45). The 25th and 75th percentiles were GHS 135 ($30) and GHS 236 ($50), respectively. Farmers assigned to the control group were notified that they would not receive farm inputs on credit. The treatment was not bundled with any other intervention or service, and all farmers, including those in the control group, could continue to use all of Farmerline's other services.

The loans were designed to be delivered to recipients before input application for the main cocoa season began. The loans had to be repaid at a 4% per-month rate with monthly payments starting at the end of 3 months following input disbursement, with a total repayment term of up to 6 months.[4] This design aimed to allow farmers to start loan repayment after harvest. Finally, the loans were uncollateralized, and farmers were informed that default would likely exclude them from Farmerline's future services.

[4] At the time of the endline, Farmerline received complete repayments from at least 88% of the borrowers. Amongst borrowers still repaying their loans, the average loan balance (principal - amount repaid) was GHS 54. Unfortunately, we could not obtain long-run repayment data from the partner, and therefore cannot comment on what proportion of repayment they ultimately received from these borrowers.

3. Study Design and Empirical Strategy

3A. Descriptive Statistics

Our sample consisted of 1,372 farmers. Cocoa was the most commonly cultivated primary crop. Over half of the farmers cultivated at least one other crop, most commonly plantain and cassava. Table 1 provides descriptive statistics.[5]

The farmers were small landholders, with a median cultivated acreage of 5.5 acres and average of 7.3 acres. The farmers reported little past usage of formal credit: only 11% of farmers had borrowed from a formal institution the prior year. However, up to 21% of farmers reported borrowing from informal sources such as moneylenders, family, and peers. Interestingly, farmers believe that credit could improve their crop yields: 65% of farmers report applying for input credit in order to “increase yield”. Over the period studied, agricultural outcomes dropped considerably, most likely due to COVID lockdowns and associated supply chain disruptions (the endline was conducted in mid-2020).

3B. Experimental Design and Compliance

We randomly assigned 917 farmers (67%) to the treatment group and 455 farmers (33%) to the control group. Columns 1–3 of Table 1 describes baseline balance tests across a range of demographic, agricultural, and other non-agricultural economic variables. The overall attrition rate was 2.7%, and little differential attrition effects were observed between treatment and control.

[5] See Appendix for the surveys.

Unfortunately, compliance with the treatment assignment was imperfect on two levels, primarily due to operational challenges faced by Farmerline: (1) Although all participants had applied for a loan and been deemed eligible, only 59% (544) of treatment farmers received a loan, while 17% (77) of control farmers did receive a loan;[6] (2) Of those who received loans, many treatment farmers did not receive the farm inputs at the optimal time for investments for the main planting season. Specifically, only about 25% of eligible treatment farmers received loans within 30 days of their application, the intended timeframe. For the other 75%, loans did not arrive in time for the optimal input application period. Ex-post focus group discussions with farmers identified this as a potential driver of impacts (or lack thereof), and thus we return to this in our empirical analysis.

For the first compliance issue (non take-up in treatment and take-up in control), farmers assigned to treatment who received a loan were similar to those who did not along many dimensions, but differ on a few: borrowers are less likely female, older, and cultivators of larger farms (Table 1, Columns 4-6). In contrast, we observe less selection within control for those that received versus did not receive a loan (Table 1, Column 7-9). These tests reinforce our belief observation that the main drivers of imperfect overall compliance were operational challenges faced by Farmerline, but that these

[6] One source of non-compliance was due to delivery of farm inputs being done in batches to a local agent or a chief farmer before being individually disbursed; some control farmers present at the scene obtained the loan product instead of any absent treatment farmers.

challenges led to selection with respect to observables (and likely unobservables) into compliance. Therefore as we describe below, we include all farmers in our analysis and focus on measuring intent-to-treat (ITT) effects.

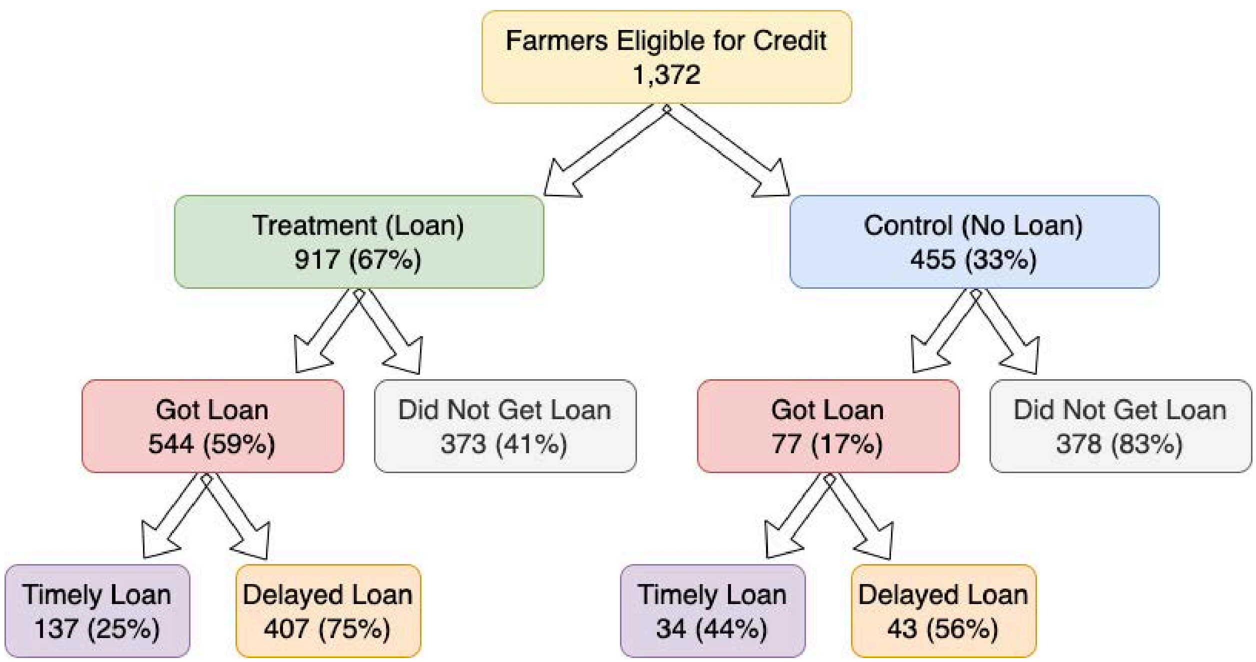
For the second issue (timeliness of loan delivery), of the 621 farmers who received loans, irrespective of being assigned to the treatment or control group, 171 farmers (27.5%) received timely loans, i.e. the loan product was delivered to them within 30 days of applying, as initially promised by Farmerline. We examine selection effects from this non-compliance by comparing baseline values and demographics for those who received timely versus less timely loans (Table 1, Column 10-12). Farmers with timely loans had *lower* input expenditures and are *less* likely to have owned a business.[7] These farmers may have been more proactive in ways that helped them to receive inputs. Focus groups support this conjecture: for example, one respondent noted how farmers like himself were "*closer to the local Farmerline agent and got access to the information*" on when the Farmerline personnel would deliver the loan products to the village, and how "t*he day the Farmerline personnel came, he only met 4 farmers*". Taken together, farmers that received more timely loans may have faced more binding credit constraints and therefore have valued access to credit more.[8] Keeping in mind these potentially endogenous causes of selection into timely credit receipt, we will estimate the differential impact using an ITT specification comparing timely to less timely loans.

[7] Notably, we do not find statistically significant differences in baseline expenditures on output, sales, profits, or fertilizers and insecticides (the main inputs offered by Farmerline).

[8] At the community level, there were wide disparities in the share of farmers who received timely loans, but we observe no clear pattern by type of community.

Figure 1 illustrates the experimental design.

Figure 1: Experimental Design and Compliance



3C. Pre-registered Hypotheses

Our theory of change posits that binding financial constraints limit farm investment, thereby lowering crop output and profits. To test this, we estimate whether and how our short-term credit intervention affects farmers' seasonal investment choices as well as their downstream agricultural and financial outcomes. We pose the following hypotheses.

First, we hypothesize that *many farmers face a binding credit constraint:* at the terms Farmerline offers, they would choose to borrow, but such terms are not available to them. Our treatment relaxes this constraint, thereby lowering the shadow cost of working capital and increasing farm investment.[9] We test this by examining treatment effects on a range of farm input expenditures and land use choices.

Second, we hypothesize that *access to credit improves downstream agricultural outcomes*. To test this, we examine farm performance, including the market value of crops produced, revenues earned from crop sales, and farm profits.[10]

Our other hypotheses posit that access to credit has positive impacts on farmers' *non-agricultural economic outcomes*, *experience with formal credit and self-perceptions of creditworthiness*, as well as *livelihood and well-being*.[11] To test these, we estimate treatment effects for several household finance and business ownership outcomes. These may be positively affected if the binding credit constraints are relaxed and

[9] An increase in investment contingent upon receiving a loan is sufficient to reject neoclassical separation. It does not imply that the farmer had no access to credit at a higher cost. If the loan displaces all borrowing from high-cost lenders this would lower the opportunity cost of capital to the farmer and induce greater investment. We are referring to such borrowers as capital constrained, even though they might be able to borrow at a cost higher than that of Farmerline.

