Safety Nets, Credit, and Investment: Evidence from a Guaranteed Income Program*

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Abstract

We examine how guaranteed income affects investment behavior by exploiting a natural experiment in India that provides a permanent, unconditional income transfer to landowning farmers. Using detailed income, investment, and credit data, we estimate that each additional dollar of guaranteed income increases farm income by $1.76. Rather than reducing effort, the transfers stimulate investment, primarily financed with credit. $1 of guaranteed income generates a $6.78 increase in formal borrowing representing 40% of the present value of perpetual cash transfers. Survey evidence suggests that guaranteed income raises credit demand by improving farmers' ability to repay in adverse states and by lowering the expected cost of default. The results suggest that uninsured income risk can constrain entrepreneurial investment through demand-side credit frictions, and that predictable income support can relax these constraints by strengthening borrowers' risk-bearing capacity.

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1 Introduction

Do safety nets, such as a guaranteed income program, encourage investment? A guaranteed income program is an identical, unconditional, recurring, and guaranteed cash transfer, sized to meet basic needs, and given to everyone within a well-defined community. Over the last decade, guaranteed income programs, such as Universal Basic Income (UBI) or Basic Income (BI) proposals, have garnered considerable attention.[1] While the debate in developed economies has focused on the potential effects of such programs on incentives to supply labor in stable jobs, in developing economies, few people hold full-time stable jobs. Instead, most workers in developing economies derive their livelihood from subsistence and micro-enterprises, such as agriculture, which face a number of constraints that limit their ability to grow (Woodruff, 2018). Moreover, in such a setting. the investment margin or the accumulation of productive assets is as salient as adjustments in labor supply or leisure (Breza and Kaur, 2025). These considerations add an important dimension to the discussion about the possible impact of guaranteed income programs on investment in the context of micro-enterprises. Specifically, can guaranteed income programs unlock untapped investment opportunities?

This debate hinges on underlying economic questions about the relative effect of guaranteed income on the incentives to work, financial constraints, and financial resilience. On the one hand, a class of theoretical models indicates that limited internal funds and uninsured shocks can lead risk-averse entrepreneurs to underinvest (Kihlstrom and Laffont, 1979; Banerjee and Newman, 1991, 1993). Proponents argue that guaranteed income will encourage investment by resolving constraints and increasing financial resilience. Moreover, a positive permanent income shock like guaranteed income can increase spending on durables or investment financed through credit (Aaronson, Agarwal, and French, 2012; Agarwal and Qian, 2014, 2017; Agarwal et al., 2025). On the other hand, most classical models of household optimization predict that the income effect of such transfers disincentivizes ambition, initiative, and hard labor. It has been challenging to resolve the ambiguity over which force prevails due to the lack of direct empirical evidence. Giving a credible empirical answer to the question has proven difficult, in part because of the challenge in identifying cash transfers that are perpetual and unconditional.[2]

We make progress on the debate by directly estimating the impact of unconditional and perpetual guaranteed income to small farmer entrepreneurs using a large natural experiment in India. We exploit a nationwide program that gives identical, unconditional, recurring, and guaranteed cash transfers to all landowning farmers in India. Our central finding is that guaranteed income leads to an increase in income from farming. We then study the mechanisms behind this effect. We find that, instead of reducing

[1] Several small pilots have been launched across the globe. We direct the readers to Gentilini et al. (2019) for documentation of such UBI-related pilots and proposals. UBI programs have been endorsed by several proponents, including Pope Francis, Barack Obama, Mark Zuckerberg, Bill Gates, Jeff Bezos, Andy Stern, Andrew Yang, and Charles Murray, among many others.

[2] In a review article, Banerjee, Niehaus, and Suri (2019), note that while conditional or one-time cash transfers in developing economies have been the subject of substantial prior research, the extant literature does not provide direct empirical evidence on the effect of unconditional and perpetual cash transfers. A notable exception is Banerjee et al. (2020a, 2023). They conduct a randomized controlled trial across 15,000 households in Kenya and analyze the effect of UBI-like transfers.

ambition and initiative, guaranteed income allows them to work differently. Specifically, guaranteed income provides protection against downside risk, which increases demand for credit and thus allows farmers to invest in a more capital-intensive mode of production.

Our results have two main implications. First, we provide evidence that safety nets – such as guaranteed income programs – can increase production by catalyzing a shift to a high capital-intensive mode of production rather than driving down ambition. Second, our results improve our understanding of whether the main obstacles to production stem from credit-supply constraints, or if uninsured risk can be the immovable demand-side barrier. Our results provide empirical support to the idea that guaranteed income can dilute demand-side barriers originating from uninsured risk. Specifically, it can reduce barriers to credit demand by reducing the probability and severity of financial distress. Therefore, our results potentially help explain why small entrepreneurs in developing economies choose a less capital-intensive mode of production despite the relaxation of credit supply constraints and despite the possibility of immense gains from capital investment, i.e., the *Euler Equation Puzzle* (Banerjee and Duflo, 2007; Woodruff, 2018; Kremer, Rao, and Schilbach, 2019).

Our study exploits a natural experiment that introduces both temporal and cross-sectional variation in the receipt of unconditional income. Initiated in March 2019, the Indian Basic Income program, Pradhan Mantri Kisan Samman Nidhi (PM-KISAN), or the Prime Minister's Farmer's Tribute Fund, provides all landowning farmers with an annual, unconditional transfer of ₹6,000 ($\approx$ \$285 in PPP terms). Four features of this policy enable credible identification. First, although PM-KISAN was intended as a nationwide policy, the state of West Bengal declined to implement it, generating sharp spatial discontinuities in eligibility and receipt near the state border. This noncompliance facilitates both a regression discontinuity design and a border district-pair framework that leverage contrasts between adjacent compliant and non-compliant regions. Second, transfers were restricted to landowning farmers, excluding tenant cultivators and landless agricultural laborers. Landownership status was defined as of December 2018, rendering it predetermined and invariant during our study period. This feature enables a stable definition of treatment and control groups and permits the inclusion of fine-grained unit (district, ZIP code, or village) $\times$ time fixed effects to absorb local time-varying confounders. Third, eligibility and transfer size are orthogonal to income, assets, or effort among eligible landowners, ensuring that the policy generates exogenous shocks to liquidity rather than reflecting underlying heterogeneity in productivity or preferences. Fourth, the policy's announcement was entirely unanticipated, eliminating scope for anticipatory behavior or pre-treatment adjustments.

We begin by exploiting the spatial discontinuity created by West Bengal's noncompliance with the PM-KISAN program and augmenting it with remote-sensing data on agricultural productivity. This combination allows us to implement a difference-in-regression discontinuity design. Restricting the sample to micro-regions within two kilometers of the state border, we compare agricultural outcomes between areas exposed to PM-KISAN and those just across the border in West Bengal. We estimate that compliant areas experienced an increase in agricultural output corresponding to a 7.4–9.1% improvement in productivity. These effects are robust to alternative bandwidth choices, are not driven by pre-existing trends, and persist for at least three years following the program's introduction.

Next, we combine household-level income data with the border district-pair design to assess whether the observed productivity gains in compliant regions translate into higher household income. This analysis leverages variation in PM-KISAN implementation within contiguous district pairs that straddle the boundary between West Bengal and its five neighboring states. The dataset also identifies whether agricultural households are landowning or landless. These two features allow us to estimate a differences-in-differences specification that includes household fixed effects, district $\times$ month fixed effects, and district-pair $\times$ treatment $\times$ month fixed effects. Each district pair comprises two contiguous districts located on opposite sides of the border, with one situated within West Bengal. This framework facilitates comparisons among landowning farmers exposed to comparable geographic, climatic, cultural, and economic conditions. The key identifying assumption underlying this analysis is that potential confounders vary smoothly across jurisdictional boundaries. We estimate that the income of landowning farmers in treated regions rises by 15.8% relative to observationally similar landowning farmers in adjacent, noncompliant districts. Moreover, our dynamic specification indicates that these results are unlikely to be driven by pre-existing trends, and income gains are concentrated during the post-policy harvest season, consistent with the interpretation that higher income reflects increased agricultural productivity.

We next study the policy's effect on agricultural investment using data on tractor sales and fertilizer consumption. Leveraging the border district-pair design, we find that, following the introduction of PM-KISAN, tractor sales increased by 14% in value and 12% in quantity. This implies an average rise in investment of approximately ₹74,171 per tractor purchase. Fertilizer consumption rose by 32% in compliant districts relative to adjacent noncompliant districts in West Bengal, with the largest increases observed for nitrogen- and phosphorus-based fertilizers.

We also document a substantial expansion in cultivated area. Specifically, total gross sown area increased by 48–55% in compliant districts relative to bordering noncompliant areas, with comparable effects across all major crop categories. These findings indicate that the cash transfers facilitated both lumpy investment in agricultural machinery and higher expenditure on variable inputs, enabling farmers to expand production. The evidence points to a structural shift toward more input- and capital-intensive farming practices, which likely account for the productivity and income gains documented earlier.

Having established substantial increases in investment and cultivated area, we next investigate how farmers finance these expenditures, given that the magnitude of investment far exceeds the annual PM-KISAN transfer of ₹6,000. To explore this mechanism, we combine monthly, ZIP code–level lending data from TransUnion CIBIL—disaggregated by lender and loan type with the border district-pair design that compares ZIP codes in districts on either side of the West Bengal state border. We document a significant rise in formal agricultural credit following the policy's introduction, suggesting that greater access to credit may have facilitated the observed investments and production expansion. Specifically, we estimate that agricultural loan amounts increased by 7.2% and the number of loans rose by 16.6% in compliant districts relative to neighboring noncompliant districts. These findings are corroborated using branch-level data from India's largest state-owned bank, which exhibits consistent patterns of increased agricultural lending after the program's rollout. Complementary household survey data further suggests that this rise in formal credit was not offset by a reduction in informal borrowing. Overall, these results indicate that recipients of the unconditional transfers used them to leverage formal credit markets and undertake larger-scale agricultural investments. The evidence suggests that liquidity injections through guaranteed income programs can amplify capital formation by easing borrowing constraints and crowding in productive credit.

We have thus far documented an increase in agricultural output, farm scale, and household income following the implementation of PM-KISAN transfers. The evidence suggests that these gains are driven by a shift among treated households toward more capital-intensive production technologies, financed through formal credit. However, our results thus far rely primarily on aggregate data with different units of analysis, such as village, ZIP code, or district. This makes it harder to collectively understand the estimates across productivity, investment, income, and credit. Moreover, the households displaying higher income growth may not be the same as those undertaking greater investment or borrowing. To address this concern, we analyze detailed farmer-level outcomes based on data from a large private-sector bank in India. The bank data offer a key advantage by allowing us to jointly observe monthly income flows and credit utilization for the same set of 65,000 farmers over time. However, the bank data is restricted to a limited set of states, none of which share a border with West Bengal. This limitation precludes the use of our border district-pair identification design. Instead, we exploit a secondary dimension of treatment heterogeneity arising from the program's eligibility criteria, that is, PM-KISAN transfers were extended only to landowning farmers, excluding tenant farmers.

This design introduces two potential sources of bias. First, sample selection bias may arise because the bank data are available only for a subset of states that is unlikely to be representative of the broader population. Specifically, the bank sample covers Karnataka, Maharashtra, and Punjab. Second, comparisons between landowning and tenant farmers may be subject to omitted variable bias if these groups differ along unobserved dimensions correlated with program exposure. The direction of either bias is ambiguous ex ante; both could plausibly lead to upward or downward shifts in the estimated effect. We conduct several sub-sample analysis using the administrative aggregate data to examine the direction and magnitude of these biases. Our results suggest that both omitted variable bias and sample selection bias likely lead to downward bias in the estimated treatment effect, implying that the true effect is potentially larger than what these restricted comparisons would indicate. Moreover, our identification strategy includes farmer fixed effects to control for all time-invariant heterogeneity due to differences in preferences and productivity among landowning and tenant farmers. Lastly, we include ZIP code $\times$ month fixed effects to account for all time-varying geographic shocks and other local fluctuations in agricultural conditions.

Using the bank data, we find that unconditional and perpetual cash transfers increase income by 12.74% among treated farmers. In elasticity terms, each additional dollar of guaranteed income generates approximately \$1.76 in additional income. The increase in income is driven by a shift towards a more capital-intensive mode of production financed using credit. On the policy's effect on credit, we estimate that an additional \$1 in guaranteed income increases term loans by \$6.78, which is equivalent to 39.30% of the perpetuity value of guaranteed income. Importantly, loan composition data indicate that the new borrowing finances investments in productive capacity rather than household consumption or short-term liquidity needs. Assuming a loan-to-value ratio of 0.8, we estimate that the policy induced a total increase in capital of \$8.48. This investment response corresponds to roughly 49.15% of the perpetuity value of the transfer. Back-of-the-envelope calculations based on observed income gains imply a return to capital of about 20.75%.

We further establish the critical role of credit markets in generating the positive income effect. We focus on the role of credit market frictions. The intuition behind this test is that individuals facing greater credit market frictions have a lower ability to finance lumpy investments with credit. We find that farmers facing high credit market frictions because of prior default or low credit scores experienced negligible effects on their income and credit.

We complement the quantitative analysis with qualitative evidence from an original survey that we conducted among 4,000 farmers. Following Ferrario and Stantcheva (2022); Stantcheva (2023) and Haaland et al. (2025), we conduct a survey that directly elicits self-reported responses to the PM-KISAN transfers concerning effort, investment, and borrowing behavior. To probe the counterfactual, the survey also asked tenant farmers, who did not receive transfers, to report how their behavior would have changed had they been eligible for the program. This exercise serves two purposes. First, it enables us to validate the counterfactual comparison between treated landowning farmers and untreated tenant farmers, which underlies our estimation strategy in the bank data. Second, it provides insights into external validity and the potential scalability of the policy across different farmer populations à la List (2020).

Our survey responses align closely with our administrative and quantitative findings. Among recipients, 65% reported an increase in effort, 70% reported higher levels of investment, and 47% indicated increased credit use following the transfers. Importantly, self-reported hypothetical responses from non-recipient tenant farmers exhibit similar patterns, suggesting that these behavioral adjustments would likely generalize beyond treated groups if transfers were extended to them. The close correspondence between the qualitative and quantitative results reinforces the robustness of our main findings. Moreover, the similarity in reported behavioral responses across recipient and non-recipient groups supports the validity of our identification strategy, indicating that untreated tenant farmers provide a credible counterfactual for treated landowning farmers.

The second part of the paper identifies the underlying economic mechanism that drives the increase in credit for small farmer entrepreneurs. Theoretically, guaranteed income can stimulate credit markets through two channels. The first channel increases the credit supply to farmers as these transfers increase their creditworthiness. The second channel increases the credit demand of farmers by providing downside risk protection during bad times. Specifically, guaranteed income can increase demand for credit by increasing the likelihood of repayment and the ability to meet basic needs after loan repayment during bad times, as well as reducing the expected cost of default, i.e., the permanent consumption loss associated with default. Put differently, by enabling farmers to build buffer stocks and sustain consumption in bad states of the world, when the marginal utility of consumption is especially high, guaranteed income increases their willingness to take on credit-financed investments.

Our most potent evidence on the demand side channel of guaranteed income comes from examining the utilization rate of a unique product called Kisan Credit Cards (KCC). The credit limit and interest rates on the product are unrelated to farmers' creditworthiness due to institutional reasons, and are unchanged by the policy. Therefore, KCC provides an ideal laboratory where we can examine changes in demand while keeping the credit supply fixed. The results indicate that the utilization rates of KCC increase by 5.8pp for the treatment group after the policy. The result indicates the existence of a credit demand effect among the treatment group.

Following Jiménez et al. (2014, 2017), we further supplement our analysis by examining the policy's effect on suggestive proxies for credit demand and supply, using the universe of loan records for farmers in our bank data. We find a 1.7% increase in the monthly probability of inquiry, our measure of the number of applications. This effect corresponds to a 41% increase over the sample mean. Meanwhile, we do not observe any statistically significant or economically meaningful changes in the probability of acceptance. Overall, the results show that treated farmers submitted more credit applications following the policy, while their acceptance rates remained unchanged. On the demand side, credit inquiries rise; on the supply side, lending standards appear stable. We interpret this pattern as evidence of greater credit demand rather than a shift in credit supply. This interpretation relies on the assumption that farmers do not expect banks to relax lending criteria as a result of PM-KISAN. Our original survey of farmers supports this assumption.

We strengthen our evidence on the credit demand channel by taking a more direct approach of eliciting underlying mechanisms discussed in Ferrario and Stantcheva (2022); Stantcheva (2023) and Haaland et al. (2025). We begin by conducting an open-ended pilot and use those responses to design a structured survey as in Colonnelli, Neto, and Teso (2025). In our survey, we ask farmers whether they believe the policy affected their borrowing primarily through changes in credit demand or credit supply. Such a belief elicitation methodology using survey data to better understand the underlying mechanism overcomes the empirical challenge of disentangling demand from supply in observational lending data. This belief elicitation methodology using survey data to better understand the underlying mechanisms has been used previously in Bursztyn et al. (2018, 2019); Breza, Kanz, and Klapper (2020); Galashin, Kanz, and Perez-Truglia (2020); Field et al. (2021); Colarieti, Mei, and Stantcheva (2024) and Fiorin, Hall, and Kanz (2025) among others.

Our survey results indicate that 80% of respondents report that higher credit demand – rather than improved credit availability – was the primary channel through which the policy increased their borrowing. This result indicates that the increased credit demand among the recipients of PM-KISAN was the key driver of their increased borrowing.

The relatively modest supply-side response is also consistent with institutional features of agricultural lending. Future government transfers are typically not pledgable as collateral, and loan officers rely heavily on historical yields, collateral, and credit scores when underwriting. Moreover, small farm sizes make cash-flow-based lending unattractive because the practicality of cash flow-based lending requires businesses to produce enough cash flows to make ex-post reorganization cost-effective for lenders (Lian and Ma, 2021).[3] These features limit the scope for a rapid supply-side response to a new, unpledgeable income stream.

To further shed light on the underlying mechanism, we elicit the beliefs of PM-KISAN recipients to understand the motivations driving their increased willingness to borrow, i.e., credit demand. 21.9% of respondents said that guaranteed income increased their credit demand by increasing their comfort in meeting basic needs after loan repayment during bad times. 39.8% of respondents rated reduction in (expected) cost of default, i.e., reduced consumption loss, as the primary reason through which guaranteed income increased their credit demand. 20.8% of respondents rated reduction in probability of default as the primary reason for increased credit demand.

We assess the effect of the policy on ex-post default to validate the survey responses. The results indicate significant improvements in both short- and medium-term loan repayment behavior, as evidenced by statistically and economically meaningful declines in one- and three-year delinquency rates among treated agricultural borrowers. The observed reduction in default aligns with the argument that guaranteed income enhances borrowers' ability to service loans during adverse shocks and increases their comfort in meeting basic needs post-repayment, rather than merely reducing the costs associated with default.