[10] To estimate profits, we are only able to capture farm input expenditures as costs.

[11] Our pre-analysis plan also hypothesized that the loans allow farmers to better deal with shocks (such as the COVID-19 crisis). However, being unable to survey farmers in the early COVID-19 outbreak period, we drop this hypothesis.

farmers divert resources from farming to higher return activities. We also test for treatment effects on several actual and perceived outcomes on farmers' credit usage. We hypothesize that Farmerline's loan approvals may provide farmers with a signal about their creditworthiness. Finally, we examine whether the treatment impacted well-being (specifically: food security, perceived social standing, and psychological well-being).

3D. Empirical Strategy

Our primary estimation uses an ITT framework that adheres to the experimental assignment to treatment irrespective of compliance:

$$Y_i = \alpha + \beta\, Treatment_i + \gamma\, BaselineY_i + \delta App\ Month_i + \theta Survey\ Month_i + \varepsilon_i$$

Outcomes *Y* are for farmer *i*. We focus on all outcomes for the main agricultural season, as the program aimed to deliver loans before the start of the main season. The variable *Treatment* is an indicator which equals 1 for farmers assigned to treatment, 0 for control, irrespective of actual loan receipt. *App Month* and *Survey Month* represent the month of loan application and follow-up survey.

4. Results

4A. Main Results

We focus first on farmers' agricultural investment choices. Table 2 Panel A reports treatment effects on farm input expenditures. Treatment led to an 11% (95% CI: -1% to 24%) increase in total farm input expenditures, compared to control (Column 1). To unpack this increase, Table 3 presents estimates on specific farm expenditures. The most precisely measured increases in expenditures are for insecticides, land rental, hired machinery, and fees farmers paid for irrigation services. These effects are quite large, ranging from 15% above the baseline mean for insecticides, to over 280% for hired machinery. While the coefficients for all other farm inputs are positive, they are noisy and not statistically significant. This paints an interesting picture: treatment farmers were likely to spend more on inputs which they were less likely to have received on credit as part of the experiment (with the possible exception of insecticides). This suggests that farmers faced binding credit constraints and that when such constraints were relaxed with key farm inputs being offered on credit, farmers spent more, on average, on other farm inputs to complement their investment decisions.

We then focus on key farm outcomes. In the rest of Table 2 Panel A, we find no statistically significant treatment effects on the market value of crops produced, crop sales, and farm profits. In the cases of production and sales, the coefficients are small and not statistically significant. For profits, the coefficient is a relatively large negative value but, once again, not statistically significant. The 95% confidence intervals allow us to rule out effect sizes of greater than 14%, 13%, and 15% of the baseline mean for crop production, sales, and profits, respectively. We cannot definitively comment on why there is such a limited impact of the loans. We could speculate that extending credit in itself is not sufficient, and perhaps could have greater impact when combined with other factors such as extension services. We argue below that one cause is the delayed delivery of loans to most farmers, which may have prevented them from making decisions that would have led to more positive outcomes.

In Panel B, we consider farmers' land use choices, another form of measurable agricultural investment. There is no detectable effect of the treatment on the area cultivated with a single crop. We are not surprised by this, especially given the short-term nature of the treatment. Perhaps surprisingly, however, we find that farmers do increase the area on which they practice mixed cropping. The negative coefficient on the area in which farmers cultivate a single crop suggests that at least some of this increase may be due to a switch from single to mixed cropping, but the estimate is noisy. As before, this is suggestive of the notion that relaxing binding credit constraints may allow farmers to cultivate more, at the intensive margin.

Panel C shows that farmers assigned to treatment have 32% more money owed by others to themselves, compared to the baseline mean. Treatment farmers have 24% more household savings compared to control group farmers, although the latter estimate is imprecise. Lending locally and to family, and saving, requires little labor and helps diversify risk from farming.

Treatment farmers are 10% less likely to own a non-farm business at the endline, compared to the average baseline non-farm business ownership (Panel D). This estimate is statistically significant at the 5% level. Treatment farmers also record negative, albeit imprecise, coefficients for non-farm business investment and income. This result is consistent with the finding in Panel A that treatment farmers spent more on inputs complementary with the in-kind inputs provided on credit. Treated households may also be providing additional household labor to their farms (which we cannot measure), and thus reducing effort on non-farm enterprises.

In Panel E, we show that treatment farmers borrow more from other microfinance lenders compared to control farmers, but there is no statistically significant difference in their borrowing from banks, moneylenders and other informal sources such as social networks.[12] Borrowing from microfinance lenders suggests that the treatment induces farmers to seek additional sources of formal credit. We find no detectable differences between treatment and control across variables aimed at capturing farmers' self-perception of how creditworthy they are, except some suggestive evidence (p=0.12) that treatment farmers are more likely to believe that they will receive a better interest rate from a different lender.

In Panel F, we examine effects on indicators of health and well-being. We note that these variables are based on subjective responses. We find no statistically significant

[12] Appendix Table A2 presents (statistically insignificant) ITT effects from additional variables capturing farmers' experiences with credit.

differences in indices capturing food security, psychological distress and subjective well-being. We note that the loans could have had a viable benefit on food security especially in the lean season (Fink et. al., 2020) that we could not capture because of the timing of our measurement. However, we do find that the treatment and control group farmers differ on their assessment of where they would place themselves on a social ladder measuring absolute wellbeing. Treatment farmers, on average, place themselves higher on the ladder.

Finally, in Appendix Table A3.1, we present adjusted p-values and q-values from several multiple hypothesis tests. While many of our results retain similar levels of significance following these tests, some of the ITT estimates are no longer statistically significant (for example, the adjusted p-value for overall farm input expenditures is 0.16).

4B. Heterogeneity

We test for heterogeneous treatment effects along three dimensions with the below regression specification. First, we explore whether there were heterogeneous effects for farmers who received timely loans, although this was not registered in our pre-analysis plan. Then, we also test for heterogeneous effects along: i) gender and ii) farming experience, both of which were pre-specified.[13]

[13] Administrative data show that over 90% of the farmers cultivated cocoa as their primary crop. Moreover, the loans were designed to be delivered in advance of the main cocoa season. Therefore, although interesting, we cannot analyze impacts by crop heterogeneity.

$$Y_i = \alpha + \beta\, Treatment_i + \lambda\, Heterogeneous\ Dimension_i$$
$$+ \mu\, Treatment_i\, X\ Heterogeneous\ Dimension_i$$
$$+ \gamma\, Baseline\ Y_i + \delta App\ Month_i + \theta Survey\ Month_i + \varepsilon_i$$

4B.1. Timeliness of Loans

We conducted 40 focus groups and 55 semi-structured individual interviews and from these a common theme emerged: many borrowers received the farm inputs later than anticipated, and these delays affected their farming operations.[14]

Those that received timely loans may have maneuvered more successfully to secure the loan, which is an indication of the value they perceive the loan to generate for them and thus also likely predictive of a selection bias positively correlated with farming outcomes. However, we proceed with estimating the non-experimental specification for two reasons. First, farmers generate higher productivity when they use farm inputs at the optimal time. Second, the very endogeneity that renders this analysis speculative may actually generate an estimate closer to the treatment effect of a policy scaled in such a way as to draw in farmers with the highest demand for credit (this conjecture is consistent with the positive selection into loans observed in Beaman et al. 2023).

To test for a timing effect, we split the ITT estimate into timely disbursal (received within 30 days) or not. Additionally, in these regressions, we control for age, baseline farm

[14] The Appendix presents several farmers' quotes from these qualitative data.

input expenditure, and baseline business ownership—covariates that are predictive of selection into timely loan take-up.

Table 2 Columns 2-3 report these results. The results show a strong pattern: mean crop sales and crop production are notably and statistically significantly higher for treatment farmers that receive timely loans, as promised, within the first month after application approval than those who do not. Similarly, profits are substantially higher for these farmers. Even though the total profit estimate is imprecisely measured (p=0.20), the point estimate illustrates a 31% increase (95% CI: -17% to 80%) over the baseline mean profits, and a 118% increase over the endline control group mean profits.[15]

We note two additional results. First, while the point estimate of the interaction is large and positive, we cannot reject the null that total farm expenditure is the same for treatment farmers receiving the loans on time as for other treatment farmers (p-value=0.14 for farm input expenditures). Second, farmers with timely loans record large increases in expenditures on fertilizer (Table 3), which they likely also receive in kind from Farmerline as part of their loan, relative to farmers whose loans are delayed. This is in contrast to the ITT effects discussed earlier that showed farmers assigned to treatment increasing spending on other inputs. Combined with the results on crop sales and profits, this is indicative of the importance of constraints farmers face in obtaining fertilizers for the crop production process.

[15] Appendix Table A3.2 presents adjusted p-values from multiple hypothesis tests of these regressions.

Our results suggest that although the overall treatment effect may have been weak, the loans, conditional on being delivered in time, may indeed have had substantial beneficial impacts on farmers. This interpretation must be tentative because the outcome of receiving a timely loan is likely determined in part by the activities of the borrower and thus correlated with unobserved determinants of farm output. We argue, however, that these estimates, despite this potential endogeneity, provide important insights in understanding the necessary conditions for credit to have impact on final outcomes. Further, as we allude to above, the “take-up” of timely loans in our settings appears to be driven by the farmers who need credit the most, and these results may be important for other external interventions offering credit to underserved farmers.