We next examine the mechanisms underlying the observed increase in credit demand. We posit that guaranteed income programs raise households' willingness to borrow by mitigating exposure to downside risk. By providing a stable and predictable income floor, PM-KISAN lowers the likelihood that farmers experience extremely low consumption states during adverse shocks, conditions under which the marginal utility of consumption is disproportionately high. This predictable safety net reduces the expected utility cost of risk, effectively relaxing liquidity and borrowing constraints and making households more willing to participate in formal financial markets. Consistent with this interpretation, we find

[3] While cash-flow based lending has become increasingly popular in India for small ticket-size loans after the introduction of digital payments, its scope is still limited to FinTechs who do not operate in the agricultural sector (Cramer et al., 2024).

that the credit response is significantly stronger in regions characterized by high rainfall risk and high basis risk in agricultural insurance markets. The heterogeneous effects across risk environments suggest that agricultural risk and incomplete insurance markets are key impediments to credit take-up, and that guaranteed income support can offset these frictions.

Further supporting this mechanism, we document an increase in farmers' ex post risk-taking behavior following the policy's implementation. Treated areas exhibit greater shifts toward cash crops and higher adoption of innovative production techniques such as organic farming. These results indicate that the policy altered farmers' risk preferences, encouraging investment in production activities associated with higher risk and higher expected return.

Addiitonally, we show that perceptions about the permanence of these cash transfers play a key role in driving the credit market effect. Using voter data as a proxy for trust in the program's continuation, we find that the policy's effects are substantially larger in regions where beneficiaries have greater confidence in the transfers' long-term stability. This pattern is consistent with the notion that guaranteed income programs can generate stronger responses when the expected permanent income effect is higher, as they enhance recipients' sense of protection against future risk.

Lastly, we rationalize the findings using a dynamic investment model with costly default, adapted from Herranz, Krasa, and Villamil (2015) and extended to allow heterogeneous entrepreneurial productivity and frequent disaster shocks such as droughts. In the model, limited internal funds make external credit necessary for capital accumulation, but disaster risk and the cost of default, through lost production capacity and future credit exclusion, make downside risk salient and discourage borrowing. Risk-averse farmers optimally choose lower leverage and smaller capital stocks in the absence of protection, while guaranteed income acts as a permanent floor on consumption in bad states, reducing both the likelihood and severity of financial distress and thereby increasing the value of credit-financed investment. Calibrating the model to match observed frequent disaster risk, we show that the empirically estimated increase in capital after the introduction of guaranteed income can be reconciled with standard coefficients of relative risk aversion between 2 and 5, indicating that this risk-based credit demand channel is quantitatively plausible.

We discuss three alternative explanations. First, the policy can directly increase investment by increasing cash-in-hand. We argue that these transfers are small and therefore the ability of such transfers to directly relax liquidity constraints for the purchase of large fixed assets is severely limited.[4] Second, the *physiological productivity effect* and the *psychological income effect* of these transfers may drive the effect on income. The two channels operate by increasing labor productivity, keeping the capital intensity fixed through the direct impact of transfers on nutrition and psychology (Banerjee et al., 2020b; Kaur et al., 2025). While we view these channels as complementary and do not deny the presence of

[4]For example, a tractor costs around ₹700,000, a cow costs around ₹150,000, and a two-wheeler costs around ₹80,000. Therefore, it is unlikely that a small payment of ₹6,000 is responsible for directly relaxing liquidity constraints on debt-less purchase of these assets. In their review article, Banerjee, Niehaus, and Suri (2019) make a similar argument on the inability of BI cash transfers to ease the purchase of lumpy investments directly.

these effects, our documented mechanism operates through the credit demand channel. Third, using data from our original survey, we show that the relaxation of down-payment constraints is likely to play only a small role in driving the credit demand effect. Additionally, we conduct a battery of robustness tests to strengthen faith in our findings. We also present a formal test for the effect of spillovers á la Berg, Reisinger, and Streitz (2021) to show that spillovers are likely to be of little concern as the input and output markets are heavily regulated.

1.1 Related Literature

This paper makes two key contributions. On the economic side, it provides a systematic empirical analysis of the demand-side channel through which a permanent income shock, and safety nets in particular, can stimulate credit demand and, in turn, investment. On the policy side, it evaluates the impact of one of the world's largest welfare programs. To the best of our knowledge, this is the first study to examine how a guaranteed income affects the production decisions of small entrepreneurs.

This paper contributes to the literature on the effects of permanent income shocks. We show that a permanent income shock delivered through guaranteed income transfers can stimulate credit demand and raise investment. Most closely related to our work, Aaronson, Agarwal, and French (2012) provide empirical evidence that increases in the minimum wage lead to higher durable spending financed with credit. This paper adds to this literature by offering systematic evidence that permanent income shocks can increase investment financed through credit markets in the context of small entrepreneurs for whom investment is an important margin of adjustment apart from consumption and labor supply. More importantly, we document the demand-side channel through which such permanent income shocks can translate into higher credit-financed investment. This demand-side channel operating through credit markets documented in this paper allows us to contribute to the literature on how risk tolerance (Knight, 1921; Kihlstrom and Laffont, 1979; Miller, 1984; Iyigun and Owen, 1998) and financial constraints (Evans and Jovanovic, 1989) can shape entrepreneurial activity.[5]

The demand-side channel presented in this paper provides a potential explanation for an unresolved puzzle in the micro-enterprise literature. Evidence from several experiments assigning grants to randomly selected micro-enterprises indicates that marginal return on capital is high.[6] However, randomized experiments providing standard loans to microenterprises that reduce supply-side frictions show little or no effect of loans on enterprise profitability or sales.[7] The phenomenon has been dubbed the *Euler Equation Puzzle*, i.e., small-scale entrepreneurs in developing countries sometimes leave high expected-return in-

[5] Woodruff (2018) presents a detailed review of the financial constraints – among other constraints – faced by small entrepreneurs in developing countries.

[6] Some studies that identify high returns on capital for small entrepreneurs in a developing-country setting include De Mel, McKenzie, and Woodruff (2008), McKenzie and Woodruff (2008), De Mel, McKenzie, and Woodruff (2012), Blattman, Fiala, and Martinez (2014), and Fafchamps et al. (2014).

[7] Banerjee, Karlan, and Zinman (2015) evaluate six studies in developing countries and argue that credit has a limited effect on the growth of micro-enterprises. Combining the data on these studies with a Bayesian hierarchical framework, Meager (2019, 2022) documents that the impact of credit on household business is likely to be negligible.

vestments unexploited (Banerjee and Duflo, 2007; Woodruff, 2018; Kremer, Rao, and Schilbach, 2019). The results of our paper suggest that the constraint may be on the demand side rather than the supply side. Hence, policies aimed at easing supply-side constraints may have a limited effect. In contrast, policies – such as basic income support – that reduce downside risk can generate greater effects. Therefore, our results complement the experimental-setting results of Karlan et al. (2014), Emerick et al. (2016), and Lane (2018) as well as the theoretical predictions of Rosenzweig and Wolpin (1993) and Donovan (2021), which show that absence of risk protection may be the binding constraint for small and poor entrepreneurs, such as farmers. Therefore, our results also present a potential demand-side explanation for a key fact documented in Hurst and Lusardi (2004) that borrowing constraints are not empirically important in deterring the majority of small business formation.

Our work also speaks to the contract design literature on credit. Standard debt contracts impose a large cost of financial distress when the borrower is unable to repay the loan (Townsend, 1979; Diamond, 1984). This cost can depress credit demand and discourage investment if enterprisers operate in a risky environment. We show that safety nets such as guaranteed income can instead relax this underinvestment margin by cushioning distress, lowering default risk, and making repayment more comfortable. We find that guaranteed income not only increases credit demand but also reduces default rates. This complements evidence from grace-period interventions as in Field et al. (2013), which stimulate credit demand by directly weakening repayment penalties but tend to raise default, by showing that guaranteed income can boost borrowing without this cost of increasing default.

Another contribution of this paper is to provide a systematic assessment of a long-term basic income program on productive activity in a developing country rolled out on a large scale therefore adding to the large literature that examines the effect of one-time or short-term cash transfers (see Bastagli et al. (2016) and Crosta et al. (2024) for a review). Our paper is closest to Banerjee et al. (2020a, 2023), who conduct a randomized controlled trial in two sub-counties in Kenya to examine the effect of UBI during the COVID-19 pandemic. They find that UBI transfers significantly reduced the effect of COVID-19 and in the short-term also increased the transition from being employed to self-employed. Our findings complement their work by evaluating the effect of such transfers during normal times and primarily focus on the role of such transfers in stimulating credit demand by increasing downside risk protection. Relatedly, Bianchi and Bobba (2013) exploit Mexico's welfare program – which targets poor rural households with cash transfers conditional on health and child education behaviors – and provide suggestive evidence that it boosted entrepreneurship by enhancing risk tolerance. Other closely related work has focused on labor supply, estimating the effects of a randomized controlled trial giving long-term cash transfers (Vivalt et al., 2024), administrative programs that provide long-term cash transfers (Jones and Marinescu, 2022; Salehi-Isfahani and Mostafavi-Dehzooei, 2018), as well as studies that exploit long-term transfers due to lottery winnings Imbens, Rubin, and Sacerdote (2001); Cesarini et al. (2017); Picchio, Suetens, and van Ours (2018); Golosov et al. (2021). These studies focus on the effect of unearned income due to these transfers on labor earnings, generally finding negative, neutral or slightly positive effects. In contrast, this paper focuses on effect of long-term cash transfers on the self-employed for whom investment is an important margin of adjustment apart from the standard labor-leisure tradeoff (Breza and Kaur, 2025). Overall, our paper contributes to the UBI literature by examining the response of investment to UBI-like transfers for self-employed individuals whose investments are limited by uninsured risk. Although insurance-based interventions can theoretically offer similar downside protection, understanding the importance of income-based approaches like guaranteed income in protecting against downside risk is especially important from a policy perspective in developing countries, where insurance-based approaches have proven to be ineffective due to basis risk, lack of trust, and low financial literacy (Cole and Xiong, 2017).

The remainder of the paper proceeds as follows: Section 2 discusses the background on Indian agriculture and the institutional details of the natural experiment. Section 3 provides a brief description of the data. Section 4 lays out the key results of the paper along with the associated empirical strategy. Section 5 presents the details of the mechanism. Section 6 presents a discussion of the results and section 7 concludes.

2 Institutional Context

India has a particularly large agricultural sector, which is the primary source of livelihood for most Indians. More than half of the Indian workforce is employed in agriculture, yet the sector generates less than one-fifth of GDP, and nearly one in four farmers lives below the poverty line. Farmers typically cultivate two seasons: *Kharif* crops (such as rice and maize) are sown with the onset of the southwest monsoon around June and harvested in October–November, while *Rabi* crops (such as wheat and mustard) are sown around November and harvested in April–May.

Indian farms are typically small, with roughly nine in ten farming households operating less than two hectares of land. Although agricultural output has risen on average since the Green Revolution, year-to-year growth remains highly volatile (Bank, 2005). Much of this volatility reflects dependence on the monsoon and relatively low irrigation coverage (Jayachandran, 2006; Cole, Healy, and Werker, 2012).

Successive Indian governments have attempted to stabilize farm incomes and expand credit. On the risk side, crop insurance schemes, most recently the Pradhan Mantri Fasal Bima Yojana, were designed to provide subsidized protection but have suffered from low take-up, basis risk, and implementation failures (Cole and Xiong, 2017). Minimum Support Prices are intended to provide a floor under output prices, yet small farmers often receive prices well below the announced support level (Bakshi and Munjal, 2018). On the credit side, agriculture is designated a priority sector, banks face lending targets, and large debt waivers are periodically announced. However, these interventions have produced at best mixed improvements in effective credit access and can distort credit allocation (Cole, 2009; Kanz, 2016; Giné and Kanz, 2018). We direct readers to Appendix A.1 for further discussion of Indian agriculture.

In practice, many small farmers remain underinsured, face limited effective risk-sharing, and make only modest use of formal credit, despite evidence of high returns to capital in similar environments. These institutional features – small, poor farmers operating in a risky environment with limited insurance – make downside risk a natural candidate for explaining underinvestment in high-return technologies, implying that small changes in risk or liquidity buffers can plausibly have first-order effects on production and investment choices.

2.1 The Details of the Policy

Pradhan Mantri Kisan Samman Nidhi (PM-KISAN, translation: Prime Minister's Farmer's Tribute Fund) is a policy launched by the Government of India (GOI) that provides unconditional and perpetual guaranteed income support to all landowning farmers. Announced in the February 2019 Union budget and launched in March 2019, PM-KISAN provides landowners, representing 67% of all farmers and 27% of the total Indian population, with an unconditional transfer of ₹6,000 per year, paid in three equal installments to their primary bank accounts.[8] In 2020 terms, this corresponds to approximately $83 at market exchange rates and $285 in PPP terms and covers roughly two-thirds of all farmers and over one-quarter of India's population (Varshney et al., 2020). We direct readers to Appendix A.2 for a more detailed discussion of the details of the policy.

Eligibility is determined by land ownership as recorded in administrative land registries as of December 2018. The policy is confined only to landowning farmers as the lack of systematic identifying data on landless farmers imposed legal restrictions on the GOI.[9] This design feature has two implications that are central to our empirical strategy. First, within the set of landowning farmers, transfers do not vary with current income, wealth, or effort and do not require any behavioral conditions. Second, because the eligibility cutoff date is fixed prior to the announcement, subsequent land transactions do not mechanically affect eligibility, reducing the scope for short-run manipulation.

Implementation of the policy relies on coordination between state and federal governments. State governments compile lists of eligible landowning farmers and link them to bank accounts; the federal government makes direct deposits once these lists are verified. Nearly all states cooperated in this process. The key exception is West Bengal, whose state government refused to transmit beneficiary lists, citing concerns over central control and data-sharing, and therefore did not implement the program. As a result, PM-KISAN was rolled out across the rest of India but not in West Bengal, generating sharp spatial discontinuities in exposure at the state border that we exploit in our empirical design.

Three additional features make PM-KISAN particularly well-suited for our questions about guar-

[8] The majority of Indian farmers have at least one bank account due to Pradhan Mantri Jan Dhan Yojana (PMJDY, translation: Prime Minister's People's Wealth Scheme) and the subsequent demonetization. According to the 2019 All India Debt and Investment Survey, about 84% of the population of age 18 years and above had at least one deposit account in banks. The primary bank account refers to the primary account linked to an individual's Aadhar Card, analogous to a social security card in the United States. The primary account for farmers is usually the account opened for them under the PMJDY.

[9] Initially, the policy was confined to landowning farmers with less than two hectares of land. However, this provision was removed shortly after the announcement.

anteed income, risk, and investment. First, the transfers are unconditional and require no means test or specific actions, providing a clean shock to recipients' cash flows that is orthogonal to contemporaneous effort and observable productivity. Second, the program is designed to be permanent, with no announced end date and strong political incentives to maintain a large, organized beneficiary group. The implied present value of the transfer stream is large relative to typical farmer savings, suggesting a meaningful increase in permanent income rather than a one-off liquidity injection. Specifically, the present value of the perpetual cash transfers is ≈ ₹103,448 or $4,926 in PPP terms, which is 28 times the average stock of savings of landowning farmers. Third, the program was announced as part of the highly confidential Union budget process, which historically has allowed little scope for advance information or pre-policy adjustment.

Taken together, these institutional features, large coverage, a sizable and plausibly permanent income increment, exogenous variation in eligibility and geographic implementation, and an unexpected rollout, make PM-KISAN a natural laboratory to study how guaranteed income affects credit demand, investment, and production decisions for small farmer-entrepreneurs operating under substantial income risk.

3 Data

This section summarizes the main data sources used in our analysis. A key contribution of this paper is assembling this rich dataset that can be employed for future research.

3.1 Remote Sensing Data on Agricultural Production

We construct plot-level measures of agricultural production from satellite imagery, since no comparable micro data on yields exist for India. We use the Enhanced Vegetation Index (EVI) from NASA's Landsat 8, which summarizes chlorophyll-sensitive plant biomass at an 8-day frequency.[10]

Our sample period extends from 2013 until 2021 as the 8-day EVI composites are available from April of 2013 until January of 2022. We query EVI values over this period for our desired micro-regions by supplying the geometry of the micro-region to the Google Earth Engine's API. EVI values obtained from each pixel are spatially averaged over the micro-regions to obtain a time-series of EVI values with an 8-day interval. We extract data for several rectangular micro-regions situated along the border. These regions are defined by combinations of lengths of 5 km, 10 km, and 20 km along the border, with widths of 100 meters extending until 2 km on each side of the border. Appendix Figure B.1 presents a pictorial depiction of the sample and the geometries. We refer to these rectangular micro-regions as units or plots.

We focus on the main monsoon growing season (kharif, June–October). For each unit-year, we construct (i) the maximum EVI during the season and (ii) the change from early-season average EVI to

[10]See Huete et al. (2002) for the construction of EVI and Asher and Novosad (2020) for validation in an economic setting.

this peak. Both measures have been shown to be strongly correlated with realized agricultural yields (Asher and Novosad, 2020).

3.2 Consumer Pyramids Household Survey

We obtain detailed data on the income and extensive margin borrowings from different sources by household from the Consumer Pyramids Household Survey (CPHS) maintained by the Centre for Monitoring Indian Economy (CMIE). CPHS is a large panel of 236,000 households surveyed repeatedly over time. The survey is conducted every month, and each household is re-surveyed each quadrimester. The data provides information on the type of employment for each household. We restrict our analysis to households engaged in agricultural activities. We classify farmers tagged as agricultural laborers as the control group and all other farmers as the treatment groups. Our internal discussions with CMIE indicate that agricultural laborers are more likely to be landless farmers and work for landowning farmers. We use this data to investigate the effect of cash transfers on income as well as borrowings from banks and other informal sources such as friends, family, and moneylenders. We present the summary statistics of the key variables alongside the corresponding regression results that utilize these variables.

3.3 Aggregate Credit Bureau Data

We utilize a novel and unique dataset of 648 million loans, the universe of formal retail loans in India from 2016 to 2021. We obtain data from India's oldest credit bureau - TransUnion CIBIL. The data is recorded at a granular level of month × ZIP code × lender type × product type. We obtain this data from March 2018, one year before the implementation of the policy, until February 2020, just before the onset of the COVID-19 pandemic, for all ZIP codes, approximately 19 thousand. We observe three outcomes: the number of loans issued, the total loan amount issued, and the number of defaulted loans that were issued in this month × ZIP × lender × product. A loan is classified as defaulted once it reaches 90 days past due (DPD) within one year of being issued. We define the default rate as the fraction of loans issued each month that have surpassed the 90 DPD mark within one year of issuance. Appendix Table B.1 presents the summary statistics of the key variables for the full sample, the sample of agricultural and non-agricultural loans.

3.4 Bank Data

We use a proprietary de-identified dataset obtained from one of the largest private banks in India to jointly measure individual income, savings, spending, and other financial activities. The bank maintains detailed information on farmers to meet regulatory and reporting requirements related to financial inclusion, agricultural credit, and crop insurance.

The sample consists of non-institutional farmers with active savings accounts.[11] We include all such farmers in Karnataka, Maharashtra, and Punjab with at least one year of pre-policy history. The

[11] Following the World Bank standard, an account is classified as active if it has at least one transaction per year.

panel runs from March 2017 through February 2020 and contains 64,761 farmers and about 1.5 million farmer-by-month observations. The data include demographics (age, gender, location), credit characteristics (credit score, interest rates, credit limits on Kisan Credit Cards), and landownership status, which is crucial for defining treatment and control.

We observe all inflows and outflows on the savings account. We construct income from work as total inflows net of loan disbursals, financial investment maturities, and PM-KISAN transfers. Most of these net inflows are deposits made in cash or via the Unified Payments Interface (UPI), the dominant real-time payment system for self-employed workers in India. We measure savings as the average monthly balance and spending as the sum of all debit- and credit-card outflows, cash withdrawals, and electronic payments. Table 1 reports summary statistics; in brief, the average farmer is around 50 years old, has used the account for roughly eight years, reports banked income around ₹9,300 per month, maintains average savings of about ₹2,800, spends roughly ₹9,200 per month, and has a mean credit score near 513, with about 15% having a prior default flag as of March 2018.

A natural concern is whether bank data are representative in a setting where some rural households might be unbanked. According to the 2018 Situation Assessment Survey (SAS), however, 98% of farm households have at least one bank account (Appendix Figure B.3), reflecting recent financial inclusion initiatives. In our own survey, all respondents report using at least one bank account. A second concern is that we may under-measure income because some earnings are kept in cash or in other banks. Comparing our 2018 income measure with SAS data, we find that average income in the bank data is about 61% of SAS income (Appendix Table B.2). In a follow-up survey, farmers report depositing about 46% of their income in bank accounts, with similar fractions for PM-KISAN recipients and non-recipients three years after the policy (Appendix Figure B.4). Both patterns suggest substantial but largely classical measurement error in income: we understate levels but do not differentially mismeasure treated and control farmers.

Two further caveats apply. First, we only observe accounts at one bank. Our survey indicates that about half of farmers have multiple accounts, so we again underestimate levels of income, savings, and credit. However, the incidence of multiple accounts is similar across recipients and non-recipients (Appendix Table B.3), suggesting that this mismeasurement is also approximately classical. Second, farmers in our sample have relatively better access to formal credit than the average farmer by construction. This selection makes the sample well-suited for studying how relaxing downside risk changes credit demand when supply-side access is already relatively strong.

3.4.1 Credit Bureau Data for the Bank Sample

For the same farmers, we collect loan-level data from TransUnion CIBIL by querying all formal credit histories. We obtain information for 43,619 farmers (about half the bank sample). For each loan, we observe the disbursal date, loan amount, stated purpose, lender type, and the dates of any credit inquiries.

The bureau data include all formal term loans from banks, financial institutions, and self-help groups, but exclude informal borrowing from moneylenders, relatives, or friends. This would be problematic if informal loans were both quantitatively dominant and differentially used by treated and control farmers. Our original survey suggests otherwise: about 60% of farmers report formal sources as their primary credit source, with similar patterns across PM-KISAN recipients and non-recipients (Appendix Table B.4). We aggregate the loan records to the farmer-by-month level, including zeros when no loan or inquiry occurs, and construct four outcomes: the probability of having a loan, the probability of a credit inquiry, the number of loans, and the total loan amount. We present the summary statistics of the key variables alongside the corresponding regression results that utilize these variables.

3.5 Original Survey of Farmers

We complement the administrative data with an original survey of farmers conducted between July and September 2022 in partnership with Krishify, a large Hindi-language social network for farmers. The platform has more than 9.5 million users and an average daily engagement of about 15 minutes. We draw a sample designed to be representative along age, state, and gender. The survey invitation yielded a response rate of 21.7%, and the final sample contains 4,003 farmers. Appendix Figure B.5 compares the survey sample with the platform population; Appendix Table B.5 reports summary characteristics. About 53% of respondents report receiving PM-KISAN transfers.

The survey has two parts. First, an online questionnaire collects socio-economic characteristics and elicited beliefs about agricultural risk-taking, ability to meet basic needs, willingness to borrow, repayment concerns, perceived cost of default, and receipt of PM-KISAN. Second, a phone interview asks recipients how PM-KISAN affected their borrowing, investment, and risk-taking. Non-recipients are asked to answer the same questions under the hypothetical scenario that they had received the transfers. We use these counterfactual responses both to assess whether non-recipients provide a credible comparison group and to evaluate external validity following the SANS framework of List (2020). Following Ferrario and Stantcheva (2022); Stantcheva (2023) and Haaland et al. (2025), we conduct an open-ended pilot to design a more structured survey as in Colonnelli, Neto, and Teso (2025), to directly evaluate the importance of different mechanisms. We also use the survey to elicit whether they believe the transfers improved their financial resilience and overall quality of life. This belief elicitation methodology using survey data to better understand the underlying mechanisms has been used previously in Bursztyn et al. (2018, 2019); Breza, Kanz, and Klapper (2020); Galashin, Kanz, and Perez-Truglia (2020); Field et al. (2021); Colarieti, Mei, and Stantcheva (2024) and Fiorin, Hall, and Kanz (2025) among others.

3.6 Other Data Sources

Finally, we link the above datasets to several auxiliary sources: monthly ZIP code–level rainfall from the Climate Data Service Portal; GIS shapefiles for ZIP codes from India Post; district-level gross sown area by crop and district-level fertilizer consumption from the Ministry of Agriculture; village-level measures of organic farming from Mission Antyodaya; and the 2019 Situation Assessment Survey of farmers from the National Sample Survey Office. We report summary statistics alongside the empirical results that use each of these variables.

4 Baseline Results

This section examines the impact of PM-KISAN transfers on agricultural productivity, farm income, investment, and credit. We estimate these effects using multiple identification strategies and diverse data sources.

We begin with a border discontinuity design that exploits the noncompliance of the state of West Bengal with the policy. This approach compares contiguous areas on either side of the West Bengal border, thereby contrasting farmers who were eligible for the transfers with those who were not, while holding constant cultural, geographic, climatic, and broader economic conditions. Next, we turn to farmer-level data from a large private-sector bank in India. These data offer an important advantage by jointly recording income flows and credit utilization for the same set of farmers. This feature enables us to explore mechanisms and estimate the effect of transfers on income and investment at the individual level. However, the bank's coverage is geographically limited and does not include states bordering West Bengal. Consequently, we cannot implement the border-based identification strategy. Instead, we exploit an alternative source of variation arising from the program's eligibility rule: PM-KISAN benefits were granted only to landowning farmers, excluding tenants. Finally, we draw on data from a large-scale original survey of farmers, which directly captures self-reported behavioral responses to the transfers, including changes in effort, investment, and borrowing.

Across these datasets and empirical methods, we find consistent evidence that PM-KISAN transfers raised farm productivity and, in turn, increased household income. The rise in income is primarily driven by a shift toward more capital-intensive production among recipients, financed chiefly through expanded access to credit.

4.1 Evidence Using Border Discontinuity Design

We first exploit the fact that West Bengal did not implement PM-KISAN and construct a border district-pair design across multiple outcomes. Comparing locations just inside and outside the West Bengal border, we show that guaranteed income raises agricultural productivity, farm income, investment, and credit use.

4.1.1 Effect on Agricultural Production

We begin with agricultural production, using satellite-based EVI data and a differences-in-discontinuity design along the West Bengal border. We partition the border into narrow plots that are 5–20 km long along the boundary of West Bengal and 100 m wide, perpendicular to the boundary of West Bengal (see Appendix Figure B.1 for details). We compare "complier" plots just outside West Bengal, where farmers received PM-KISAN, with adjacent "non-complier" plots just inside West Bengal, which share similar agro-climatic and geographic conditions. Our key identifying assumption is that, in the absence of the policy, agricultural outcomes would evolve smoothly across the state boundary. Formally, we estimate the following regression specification:

$$ln(y_{i,t}) = \beta \cdot Complier_i \times Post_t + \theta_i + \theta_{j,t} + \varepsilon_{i,t} \tag{1}$$

where $\ln(y_{i,t})$ is log EVI-based agricultural output for plot i in year t; Complier_i equals one for plots outside West Bengal; Post_t is one in years after 2019; θ_i are plot fixed effects; and $\theta_{j,t}$ are boundary×year fixed effects, so β is identified from variation across immediately adjacent plots on either side of each boundary segment.

Across a range of bandwidths and plot lengths, as shown in Table 2, we find that the estimate of interest associated with the interaction term of Complier and Post is positive and statistically significant. Specifically, our results indicate that areas that complied with PM-KISAN experienced an increase in agricultural production of approximately 0.43 to 0.49% post-policy, relative to non-complying areas. Economically, this translates to a roughly 7.4 to 9.1% boost in agricultural productivity, as detailed in Appendix Table C.1. This magnitude is comparable to the 10% increase in agricultural yield reported by Emerick et al. (2016) among rice farmers in India following the adoption of new technological innovations that reduce downside risk.

Our identification does not require the complier and non-complier plots to be identical; instead, the key identifying assumption underlying this analysis is that, absent the policy, areas within the complier and non-complier regions would have followed similar trajectories. Although this assumption cannot be directly tested, Figure 1 reports the dynamic version of equation 1 to provide support for our identifying assumption by conducting a pre-trends assessment. Two key takeaways emerge from this assessment: first, the two groups display similar, parallel trends before the policy was implemented, suggesting they would have evolved similarly without the intervention. Second, we observe that the complier group experiences a relative increase in agricultural production following the policy, with this effect gradually growing over time.

4.1.2 Effect on Income

We next ask whether higher production translates into higher farm income. Using monthly household income data from CMIE's Consumer Pyramids and the border district-pair framework, we compare landowning farmers in districts just outside West Bengal (compliers) to landowning farmers in neighboring West Bengal districts (non-compliers), as shown in Appendix Figure B.2. Specifically, we estimate the following regression specification:

$$\frac{y_{i,t}}{\mathbb{E}[y_{i,t}|t = Pre]} = \beta \cdot \underbrace{Landowning_i}_{Treatment_i} \times \underbrace{\text{Outside WB}_d}_{Complier_d} \times Post + \theta_i + \theta_{d,t} + \theta_{p(d \in p),T,t} + \varepsilon_{i,t} \tag{2}$$

where $y_{i,t}$ is household i's income in month t; Landowning$_i$ indicates landowning farmers or the treatment group; Outside WB$_d$ indicates districts outside West Bengal or the complier group; Post$_t$ is one from March 2019 onward; θ_i are household fixed effects; $\theta_{d,t}$ are district × month fixed effects; and $\theta_{p(d\in p),T,t}$ are district-pair × treatment × month fixed effects.

This design compares landowning farmers in treated districts to observationally similar landowning farmers in adjacent non-compliant districts, while flexibly absorbing time-varying shocks at the district level using district × month fixed effects, including any changes in state-level policies. The inclusion of district-pair × treatment × month fixed effects allows the coefficient of interest to be estimated using variation across landowning farmers within a contiguous district-pair

Table 3 shows that the triple-interaction coefficient is positive, robust, and stable across increasingly rich fixed-effects specifications and controls. The estimates imply that landowning farmers in compliant districts experience a 15.8% increase in income, or about ₹1,311 per month, relative to comparable landowning farmers in neighboring West Bengal districts.

To better understand when this income growth occurs, we examine the dynamics of the effect over time. Figure 2 presents the results. There are two key takeaways from this analysis. First, the estimated effect – presented in Table 3 – is unlikely to be driven by pre-existing trends. Second, the timing of the increase indicates that the income gains for treated farmers appear during the second harvest season (kharif) after the transfers. This pattern suggests that the cash transfers substantially supported agricultural production, as shown in Table 2, and that the resulting improvements in output translated into higher farm incomes.

4.1.3 Effect on Investment

We then examine whether the documented income gains are associated with a shift toward more capital- and input-intensive production. Using the border district-pair design around West Bengal, we evaluate the effect of PM-KISAN on three outcomes: tractor purchases, fertilizer use, and cultivated area.

Tractors. Using monthly, ZIP code–level data on tractor sales from NITI Aayog, we estimate border-pair regressions with district-pair × month fixed effects. The key coefficient is the interaction between Complier and Post, capturing changes in tractor sales in compliant districts relative to adjacent West Bengal districts after PM-KISAN. Columns (1) and (2) of Table 4 show that tractor sales rise by about 14% in value and 12% in quantity, corresponding to an average increase in investment of ₹74,171 per tractor purchase.

Furthermore, we strengthen our identification by exploiting information on the intended purchase purpose, which allows us to include ZIP code × month fixed effects and control for all time-varying differences between neighboring districts, including differences and changes in state-level policies. The estimates reported in columns (3) and (4) of Table 4 suggest that the increase is concentrated in tractors purchased for agricultural production.

Fertilizer. Next, we combine annual, season-wise district-level fertilizer data with the border district-pair design and include district-pair × season × year fixed effects. Table 5 reports that total fertilizer consumption increases by roughly 32% in compliant districts relative to bordering West Bengal districts after PM-KISAN, with particularly pronounced effects for nitrogen- and phosphorus-based fertilizers.

Cultivated area. Finally, using annual, season-wise district-level data on gross sown area, we estimate the same border-pair specification that includes district-pair × season × year fixed effects. Table 6 indicates that total gross sown area rises by 48–55% in compliant districts, with similar increases across major crop categories.

Taken together, the tractor, fertilizer, and cultivated area results point to a sizable shift toward more input- and capital-intensive farming practices and an expansion in the scale of production following the introduction of PM-KISAN.

4.1.4 Effect on Credit

The scale of these investments far exceeds the annual transfer of ₹6,000, suggesting that farmers likely leverage formal credit. We test this directly using monthly ZIP code–level lending data from TransUnion CIBIL, disaggregated by lender and loan type, combined with the border district-pair design.

Table 7 presents our main estimates. Restricting to agricultural loans, we regress log new loan amounts (Panel A) and log counts of new loans (Panel B) on Complier × Post, progressively adding ZIP code × lender-type and district-pair × lender-type × month fixed effects. Across specifications, coefficients are positive and statistically significant. In our preferred specification, PM-KISAN increases agricultural loan amounts by about 7.2% and the number of agricultural loans by 16.6%.

We further strengthen our identification by leveraging a distinguishing feature of our data, which enables us to analyze the effect of PM-KISAN cash transfers on agricultural loans relative to other loan types. This approach offers a key advantage as it permits the inclusion of ZIP code × lender-type × month fixed effects, effectively controlling for all time-varying heterogeneity at both the ZIP code and lender-type levels. By doing so, the specification accounts for any residual systematic differences that may exist across the state border. The estimate of the triple interaction of the agricultural-loan indicator, Complier, and Post, reported in column (6) of Panels A and B, is positive and statistically significant, indicating that the expansion of credit is especially pronounced in the agricultural sector.

We cross-check these findings using branch-level agricultural lending data from the State Bank of India, India's largest state-owned bank. Appendix Table C.2 shows that branches in compliant districts increase agricultural lending relative to branches in adjacent West Bengal districts, yielding estimates that closely mirror the CIBIL results.

Finally, we use CMIE Consumer Pyramids to examine borrowing at the household level and to distinguish formal from informal credit. Using the border district-pair specification, Appendix Table C.3 shows that total borrowing rises for treated agricultural households in compliant districts, driven primarily by increases in formal bank borrowing. We do not observe a corresponding increase in informal borrowing from friends, relatives, money lenders, or shopkeepers.

Overall, the evidence indicates that PM-KISAN induces farmers in compliant areas to expand formal borrowing, especially agricultural credit, and to use this credit to finance higher input use, greater adoption of machinery, and expansion in the cultivated area, consistent with the observed gains in productivity and income.

4.2 Evidence Using Farmer-Level Data

We have thus far shown that PM-KISAN raises agricultural output, farm scale, and household income, and that these gains are associated with more capital-intensive production financed by formal credit. A remaining concern is that the households driving income gains may not be the same as those expanding investment or borrowing. To link these outcomes for the same individuals, we turn to detailed farmer-level data from a large private-sector bank in India, discussed in Section 3.4.

The bank data allow us to jointly observe income flows and credit utilization at the farmer level. The sample is restricted to three states of Karnataka, Maharashtra, and Punjab, which do not border West Bengal. This limitation precludes our border-based identification design. Instead, we exploit treatment heterogeneity from the program's eligibility rule: PM-KISAN transfers were extended only to landowning farmers, excluding tenant farmers.

4.2.1 Discussion of Bias

This design raises two concerns. First, because our bank sample covers only three states, it may not be representative of the full set of treated regions (sample selection). Second, landowning and tenant farmers may differ systematically along unobserved dimensions correlated with treatment status (omitted variables). Either source of bias could in principle attenuate or inflate our estimates.

We address these concerns in two steps. Our main specifications include farmer fixed effects to absorb all time-invariant differences between landowners and tenants. In addition, we use the income data described in Section 4.1.2 to replicate our analysis within the bank states and to compare landowning and tenant farmers in a manner parallel to the bank-data design. This exercise provides suggestive evidence on the direction and magnitude of both sample selection and omitted variable bias.

Appendix Table C.4 reports four sets of estimates. Column (1) compares landowning farmers in the rest of India with those in West Bengal. Column (2) compares landowning and tenant farmers within the rest of India, excluding West Bengal. Column (3) replicates Column (1) but restricts the sample to Karnataka, Maharashtra, Punjab, and West Bengal. Column (4) replicates Column (2) within the same bank-sample states, excluding West Bengal. Comparing Columns (1) to (3) isolates sample selection, and comparing Columns (1) to (2) and (3) to (4) isolates omitted variable bias from landowner–tenant differences. In both cases, estimated effects are smaller in the more restrictive designs. This pattern suggests that both sample selection and omitted variable bias likely attenuate our estimates, suggesting that the true treatment effect is likely to be larger than what we obtain in the bank data.

4.2.2 Comparison of Treatment and Control Farmers in Bank Data

We next assess how landowning and tenant farmers differ in observables. Table 1 reports sample means and both unconditional and within–ZIP code comparisons. Unconditionally, the two groups differ on several dimensions, and these differences are statistically significant. However, their economic magnitudes are modest relative to sample means. Once we compare farmers within the same ZIP code, the differences shrink further and are typically both economically small and statistically insignificant. This pattern highlights the importance of including farmer fixed effects and ZIP code × month fixed effects. Therefore, our empirical strategy compares similar farmers in the same locality while controlling for time-invariant heterogeneity across landowners and tenants using farmer fixed effects.

4.2.3 Effect on Income

We present three sets of evidence, along with a series of robustness checks, indicating that PM-KISAN raises income from work among treated farmers.

First, we estimate farmer-level regressions of log income from work for treatment and control farmers. Panel A of Table 8 reports the results. The coefficient on the treatment-by-post interaction is positive, statistically significant across specifications, and stable in magnitude. Under the Oster (2019) framework, the increase in the estimated coefficient as we enrich the set of controls from Column (1) to Column (4) suggests that unobservables are likely biasing our estimates downward. Our preferred estimate implies a 12.74% increase in income from work for treated farmers relative to control farmers after the policy.