Finally, we note that it may be the case that assignment to treatment harmed farmers if they had to wait longer than promised to receive their inputs. In that case, our estimated average effects may comprise benefits and harms across different sets of treatment farmers depending on timely loan receipt. We undertake multiple approaches to examine this issue—including estimating our regressions with a predicted timely loan receipt variable, and estimating treatment effects on subsamples depending on timeliness of loan receipt.[16] Our findings suggest that such harms, if any, were likely not substantively large in magnitude. However, we do not have the necessary predictive power to draw strong conclusions regarding possible negative impacts of assignment to treatment.

[16] Results reported in Appendix Tables A4.1 and A4.2.

4B.2. Gender

Our motivation to test for heterogeneous effects by gender stems from strong regional evidence that plots farmed by women (versus men) receive fewer inputs. This evidence implies that intra-household agricultural resource allocation can be Pareto inefficient (Udry, 1996). Additionally, traditional microcredit models have often intentionally targeted women (Banerjee, 2013) and we believe that it is useful to document whether and how outcomes vary by gender.

Table 2 Columns 4-5 show that treatment effects on farm expenditures were entirely driven by male farmers. While virtually all categories of farm input expenditures record a negative coefficient for the interaction term of treatmentXfemale, the most precisely measured coefficients are for insecticides, rented equipment, and fees paid for irrigation and registration. Female treatment farmers also borrow statistically significantly less from informal networks such as relatives and peer groups.

We do not detect any statistically significant heterogeneous treatment effects on crop production and sales: these point estimates are large, positive and quite imprecise. We do observe a positive differential effect on profits for treated women vs treated male farmers, but with p-value=0.09. We believe, however, that the most striking result is that treatment leads to a substantial *increase* in non-farm business income for women farmers relative to male farmers. Importantly, this relative increase in business is driven almost entirely by the intensive margin, as we do not detect any business ownership extensive margin effects.

Taken together, these estimates suggest that women did not fully utilize the farm inputs they received. They may have given them away to their (unsurveyed) husbands.[17] Alternatively, they may have sold the inputs and used the proceeds elsewhere, such as in their non-farm enterprises. However, we note certain caveats: we cannot rule out that at least a part of the increase in business income, and the accompanying marginally significant increase in farm profits, may be reported due to sales of the loan products, rather than use. Additionally, we are not equipped to comment on aggregate household-level welfare effects.[18, 19]

4B.3. Farming Experience

We consider heterogeneous effects by farming experience as it is plausible that farming knowledge accumulates with experience and, all else equal, more experienced farmers may be able to make better use of relaxed credit constraints compared to less experienced farmers.

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[17] Previous research suggests that women, in particular, feel pressured to share income with their kin (Jakiela and Ozier, 2016).

[18] Appendix Tables A5.1–5.3 show robustness to a single specification that contains all heterogeneity dimensions.

[19] Our analytical audits indicated 5 observations with likely incorrectly recorded loan applications and delivery dates. Appendix Tables A6–A7 show that without these observations (i.e., with N = 1,331 at endline; with 1 attrited respondent), our main ITT, timely loans, and gender results remain very similar.

To test for heterogeneity, we construct an indicator variable that equals 1 if the farmer has above median years of farming experience, 0 otherwise. We report these results in Columns 2–3 of Appendix Tables A1.1–A1.3.

We find little evidence of heterogeneity by farmer experience across most outcomes. There are, however, a few exceptions. First, we find evidence that treated experienced farmers spend more on fertilizers and insecticides, and less on land rent relative to treated inexperienced farmers. This is similar to what we find with respect to farmers who received timely loans, and may reflect experienced farmers's ability to better manage the uncertain timing of loan delivery by modifying practices. We do not, however, find a significant relative increase in aggregate farm input expenditures for more experienced treatment farmers.

Second, we find that treatment is associated with more experienced farmers increasing business ownership at the extensive margin, compared to less experienced farmers. While speculative, this could occur if a set of more experienced farmers gauge that the delayed loans would not be as useful in agriculture and therefore decide to divert resources to other enterprises.

Finally, we cautiously note that the average farmer in our experiment has over 18 years of farming experience. Given this high farming experience, it is perhaps not surprising that we observe no substantial heterogeneous treatment effects.

5. Conclusion

We document the effects of access to agricultural inputs on credit for farmers in a major cocoa-growing region of Ghana through digital credit tools. Farmers randomly assigned access to credit increased overall farm input expenditures although there was no average effect of the intervention on crop output, sales or farm profits.

Although it was not the intention of the research design (and thus is not as well identified econometrically as the average impacts), we document an important lesson on the importance of timely access to loans for smallholder farmers. New technologies like digital credit platforms can tackle persistent issues of rural financial market imperfections, but the successful logistics of loan and input delivery remains essential. Our research, thus, adds to the emerging literature on digital finance, which is rapidly evolving as a promising improvement to traditional microcredit models in developing countries (Blumenstock, Francis, and Robinson, 2017; Karlan, Kendall, et al., 2016).

Another possible reason for the muted impact of the overall intervention is that credit itself may not be enough to generate increases in crop production and sales. Perhaps other services, such as extension workers, can provide farmers with the knowledge to use farm inputs more efficiently. Alternatively, farmers may face other binding constraints due to other market imperfections, such as the lack of insurance. One promising relatively underexplored avenue of research would be to test the role of local agents in a similar setting. Local agents appointed by the credit provider work simultaneously as extension workers, helping farmers improve their agricultural decision making and investment choices, and as loan recovery agents, allowing credit providers to improve loan recovery and reduce default rates. Whether designing incentive structures for such agents can impact farmers’ outcomes to a greater extent is left for future research.

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Table 1: Baseline Summary Statistics, Balance Tests, and Selection Analysis
Means (standard deviations / standard errors)

Analysis:	**Treatment Assignment Balance**			**Compliance Analysis (All Loans)**						**Take Up Analysis (Timely Loans)**		
Sample of Farmers:	**All Farmers**			**Treatment Group**			**Control Group**			**All Borrowers**		
	Control Mean (Std Dev)	Diff in Means: Treat - Control (Std Error)	p-value of Diff	No Loan Mean (Std Dev)	Diff in Means: Got Loan - No Loan (Std Error)	p-value of Diff	No Loan Mean (Std Dev)	Diff in Means: Got Loan - No Loan (Std Error)	p-value of Diff	Late Loan Mean (Std Dev)	Diff in Means: Timely - Late Loan (Std Error)	p-Value of Diff
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Demographics												
Age	51.0	-1.1	0.12	48.8	1.7	0.04	51.0	-0.06	0.97	49.7	3.5	0.00
	(12.6)	(0.72)		(12.5)	(0.85)		(12.8)	(1.58)		(12.5)	(1.1)	
Female (Indicator)	0.28	-0.02	0.47	0.32	-0.09	0.00	0.27	0.04	0.49	0.22	0.07	0.09
	(0.45)	(0.03)		(0.47)	(0.03)		(0.45)	(0.06)		(0.41)	(0.04)	
Years Farming	18.3	0.26	0.64	18.3	-0.42	0.53	18.7	-2.1	0.07	18.3	0.77	0.36
	(9.4)	(0.56)		(10.3)	(0.66)		(9.7)	(1.2)		(9.5)	(0.84)	
Household Education	4.0	0.07	0.34	4.2	-0.08	0.32	4.0	0.01	0.96	4.0	0.11	0.28
	(1.2)	(0.07)		(1.2)	(0.08)		(1.2)	(0.15)		(1.2)	(0.11)	
Farm Finances												
Value of Agricultural Assets	699.9	25.6	0.68	666.6	100.3	0.19	698.5	8.3	0.95	735.8	82.5	0.42
	(1041.4)	(63.0)		(1078.6)	(75.6)		(1055.6)	(130.4)		(1161.6)	(101.9)	
Farm Input Expenditures	1313.9	116.8	0.17	1436.3	-9.5	0.93	1332.4	-109.7	0.52	1487.3	-311.7	0.02
	(1374.4)	(84.5)		(1626.3)	(102.3)		(1388.3)	(172.0)		(1536.4)	(127.9)	
Value of Crops Produced	3809.0	371.6	0.39	4312.5	-222.3	0.65	3804.4	27.2	0.98	4161.8	-376.6	0.57
	(7756.2)	(429.2)		(7583.6)	(494.1)		(7692.3)	(970.8)		(7616.9)	(656.1)	
Crop Sales	3476.0	498.7	0.20	4160.9	-313.9	0.49	3426.2	294.3	0.73	3885.1	-195.6	0.74
	(6694.1)	(386.8)		(7158.5)	(455.3)		(6506.5)	(837.8)		(6823.2)	(596.3)	
Farm Profits	2495.2	254.7	0.54	2876.1	-212.7	0.66	2472.0	136.9	0.88	2674.5	-64.9	0.92
	(7504.9)	(416.5)		(7123.7)	(480.1)		(7481.7)	(939.4)		(7538.1)	(648.6)	
Other Farm Characteristics												
Total Cultivated Area	7.0	0.41	0.32	7.0	1.2	0.02	7.2	-0.89	0.30	7.8	0.44	0.52
	(6.8)	(0.41)		(7.4)	(0.51)		(6.9)	(0.86)		(7.4)	(0.68)	
Crop Diversification	0.84	-0.00	0.97	0.86	-0.03	0.21	0.84	0.03	0.52	0.83	0.01	0.66
	(0.36)	(0.02)		(0.34)	(0.02)		(0.37)	(0.05)		(0.37)	(0.03)	
Farm Shocks (Std Index)	-0.02	0.03	0.61	-0.04	0.08	0.23	0.02	-0.23	0.07	-0.01	0.08	0.42
	(1.0)	(0.06)		(1.0)	(0.07)		(1.0)	(0.13)		(1.0)	(0.09)	
Cocoa Prior Season (Indicator)	0.47	0.02	0.45	0.47	0.04	0.25	0.47	0.01	0.81	0.49	0.06	0.20
	(0.50)	(0.03)		(0.50)	(0.03)		(0.50)	(0.06)		(0.50)	(0.04)	
Non Farm Characteristics												
No. of Loans in the Last 1 Year	0.46	-0.02	0.74	0.39	0.08	0.13	0.48	-0.11	0.22	0.48	-0.06	0.39
	(0.74)	(0.05)		(0.75)	(0.06)		(0.77)	(0.09)		(0.88)	(0.08)	
Business Ownership	0.48	0.02	0.53	0.51	-0.01	0.74	0.48	0.03	0.67	0.53	-0.11	0.02
	(0.50)	(0.03)		(0.50)	(0.03)		(0.50)	(0.06)		(0.50)	(0.04)	
Food Security (Index)	0.04	-0.06	0.27	-0.03	0.01	0.91	0.08	-0.25	0.04	-0.02	-0.05	0.56
	(0.99)	(0.06)		(1.0)	(0.07)		(0.95)	(0.12)		(1.0)	(0.09)	
Number of observations		1372			917			455			621	
F-stat (p-val) multivariate test		0.93 (0.53)			2.2 (0.00)			1.1 (0.35)			2.2 (0.01)	
Survey Attrition Rate	3.1%	2.5%	0.55	2.7%	2.4%	0.78	3.2%	2.6%	0.78	2.2%	2.9%	0.63
Take-up rate	16.9%	59.3%	0.00									

Table 2: Intent to Treat (ITT) Estimates

	Base Spec	Timeliness of Loans		Gender		Means	
	ITT Full Sample	ITT	ITT x Timely Loan	ITT	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable							
Panel A: Farm Financial Outcomes							
Total Farm Input Expenditures	158.9*	118.7	275.1	255.7**	-376.3**	1391.9	1556.2
	(90.2)	(97.5)	(285.2)	(110.3)	(187.8)	(1474.3)	(1459.4)
Market Value of Crops Produced	-8.8	-236.2	1410.7**	-169.8	554.7	4057.4	2258.1
	(283.5)	(298.5)	(669.0)	(360.1)	(549.5)	(7483.7)	(4945.3)
Crop Sales	-48.5	-248.4	1280.4**	-187.9	481.7	3809.3	2172.9
	(277.8)	(292.9)	(653.3)	(353.5)	(536.5)	(6746.8)	(4840.8)
Crop Profits	-173.8	-348.9	1179.2*	-432.9	932.9*	2665.5	702.0
	(284.0)	(302.4)	(726.4)	(357.6)	(561.2)	(7261.2)	(4787.8)
Panel B: Farm Land Use							
Sole Crops Area	-0.24	-0.35	0.50	-0.22	-0.09	3.9	2.6
	(0.33)	(0.35)	(0.86)	(0.43)	(0.65)	(6.4)	(5.5)
Mixed Crops Area	0.61**	0.59**	0.30	0.50	0.28	3.3	3.3
	(0.27)	(0.29)	(0.75)	(0.34)	(0.51)	(4.3)	(4.2)
Crop Diversification	0.03	0.01	0.15	0.06**	-0.12**	0.85	0.74
	(0.03)	(0.03)	(0.09)	(0.03)	(0.06)	(0.36)	(0.44)
Panel C: Household Finances							
Money Owed to Respondent	149.5**	122.7*	146.7	188.9***	-154.5	462.9	438.2
	(59.9)	(64.6)	(153.6)	(73.7)	(121.0)	(1030.7)	(1092.4)
Household Savings	115.9	94.5	-272.0	119.0	-29.8	483.6	746.4
	(89.8)	(94.4)	(291.7)	(112.9)	(172.0)	(1072.8)	(1737.9)
Panel D: Business Outcomes							
Owning a Business (Indicator)	-0.05**	-0.04	-0.12	-0.05*	0.02	0.50	0.47
	(0.03)	(0.03)	(0.11)	(0.03)	(0.06)	(0.50)	(0.50)
Investment into Business	-54.6	-79.3	62.9	-75.9	73.6	475.8	395.3
	(55.0)	(55.8)	(199.1)	(67.1)	(117.0)	(1327.6)	(947.0)
Income from Business	-60.0	-68.9	28.8	-120.7*	216.5**	540.6	348.2
	(50.2)	(54.7)	(138.1)	(65.8)	(97.5)	(1158.0)	(916.4)
Panel E: Experience with Credit							
Credit Received -- Banks	40.5	24.3	108.2	10.0	113.2	262.3	325.5
	(73.1)	(81.1)	(180.3)	(93.9)	(134.5)	(1056.3)	(1425.1)
Credit Received -- Microfinance	25.1***	27.5***	-5.5	24.0**	4.2	16.5	2.5
	(9.3)	(10.9)	(21.7)	(11.1)	(20.2)	(177.9)	(47.9)
Credit Received -- Moneylender	-27.2	-37.4	68.6	-46.6	67.8	57.0	109.8

	(42.2)	(45.7)	(97.0)	(57.3)	(69.0)	(339.1)	(826.1)
Credit Received -- Informal	26.5	33.2	-109.6*	57.4	-116.7**	167.1	64.2
	(31.0)	(31.9)	(67.5)	(43.6)	(58.2)	(718.9)	(261.6)
Perceived Creditworthiness (Index)	0.08	0.08	-0.07	0.11*	-0.14	-	-0.05
	(0.06)	(0.06)	(0.21)	(0.07)	(0.13)		(0.98)
Panel F: Health and Well Being							
Social Ladder Position, Absolute Wellbeing	0.11**	0.10*	0.02	0.18***	-0.27**	-	-0.07
	(0.06)	(0.06)	(0.19)	(0.07)	(0.13)		(0.94)
Food Security (Index)	-0.04	-0.04	-0.16	-0.03	-0.00	0.0	0.0
	(0.06)	(0.06)	(0.21)	(0.07)	(0.13)	(1.0)	(0.99)
Psychological Distress (Index)	-0.02	-0.03	0.10	-0.02	-0.02	-	0.02
	(0.06)	(0.06)	(0.19)	(0.07)	(0.13)		(0.98)
Subjective Well Being (Index)	-0.01	0.02	-0.31	-0.00	-0.01	-	0.01
	(0.06)	(0.06)	(0.21)	(0.07)	(0.13)		(0.98)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise. Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table 3: ITT Estimates of Impact on Farm Input Expenditures

	Base Spec	Timeliness of Loans		Gender		Means	
	ITT Full Sample	ITT	ITT x Timely Loan	ITT	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable							
Fertilizers	27.3	6.7	162.5*	46.4	-73.4	191.7	281.8
	(27.8)	(29.6)	(90.9)	(34.5)	(58.0)	(449.8)	(449.1)
Insecticides	35.8*	22.0	64.3	63.5***	-104.7**	231.8	208.4
	(19.8)	(21.1)	(55.7)	(22.8)	(46.4)	(386.3)	(316.6)
Herbicides and Weedicides	5.9	-0.73	33.6	15.8	-39.3	125.4	148.4
	(15.0)	(16.7)	(42.7)	(18.3)	(31.6)	(183.5)	(262.4)
Land Rental	45.5**	44.3*	-39.4	52.7*	-30.0	106.7	81.9
	(21.2)	(23.3)	(58.0)	(28.1)	(34.5)	(404.5)	(306.7)
Hired Labor	18.9	5.1	50.1	35.7	-66.3	403.8	494.7
	(38.7)	(41.9)	(111.7)	(41.5)	(98.8)	(526.2)	(718.0)
Hired Tractor	7.1*	7.0*	-1.9	9.2*	-8.3	2.5	9.6
	(3.8)	(4.0)	(5.0)	(4.9)	(6.4)	(29.5)	(51.0)
Hired Animals	0.83	1.2	-1.0	0.24	2.2	0.16	0.8
	(1.2)	(1.5)	(1.7)	(1.3)	(3.0)	(4.3)	(14.3)
Seeds	3.8	0.45	6.4	5.3	-9.2	208.4	225.8
	(23.0)	(24.6)	(63.7)	(30.3)	(41.2)	(351.5)	(375.7)
Rented Equipment	6.5	7.7	-8.0	14.9*	-30.9**	62.8	41.3
	(6.9)	(7.5)	(18.6)	(8.3)	(14.3)	(145.6)	(97.5)
Irrigation and Registration Fees	18.1**	21.0**	-18.8	24.1**	-23.3*	34.0	31.9
	(7.7)	(8.5)	(12.7)	(10.3)	(12.8)	(143.6)	(90.6)
Other Inputs	6.9	6.1	11.1	11.0	-16.1	24.7	31.5
	(6.6)	(7.2)	(14.6)	(8.5)	(12.5)	(133.3)	(99.1)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise. Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Appendix

A. Focus Groups

Quotes from focus groups discussions about input delays:

- “Because the input did not arrive on time, we couldn’t apply it to increase our production hence we couldn’t make money. So, this also resulted in the fact that some people were also not able to pay the loan. There are some people whose primary work is cultivating cocoa and they don't do any other work. So, because it couldn’t come on time, they were not able to increase their crop production.”