Second, we collapse the monthly data into a farmer-period panel with two observations per farmer: income over the twelve months before and the twelve months after implementation. Panel B of Table 8 reports the corresponding estimates. This specification allows us to include farmer fixed effects and ZIP code × post fixed effects, so identification comes from within-farmer changes in income and variation in treatment status among farmers in the same ZIP code. The treatment-by-post coefficient remains positive and statistically significant as we progressively add fixed effects from Columns (1) to (4). Our preferred specification, with both sets of fixed effects, implies a 12.68% increase in income from work for treated farmers.

Economically, these estimates correspond to a relative increase of approximately ₹10,543–₹13,656 in annual income for treated farmers. Comparing this magnitude to the transfer size implies that each \$1 of guaranteed income generates about \$1.76 in additional earned income over the subsequent twelve months. Thus, total income rises by roughly \$2.76 per \$1 of guaranteed transfer, combining the direct transfer and induced income gains.

Third, we estimate a farmer-month differences-in-differences specification with both farmer fixed effects and ZIP code × month fixed effects. Table 9 presents these results. The coefficient on treatment-by-post remains positive and significant across Columns (1)–(5). As we add richer fixed effects, the R^2 rises sharply and the coefficient magnitude decreases. Applying the Oster (2019) procedure to the change in coefficient and the R^2 between Columns (1) and (5) yields a positive lower bound that excludes zero, suggesting that omitted variables are unlikely to fully explain the effect. Our preferred specification implies a 13.90% increase in income from work for treated farmers in the post-policy period.

Alternative Estimation Methods: We show that these results are robust to alternative estimators. Our baseline follows Chen and Roth (2024), estimating treatment effects relative to pre-period means in the presence of zeros. We also estimate Poisson pseudo–maximum-likelihood model, as suggested by Cohn, Liu, and Wardlaw (2022). Appendix Table C.5 shows that the treatment effect is stable across specifications.

Spillovers: A key concern is that the Stable Unit Treatment Value Assumption may be violated if transfers generate spillovers onto control farmers, for example by altering local input or output prices. Positive spillovers would bias our estimates toward zero, while negative spillovers would be more problematic for interpretation. Following Berg, Reisinger, and Streitz (2021), we test for spillovers by allowing outcomes to depend on local treatment intensity at the district and ZIP code levels. Appendix Table C.6 shows that estimates are virtually unchanged when we include these spillover terms relative to specifications that ignore them. This pattern suggests that any spillovers are small, consistent with the highly regulated structure of Indian agricultural markets, which limits competitive price adjustments across farmers.

Controlling for Covariates: To address the possibility that treatment effects are confounded by differences in observed characteristics, we augment the baseline specification with interactions between the post indicator, $Post_t$, and a rich set of pre-policy farmer covariates, X_i. Appendix Table C.7 reports the results. Covariates include pre-period averages of savings, income, spending, credit card usage, fixed and recurring deposits, provident fund contributions, stock holdings, transaction frequency, credit scores, interest rates, Kisan credit card limits, age, account age, religion, and prior default. The treatment-by-post coefficient remains robust and, if anything, becomes larger and more precisely estimated when we include the full set of interactions. This pattern is consistent with omitted variables having attenuated our baseline estimates.

Placebo Tests: Finally, we conduct placebo tests to probe whether our findings reflect differential seasonality or shocks coinciding with policy implementation, such as federal elections. We re-estimate our baseline specification in pre-policy years in which no transfers were made. Appendix Table C.8 reports results for placebo years 2015, 2014, 2013, and 2012.[12] Across all placebo years, coefficients are statistically insignificant and typically negative, the opposite sign of our main estimate. The absence

[12]We exclude 2016 and 2017 because the sample required for those placebo tests overlaps substantially with the demonetization episode, which rendered 86% of cash in circulation invalid. See Chodorow-Reich et al. (2020) for details of this episode.

of effects in 2014, a federal election year, further suggests that our baseline results are not driven by election-related shocks.

Homogeneity of Treatment Intensity: A separate concern is that the effective transfer may vary across the income distribution after taxes, violating the assumption of homogeneous treatment intensity (Saez, 2002; Hanna and Olken, 2018). In our setting, this issue is mitigated by an institutional feature of India's tax system: all agricultural income is exempt from income tax, regardless of farmer income or wealth. Since our sample includes only farmers, the after-tax value of PM-KISAN transfers is uniform across treated units.

Stability of Treatment and Control Groups: Finally, treatment status could, in principle, change over time if farmers buy or sell land. The policy design prevents this. The beneficiary list was fixed based on landownership as of December 2018, prior to the program's announcement in February 2019. Farmers who purchased land after that date were not eligible. As a result, landownership status and, therefore, the treatment status, are effectively fixed over our sample period.

4.2.4 Effect on Credit

We next examine how PM-KISAN affects credit at the farmer level. Our goal is to understand whether the increased investment documented in Section 4.1.3 is financed by additional borrowing. For each farmer in the bank sample, we obtain loan-level information from India's largest credit bureau (TransUnion CIBIL). We study both the extensive margin of credit (whether a farmer takes any new loan in a given month) and the intensive margin (the number and value of new loans). We construct a balanced farmer-month panel with twelve months before and twelve months after policy implementation. Table 10 reports the baseline results; Appendix Table C.9 shows that they are robust to Poisson pseudo–maximum-likelihood specifications.

Columns (1) and (2) focus on the extensive margin. The policy raises the probability of taking a new loan by 4.7%, which corresponds to a 10% increase relative to the pre-period mean of 48%. The number of new loans rises by 14.2%, or about 0.09 additional loans per month relative to the pre-policy mean. Column (3) shows that the intensive margin also responds strongly: the monthly loan amount increases by 35.9% for treated farmers, or about ₹40,703 over the twelve months following the policy. This increase in borrowing is economically large: it is roughly 6.8 times the annual transfer of ₹6,000 and equals 39.3% of the present discounted value of the guaranteed income stream.[13]

Does the New Credit Finance Consumption or Productive Capacity? We next ask whether this additional credit finances consumption or productive investment. For the policy to raise investment in agriculture, new credit must instead flow toward productive capacity.[14]

[13] We compute 0.393 by comparing the increase in loan amounts of approximately ₹41,000 to the present value of a perpetuity paying ₹6,000 annually, discounted at a risk-free rate of 5.8%. The risk-free rate is obtained by subtracting a sovereign risk premium of 1.2% from the average 10-year Indian Treasury rate of 7% in 2019.

[14] Another reason for investigating if the new credit finances productive capacity or consumption is that if the majority of the new credit goes into financing household consumption, it could potentially generate a *"bad"* credit boom (Mian, Sufi, and Verner, 2017, 2020; Mian and Sufi, 2018).

We classify loans based on their stated purpose. Loans used to purchase farm equipment or tagged as priority sector loans for business activities are classified as productive; all others are classified as consumption. Appendix Table B.6 summarizes the classification. Table 11 reports the results. Columns (1)–(3) show that the probability, number, and value of new loans all rise for productive loans, mirroring the baseline effects. Columns (4)–(6) show no economically or statistically meaningful changes in consumption loans. These results indicate that nearly all of the new borrowing is directed toward productive capacity rather than consumption.

We then exploit a "long" panel in which each observation is a farmer–loan-type–month. Our main coefficient of interest is a triple interaction between loan type, treatment status, and the post-policy indicator. This specification absorbs farmer × month fixed effects, so identification comes from within-farmer differences between productive and consumption loans over time. Columns (7)–(9) of Table 11 report the estimates. We find a significant increase in the likelihood, number, and value of loans for productive investment relative to consumption borrowing among treated farmers in the post-policy period. Because the comparison is within farmer, this design further mitigates concerns about systematic differences between landowners and tenants by including farmer × month fixed effects.

Taken together, the farmer-level evidence shows that PM-KISAN raises income from work and induces substantial increases in formal borrowing, with the new credit primarily directed toward productive agricultural investment rather than consumption.

4.3 Evidence from Original Survey of Farmers

We complement the administrative evidence with an original survey of farmers that directly elicits self-reported responses to the PM-KISAN transfers. The survey asks landowning recipients how the transfers affected their effort, investment, and borrowing, and asks tenant farmers – who do not receive PM-KISAN – how these behaviors would change if they received an unconditional transfer of ₹6,000 per year.[15]

This exercise offers two key advantages. First, it allows us to assess the validity of the counterfactual by benchmarking the untreated tenant farmers against the treated landowning farmers. Such an exercise is important for the interpretation of the estimates presented in Section 4.2 which compares landowning farmers with tenant farmers. Second, it provides a simple test of external validity in the spirit of List (2020), by examining whether expected responses among currently untreated farmers resemble those of treated farmers.

Table 12 summarizes the results. Panels A, B, and C report perceived effects on physical effort, agricultural investment, and credit use, respectively. Farmers report whether the transfer would increase, decrease, or not affect each outcome. Column (1) shows overall responses; Columns (2) and (3) separate landowning PM-KISAN recipients from tenant non-recipients.

[15]To avoid any perception that responses might affect program eligibility, survey questions referred only to a generic unconditional transfer of ₹6,000 per year and did not mention PM-KISAN by name. Enumerators also emphasized that the study was independent of the government and could not influence current or future access to transfers.

There are three key takeaways from this analysis. First, farmers overwhelmingly expect the transfers to raise effort, investment, and borrowing: 65 percent report higher effort, 70 percent higher investment, and 47 percent higher credit use. Second, these patterns are similar for recipients and non-recipients, suggesting that tenant farmers form expectations about the transfer that closely mirror realized responses among landowning farmers. Third, the qualitative responses line up with the quantitative evidence on income, investment, and credit documented above, reinforcing both the credibility of our identification strategy and the view that the effects we estimate are likely to generalize to other small farmers facing similar constraints.

5 Mechanism

This section examines why guaranteed income raises income from work and agricultural investment. We show that credit markets are central to this response, that the transfers are too small to directly finance lumpy investment, and that credit demand is likely to be an important margin of adjustment, especially among farmers facing greater downside risk and incomplete insurance.

5.1 Importance of Credit Markets

We first test whether access to formal credit is necessary for income to respond. The intuition behind this test is that if guaranteed income works primarily by allowing farmers to leverage credit, then effects should be concentrated among borrowers who face lesser credit market frictions.

We exploit heterogeneity in credit market frictions. Following Garmaise and Natividad (2017), a prior default tag sharply reduces financial access, lowering credit scores and raising interest rates. We therefore re-estimate our baseline income regressions separately for farmers with and without a default tag before March 2018. Table 13 reports the results. For farmers without prior default, the treatment effect on income is positive and statistically significant. For farmers with a prior default tag, the point estimate is economically small and statistically insignificant. Farmers effectively cut off from credit markets do not experience meaningful income gains.

We obtain similar results in credit outcomes. Table 14 shows that increases in borrowing are driven entirely by farmers with no prior default (Panel A), while treated farmers with prior default show no change in credit use (Panel B). Finally, Appendix Table D.1 documents that the policy's effect on credit is concentrated among farmers with higher pre-policy credit scores, who face lower frictions. Taken together, these results indicate that the income gains induced by guaranteed income operate through formal credit markets rather than directly through cash-on-hand.

Are Transfers Large Enough to Directly Finance Investment? An alternative explanation is that the transfers themselves loosen liquidity constraints enough to fund lumpy investments. This channel appears too small to explain our findings. The annual transfer of ₹6,000 amounts to only about 7% of the average farmer's annual income. It also pales relative to the size of typical capital expenditures: a tractor costs roughly ₹700,000, a cow around ₹150,000, and even one input in tractor operation, diesel for a cultivation season, can consume more than the full yearly transfer.[16] The transfer is thus far below the scale needed to move farmers into a high capital-intensive regime on its own. Banerjee, Niehaus, and Suri (2019) make a similar argument for small UBI-style transfers. Our evidence instead points to guaranteed income acting as a catalyst for borrowing and investment, not as the main source of investable funds.

5.2 Role of Credit Demand

We now turn to the demand side of the credit market. The previous subsection showed that credit access is necessary for income to respond. Here, we show that the policy primarily increases credit demand, rather than relaxing credit supply.

5.2.1 Existence of a Credit Demand Effect: Evidence from Kisan Credit Cards

We begin with Kisan Credit Cards (KCCs), a standardized credit line for farmers at subsidized rates. KCCs are issued for five years, with initial limits based on land cultivated and crop type, and subsequent limits growing mechanically by a fixed annual percentage. Limits and interest rates do not respond to changes in a farmer's income or credit score over the card's life. Consistent with this institutional design, Appendix Figure D.4 shows no relationship between KCC limits or interest rates and farmers' credit scores in the pre-policy period, and Appendix Table D.2 shows no effect of PM-KISAN on KCC limits or rates. KCCs, therefore, provide a clean setting in which we can observe changes in demand, holding credit supply effectively fixed.

Table 15 reports the effect of PM-KISAN on KCC utilization. The treatment-by-post coefficient is positive and statistically significant across specifications. Utilization increases by 5.8 percentage points from a baseline of 19.6%, corresponding to an increase of roughly ₹20,000 in KCC borrowing. The KCC results provide direct evidence on the existence of the credit demand effect, i.e., the demand for credit rises following the guaranteed income shock.

5.2.2 Credit Inquiries and Acceptance Rates

We next use credit bureau inquiry data as a proxy for applications, following Jiménez et al. (2014, 2017).[17] Panel A of Table 16 shows that PM-KISAN increases the monthly probability of inquiry by 1.7 percentage points. Given a baseline application probability of 4.1%, this represents a 41% increase. Panel B shows that the acceptance rate conditional on inquiry is essentially unchanged: the treatment effect is statistically

[16] Assume a small tractor of 21-35 HP requires a minimum of 5 litres of diesel per hour and operating for a minimum of 20 hours during a cultivation season. At an average price of ₹67 per litre for diesel during 2019, the minimum cost of diesel to operate the tractor would be ₹6,700. This is just an example of one of the several costs associated with operating a tractor, let alone the cost of agriculture.

[17] A caveat with using inquiry data as a proxy for credit applications is that it may understate applications. For instance, Mishra, Prabhala, and Rajan (2022) note that state-owned banks do not always inquire about a prospective customer in the credit bureau. The application-inquiry gap is likely to be of little concern as it will understate the policy's effect on application, and also the majority of credit for our sample farmers comes from private sector banks which have a very small application-inquiry gap (Mishra, Prabhala, and Rajan, 2022). This characteristic is not exclusive to our study and is also observed in Jiménez et al. (2014, 2017) and Cramer et al. (2024). Thus, credit bureau inquiries are a reasonable proxy for credit applications but not a perfect measure.

insignificant and economically small relative to the average monthly acceptance rate of 3.8%. Treated farmers apply more often, but conditional on applying, their chances of approval do not change.

We interpret these results as suggestive evidence of an increased demand for credit with a relatively stable credit supply. This interpretation requires that farmers do not expect banks to significantly relax lending standards in response to PM-KISAN; otherwise, higher applications could partly reflect perceived easier credit. Our original survey supports this assumption, as shown in Appendix Table D.3. Particularly, nearly half of farmers report expecting lending standards to tighten or remain unchanged after the policy, rather than becoming more lenient. Overall, the inquiry and acceptance evidence, together with the KCC results, point toward a demand-driven increase in borrowing.

5.2.3 Survey Evidence on Demand vs. Supply

To more directly distinguish demand from supply, we elicit beliefs of PM-KISAN recipients about why the policy increased their borrowing. This belief elicitation methodology using survey data to better understand the underlying mechanisms has been used previously in Bursztyn et al. (2018, 2019); Breza, Kanz, and Klapper (2020); Galashin, Kanz, and Perez-Truglia (2020); Field et al. (2021); Colonnelli, Neto, and Teso (2025) and Fiorin, Hall, and Kanz (2025) among others. The respondents choose between two explanations: (a) "It made me more comfortable to borrow," or (b) "It made the bank more willing to accept my application and/or lend at a lower rate." We interpret option (a) as a demand channel and option (b) as a supply channel.

Figure 3 shows the distribution of responses among farmers who received PM-KISAN transfers across these two categories. Our results indicate that 80% of respondents report that higher credit demand – rather than improved credit availability – was the primary channel through which the policy increased their borrowing. This survey evidence complements the KCC and inquiry results and reinforces the view that guaranteed income raises borrowing by boosting borrowers' willingness to take on debt.

Why is the Supply-side Response Limited? The relatively modest supply-side response is also consistent with institutional features of agricultural lending. Future government transfers are typically not pledgable as collateral and loan officers rely heavily on historical yields, collateral, and credit scores when underwriting. Moreover, small farm sizes make cash-flow-based lending unattractive because the practicality of cash flow-based lending requires businesses to produce enough cash flows to make ex-post reorganization cost-effective for lenders (Lian and Ma, 2021).[18] These features limit the scope for a rapid supply-side response to a new, unpledgeable income stream.

5.2.4 Effect on Ex-Post Default

Finally, we study how guaranteed income affects repayment behavior. Theoretically, default could either rise if higher borrowing is driven by lower perceived costs of default or fall if borrowing rises because

[18] Additionally, Lian and Ma (2021) argue that Chapter 11–type corporate bankruptcy systems that facilitate reorganization tend to favor cash flow-based lending. In contrast, personal bankruptcy systems in India are not well-developed to foster reorganization.

transfers improve borrowers' ability to repay and meet basic needs even in bad states.

We use ZIP code–level TransUnion CIBIL data, combined with the border district-pair design, to estimate the effect of PM-KISAN on delinquency among agricultural loans. Table 17 reports the results. Columns (1)–(5) restrict to agricultural loans and progressively absorb richer fixed effects, including ZIP code × lender-type and district-pair × lender-type × month fixed effects. Across all specifications, the treatment effect is negative and statistically significant. Our preferred specification implies that one-year delinquency falls by 2.8% and three-year delinquency falls by 8.7%.

Column (6) further compares agricultural to non-agricultural loans using a triple-differences specification that allows us to control for ZIP code × lender-type × month fixed effect. The coefficient on the triple interaction between the agricultural loan indicator, Complier, and Post is negative and significant, indicating that delinquency declines are especially pronounced in agricultural lending. These findings suggest that guaranteed income does not induce a "reckless" credit boom. Instead, it improves repayment behavior in both the short and medium run, supporting the sustainability of expanded credit access and suggesting that higher credit demand may stem from improved ability to repay and maintain basic consumption, rather than from lower perceived costs of default.

5.3 What Drives Credit Demand?: Role of Downside Risk Protection

We next ask why PM-KISAN increases credit demand. Credit contracts can be particularly costly in adverse states (*bad times*). During shocks such as droughts, farmers with limited liquidity may struggle to meet basic needs—food, clothing, shelter—after repaying loans, or may fail to meet minimum repayment requirements and incur default costs such as losing productive assets or being excluded from future credit, with potentially permanent consequences for consumption. Figure 4 schematically summarizes these concerns. We argue that guaranteed income can mitigate them by: (i) improving the ability to meet basic needs after loan repayment in bad times, (ii) improving the ability to repay loans in bad times, and (iii) reducing the expected consumption loss associated with default.