- “Most of the problem that happens comes from your end. The input doesn’t come on time. Just take a look at my hands. If I had this input, I would have done a lot of work with it. I have cultivated cocoa, cassava and plantain. All this is done by one person. Sometimes I had to use my own money to buy inputs but I believe if your input had come on time all the efforts and energy I use will be minimal and I will not go and labor for others to get money to continue my crop production.”

- “If I should receive the input now, the kind of work I will do with it will not be small. Because I have not received the input, it has really slowed my work. I would have sprayed all the weeds around the cocoa farm but because I don’t have it, the farm has been left unattended."

- "The women who received the inputs had a great farming season but those whose inputs were delayed or did not come did not have a successful farming season. There were those women who had worked hard and cleared the land wanting to plant plantain, cocoyam, etc. and were waiting for the inputs to apply on the farm but the inputs were delayed so they didn't even have the strength to continue."

- "Those who did not get the input credit went out for loans on their own to purchase inputs. Those of us who received did not receive on time. For instance, if I plan to apply fertilizer on my farm this week, I have to make sure I am able to get the fertilizer for application. Based on the promise, I had to wait to hope to receive the input, but the inputs did not arrive as promised. We must also note that, these input applications are done routinely, a delay in fertilizer application on a crop can affect its market price and in turn one's revenue and vice versa. What will make us happy joining this initiative is when we receive the inputs on time. After all, farmers cannot refuse the delayed inputs but unfortunately, when you record low yield as a result of that, you would still have to pay back the loan. So if you promise to bring me fertilizer and do not bring it at the appropriate time for usage, you must as well not bring it at all."

Table A1.1: LATE Estimates and Heterogeneous Effects by Farmer Experience - Main Outcomes

	LATE Estimates	Farmer Experience	
	LATE Full Sample	ITT	ITT x High Exper.
	(1)	(2)	(3)
Dependent Variable			
Panel A: Farm Financial Outcomes			
Total Farm Input Expenditures	122.6	65.0	181.3
	(230.7)	(139.6)	(184.8)
Market Value of Crops Produced	480.6	285.9	-535.4
	(691.0)	(325.5)	(559.8)
Crop Sales	483.8	266.6	-574.1
	(680.9)	(315.2)	(547.8)
Crop Profits	342.3	194.0	-674.4
	(691.7)	(336.8)	(562.9)
Panel B: Farm Land Use			
Sole Crops Area	-0.81	0.22	-0.81
	(0.90)	(0.28)	(0.69)
Mixed Crops Area	0.48	0.64	-0.05
	(0.70)	(0.38)	(0.54)
Crop Diversification	-0.00	0.04	-0.02
	(0.06)	(0.04)	(0.05)
Panel C: Household Finances			
Money Owed to Respondent	230.3	164.2*	-31.2
	(147.7)	(86.5)	(121.9)
Household Savings	-1.6	210.6	-195.5
	(211.6)	(129.9)	(180.5)
Panel D: Business Outcomes			
Owning a Business (Indicator)	-0.01	-0.10***	0.11**
	(0.07)	(0.04)	(0.05)
Investment into Business	54.6	-67.9	24.6
	(129.5)	(70.2)	(108.7)
Income from Business	191.5*	-29.4	-61.4
	(109.9)	(74.2)	(100.0)
Panel E: Experience with Credit			
Credit Received -- Banks	87.2	-18.5	115.0
	(148.4)	(120.8)	(148.8)
Credit Received -- Microfinance	45.9	12.3	25.3
	(29.7)	(10.4)	(18.5)
Credit Received -- Moneylender	55.7	-72.8*	92.4
	(83.6)	(38.1)	(85.0)
Credit Received -- Informal	15.5	-7.6	67.0
	(77.9)	(36.3)	(61.5)
Perceived Creditworthiness (Index)	0.06	0.08	-0.03
	(0.14)	(0.08)	(0.11)

Panel F: Health and Well Being			
Food Security (Index)	0.08	0.01	-0.08
	(0.13)	(0.08)	(0.11)
Social Ladder Position, Absolute Wellbeing	0.68***	0.19**	-0.15
	(0.15)	(0.08)	(0.11)
Psychological Distress (Index)	0.08	-0.03	0.01
	(0.14)	(0.08)	(0.12)
Subjective Wellbeing (Index)	0.10	0.01	-0.03
	(0.14)	(0.08)	(0.11)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A1.2: LATE and Heterogeneous Effects by Farmer Experience - Composition of Input Expenditure

	LATE Estimates	Farmer Experience	
	LATE Full Sample	ITT	ITT x High Exper.
	(1)	(2)	(3)
Dependent Variable			
Fertilizers	134.0*	-38.5	128.7**
	(75.6)	(40.6)	(57.2)
Herbicides and Weedicides	50.7	8.5	-5.4
	(35.6)	(18.2)	(29.4)
Insecticides	89.2*	-3.0	77.2*
	(46.9)	(30.2)	(39.7)
Land Rental	1.7	88.1***	-84.0**
	(52.8)	(27.6)	(40.8)
Hired Labor	-27.4	16.3	4.8
	(91.3)	(63.9)	(81.3)
Hired Tractor	12.6	8.3*	-2.7
	(11.1)	(4.6)	(7.5)
Hired Animals	5.4	0.41	0.79
	(3.4)	(2.0)	(2.2)
Seeds	-74.8	-10.2	25.8
	(60.3)	(35.7)	(47.1)
Rented Equipment	5.6	3.7	5.3
	(19.3)	(10.1)	(14.1)
Irrigation and Registration Fees	-27.4	10.8	14.0
	(23.0)	(11.1)	(15.3)
Other Inputs	24.5	6.2	1.3
	(16.5)	(8.7)	(12.9)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A1.3: LATE and Heterogeneous Effects by Farmer Experience - Experience with Credit

	LATE Estimates	Farmer Experience	
	LATE Full Sample	ITT	ITT x High Exper.
	(1)	(2)	(3)
Dependent Variable			
Credit Applied for -- Banks	101.0	-55.6	175.9
	(192.1)	(134.9)	(179.4)
Credit Applied for -- Microfinance	35.8	8.9	16.7
	(31.0)	(13.5)	(24.5)
Get Loan at Oth. Institution (Indicator)	0.02	0.02	0.02
	(0.07)	(0.04)	(0.06)
Get Better Interest Rate (Indicator)	0.06	0.05	-0.02

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A2: Additional ITT Estimates of Impact on Experience with Credit

	Base Spec	Timeliness of Loans		Gender		Means	
	ITT Full Sample	ITT	ITT x Timely Loan	ITT	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable							
Credit Applied for -- Banks	33.7	27.5	-79.7	-19.8	196.2	295.7	407.7
	(87.3)	(92.3)	(465.5)	(110.3)	(169.1)	(1226.0)	(1755.5)
Credit Applied for -- Microfinance	17.3	19.1	3.3	12.7	17.1	18.6	11.6
	(12.2)	(14.0)	(23.6)	(15.3)	(23.5)	(196.8)	(171.6)
Get Loan Elsewhere (Ind.)	0.03	0.03	-0.00	0.04	-0.05	-	0.51
	(0.03)	(0.03)	(0.10)	(0.03)	(0.06)		(0.50)
Get Better Rate Elsewhere (Ind.)	0.04	0.05*	-0.09	0.06**	-0.08	-	0.32
	(0.03)	(0.03)	(0.10)	(0.03)	(0.06)		(0.47)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise. Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A3.1: Multiple Hypotheses Tests

	Unadjusted p-values	Holm adjusted p-values	Westfall-Young adjusted p-values	FDR sharpended q-values
	(1)	(2)	(3)	(4)
Main Outcomes (Table 2)				
Panel A: Farm Financial Outcomes				
Total Farm Input Expenditures	0.08	0.17	0.16	0.45
Market Value of Crops Produced	0.97	0.98	0.98	1.00
Crop Sales	0.86	0.90	0.91	1.00
Crop Profits	0.54	0.65	0.66	1.00
Panel B: Farm Land Use				
Sole Crops Area	0.48	0.48	0.51	0.46
Mixed Crops Area	0.03	0.07	0.09	0.10
Crop Diversification	0.28	0.47	0.51	0.40
Panel C: Household Finances				
Money Owed to Respondent	0.01	0.02	0.04	0.03
Household Savings	0.20	0.20	0.21	0.11
Panel D: Business Outcomes				
Owning a Business (Indicator)	0.08	0.22	0.23	0.34
Investment into Business	0.31	0.33	0.40	0.34
Income from Business	0.23	0.38	0.40	0.34
Panel E: Experience with Credit				
Credit Received -- Banks	0.58	0.59	0.81	0.87
Credit Received -- Microfinance	0.01	0.17	0.15	0.04
Credit Received -- Moneylender	0.52	0.79	0.81	0.87
Credit Received -- Informal	0.39	0.79	0.81	0.87
Perceived Creditworthiness (Index)	0.19	0.55	0.62	0.60
Panel F: Health and Wellbeing				
Social Ladder Position, Absolute Wellbeing	0.04	0.15	0.16	0.22
Food Security (Index)	0.52	0.88	0.88	1.00
Psychological Distress (Index)	0.71	0.92	0.92	1.00
Subjective Well Being (Index)	0.93	0.93	0.92	1.00
Input Expenditure Outcomes (Table 3)				
Fertilizers	0.33	0.84	0.90	0.53
Insecticides	0.07	0.40	0.45	0.21
Herbicides and Weedicides	0.69	0.91	0.94	0.94
Land Rental	0.03	0.27	0.30	0.21
Hired Labor	0.62	0.94	0.94	0.94
Hired Tractor	0.06	0.41	0.45	0.21
Hired Animals	0.48	0.94	0.94	0.72
Seeds	0.87	0.86	0.94	1.00
Rented Equipment	0.34	0.88	0.90	0.53
Irrigation and Registration Fees	0.02	0.16	0.21	0.21
Other Inputs	0.29	0.87	0.91	0.53

Table A3.2: Multiple Hypotheses Tests for Timely Loan Interaction Terms

	Unadjusted p-values	Holm adjusted p-values	Westfall-Young adjusted p-values	Romano-Wolf adjusted p-values
	(1)	(2)	(3)	(4)
Main Outcomes (Table 2)				
Panel A: Farm Financial Outcomes				
Total Farm Input Expenditures	0.33	0.33	0.37	0.33
Market Value of Crops Produced	0.05	0.15	0.10	0.11
Crop Sales	0.03	0.16	0.08	0.09
Crop Profits	0.10	0.21	0.19	0.19
Panel B: Farm Land Use				
Sole Crops Area	0.56	1.0	0.81	0.57
Mixed Crops Area	0.67	0.68	0.81	0.68
Crop Diversification	0.11	0.38	0.32	0.33
Panel C: Household Finances				
Money Owed to Respondent	0.34	0.68	0.61	0.57
Household Savings	0.35	0.64	0.61	0.64
Panel D: Business Outcomes				
Owning a Business (Indicator)	0.27	0.87	0.58	0.57
Investment into Business	0.75	1.0	0.92	0.93
Income from Business	0.83	0.84	0.92	0.84
Panel E: Experience with Credit				
Credit Received -- Banks	0.41	1.0	0.80	0.92
Credit Received -- Microfinance	0.80	0.82	0.92	0.82
Credit Received -- Moneylender	0.48	1.0	0.86	0.95
Credit Received -- Informal	0.10	0.83	0.42	0.60
Perceived Creditworthiness (Index)	0.76	1.0	0.92	0.95
Panel F: Health and Wellbeing				
Social Ladder Position, Absolute Wellbeing	0.93	0.93	0.93	0.93
Food Security (Index)	0.44	1.0	0.84	0.82
Psychological Distress (Index)	0.62	1.0	0.90	0.85
Subjective Well Being (Index)	0.14	0.63	0.46	0.45
Input Expenditure Outcomes (Table 3)				
Fertilizers	0.07	0.89	0.57	0.57
Insecticides	0.25	1.0	0.93	0.99
Herbicides and Weedicides	0.43	1.0	0.99	0.91
Land Rental	0.50	1.0	0.99	0.99
Hired Labor	0.65	1.0	0.99	0.98
Hired Tractor	0.70	1.0	0.99	0.91
Hired Animals	0.53	1.0	0.99	0.98
Seeds	0.92	0.92	0.99	0.92
Rented Equipment	0.66	1.0	0.99	0.96
Irrigation and Registration Fees	0.14	1.0	0.78	0.70
Other Inputs	0.45	1.0	0.99	0.98

Table A4.1 Robustness Checks with Timely Loans

	ITT	ITT x Community Timely Loan	ITT	ITT x Predicted Timely Loan
	(1)	(2)	(3)	(4)
Dependent Variable				
Panel A: Farm Financial Outcomes				
Total Farm Input Expenditures	113.9	54.5	131.9	203.6
	(92.4)	(159.1)	(99.2)	(230.6)
Market Value of Crops Produced	-143.2	622.3	-56.4	405.7
	(296.3)	(396.9)	(301.7)	(920.5)
Crop Sales	-193.6	512.6	-97.4	414.4
	(295.4)	(432.7)	(294.3)	(916.2)
Crop Profits	-247.0	589.8*	-210.7	297.6
	(280.7)	(351.5)	(302.8)	(921.4)
Panel B: Farm Land Use				
Sole Crops Area	-0.22	1.0	-0.17	-0.57
	(0.40)	(0.92)	(0.36)	(1.1)
Mixed Crops Area	0.62**	-1.1	0.57**	0.06
	(0.29)	(1.0)	(0.29)	(0.79)
Crop Diversification	-0.01	0.12*	0.03	0.00
	(0.03)	(0.07)	(0.03)	(0.08)
Panel C: Household Finances				
Money Owed to Respondent	145.7**	-24.5	159.0**	-54.9
	(59.5)	(116.2)	(64.3)	(177.6)
Household Savings	198.7	-129.8	127.7	-53.5
	(89.0)	(209.1)	(100.1)	(190.4)
Panel D: Business Outcomes				
Owning a Business (Indicator)	-0.03	-0.07	-0.04	-0.02
	(0.03)	(0.06)	(0.03)	(0.08)
Investment into Business	-53.2	-90.6	-70.6	113.0
	(58.3)	(185.4)	(58.2)	(181.8)
Income from Business	-69.3	42.3	-72.8	109.8

	(62.8)	(140.4)	(55.2)	(129.5)
Panel E: Experience with Credit				
Credit Received -- Banks	74.3	-211.0	36.3	40.9
	(87.4)	(237.1)	(80.8)	(136.1)
Credit Received -- Microfinance	32.0**	-21.8	25.4**	-2.3
	(15.4)	(16.9)	(10.1)	(27.8)
Credit Received -- Moneylender	-19.8	-75.8	-37.3	84.7
	(41.2)	(235.9)	(46.8)	(84.8)
Credit Received -- Informal	-18.7	-8.1	29.6	-22.0
	(23.7)	(43.5)	(36.0)	(56.7)
Perceived Creditworthiness (Index)	0.09	-0.25	0.06	0.17
	(0.06)	(0.21)	(0.06)	(0.17)
Panel F: Health and Well Being				
Social Ladder Position, Absolute Wellbeing	0.16**	-0.08	0.06	0.40**
	(0.06)	(0.18)	(0.06)	(0.17)
Food Security (Index)	-0.04	-0.04	0.01	-0.38**
	(0.07)	(0.18)	(0.06)	(0.18)
Psychological Distress (Index)	-0.02	-0.18	-0.02	0.02
	(0.07)	(0.13)	(0.06)	(0.17)
Subjective Well Being (Index)	-0.02	-0.15*	-0.05	0.39**
	(0.06)	(0.08)	(0.06)	(0.17)

Col (1)-(2): N = 1,101. The variable "Community Timely Loan" is assigned a value of 1 if the average loan delay in the community is less than 30 days, and 0 otherwise. The number of observations is lower than the main specification because in some communities, there are no loan recipients. In such communities, the average loan delay is undefined. Therefore, we drop those observations from our analysis.
Col (3)-(4) N = 1,335. Timely loans are predicted using a logistic regression baseline variables including all key outcomes in Table 2 and demographics such as age, gender, and farming experience. The variable "Predicted Timely Loan" is assigned a value of 1 if the predicted scores are above the 87.5th percentile, and 0 otherwise.
See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A4.2: Comparing Treatment Group Subsamples

Treatment Group Sample:	Full Sample	No Loan	Got Loan	Got Loan But Not Timely Loan	Got Timely Loan	Got Timely Loan (Plus Baseline Predictors)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable						
Total Input Expenditure	158.9*	171.3	143.2	100.5	238.8	273.0
	(90.2)	(133.7)	(95.9)	(100.0)	(178.5)	(177.5)
Crop Value	-8.8	-139.6	119.7	-36.1	495.6	537.2
	(283.5)	(361.6)	(321.0)	(339.0)	(531.5)	(530.3)
Farm Revenue	-48.5	-183.9	72.0	-54.8	343.1	384.1
	(277.8)	(355.8)	(315.0)	(332.4)	(524.3)	(523.4)
Farm Profits	-173.8	-313.8	-25.0	-144.6	291.8	281.1
	(284.0)	(371.1)	(316.5)	(333.6)	(553.5)	(553.6)
N	1335	804	972	839	574	574

Note: In each regression, the relevant sample in the treatment group is compared to the entire control group. See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A5.1: Results with Timely Loans and Gender Interactions in the Same Spec - Main Outcomes