To shed light on the underlying mechanism, we elicit the beliefs of PM-KISAN recipients about why the program makes them more willing to borrow. We first validate the premise that farmers are deeply concerned about debt in bad times. Figure 5 presents three facts. First, farmers report a high and persistent level of worry about the consequences of debt during bad times. Second, they attribute this worry primarily to the risk of default and the difficulty of meeting basic needs after repayment. Third, when asked about the costs of default, they highlight the loss of means of production and future exclusion from credit markets as the most salient consequences.

To assess which channels matter most for credit demand, we follow Ferrario and Stantcheva (2022); Stantcheva (2023) and Haaland et al. (2025), and we conduct an open-ended pilot to design a more structured survey as in Colonnelli, Neto, and Teso (2025), to directly evaluate the importance of different mechanisms. Specifically, we ask: *"Which of the following channels was most significant in increasing* *your credit demand?"* Respondents choose one of four options (with internal labels in italics):

1. My concern before the policy was not default but meeting basic needs after repayment during bad times; the money reduced this concern *(Increased comfort in repayment)*.

2. The money does not increase my ability to service debt during bad times, but it makes me more comfortable meeting basic needs in case I default *(Reduced consumption loss in case of default)*.

3. The money makes it possible for me to service debt during bad times *(Reduced probability of default)*.

4. The money helped me meet the down-payment requirements *(Reduced down-payment constraint)*.

Table 18 reports the results of the survey. 21.9% of the respondents report that guaranteed income increased their credit demand by increasing their comfort in meeting basic needs after loan repayment during bad times. 39.8% of the respondents rated the reduction in the (expected) cost of default, i.e., the reduction of consumption loss, as the primary reason for the increase in their credit demand. 20.8% of respondents rated a reduction in the probability of default as the primary reason for increased credit demand. Additionally, Table 18 is also informative about an alternative channel, i.e. guaranteed income increases credit demand by reducing down-payment constraints. 17.5% of respondents reported a reduction in down-payment constraints as the primary driver. Overall, the majority of respondents attribute higher credit demand to improvements in repayment comfort and reduced costs and likelihood of default in bad states, rather than to standard liquidity constraints at the time of borrowing.

The results reported in Table 18 indicate that by providing a predictable income floor, guaranteed income can increase expected utility in bad states and thereby relax demand-side credit constraints. Using administrative data, we provide two additional pieces of evidence consistent with this interpretation: stronger effects where rainfall risk is higher and stronger effects where rainfall insurance is less effective.

5.3.1 Role of Risk

We first examine heterogeneity by rainfall risk. Roughly 60% of India's agricultural land is rainfed, and 80–90% of annual precipitation arrives in the June–September monsoon (Jayachandran, 2006). Moreover, rainfall shocks affect the entire village economy, thereby limiting informal risk-sharing (Townsend, 1994).

We measure rainfall risk at the ZIP code level using monsoon-season precipitation from 2014–2017. For each ZIP code, we construct the frequency of "drought" years, those in which monsoon rainfall falls below the fifth percentile of the historical distribution, and classify ZIP codes above the median drought probability as high-risk and those below as low-risk. In our data, low-risk areas face a 2.8% drought probability, compared to 13.2% in high-risk areas.

Columns (1) and (2) of Table 19 estimate the treatment effect on credit separately for low- and high-risk ZIP codes. In low-risk areas, the estimated effect on borrowing is small and statistically insignificant.

In high-risk areas, the effect is both statistically significant and roughly four times larger than in low-risk areas; the difference in coefficients is statistically significant (F-statistic 3.19). These patterns indicate that guaranteed income has a much stronger impact on borrowing where downside risk is greater.

We interpret this heterogeneity as driven by demand. Panel A of Appendix Table D.4 shows no meaningful variation in the treatment effect on loan acceptance rates by rainfall risk. Because large banks are geographically diversified, rainfall shocks are largely idiosyncratic from the lender's perspective, and we see no evidence of an asymmetric supply response by risk level. This lack of supply-side response by Indian banks to droughts is consistent with the results reported in Cramer et al. (2024).

5.3.2 Role of Incomplete Insurance

We next consider incompleteness in formal insurance. Rainfall index insurance contracts pay based on rainfall measured at official stations rather than on farm-level rainfall, creating basis risk when fields are far from stations. Existing work shows that basis risk is a first-order determinant of insurance demand: doubling the distance to a reference weather station significantly reduces demand for index insurance in India (Hill, Robles, and Ceballos, 2016; Mobarak and Rosenzweig, 2013; Cole, Giné, and Vickery, 2017).

We proxy basis risk at the ZIP code level by regressing ZIP code rainfall on rainfall at the nearest station and defining basis risk as one minus the regression R^2. Appendix Figure D.5 shows that basis risk rises with distance to the nearest rainfall station, consistent with prior work. We classify ZIP codes into high- and low–basis risk areas and estimate our main credit specification separately for each group.

Columns (3) and (4) of Table 19 report the results. In low–basis risk areas, the treatment effect on borrowing is small and statistically insignificant. In high–basis risk areas, the effect is large and precisely estimated, with a magnitude about four times that in low–basis risk areas. As with the risk of rainfall, we do not find a corresponding heterogeneity in the acceptance rates (Panel B of the Appendix Table D.4), consistent with a demand-side interpretation. Thus, guaranteed income has the largest impact on borrowing, where insurance markets are least effective at protecting farmers from downside risk.

5.4 Role of Perpetual Nature of Guaranteed Income

The policy's effect is likely to crucially depend on the expectations of the treatment group that the cash transfers will continue perpetually and protect against future risk. This section uses the trust in government commitment as a proxy for the belief in the continuance of these transfers and their ability to protect against future risk. We use the Bharatiya Janata Party (BJP) vote share in 2019 to identify spatial heterogeneity in the trust in the continuance of the policy. The intuition behind this test is that the ZIP codes with a higher level of BJP vote share are likely to have greater trust in the commitment of the BJP-run federal government to continue these transfers and provide protections against future risk.

To this end, we estimate the heterogeneity in the treatment effect on credit market outcomes by BJP vote share. We estimate the main specification separately for ZIP codes categorized as having low, medium and high basis risk. Figure 6 presents the estimates for the three sub-samples. The results indicate that the total treatment effect increases with BJP vote share. This result suggests that the perpetual nature of these transfers is an important element of the ability of guaranteed income to protect against future risk.

5.5 Effect of the Policy on Hedging Activity and Risk Taking

We next examine how guaranteed income affects risk management in agriculture. Our previous results show that PM-KISAN strengthens downside-risk protection and raises credit demand. A natural implication is that social safety nets may also reshape farmers' risk-taking and hedging decisions. When downside risk is substantial, farmers employ self-insurance strategies such as cultivating low-risk, low-return crops. Safety nets can reduce downside risk exposure and act as a substitute for these costly self-insurance strategies. This idea parallels Karlan et al. (2014), who show that formal insurance can crowd out traditional risk-management practices. Similarly, Cole, Giné, and Vickery (2017) find that rainfall insurance induces farmers to move toward riskier, higher-return crops.

Traditional agriculture relies on several hedging strategies, including the cultivation of non-cash, subsistence crops. These crops typically offer lower returns but provide a stable source of food, insuring households against income volatility and crop failure in more commercial activities. We hypothesize that guaranteed income reduces the incentive to self-insure through low-risk cultivation and instead encourages a shift toward higher-return, higher-risk cash crops. To test this hypothesis, we assemble district-level data on cultivated area by crop and compute the share of land devoted to cash crops in each district. We combine these data with the border district-pair design, comparing districts on either side of the West Bengal border.

Table 20 reports the results. Columns (1)–(4) progressively add fixed effects, with our preferred specification in Column (4). The coefficient on the Complier × Post interaction is positive and statistically significant in all specifications and remains stable even as the model R^2 rises by nearly 90 percentage points from the simplest to the most saturated specification. The estimates imply that the share of land under cash crops increases by 3.7% after treatment, corresponding to a 33% rise relative to the pre-period mean of 9.9%. This shift toward cash crops is consistent with farmers taking on more production risk in the presence of guaranteed income.

5.5.1 Effect on Adoption of New Farming Techniques

We also study whether guaranteed income encourages adoption of new, riskier production technologies. Using village-level survey data from Mission Antyodaya, we examine changes in the share of farmers engaged in organic farming. Organic farming is innovative in the Indian context: it departs from conventional methods, can open access to premium markets, and offers higher potential returns. At the same time, it involves transitional yield risk, cash-flow stress for smallholders, and requires specialized knowledge and certification, making it a high-risk, high-return strategy.

Appendix Table D.5 combines the village-level data with the border district-pair design. Villages in compliant districts experience an increase in the fraction of farmers adopting organic farming relative to comparable villages just across the border. This result is robust to including village fixed effects and district-pair × year fixed effects, so identification comes from differences between villages in adjacent districts straddling the West Bengal border. The preferred estimate indicates a 0.4 percentage point rise in the share of farmers practicing organic farming, equivalent to a 4.4% increase over the pre-period mean of 8.4%. This pattern suggests that guaranteed income enables farmers to undertake riskier, potentially more profitable production choices.

5.5.2 Evidence from Original Survey of Farmers

The survey evidence further reinforces the view that guaranteed income increases risk-taking. Appendix Table D.6 reports that 41% of surveyed farmers indicate an increase in their risk-taking. Among actual PM-KISAN recipients, 38% report higher risk-taking after receiving transfers. Among non-recipients, 44% state that they would increase their risk-taking if provided with an unconditional transfer of similar size. These responses suggest that both realized and anticipated behavior shift toward greater risk exposure when farmers are insured by a guaranteed income stream.

5.5.3 Do Farmers Build Buffer Stocks?

A complementary channel through which guaranteed income can provide downside risk protection and alter risk-taking is by allowing farmers to build buffer stocks. A predictable transfer can be used to accumulate precautionary savings or reserves, which then serve as self-insurance against shocks such as droughts or floods. These buffers can support both consumption smoothing and repayment, thereby making it easier to finance productive investment with risky debt.

Qualitative evidence from our survey supports this mechanism. Appendix Table D.7 shows that 53% of surveyed farmers report increasing their precautionary savings after receiving transfers. The same share of recipients report higher savings, and 53% of non-recipients say they would respond similarly if they obtained an unconditional transfer of comparable magnitude. These patterns indicate that guaranteed income helps farmers build buffer stocks and strengthen financial resilience.

Taken together, the quantitative evidence on crop choices and organic adoption, along with the survey evidence on risk-taking and savings, points to a consistent mechanism: by reducing downside risk and enabling buffer-stock accumulation, social safety nets encourage farmers to move away from low-risk hedging strategies toward higher-risk, higher-return agricultural investments.

6 Discussion of the Results

This section summarizes and discusses the effect of guaranteed income on income from work, investment, and credit presented in this paper.

6.1 Magnitude of the Effect

We find that unconditional and perpetual cash transfers increase income by 12.74%. Specifically, a promise of an additional \$1 in guaranteed income generates an additional income of \$1.76. The increase in income is driven by a shift towards a more capital-intensive mode of production financed using credit. On the policy's effect on credit, we estimate that additional \$1 in guaranteed income increases loans by \$6.78, which is equivalent to 39.30% of the perpetuity value of guaranteed income. Assuming a loan-to-value ratio of 0.8, our estimate of the policy's effect on capital is \$8.48. This increase in investment is equivalent to 49.15% of the perpetuity value of guaranteed income. The capital to income ratio implies returns to capital of 20.75%.

Why is the Effect Large?: The magnitude of the effect on credit and investment is large. So, how can such a small transfer each period have such a sizeable effect on investment? We argue that while credit is crucial for investment, especially in the presence of liquidity constraints, the increased downside risk associated with debt contracts can negatively affect credit demand and lead to under-investment.[19]

Specifically, underinvestment can arise due to the negative covariance between marginal returns to risky investment and marginal utility of consumption. In other words, when investment returns are expected to be low in the bad states of the world, where the marginal utility of consumption is high, an entrepreneur is likely to underinvest. This result hinges on three crucial assumptions – high risk-aversion, the presence of large uncertainty, and binding consumption or liquidity constraints in the bad states of the world. All three conditions are likely to be present in our setting, making the negative covariance problem prominent, because agriculture is a risky activity and most farmers are small. Moreover, the problem is made worse if investment is financed with credit because debt contracts impose a large cost of financial distress when the entrepreneur is unable to repay her loans in the bad states of the world. Therefore, when ex-post consumption constraints are more likely to bind due to limited ex-post coping capacity and the underlying economic activity is risky, the choice of investment and credit demand is negatively affected.

We argue that guaranteed income attenuates the severity of this problem by reducing ex-post consumption constraints or increasing ex-post coping capacity. Simply put, guaranteed income stimulates credit demand and investment by increasing financial resilience. Therefore, a small amount of basic income support can have a catalytic effect generating a large investment effect by increasing the willingness to bear risk. An alternative way of framing this argument is that guaranteed income increases credit demand for risky investment by reducing risk-aversion through the classic wealth effect of Pratt (1964).

[19]We highlight an important caveat of our findings. Our results do not imply that credit-supply expansions are unimportant or borrowing constraints are never binding in emerging markets. Our results highlight the importance of demand-side constraints originating from uninsured income volatility. The results presented in Section 5.1 show that farmers facing greater frictions in access to credit markets are unable to take advantage of the relaxed credit-demand constraints after the introduction of downside risk protections. Improvements in access to credit for such a population is likely to generate positive effects. Therefore, our results indicate that access to credit markets is necessary, but may not be sufficient, for economic development when uninsured risk is the binding constraint.

Is the Effect Reasonable?: We rationalize our findings by estimating a dynamic partial-equilibrium model of Herranz, Krasa, and Villamil (2015), which features borrowing, investment, and an explicit cost of default. Appendix section E presents this model. We extend the framework along two dimensions that are salient in our setting: (i) entrepreneurial farmers differ in productivity, and (ii) they face frequent disaster shocks, such as droughts. Limited internal funds make external credit essential for lumpy investment, while recurrent disasters make the downside of credit-financed investment first order. Downside risk is amplified both by tight liquidity in bad years, which makes repayment difficult, and by the cost of default, which combines a persistent loss in productive capacity with exclusion from future credit markets.

The model plays two roles. First, it formalizes the trade-off we document empirically: optimal investment equates higher expected returns to capital with the higher downside risk of debt-financed expansion. In equilibrium, more risk-averse farmers choose lower leverage and smaller capital stocks, precisely because credit exposes them to distress in bad states. Guaranteed income enters as a permanent, state-contingent floor on consumption, which reduces the probability of distress and the severity of default. This stable income floor raises the value of risky, credit-financed investment and therefore increases credit demand and capital for risk-averse farmers.

Second, we use the model to assess the quantitative plausibility of this channel. We feed in a disaster process calibrated to match the frequency of agricultural shocks and consider standard CRRA preferences. We then ask whether the observed increase in capital following the policy can be rationalized by the change in downside risk induced by guaranteed income. Appendix Figure E.1b shows that, under frequent disaster risk, the empirically estimated change in capital can be matched with conventional coefficients of relative risk aversion between 2 and 5. This exercise suggests that the risk-based credit demand channel we document is not only qualitatively consistent with the data but also quantitatively plausible.

6.2 External Validity

Our objective is not to claim that guaranteed income programs such as UBI will have identical effects in all settings. Rather, we highlight a partial equilibrium mechanism through which such programs can stimulate credit demand, investment, and production by strengthening financial resilience. In doing so, we aim to inform, rather than resolve, the broader policy debate. We show that the demand-side channel operates when households are highly risk-averse, face binding consumption or liquidity constraints, and confront substantial uninsured risk. Because these conditions are common among small entrepreneurs and poor households in many environments, our findings may speak to discussions of guaranteed income beyond farmers in India.

Recent evidence from a randomized guaranteed-income program in the United States, which provided payments for up to three years, finds a decline in labor income among recipients (Vivalt et al., 2024).

In contrast, we find that guaranteed income increases income from work, primarily through higher investment. These results reflect differences in underlying populations rather than a contradiction. Participants in Vivalt et al. (2024) are primarily wage earners facing a standard labor–leisure trade-off, where unconditional transfers can reduce labor supply (Hoynes and Rothstein, 2019). By contrast, our subjects are self-employed farmers who choose both capital and labor inputs (Breza and Kaur, 2025). In this setting, transfers relax investment constraints and can increase productive effort when self-employed individuals underinvest due to downside risk. A growing development literature further suggests that labor-supply distortions associated with social insurance in high-income settings may be less salient in low-income economies (Baird, McKenzie, and Özler, 2018; Banerjee et al., 2024). For example, Banerjee et al. (2017) re-analyze seven large conditional cash transfer experiments in which earnings were not part of the conditionality and find no evidence that transfers reduce work. Our findings are closer in spirit to Banerjee et al. (2020a, 2023), who document shifts from wage employment to self-employment following a universal basic income experiment in Kenya.

Our results also highlight the importance of the long-term nature of transfers. Using BJP vote share as a proxy for trust in the government's commitment to continue PM-KISAN, we find larger treatment effects in areas with higher support for the incumbent party. This suggests that perceived permanence is central to the program's impact on credit and investment. The result echoes Bianchi and Bobba (2013) and Banerjee et al. (2024), who show that longer-horizon transfers have more powerful effects than short-lived programs.

Finally, we compare our findings to Egger et al. (2023), who study a large one-time cash transfer in rural Kenya. The perpetuity value of PM-KISAN (about $1,400) is comparable in size to the lump-sum transfer ($1,000) in their experiment, permitting a qualitative comparison of wealth shocks delivered over time versus as a one-time payment. In a frictionless benchmark, these two modes are isomorphic. In practice, the outcomes differ. Egger et al. (2023) find that recipients spend most of the lump-sum transfer on consumption and non-productive durables, generating higher local enterprise revenues and substantial spillovers to non-recipients, but limited increases in productive investment by recipient enterprises. By contrast, we find that when a similar wealth shock is delivered as a perpetuity, it primarily increases financial resilience, spurs credit demand, and raises investment in productive assets and output, with little evidence of large spillovers onto non-recipient households.

These differences may arise because long-term transfers provide more effective protection against future risk, or because market imperfections (such as limited savings technology and credit frictions) and behavioral factors (such as present bias or limited self-control) impede the costless conversion of a lump-sum into a perpetuity and vice versa.[20] A precise decomposition of these forces is beyond the scope of our natural experiment, but our results highlight that the timing and predictability of transfers are first-order features of how guaranteed income affects investment and credit markets.

[20] Existing work already makes some progress on this question (Banerjee et al., 2020a, 2023), and we view a fuller comparison of long-term and lump-sum transfers as a promising direction for future research.