	Timely Loans and Gender Interactions			**Means**	
	ITT	ITT x Timely Loan	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)
Dependent Variable					
Panel A: Farm Financial Outcomes					
Total Farm Input Expenditures	218.2*	288.6	-390.8**	1391.9	1556.2
	(116.6)	(285.9)	(186.4)	(1474.3)	(1459.4)
Market Value of Crops Produced	-401.5	1444.1**	573.0	4057.4	2258.1
	(373.4)	(682.01)	(546.6)	(7483.7)	(4945.3)
Crop Sales	-394.4	1312.5**	506.2	3809.3	2172.9
	(366.0)	(665.0)	(535.1)	(6746.8)	(4840.8)
Crop Profits	-608.8	1198.4*	941.0*	2665.5	702.0
	(374.1)	(736.2)	(563.2)	(7261.2)	(4787.8)
Panel B: Farm Land Use					
Sole Crops Area	-0.34	0.52	-0.07	3.9	2.6
	(0.45)	(0.86)	(0.66)	(6.4)	(5.5)
Mixed Crops Area	0.48	0.35	0.30	3.3	3.3
	(0.36)	(0.75)	(0.51)	(4.3)	(4.2)
Crop Diversification	0.05	0.15*	-0.12**	0.85	0.74
	(0.03)	(0.09)	(0.05)	(0.36)	(0.44)
Panel C: Household Finances					
Money Owed to Respondent	164.6**	152.2	-163.5	462.9	438.2
	(77.7)	(152.7)	(120.1)	(1030.7)	(1092.4)
Household Savings	104.6	-263.1	-52.6	483.6	746.4
	(117.4)	(292.4)	(168.5)	(1072.8)	(1737.9)
Panel D: Business Outcomes					
Owning a Business (Indicator)	-0.04	-0.12	0.01	0.50	0.47
	(0.03)	(0.11)	(0.06)	(0.50)	(0.50)
Investment into Business	-97.9	63.9	67.6	475.8	395.3
	(66.4)	(199.1)	(115.4)	(1327.6)	(947.0)
Income from Business	-123.8*	32.3	198.1**	540.6	348.2
	(69.6)	(138.3)	(98.9)	(1158.0)	(916.4)
Panel E: Experience with Credit					
Credit Received -- Banks	-4.6	108.0	108.0	262.3	325.5
	(102.0)	(180.3)	(131.7)	(1056.3)	(1425.1)

Credit Received -- Microfinance	26.2**	-5.7	4.9	16.5	2.5
	(12.2)	(21.8)	(20.4)	(177.9)	(47.9)
Credit Received -- Moneylender	-57.8	71.6	71.4	57.0	109.8
	(61.3)	(97.0)	(72.1)	(339.1)	(826.1)
Credit Received -- Informal	61.5	-109.0	-106.3*	167.1	64.2
	(43.1)	(68.1)	(54.7)	(718.9)	(261.6)
Perceived Creditworthiness (Index)	0.12*	-0.07	-0.15	-	-0.05
	(0.07)	(0.21)	(0.13)		(0.98)
Panel F: Health and Well Being					
Social Ladder Position	0.17**	0.02	-0.28**	-	-0.07
	(0.07)	(0.19)	(0.13)		(0.94)
Social Ladder Position, Absolute Wellbeing	0.03	-0.30	-0.03	-	0.01
	(0.07)	(0.21)	(0.13)		(0.98)
Food Security (Index)	-0.04	-0.16	-0.01	0.0	0.0
	(0.07)	(0.21)	(0.13)	(1.0)	(0.99)
Psychological Distress (Index)	-0.03	0.11	-0.01	-	0.02
	(0.07)	(0.19)	(0.13)		(0.98)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise. Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A5.2: Results with Timely Loans and Gender Interactions in the Same Spec - Additional Outcomes for Composition of Input Expenditure

	Timely Loans and Gender Interactions			Means	
	ITT	ITT x Timely Loan	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)
Dependent Variable					
Fertilizers	26.3	165.1*	-76.6	191.7	281.8
	(36.2)	(91.1)	(57.7)	(449.8)	(449.1)
Insecticides	49.1**	65.7	-103.1**	231.8	208.4
	(24.0)	(55.4)	(45.2)	(386.3)	(316.6)
Herbicides and Weedicides	8.9	35.2	-38.2	125.4	148.4
	(19.9)	(42.8)	(31.8)	(183.5)	(262.4)
Land Rental	52.0*	-37.5	-31.6	106.7	81.9
	(30.1)	(57.9)	(34.1)	(404.5)	(306.7)
Hired Labor	22.1	52.1	-65.8	403.8	494.7
	(43.4)	(111.7)	(99.7)	(526.2)	(718.0)
Hired Tractor	9.2*	-1.7	-8.5	2.5	9.6
	(5.2)	(5.0)	(6.4)	(29.5)	(51.0)
Hired Animals	0.52	-1.0	2.4	0.16	0.8
	(1.5)	(1.7)	(3.0)	(4.3)	(14.3)
Seeds	0.24	8.6	-2.6	208.4	225.8
	(31.6)	(63.8)	(41.0)	(351.5)	(375.7)
Rented Equipment	16.1*	-8.1	-31.1**	62.8	41.3
	(9.0)	(18.4)	(14.2)	(145.6)	(97.5)
Irrigation and Registration Fees	26.8**	-18.0	-22.9*	34.0	31.9
	(11.1)	(12.7)	(12.9)	(143.6)	(90.6)
Other Inputs	10.0	11.7	-15.5	24.7	31.5
	(9.2)	(14.6)	(12.5)	(133.3)	(99.1)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise. Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A5.3: Results with Timely Loans and Gender Interactions in the Same Spec - Additional Outcomes for Experience with Credit

	Timely Loans and Gender Interactions			Means	
	ITT	ITT x Timely Loan	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)
Dependent Variable					
Credit Applied for -- Banks	-23.1	-78.8	186.8	295.7	407.7
	(117.5)	(464.4)	(164.6)	(1226.0)	(1755.5)
Credit Applied for -- Microfinance	14.4	3.2	17.5	18.6	11.6
	(16.6)	(23.8)	(23.5)	(196.8)	(171.6)
Get Loan Elsewhere (Ind.)	0.04	-0.00	-0.06	-	0.51
	(0.03)	(0.10)	(0.06)		(0.50)
Get Better Rate Elsewhere (Ind.)	0.07**	-0.09	-0.08	-	0.32
	(0.03)	(0.10)	(0.06)		(0.47)

N = 1,335 (Baseline: 1,372, Endline: 1,335, Attrition Rate: 2.7%). Baseline mean values are missing for questions asked only at endline (and not at baseline). The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise. Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables. *, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A6: Intent to Treat (ITT) Estimates with Incorrectly Recorded Observations Dropped

Note: 5 observations were dropped from overall sample where loan delivery was recorded to be before loan application

	Base Spec	**Timeliness of Loans**		**Gender**		**Means**	
	ITT Full Sample	ITT	ITT x Timely Loan	ITT	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable							
Panel A: Farm Financial Outcomes							
Total Farm Input Expenditures	155.5*	119.1	250.8	249.5**	-364.6*	1391.9	1559.3
	(90.5)	(97.5)	(293.7)	(110.7)	(188.4)	(1474.3)	(1461.5)
Market Value of Crops Produced	-21.6	-236.3	1512.7**	-210.3	659.6	4057.4	2245.6
	(282.7)	(298.2)	(633.3)	(358.4)	(546.8)	(7483.7)	(4941.5)
Crop Sales	-62.8	-249.3	1373.3**	-229.5	585.4	3809.3	2160.1
	(276.8)	(292.5)	(615.7)	(351.7)	(533.5)	(6746.8)	(4836.3)
Crop Profits	-180.7	-349.2	1313.4*	-464.6	1025.3*	2665.5	686.4
	(283.6)	(302.1)	(702.2)	(356.4)	(558.9)	(7261.2)	(4783.6)
Panel B: Farm Land Use							
Sole Crops Area	-0.24	-0.35	0.53	-0.23	-0.04	3.9	2.6
	(0.33)	(0.35)	(0.87)	(0.43)	(0.65)	(6.4)	(5.5)
Mixed Crops Area	0.59**	0.57**	0.46	0.51	0.23	3.3	3.3
	(0.27)	(0.29)	(0.76)	(0.34)	(0.51)	(4.3)	(4.2)
Crop Diversification	0.03	0.01	0.16	0.06**	-0.12**	0.85	0.74
	(0.03)	(0.03)	(0.10)	(0.03)	(0.06)	(0.36)	(0.44)
Panel C: Household Finances							
Money Owed to Respondent	147.3**	123.2*	130.2	185.6**	-150.0	462.9	440.2
	(60.0)	(64.5)	(156.2)	(73.7)	(121.0)	(1030.7)	(1094.5)
Household Savings	121.8	96.1	-266.2	128.8	-43.2	483.6	749.8
	(89.9)	(94.4)	(300.1)	(113.0)	(172.2)	(1072.8)	(1741.1)
Panel D: Business Outcomes							
Owning a Business (Indicator)	-0.05*	-0.04	-0.15	-0.05*	0.02	0.50	0.47
	(0.03)	(0.03)	(0.11)	(0.03)	(0.06)	(0.50)	(0.50)
Investment into Business	-66.3	-79.7	-6.3	-91.7	92.1	475.8	397.1
	(54.6)	(55.7)	(200.8)	(66.2)	(116.7)	(1327.6)	(948.8)
Income from Business	-65.4	-68.6	-12.9	-127.5*	224.0**	540.6	349.8
	(50.3)	(54.7)	(140.1)	(65.7)	(97.5)	(1158.0)	(918.2)
Panel E: Experience with Credit							
Credit Received -- Banks	40.9	24.2	122.9	10.3	113.1	262.3	327.0
	(73.4)	(81.1)	(186.6)	(94.3)	(135.0)	(1056.3)	(1428.2)
Credit Received -- Microfinance	25.0***	27.6***	-11.9	23.9**	4.3	16.5	2.5
	(9.3)	(11.0)	(19.9)	(11.1)	(20.1)	(177.9)	(48.0)
Credit Received -- Moneylender	-27.2	-37.4	69.7	-46.7	68.2	57.0	110.3