6.3 Other Interventions to Reduce Downside Risk

We note that the guaranteed income program is one of the ways to provide downside risk protection. For instance, Hombert et al. (2020) and Gottlieb, Townsend, and Xu (2021) document an increase in entrepreneurship following an increase in downside protection due to unemployment insurance in France and protected maternity leave in Canada, respectively. These policies increase entrepreneurship by providing some sort of insurance. This is an important difference that may be context specific. Examining an income-based protection mode is especially important in a developing country since insurance-based approaches have proven to be ineffective in developing markets due to basis risk, lack of trust, financial constraints, and financial literacy, among others (Cole and Xiong, 2017).

7 Conclusion

This paper identifies the effect of guaranteed income on the production activity of small entrepreneurs. We broaden the understanding of the effect of such cash transfers in three ways. First, we show that guaranteed income can increase entrepreneurial income by increasing investment in productive capital. Second, we show that credit plays a crucial role in financing the shift from a labor-intensive to a capital-intensive mode of production. Third, we document that the increased credit usage may be driven by credit demand. We argue that safety nets – such as guaranteed income – can spur credit demand, especially when households face incompletely insured idiosyncratic risk. The demand channel of guaranteed income operates by providing downside protection during bad times. Specifically, we show that guaranteed income can increase credit demand by increasing the likelihood of repayment and the ability to meet basic needs after loan repayment during bad times, as well as reducing the expected cost of default, i.e., the permanent consumption loss associated with default. Therefore, a small amount of basic income support can have a catalytic effect, generating a large investment effect by increasing the willingness to bear risk.

Our results have implications for both policymakers and academics. First, our results highlight the role played by the costs imposed by debt contracts during bad times in generating the under-investment problem among small entrepreneurs. Specifically, our results suggest the importance of safety nets in attenuating the adverse effects of these costs. Second, our results indicate the relevance of the "*poverty as vulnerability*" view of Banerjee (2004), i.e., poor entrepreneurs forgo profitable opportunities because they are vulnerable and afraid of losses. Third, several policymakers have recently been discussing UBI as a solution to fix disruptions caused by market failures or large shocks such as COVID-19. Our results inform policymakers on the positive effects – and the underlying mechanism generating the positive effects – of safety nets, in general, and guaranteed income programs, in particular. Fourth, our results inform agricultural policymakers in developing countries. We argue that incompletely insured income volatility is a cause of agricultural inefficiency and that the availability of certain non-agricultural income – basic income support in this case – has a substantial positive effect on agricultural output and efficiency.

Our results on the importance of protection by providing fixed income are especially important in the context of developing countries since insurance-based approaches to safeguard against risk have proven to be ineffective in developing markets.

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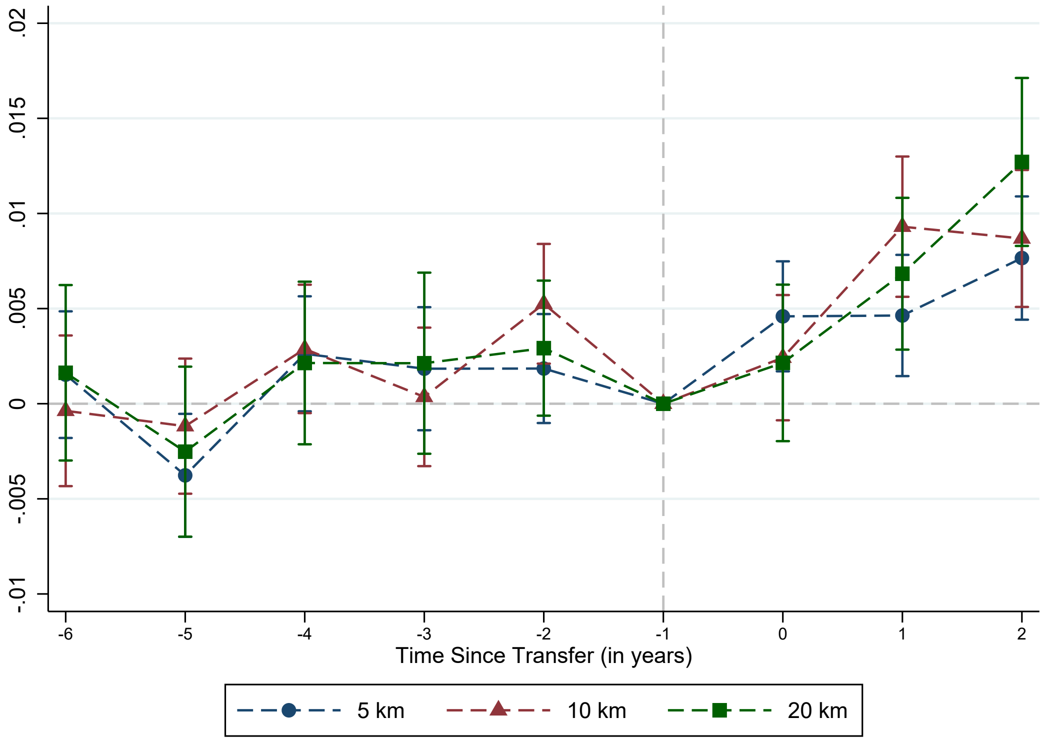
Figure 1: Assessment of Pre-Trends: Guaranteed Income & Agricultural Production

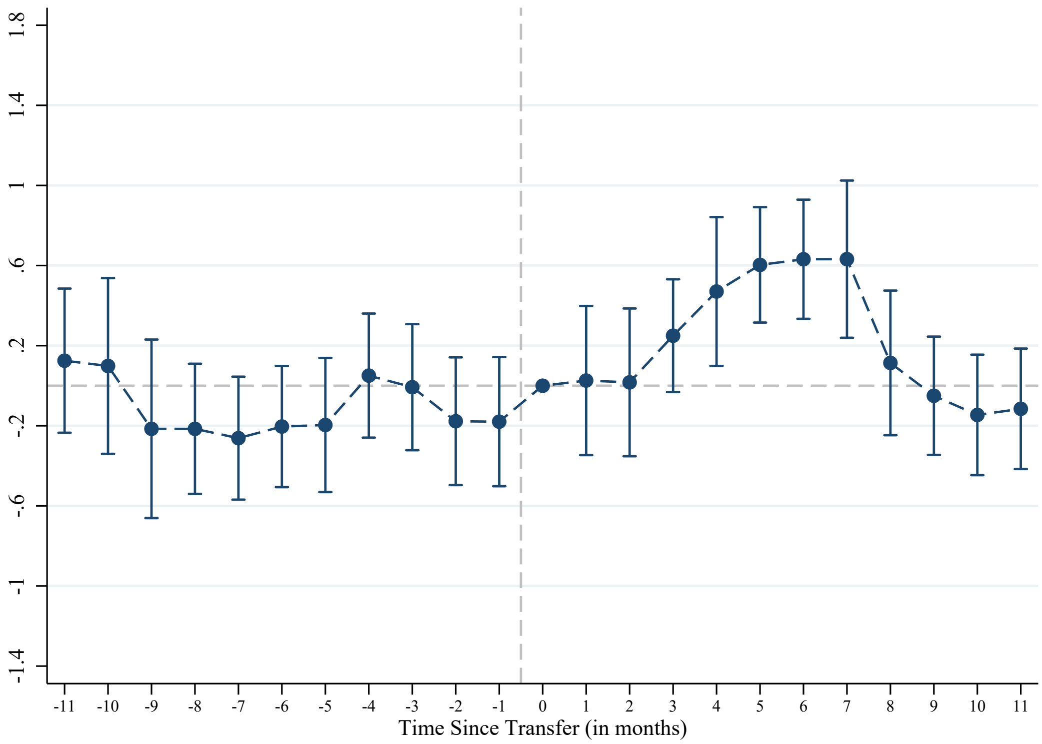


The figure plots the estimates of β_j and the 95% confidence intervals from the following regression equation:

$$LN(y_{i,t}) = \sum_{j=-6, j\neq -1}^{j=+2} \beta_j \times Complier_i \cdot \mathbb{1}\{t = j\} + \theta_i + \theta_{j,t} + \varepsilon_{i,t}$$

where, $ln(y_{i,t})$ is the natural logarithm of EVI-derived agricultural output for plot i at time t. The indicator Complier$_i$ equals one for plots outside West Bengal (treatment group) and zero for those inside (control group). $\mathbb{1}\{t = j\}$ is the time indicator variable taking a value of one if the year is j years before/after 2019, and 2019 is denoted by $j = 0$. θ_i denotes fixed effects at the unit (or plot) level. Each plot measures between 5 and 20 km along the border and is 100 m wide, with EVI data collected within a 2 km bandwidth on either side of the border in 100 m increments. Finally, $\theta j, t$ denotes the boundary × year fixed effect. All continuous variables are winsorized at the 1% level. The 95% error bands are estimated by clustering the standard errors at the unit level. We estimate this specification for three sub-samples with plots (or units) of length 5 km, 10 km, and 20 km along the border.

Figure 2: Guaranteed Income & Income from Work

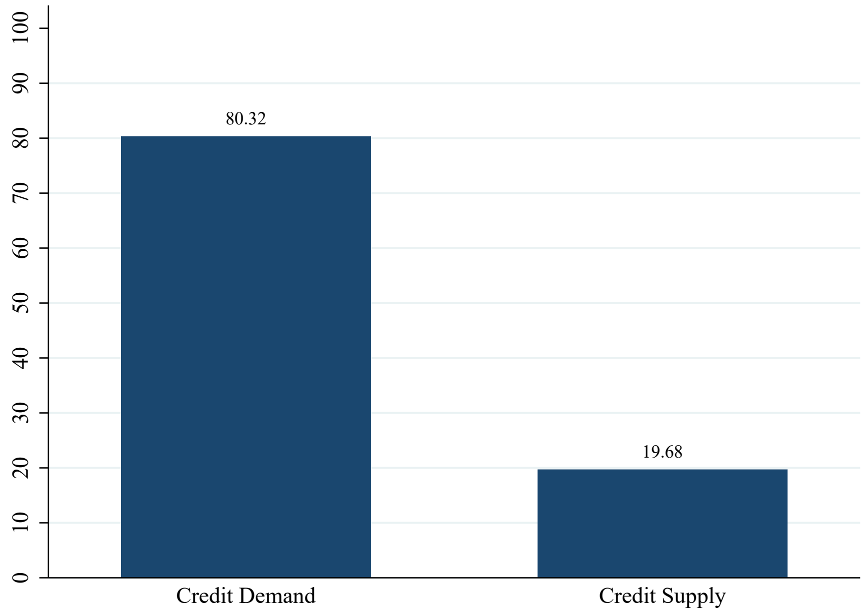


The figure plots the estimates of β_j and the 95% confidence intervals from the following regression equation:

$$\frac{y_{i,t}}{\mathbb{E}[y_{i,t}|t = Pre]} = \sum_{j=-11, j\neq -1}^{j=+11} \beta_j \cdot \underbrace{Landowning_i}_{Treatment_i} \times \underbrace{\text{Outside WB}_d}_{Complier_d} \times \mathbb{1}\{t = j\} + \theta_i + \theta_{d,e,g,t} + \theta_{p(d\in p),T,e,g,t} + \varepsilon_{i,t}$$

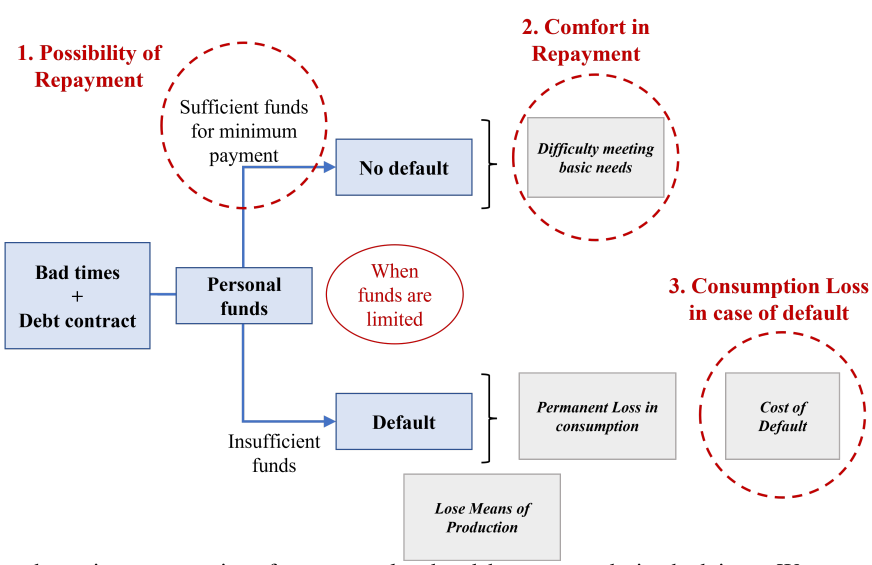
where $y_{i,t}$ denotes the dependent variable of interest measured for household i at time (month) t. $\mathbb{E}[y_{i,t}|t = Pre]$ denotes the sample average of the variable of interest during the pre-policy period. $Treatment_i$ takes a value of one for treatment farmer households and a value of zero for control farmer households. Control households are defined as farmer households in the sample whose occupation is tagged as agricultural labourers. All other farmer households are landowning and are defined to be treatment households. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. $\mathbb{1}\{t = j\}$ is the time indicator variable taking a value of one if the month is j months before/after March 2019, and March 2019 is denoted by $j = 0$. θ_i denotes household fixed effects. $\theta_{d,e,g,t}$ denotes district × education group of household × gender group of household × month fixed effects, where d refers to the district where farmer i operates. $\theta_{p(d\in p),T,e,g,t}$ denotes district-pair × treatment × education group of household × gender group of household × month fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. The sample comes from the consumer pyramids survey conducted by the CMIE from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure B.2. The key dependent variable is the reported household income from work. Gender group is a categorical variable that indicated if the household is gender balanced, female dominated, male dominated, only females and only males. Education group is another categorical variable that indicates if the household comprises of all graduates, all matriculates, graduated dominated, graduate minority, all literates, all illiterates, etc. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level.

Figure 3: What drives increased Borrowing?: Evidence from the Original Survey of Farmers



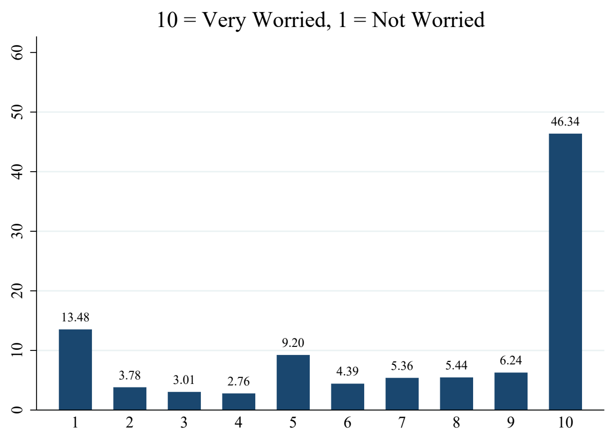
The figure presents the percentage of respondents choosing the primary reason for the increase in borrowings. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey was – *"In what way did this money increase your borrowings?: a. It made me more comfortable to borrow, b. It made the bank more willing to accept my application and/or lend me money at a low-interest rate."* We label option (a) as the credit demand channel and option (b) as the credit supply channel.

Figure 4: Schematic Representation of Concerns Related to Debt Contracts during Bad Times

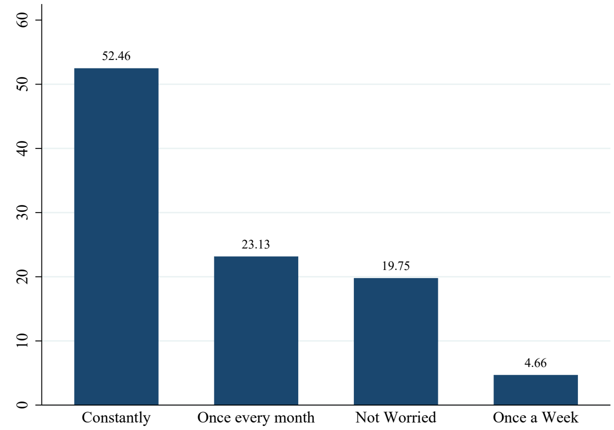


The figure presents the schematic representation of concerns related to debt contracts during bad times. We argue that the costs imposed by credit contracts on borrowers during times of adverse shocks (*bad times*) can depress credit demand. Specifically, during events such as droughts, farmers with limited funds may find it difficult to meet basic needs of food, clothing, and shelter after repayment of loans or they may be unable to meet the minimum loan repayment requirements following which they need to bear costs of default such as losing their means of production or future exclusion from credit markets leading to a permanent consumption loss.

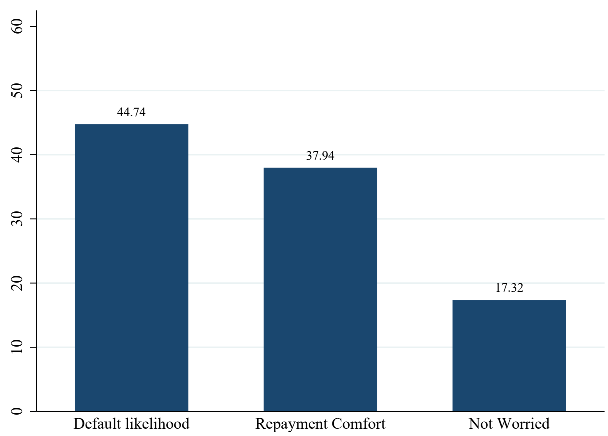
Figure 5: The effect of credit contracts during bad times



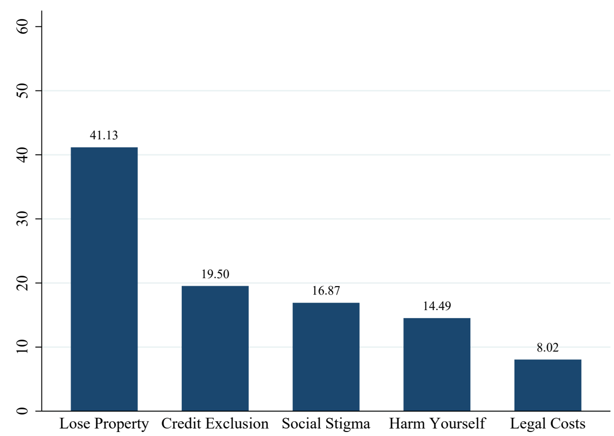
(a) Add'l worry of bad times due to debt



(b) How often do you worry?



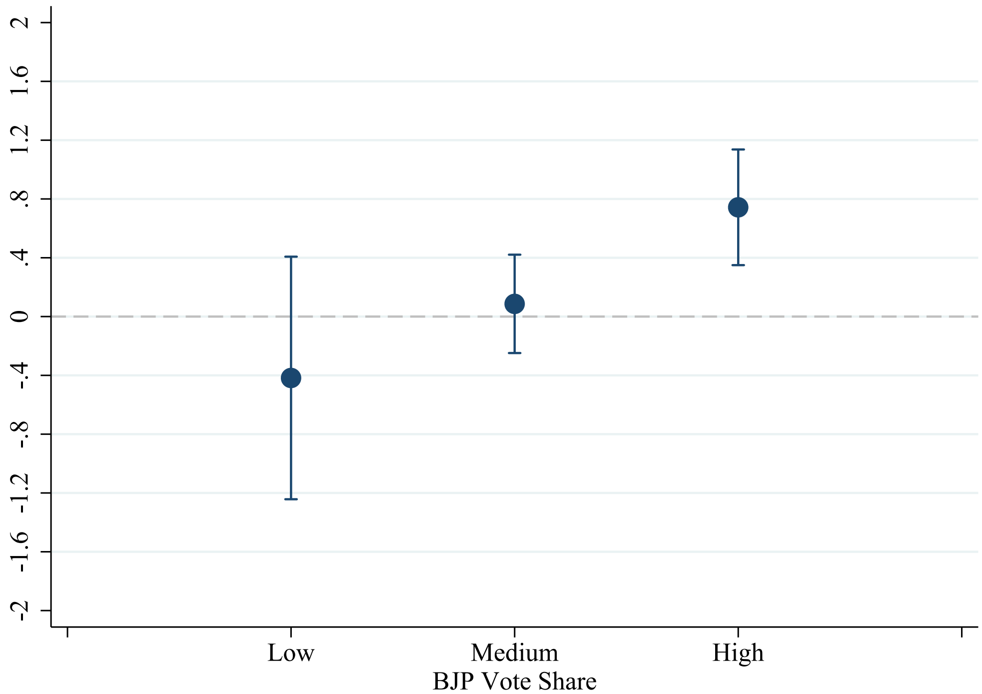
(c) Why do you worry?



(d) Why worry about default?

The figure presents the effect of debt contracts during bad times. Panel 5a presents the add'l (Additional) worry of bad times due to debt. Specifcially, the responses of the panel are based on the survey question – *With respect to your borrowing, please tell us how worried you are about bad times when you have debt obligation relative to no debt obligations. Use a scale from 1 to 10, where 10 means you are "very worried" and 1 means you are "not at all worried." You can use any number between 1 and 10 to rate yourself on the scale. You can think of bad times as times of drought, hailstorm, etc.* Panel 5b presents how often are farmers worried about the negative effect of debt contracts during bad times. Specifically, the figure plots the percentage of respondents choosing the option to the following question – *How often (if any) do you worry about bad times because of a debt obligation? If you do not have a debt obligation, please answer this question as if you had a debt obligation. You can think of bad times as times of drought, hailstorm, etc. Your options are (a) No additional worry due to debt; (b) Once every month; (c) Once a week; (d) Daily; (e) Constantly.* Panel 5c presents the key concerns because of which farmers are worried about debt contracts during bad times. Specifically, the figure plots the percentage of respondents choosing the option to the following question – *When you think about taking an agricultural loan, what (if anything) concerns you the most about the loan? If you don't have a loan, please answer this question as if you had a loan. Please choose one of the following options. (a) I am most worried about defaulting on the loan during bad times such as drought, (b) I am most worried about meeting basic needs of food clothing and shelter, after I repay the loan EMI (service debt) during bad times such as drought, (c) I can take a loan without any concern or worry.* Panel 5d presents the most prominent (expected) costs of default. Specifically, the figure plots the percentage of respondents choosing the option to the following question – *Please tell us which of the following issues concern you the most about being unable to repay a loan. (a) Your land and other assets will be taken away from you, (b) You will not be able to show your face to family and friends, (c) You will have to go to jail or be stuck in a court case, (d) You will never be able to borrow again cheaply, (e) You will be forced to do something bad such as hurt yourself.* We randomized the order in which the options were presented across different respondents for the question. The survey questions were asked in Hindi in the online survey form on the Krishify mobile application.

Figure 6: Role of Perpetual Nature of Guaranteed Income: Heterogneiety by BJP Vote Share



The figure presents the estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$\frac{\text{Loan Amt}_{i,t}}{Avg(\text{Loan Amt}_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where Loan $\text{Amt}_{i,t}$ denotes the dependent variable of interest (loan amount) measured for farmer i at time (month) t. $Avg(\text{Loan Amt}_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. We classify ZIP codes into three groups (tertiles or terciles) based on values of BJP vote share in ZIPs where the party contested in the election. The figure plots the estimate associated with the interaction term of treatment and post for the three subsample of ZIP codes. Capped spikes drawn with the estimated economic effects indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

Table 1: Summary Statistics & Comparison of Treatment and Control groups in Bank Data

	(1)	(2)	(3)	(4)	(5)
	Sample Average	Group-wise Average		Difference (T-C) *unconditional*	Difference (T-C) *within ZIP*
		Control (C)	Treatment (T)		
Income	9,297.497	10,739.050	9,271.228	-1467.674**	-374.111
	(334.204)	(756.040)	(335.240)	(715.864)	(683.095)
Savings	2,766.572	3,369.768	2,755.580	-614.202***	-298.177
	(75.206)	(226.306)	(75.182)	(215.958)	(204.050)
Expenditure	9,157.275	10,764.010	9,127.767	-1636.140**	-327.983
	(331.324)	(767.165)	(332.342)	(729.043)	(694.694)
Credit Score	513.901	525.231	513.703	-11.528*	-5.256
	(2.772)	(6.485)	(2.776)	(6.058)	(5.169)
Interest Rate	11.060	11.328	11.055	-0.273***	-0.211***
	(0.022)	(0.044)	(0.022)	(0.041)	(0.043)
Frac. Default	0.148	0.125	0.148	0.023**	0.030***
	(.005)	(.011)	(.005)	(0.011)	(0.009)
KCC Credit Limit	479,177.900	534,119.700	478,176.700	-55,935.440**	-14,551.720
	(10,511.410)	(32,325.870)	(10,379.220)	(28,335.720)	(20,414.100)
Frac. CC User	0.006	0.003	0.006	0.002	0.003
	(<0.001)	(0.002)	(<0.001)	(0.002)	(0.002)
Frac. Oth Inv	0.003	0.007	0.003	-0.004*	-0.004
	(<0.001)	(0.002)	(<0.001)	(0.002)	(0.002)
Account Age	8.511	10.531	8.474	-2.056***	-1.711***
	(0.027)	(0.088)	(0.027)	(0.081)	(0.069)
# Trnx per day	0.020	0.024	0.020	-0.004***	-0.003*
	(<.001)	(0.002)	(<0.001)	(0.002)	(0.001)
Farmer Age	51.295	52.485	51.273	-1.212***	-0.335
	(0.121)	(0.379)	(0.121)	(0.379)	(0.377)
Frac. Female	0.048	0.035	0.049	0.013**	0.008
	(0.001)	(0.005)	(0.001)	(0.006)	(0.006)

The table compares the key metrics across the treatment and control groups for our sample. The treatment group comprises of landowning farmers, and the control group comprises of non-landowning farmers. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra and Karnataka. For comparison of the treatment and control groups we use the data for the year 2018. The variable income from work is calculated as the sum of all cash inflows in the account after subtracting inflows due to the disbursal of loans, maturity of financial markets investments, and PM-KISAN transfers. Savings are computed using the monthly average balance in the savings account. Expenditure or spending is calculated as the sum of all outflows from debit and credit card transactions, cash withdrawals in-person and through Automated Teller Machines (ATM), and electronic transactions captured through the bank account. Frac. Default indicates the fraction of farmers with a history of default. KCC Credit limit reveres to the credit limit on kisan credit cards. Frac. CC user refers to the fraction of farmers using credit cards other than kisan credit cards. Frac. Oth Inv refers to the fraction of farmers with investment in other instruments, such as stock markets. Column (1) reports the overall monthly sample average and standard error of the variables. Columns (2) and (3) report the sample average and standard error for the control and treatment groups, respectively. Column (4) reports the unconditional difference of averages across the treatment and control groups and the associated standard error for the difference between the two groups. Column (5) report the within-ZIP code difference of averages across the treatment and control groups and the associated standard error. The number if parenthesis are standard errors computed using clustering at the ZIP code level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Guaranteed Income & Agricultural Production: Evidence from Geographic RD Design

Panel A: Plot Segment Length of 5 km					
Dep. Var: LN(Max EVI)	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.0031**	0.0037***	0.0040***	0.0043***	0.0043***
	(0.0012)	(0.0011)	(0.0011)	(0.0010)	(0.0010)
Unit FE	Yes	Yes	Yes	Yes	Yes
Boundary X Year FE	Yes	Yes	Yes	Yes	Yes
Area Quantiles X Year FE	Yes	Yes	Yes	Yes	Yes
# Obs	41,400	53,820	62,100	74,520	78,660
R^2	0.9414	0.9356	0.933	0.9309	0.9306
Adj. R^2	0.9238	0.9178	0.9152	0.9133	0.9132
Bandwidth (in km)	≤ 1.0	≤ 1.3	≤ 1.5	≤ 1.8	≤ 2.0

Panel B: Plot Segment Length of 10 km					
Dep. Var: LN(Max EVI)	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.0033**	0.0040***	0.0046***	0.0049***	0.0049***
	(0.0013)	(0.0012)	(0.0012)	(0.0011)	(0.0011)
Unit FE	Yes	Yes	Yes	Yes	Yes
Boundary X Year FE	Yes	Yes	Yes	Yes	Yes
Area Quantiles X Year FE	Yes	Yes	Yes	Yes	Yes
# Obs	20,634	26,832	30,960	37,152	39,216
R^2	0.9573	0.9528	0.9504	0.9482	0.9479
Adj. R^2	0.9435	0.9389	0.9365	0.9344	0.9342
Bandwidth (in km)	≤ 1.0	≤ 1.3	≤ 1.5	≤ 1.8	≤ 2.0

Panel C: Plot Segment Length of 20 km					
Dep. Var: LN(Max EVI)	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.0032*	0.0039**	0.0044***	0.0047***	0.0047***
	(0.0017)	(0.0015)	(0.0014)	(0.0013)	(0.0013)
Unit FE	Yes	Yes	Yes	Yes	Yes
Boundary X Year FE	Yes	Yes	Yes	Yes	Yes
Area Quantiles X Year FE	Yes	Yes	Yes	Yes	Yes
# Obs	10,194	13,260	15,300	18,360	19,380
R^2	0.9662	0.9623	0.9604	0.9587	0.9585
Adj. R^2	0.9534	0.9497	0.948	0.9465	0.9465
Bandwidth (in km)	≤ 1.0	≤ 1.3	≤ 1.5	≤ 1.8	≤ 2.0

This table presents the results from the estimation of the following regression specification:

$$ln(y_{i,t}) = \beta \cdot Complier_i \times Post_t + \theta_i + \theta_{j,t} + \varepsilon_{i,t}$$

where, $ln(y_{i,t})$ is the natural logarithm of EVI-derived agricultural output for plot i at time t. The indicator Complier$_i$ equals one for plots outside West Bengal (treatment group) and zero for those inside (control group). Post$t$ is one for years after 2019, the policy implementation date. θ_i denotes fixed effects at the unit (or plot) level. Each plot measures between 5 and 20 km along the border and is 100 m wide, with EVI data collected within a 2 km bandwidth on either side of the border in 100 m increments. Finally, $\theta j, t$ denotes the boundary × year fixed effect. Panels A, B and C use the EVI-based measures for plots with lengths of 5 km, 10 km, and 20 km, respectively. The dependent variable is the natural logarithm of the maximum EVI value observed during the kharif season in year t for unit i. Columns (1)-(5) use bandwidths of 1.0 km, 1.3 km, 1.5 km, 1.8 km, and 2 km on either side of the border. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the unit level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

Table 3: Guaranteed Income & Income from Work: Evidence from Border District-pair Design

Dep Var: $\frac{y_{i,t}}{Avg(y_{Pre})}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment × Complier × Post	0.1581*	0.1074**	0.1522***	0.1520***	0.1509***	0.1578***	0.3269***
	(0.0820)	(0.0455)	(0.0418)	(0.0418)	(0.0419)	(0.0491)	(0.0798)
Treatment X Month FE	Yes	Yes	Yes	Yes	Yes		
Complier X Month FE	Yes	Yes					
Treat X Complier FE	Yes	Yes					
Household FE		Yes	Yes	Yes	Yes	Yes	Yes
District X Month FE			Yes	Yes	Yes	Yes	
District Pair X Month FE				Yes	Yes		
District Pair X Treatment FE					Yes		
District Pair X Treatment X Month FE						Yes	
District X Month X Education X Gender FE							Yes
District Pair X Treat. X Month X Education X Gender FE							Yes
# Obs	49,778	49,778	49,778	49,778	49,778	49,778	38,189
R^2	0.2034	0.7594	0.7897	0.7898	0.7898	0.7958	0.8833
Adj. R^2	0.2022	0.7522	0.781	0.7777	0.7775	0.7811	0.8165
Sample Mean	7,664.63	7,664.63	7,664.63	7,664.63	7,664.63	7,664.63	7,664.63
Sample SD	5,650.27	5,650.27	5,650.27	5,650.27	5,650.27	5,650.27	5,650.27

The table estimates the relative effect of PM-KISAN cash transfers on income from work for the treatment farmers in complier groups according to the following specification:

$$\frac{y_{i,t}}{\mathbb{E}[y_{i,t}|t = Pre]} = \beta \cdot \underbrace{Landowning_i}_{Treatment_i} \times \underbrace{\text{Outside WB}_d}_{Complier_d} \times Post + \theta_i + \theta_{d,t} + \theta_{p(d\in p),T,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for household i at time (month) t. $\mathbb{E}[y_{i,t}|t = Pre]$ denotes the sample average of the variable of interest during the pre-policy period. $Treatment_i$ takes a value of one for treatment farmer households and a value of zero for control farmer households. Control households are defined as farmer households in the sample whose occupation is tagged as agricultural labourers. All other farmer households are landowning and are defined to be treatment households. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes household fixed effects. $\theta_{d,t}$ denotes district × month fixed effects, where d refers to the district where farmer i operates. $\theta_{p(d\in p),T,t}$ denotes district-pair × treatment × month fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. The sample comes from the consumer pyramids survey conducted by the CMIE from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure B.2. The key dependent variable is the reported household income from work. Gender group is a categorical variable that indicated if the household is gender balanced, female dominated, male dominated, only females and only males. Education group is another categorical variable that indicates if the household comprises of all graduates, all matriculates, graduated dominated, graduate minority, all literates, all illiterates, etc. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Guaranteed Income & Tractor Sales: Evidence from Border District-pair Design

Dep Var: $\frac{y_{z,t}}{Avg(y_{Pre})}$	Sales Amount	Numbers Sold	Sales Amount	Numbers Sold
	(1)	(2)	(3)	(4)
Complier × Post	0.1429**	0.1170**		
	(0.0601)	(0.0501)		
Agricultural Use × Complier × Post			0.8306***	0.6382***
			(0.1332)	(0.1174)
ZIP FE	Yes	Yes		
District Pair X Month FE	Yes	Yes		
ZIP X Month FE			Yes	Yes
ZIP X Agricultural Use FE			Yes	Yes
District Pair X Agri Use X Month FE			Yes	Yes
# Obs	17,597	17,597	35,194	35,194
R^2	0.7225	0.7219	0.8508	0.8625
Adj. R^2	0.704	0.7033	0.7875	0.8042
Sample Mean	519,042.10	0.7327	1,419,998	2.1872
Sample SD	2,168,490.00	3.0589	2,888,651.00	4.4657

The table estimates the relative effect of PM-KISAN cash transfers on tractor sales in ZIP codes located in complier and non-complier districts according to the following specification:

$$\frac{y_{z,t}}{Avg(y_{Pre})} = \beta \cdot Complier_{d(z\in d)} \times Post_t + \theta_z + \theta_{p(z\in p),t} + \varepsilon_{z,t}$$

$$\frac{y_{z,u,t}}{Avg(y_{Pre})} = \beta \cdot \text{Agricultural Use}_u \times Complier_{d(z\in d)} \times Post_t + \theta_{z,t} + \theta_{z,u} + \theta_{p(z\in p),u,t} + \varepsilon_{z,t}$$

where $y_{z,t}$ denotes the dependent variable of interest measured for ZIP code z at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. θ_z denotes ZIP code fixed effects. $\theta_{p(z\in p),T,t}$ denotes district-pair × month fixed effect. $\theta_{z,t}$ denotes ZIP code × month fixed effects. $\theta_{z,u}$ denotes ZIP code × agricultural use fixed effects.$\theta_{p(z\in p),T,t}$ denotes district-pair × agricultural use × month fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. The sample comes from the tractor sales data collected by NITI Aayog from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure B.2. The key dependent variable is the sales amount in Columns (1) and (3), and number of tractors sold in Columns (2) and (4). Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Guaranteed Income & Fertilizer Consumption: Evidence from Border District-pair Design

Dep.Var: LN(Amount of Fertilizer)	Total	Nitrogen	Phosphorus	Potassium
	(1)	(2)	(3)	(4)
Complier × Post	0.3168***	0.3800***	0.5645***	-0.0483
	(0.0900)	(0.0885)	(0.1454)	(0.1388)
District X Season FE	Yes	Yes	Yes	Yes
District Pair X Season X Year FE	Yes	Yes	Yes	Yes
# Obs	642	642	628	464
R^2	0.9751	0.9715	0.9412	0.9568
Adj. R^2	0.941	0.9325	0.8603	0.8908
Sample Mean	15.9089	15.4194	14.2761	14.4016
Sample SD	1.8582	1.7629	2.0733	2.1744

The table estimates the relative effect of PM-KISAN cash transfers on tractor sales in ZIP codes located in complier and non-complier districts according to the following specification:

$$LN(y_{d,s,t}) = \beta \cdot Complier_d \times Post_t + \theta_{d,s} + \theta_{p(d\in p),s,t} + \varepsilon_{d,s,t}$$

where $LN(y_{d,s,t})$ denotes the natural logarithm of the dependent variable of interest measured for district d during cultivation season s in year t. The key dependent variable is total fertilizer consumption, consumption of nitrogen based fertilizers, consumption of phosphorus based fertilizers, and the consumption of potash based fertilizers in Columns (1), (2), (3), and (4) respectively. $Post_t$ takes a value of one for seasons after fiscal year 2019 and zero otherwise. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. $\theta_{d,s}$ denotes district × season fixed effects.$\theta_{p(d\in p),s,t}$ denotes district-pair × season × year fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. Each year refers to fiscal year starting in April of the calendar year and ending in the March of the next calendar year. Each fiscal year has two cultivation seasons – kharif and rabi. The sample employed in the analysis is shown in Appendix Figure B.2. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Guaranteed Income & Production Scale: Evidence from Border District-pair Design

Dep.Var: LN(Gross Sown Area)	All	Foodgrain	Cereal	Pulses	Oilseed
	(1)	(2)	(3)	(4)	(5)
Complier × Post	0.6377***	0.5504***	0.4831***	0.7385***	0.6610***
	(0.0933)	(0.0827)	(0.0762)	(0.1838)	(0.1849)
District X Season FE	Yes	Yes	Yes	Yes	Yes
District Pair X Season X Year FE	Yes	Yes	Yes	Yes	Yes
# Obs	596	596	596	262	402
R^2	0.9461	0.9617	0.9754	0.8801	0.9248
Adj. R^2	0.8706	0.9082	0.9409	0.7049	0.8066
Sample Mean	4.0790	3.9512	3.7471	1.3666	0.9283
Sample SD	1.7079	1.7469	1.9249	1.6664	1.9320