	(42.3)	(45.7)	(100.6)	(57.5)	(69.2)	(339.1)	(827.9)
Credit Received -- Informal	28.6	33.2	-97.0	60.9	-121.4**	167.1	64.5
	(32.1)	(32.1)	(64.1)	(45.4)	(60.2)	(718.9)	(262.2)
Perceived Creditworthiness (Index)	0.08	0.08	-0.05	0.12*	-0.15	-	-0.05
	(0.06)	(0.06)	(0.22)	(0.07)	(0.13)		(0.97)
Panel F: Health and Well Being							
Social Ladder Position, Absolute Wellbeing	0.11**	0.10*	0.01	0.19***	-0.28**	-	-0.07
	(0.06)	(0.06)	(0.20)	(0.07)	(0.13)		(0.94)
Food Security (Index)	-0.03	-0.04	-0.16	-0.03	-0.01	0.0	0.02
	(0.06)	(0.06)	(0.21)	(0.07)	(0.13)	(1.0)	(1.0)
Psychological Distress (Index)	-0.03	-0.03	-0.01	-0.03	-0.01	-	0.02
	(0.06)	(0.06)	(0.18)	(0.07)	(0.13)		(0.97)
Subjective Well Being (Index)	-0.01	0.02	-0.33	-0.01	-0.01	-	0.01
	(0.06)	(0.06)	(0.21)	(0.07)	(0.13)		(0.98)

N = 1,331. N is different from the main specifications in Tables 2 and 3 because the loan delivery and receipt dates were incorrectly recorded for 5 observations (4 at endline, with 1 attrited respondent), with loan delivery noted to be before loan application. Therefore, these observations were unusable to accurately determine timely loan delivery.
Baseline mean values are missing for questions asked only at endline (and not at baseline).
The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise. Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables.
*, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Table A7: ITT Estimates of Impact on Farm Input Expenditures with Incorrectly Recorded Observations Dropped

Note: 5 observations were dropped from overall sample where loan delivery was recorded to be before loan application

	Base Spec	**Timeliness of Loans**		**Gender**		**Means**	
	ITT Full Sample	ITT	ITT x Timely Loan	ITT	ITT x Female	Baseline: All	Endline: Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable							
Fertilizers	27.3	6.8	173.3*	45.4	-69.3	191.7	282.0
	(27.9)	(29.6)	(92.8)	(34.6)	(58.1)	(449.8)	(449.8)
Insecticides	34.7*	22.1	55.0	61.6***	-101.6**	231.8	208.6
	(19.8)	(21.1)	(56.4)	(22.9)	(46.5)	(386.3)	(317.2)
Herbicides and Weedicides	5.1	-0.76	31.2	14.7	-38.0	125.4	148.6
	(15.0)	(16.7)	(43.9)	(18.3)	(31.6)	(183.5)	(263.0)
Land Rental	44.9**	44.4*	-51.8	51.8*	-28.9	106.7	82.3
	(21.3)	(23.4)	(59.3)	(28.1)	(34.6)	(404.5)	(307.3)
Hired Labor	17.0	5.1	31.3	33.4	-64.4	403.8	496.3
	(38.8)	(41.9)	(115.0)	(41.6)	(99.2)	(526.2)	(719.2)
Hired Tractor	7.1*	7.0*	-1.4	9.3*	-8.4	2.5	9.6
	(3.8)	(4.0)	(5.0)	(5.0)	(6.4)	(29.5)	(51.1)
Hired Animals	0.84	1.2	-1.0	0.24	2.2	0.16	0.8
	(1.2)	(1.5)	(1.7)	(1.3)	(3.0)	(4.3)	(14.3)
Seeds	4.5	0.50	11.3	6.1	-9.3	208.4	226.2
	(23.1)	(24.6)	(65.7)	(30.4)	(41.3)	(351.5)	(376.4)
Rented Equipment	6.8	7.6	-3.5	15.2*	-31.1**	62.8	41.2
	(6.9)	(7.5)	(19.0)	(8.3)	(14.4)	(145.6)	(97.7)
Irrigation and Registration Fees	18.0**	21.0**	-19.9	23.9**	-23.2*	34.0	32.1
	(7.8)	(8.5)	(12.8)	(10.3)	(12.8)	(143.6)	(90.8)
Other Inputs	6.7	6.1	10.7	10.8	-16.0	24.7	31.6
	(6.6)	(7.2)	(15.0)	(8.5)	(12.6)	(133.3)	(99.3)

N = 1,331. N is different from the main specifications in Tables 2 and 3 because the loan delivery and receipt dates were incorrectly recorded for 5 observations (4 at endline, with 1 attrited respondent), with loan delivery noted to be before loan application. Therefore, these observations were unusable to accurately determine timely loan delivery.
Baseline mean values are missing for questions asked only at endline (and not at baseline).
The "Timely Loan" variable equals 1 if the loan product was delivered to the farmer within 30 days of applying, and equals 0 otherwise.
Timely loan regressions include controls for age, farm input expenditures, and business ownership, the three variables that predict timely loan takeup with p-value<0.05 in Table 1. See Data Appendix for definitions of all variables.
*, **, *** refer to statistical significance at 1%, 5%, and 10% respectively.

Data Appendix: Description of Variables

Total Farm Input Expenditure	Sum of expenditures (GHS) on a series of farm inputs comprising: (i) Fertilizers, (ii) Herbicides/Weedicides, (iii) Insecticides, (iv) Land Rental, (v) Hired Labor, (vi) Hired tractor, (vii) Hired animals, (viii) Seeds, (ix) Rented equipment, (x) Fees (for registration, irrigation), (xi) Other inputs.
Market Value of Crops Produced	Sum, across all crops produced, of the number of units of crop produced x market value of each unit (GHS)
Crop Sales	Sum, across all crops produced, of the number of units sold x market value of each unit (GHS)
Crop Profits	Difference (GHS) between crop sales and the total expenditure on farm inputs. Note: we cannot account for additional costs such as the farmers' cost of time.
Sole Crops Area	Area (acres) of land in which only a single crop is grown.
Mixed Crops Area	Area (acres) of land in which mixed cropping is practiced
Crop Diversification	Indicator for whether the farmer cultivates multiple crops. While the cultivated area under different crops and practices are self reported, admin data provides a rough estimate of total land area at baseline.
Owning a Business	Indicator for whether the farmer or a household member had a business in the past 12 months
Investment into Business	Amount (GHS) invested in non-farm business in the last 30 days
Income from Business	Amount (GHS) earned from non-farm business in the last month of revenue generating activities
Credit Received -- Banks	Amount (GHS) received in loans from banks, irrespective of the amount applied for, in the past 12 months
Credit Received -- Microfinance	Amount (GHS) received in loans from microfinance institutions, irrespective of the amount applied for, in the past 12 months
Credit Received -- Moneylenders	Amount (GHS) received in loans from moneylenders in the past 12 months
Credit Received -- Informal	Amount (GHS) received in loans from other informal sources including relatives and susu groups
Perceived Creditworthiness Index	Standardized index comprising variables capturing: (i) Whether the respondent believes they would receive a loan at a different financial institution (indicator) and (ii) Whether the respondent believes they would get a better interest rate at the institution
Social Ladder, Absolute Wellbeing	Respondent's perceived position on a social ladder where the top (10) and bottom (0) represent the best and worst possible lives for the respondent
Food Security Index	Standardized index comprising variables capturing: (i) Whether anyone in the household could not afford enough food and therefore missed meals in the last 30 days, (ii) Whether anyone in the household could not afford enough meat in the last 30 days, (iii) The number of days in the last 30 days where the household consumed meat or fish
Psychological Distress Index	Standardized index comprising variables capturing: (i) How often the respondent felt nervous in the last 30 days, (ii) How often the respondent felt depressed in the last 30 days, (iii) How often the respondent felt everything was an effort in the last 30 days. All questions were answered on 5-point scale ranging from "None of the time" to "All of the time".
Subjective Wellbeing Index	Standardized index comprising variables capturing: (i) How satisfied the respondent felt in the last 30 days about their financial wellbeing, and (ii) How satisfied the respondent felt in the last 30 days about their overall wellbeing. All questions were answered on a 5-point scale ranging from "Very dissatisfied" to "Very satisfied".

Survey Instruments

Baseline: https://app.box.com/s/xt1ivv14l80qr4oa5s8713mmvi76g0ma

Endline: https://app.box.com/s/iekzwxtoxauswrwunq4n8izix0zp2g27