The table estimates the relative effect of PM-KISAN cash transfers on tractor sales in ZIP codes located in complier and non-complier districts according to the following specification:

$$LN(y_{d,s,t}) = \beta \cdot Complier_d \times Post_t + \theta_{d,s} + \theta_{p(d \in p),s,t} + \varepsilon_{d,s,t}$$

where $LN(y_{d,s,t})$ denotes the natural logarithm of the dependent variable of interest measured for district d during cultivation season s in year t. The key dependent variable is total gross sown area (GSA), GSa under foodgrains, GSA under cereals, GSA under pulses, and GSA under oilseeds in Columns (1), (2), (3), (4), and (5) respectively. $Post_t$ takes a value of one for seasons after fiscal year 2019 and zero otherwise. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. $\theta_{d,s}$ denotes district × season fixed effects.$\theta_{p(d \in p),s,t}$ denotes district-pair × season × year fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. Each year refers to fiscal year starting in April of the calendar year and ending in the March of the next calendar year. Each fiscal year has two cultivation seasons – kharif and rabi. The sample employed in the analysis is shown in Appendix Figure B.2. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Guaranteed Income & Formal Credit: Evidence from Border District-pair Design

Dep. Var: LN(Loan Amount)	Panel A					
	(1)	(2)	(3)	(4)	(5)	(6)
Complier × Post	0.0632**	0.0719**	0.0670**	0.0608*	0.0724**	
	(0.0293)	(0.0329)	(0.0338)	(0.0342)	(0.0357)	
Agricultural Loan × Complier × Post						0.1137***
						(0.0407)
Month FE	Yes					
ZIP FE	Yes	Yes	Yes			
District Pair X Month FE		Yes	Yes	Yes		
Month X Lender Type FE			Yes	Yes		
ZIP X Lender Type FE				Yes	Yes	
District Pair X Month X Lender Type FE					Yes	
District Pair X Month X Lender Type X Loan Type FE						Yes
ZIP X Loan Type FE						Yes
ZIP X Month X Lender Type FE						Yes
# Obs	44,826	44,826	44,826	44,826	44,826	310,985
R^2	0.4662	0.4790	0.5590	0.6681	0.6773	0.7862
Adj. R^2	0.4571	0.4615	0.5437	0.6514	0.6560	0.7443
Sample	Agri loans	Agri loans	Agri loans	Agri loans	Agri loans	All loans

Dep. Var: LN(Number of loans)	Panel B					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	0.1032***	0.1777***	0.1538***	0.1563***	0.1663***	
	(0.0316)	(0.0370)	(0.0323)	(0.0330)	(0.0339)	
Agricultural Loan × Treatment × Post						0.2050***
						(0.0348)
Month FE	Yes					
ZIP FE	Yes	Yes	Yes			
District Pair X Month FE		Yes	Yes	Yes		
Month X Lender Type FE			Yes	Yes		
ZIP X Lender Type FE				Yes	Yes	
District Pair X Month X Lender Type FE					Yes	
District Pair X Month X Lender Type X Loan Type FE						Yes
ZIP X Loan Type FE						Yes
ZIP X Month X Lender Type FE						Yes
# Obs	44,826	44,826	44,826	44,826	44,826	311,694
R^2	0.2978	0.3113	0.7636	0.8675	0.8727	0.8696
Adj. R^2	0.2857	0.2882	0.7554	0.8609	0.8643	0.8441
Sample	Agri loans	Agri loans	Agri loans	Agri loans	Agri loans	All loans

The table estimates the relative effect of PM-KISAN cash transfers on formal credit in ZIP codes located in complier and non-complier districts according to the following specification:

$$LN(y_{z,l,t}) = \beta \cdot Complier_{d(z\in d)} \times Post_t + \theta_{z,l} + \theta_{p(z\in p),l,t} + \varepsilon_{z,l,t}$$

$$LN(y_{z,l,p,t}) = \beta \cdot \text{Agricultural Loan}_p \times Complier_{d(z\in d)} \times Post_t + \theta_{z,l,t} + \theta_{z,p} + \theta_{p(z\in p),l,p,t} + \varepsilon_{z,t}$$

where $LN(y_{z,l,p,t})$ denotes the natural logarithm of the dependent variable of interest measured for ZIP code z by lender-type l and product-type or loan-type p at time (month) t. The key dependent variable is the natural logarithm of loan amount and number of loans in Panel A and B, respectively. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. Agricultural Loan$_p$ takes a value of one for agricultural loans and zero for all other loan types. $\theta_{z,l}$ denotes ZIP code × lender-type fixed effects. $\theta_{p(z\in p),l,t}$ denotes district-pair × lender-type × month fixed effect. $\theta_{z,l,t}$ denotes ZIP code × lender-type × month fixed effects. $\theta_{z,p}$ denotes ZIP code × loan-type fixed effects. $\theta_{p(z\in p),l,p,t}$ denotes district-pair × lender-type × loan-type × month fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. The sample comes from the Transunion CIBIL credit bureau data from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure B.2. The specifications in Columns (1) through (5) restrict the analysis to agricultural loans only. Column (6) uses data for all loan types. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Guaranteed Income & Income from Work: Farmer-level Analysis Using bank Data

Dep Var: Income Growth	**Panel A (Dep Var: $LN(\frac{y_{i,Post}}{y_{i,Pre}})$)**			
	(1)	(2)	(3)	(4)
Treatment	0.1219*	0.1579**	0.1375**	0.1274**
	(0.0642)	(0.0636)	(0.0637)	(0.0635)
State FE		Yes		
District FE			Yes	
ZIP FE				Yes
# Obs	67,966	67,966	67,966	67,966
R^2	0.0000	0.0065	0.0133	0.0526
Adj. R^2	0.0000	0.0065	0.0121	0.0279
Dep Var: LN(Income)	**Panel B (Dep Var: $LN(y_{i,t})$)**			
	(1)	(2)	(3)	(4)
Treatment X Post	0.1164*	0.1164*	0.1164*	0.1268**
	(0.0639)	(0.0639)	(0.0639)	(0.0633)
Treatment	-0.1037			
	(0.0784)			
Post	0.2092***	0.2092***		
	(0.0625)	(0.0625)		
Farmer FE		Yes	Yes	Yes
Post FE			Yes	
ZIP X Post FE				Yes
# Obs	135,932	135,932	135,932	135,932
R^2	0.0047	0.7605	0.7605	0.7731
Adj. R^2	0.0047	0.5210	0.5210	0.5219

This table reports estimates of the relative effect of cash transfers under the PM-KISAN program on income from work for treated and control households. Panel A and Panel B correspond to two complementary specifications:

$$LN(\frac{y_{i,Post}}{y_{i,Pre}}) = \beta \cdot Treatment_i + \theta_z + \varepsilon_i$$

$$LN(y_{i,t}) = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

Here, $y_{i,Pre}$ and $y_{i,Post}$ denote the sum of income from work for farmer i over the twelve months preceding and following the implementation of PM-KISAN, respectively. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. θ_z denotes ZIP code fixed effects, θ_i farmer fixed effects, and $\theta_{z,t}$ ZIP code $\times$ post-period fixed effects. In Panel A, the unit of observation is the farmer, and the dependent variable is the log difference in income between the post- and pre-policy periods. Column (1) reports estimates without fixed effects. Columns (2) through (4) sequentially introduce state, district, and ZIP code fixed effects. In Panel B, the unit of observation is the farmer-period, yielding two observations per farmer—one corresponding to the total income during the twelve months before and one corresponding to the total income during the twelve months after policy implementation. Column (1) reports the baseline estimate without fixed effects, while Columns (2) through (4) progressively include farmer, post, and ZIP code $\times$ post fixed effects. The estimation sample is constructed from transaction-level administrative bank data covering farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Income from work is defined as the sum of all cash inflows into the farmer's account, net of inflows linked to loan disbursals, financial investment maturities, and PM-KISAN transfer receipts. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Guaranteed Income & Income from Work: Differences-in-Differences Using Bank Data

Dep Var: $\frac{y_{i,t}}{Avg(y_{Pre})}$	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.2438***	0.2396***	0.1981***	0.1208*	0.1390**
	(0.0728)	(0.0728)	(0.0735)	(0.0698)	(0.0688)
Treatment	-0.2753***	-0.2682***	-0.0781		
	(0.0903)	(0.0905)	(0.0847)		
Post	0.0787				
	(0.0722)				
Farmer FE				Yes	Yes
Month FE		Yes		Yes	
ZIP × Month FE			Yes		Yes
# Obs	1,532,700	1,532,700	1,532,700	1,532,700	1,532,700
R^2	0.0010	0.0112	0.1087	0.2596	0.3091
Adj. R^2	0.0010	0.0112	0.0823	0.2241	0.2535
Sample Mean	9,297.50	9,297.50	9,297.50	9,297.50	9,297.50
Sample SD	21,100.16	21,100.16	21,100.16	21,100.16	21,100.16

The table estimates the relative effect of cash transfers under PM-KISAN on income from work for the treatment and control groups according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. Column (1) reports the estimate of β without any fixed effects. Columns (2), (3), and (4) report the estimate of β by sequentially adding fixed effects, to finally estimate key equation highlighted above in Column (5). The estimation sample is constructed from transaction-level administrative bank data covering farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Income from work is defined as the sum of all cash inflows into the farmer's account, net of inflows linked to loan disbursals, financial investment maturities, and PM-KISAN transfer receipts. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Effect of the Policy on Credit: Farmer-level Analysis Using bank Data

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.0467***	0.1415***	0.3593***
	(0.0095)	(0.0275)	(0.1122)
Farmer FE	Yes	Yes	Yes
ZIP $\times$ Month FE	Yes	Yes	Yes
# Obs	1,199,836	1,199,836	1,199,836
R^2	0.1237	0.1693	0.0994
Adj. R^2	0.0562	0.1054	0.0301
Sample Mean	0.4783	0.6340	9,440.35
Sample SD	0.4995	0.8049	49,290.08

The table estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Column (1) uses a binary variable as the dependent variable taking a value of one if the farmer received at least one new loan during the period, and zero otherwise. Column (2) uses the number of new loans as the dependent variable divided by the pre-period sample average. Column (3) uses the total loan amount as the dependent variable divided by the pre-period sample average. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Does the New Credit Finance Productive Capacity or Consumption?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sample: Productive Loans			Sample: Consumption Loans			Sample: All Loans		
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.0641***	0.2801***	0.6426***	0.0041	-0.0106	0.0318			
	(0.0118)	(0.0392)	(0.1678)	(0.0099)	(0.0311)	(0.1344)			
Productive X Treatment X Post							0.0432**	0.2118***	0.4737**
							(0.0170)	(0.0601)	(0.2351)
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes			
ZIP X Month FE	Yes	Yes	Yes	Yes	Yes	Yes			
Farmer X Month FE							Yes	Yes	Yes
Productive X Farmer FE							Yes	Yes	Yes
Productive X ZIP X Month FE							Yes	Yes	Yes
# Obs	1,071,090	1,071,090	1,071,090	624,460	624,460	624,460	991,416	991,416	991,416
R^2	0.0758	0.0808	0.0840	0.0942	0.1162	0.1402	0.5518	0.5639	0.5738
Sample Mean	0.3728	0.4202	6,945.65	0.3959	0.4970	4,613.55	0.3813	0.4485	6,085.97
Sample SD	0.4835	0.6036	40,554.85	0.4890	0.7150	27,018.14	0.4857	0.6480	36,176.94

The table estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Columns (1), (4), and (7) use a binary variable as the dependent variable taking a value of one if the farmer received at least one new loan during the period, and zero otherwise. Columns (2), (5), and (8) use the number of new loans as the dependent variable divided by the pre-period sample average. Columns (3), (6), and (9) use the total loan amount as the dependent variable divided by the pre-period sample average. Columns (1) through (3) use the sample of productive loans and Columns (4) through (6) use the sample of consumption loans. Appendix Table B.6 presents the classification of different loan types into productive and consumption loans. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Effect of the policy: Evidence from original Survey of Farmers in India

Panel A: Effect on Physical Effort

	All Respondents	PM-KISAN Recipients	
		Yes	No
Increase	65.26	63.25	67.70
No Change	17.39	19.36	15.01
Decrease	17.34	17.39	17.29
# Obs (Respondents)	3,990	2,185	1,805

Panel B: Effect on Investment

	All Respondents	PM-KISAN Recipients	
		Yes	No
Increase	69.57	68.83	70.47
No Change	12.56	13.41	11.52
Decrease	17.87	17.76	18.01
# Obs (Respondents)	3,990	2,185	1,805

Panel C: Effect on Borrowing

	All Respondents	PM-KISAN Recipients	
		Yes	No
Increase	47.32	44.26	51.02
No Change	29.30	31.76	26.32
Decrease	23.38	23.98	22.66
# Obs (Respondents)	3,990	2,185	1,805

The table presents the percentage of respondents choosing their response to the effect of PM-KISAN transfers on physical effort in Panel A, agricultural investment in Panel B and borrowings in Panel C. The data comes from the original survey of farmers designed by authors and conducted by Krishify. Column (1) reports the percentage of respondents choosing each option. Columns (2) and (3) present the percentage of respondents choosing each option that received and did not receive PM-KISAN transfers, respectively. Panel A reports the effect of PM-KISAN on physical effort. The precise question of the survey for PM-KISAN recipients was – *"How has the money from the government changed the following for you? Please select either increase/decrease/no change for each question: Physical effort in agriculture."* The precise question of the survey for PM-KISAN non-recipients was – *"How would the following change for you after receiving a cash transfer of ₹6,000 each year? Please select either increase/decrease/no change for each question: Physical effort in agriculture."* Panel B reports the effect of PM-KISAN on agricultural investment. The precise question of the survey for PM-KISAN recipients was – *"How has the money from the government changed the following for you? Please select either increase/decrease/no change for each question: Spending money on agriculture investment."* The precise question of the survey for PM-KISAN non-recipients was – *"How would the following change for you after receiving a cash transfer of ₹6,000 each year? Please select either increase/decrease/no change for each question: Spending money on agriculture investment."* Panel C reports the effect of PM-KISAN on borrowing. The precise question of the survey for PM-KISAN recipients was – *"With respect to borrowings, how did the transfers affect your borrowing comfort? a. Increase, b. Decrease, c. No Change."* The precise question of the survey for PM-KISAN non-recipients was – *"With respect to borrowings, how will the annual transfer of ₹6,000 affect your borrowing comfort? a. Increase, b. Decrease, c. No Change."* This question was asked to all respondents.

Table 13: Effect of the Policy on Income from Work by Prior Default Status

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)
Treatment × Post	0.1390**	0.1732**	-0.0089
	(0.0688)	(0.0778)	(0.1290)
Farmer FE	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes
# Obs	1,532,700	1,305,563	216,492
R^2	0.3091	0.3084	0.3514
Adj. R^2	0.2535	0.2493	0.2576
Sample	Full	No Prior Default	Prior Default

The table estimates the relative effect of cash transfers under PM-KISAN on income from work for the treatment and control groups according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Column (1) reports the estimate for the full sample. Column (2)reports the estimate for the sample of farmers with no default tag prior to March 2018. Column (3) reports the estimate for the sample of farmers with a default tag prior to March 2018. Income from work is defined as the sum of all cash inflows into the farmer's account, net of inflows linked to loan disbursals, financial investment maturities, and PM-KISAN transfer receipts. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 14: Effect of the Policy on Credit: Heterogeneity by Prior Default Status

Panel A: Sample of Farmers with No Prior Default

Dep Var: $\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$	(1) All loans	(2) Productive Loans	(4) Consumption Loans	(4) All loans
Treatment X Post	0.3980***	0.7023***	0.0338	
	(0.1158)	(0.1670)	(0.1443)	
Productive X Treatment X Post				0.5882**
				(0.2423)
Farmer FE	Yes	Yes	Yes	
ZIP X Month FE	Yes	Yes	Yes	
Farmer X Month FE				Yes
Productive X Farmer FE				Yes
Productive X ZIP X Month FE				Yes
# Obs	1,078,643	967,726	565,608	908,900
R^2	0.1001	0.0851	0.1428	0.5749

Panel B: Sample of Farmers with Prior Default

Dep Var: $\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$	(1) All loans	(2) Productive Loans	(4) Consumption Loans	(4) All loans
Treatment X Post	0.0767	0.1995	-0.1580	
	(0.3930)	(0.7170)	(0.4977)	
Productive X Treatment X Post				-0.1080
				(1.0816)
Farmer FE	Yes	Yes	Yes	
ZIP X Month FE	Yes	Yes	Yes	
Farmer X Month FE				Yes
Productive X Farmer FE				Yes
Productive X ZIP X Month FE				Yes
# Obs	114,476	96,897	52,338	70,024
R^2	0.2028	0.1957	0.2526	0.6484

The table estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$\frac{\text{Loan Amt}_{i,t}}{Avg(\text{Loan Amt}_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where Loan $\text{Amt}_{i,t}$ denotes the dependent variable of interest (loan amount) measured for farmer i at time (month) t. $Avg(\text{Loan Amt}_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Panel A estimates the above equation for the sample of farmers with no default before March 2018. Panel B estimates the above equation for the sample of farmers with default before March 2018. Columns (1), (2), and (3) uses the sample of all loans, productive loans and consumption loans, respectively. Column (4) uses the long-form sample with two observations at the farmer-time level one for productive loans and another for consumption loans. Appendix Table B.6 presents the classification of different loan types into productive and consumption loans. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15: Effect of the Policy on Utilization Rates for Kisan Credit Cards

Dep Var: Utilization Rate	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.0563**	0.0560***	0.0760***	0.0428**	0.0583***
	(0.0209)	(0.0205)	(0.0218)	(0.0182)	(0.0199)
Treatment	-0.0183	-0.0181	-0.0398		
	(0.0234)	(0.0228)	(0.0246)		
Post	-0.1020***				
	(0.0206)				
Farmer FE				Yes	Yes
Month FE		Yes		Yes	
ZIP × Month FE			Yes		Yes
# Obs	34,035	34,035	34,035	34,035	34,035
R^2	0.0085	0.0510	0.3107	0.2681	0.4743
Sample Mean	0.1960	0.1960	0.1960	0.1960	0.1960
Sample SD	0.3676	0.3676	0.3676	0.3676	0.3676
Mean KCC Limit	349,753.70	349,753.70	349,753.70	349,753.70	349,753.70

The table estimates the relative effect of cash transfers under PM-KISAN on the utilization rate (UR) on kisan credit cards (KCC) for the treatment and control groups according to the following specification:

$$\text{Utilization Rate}_{i,t} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where Utilization $\text{Rate}_{i,t}$ denotes the dependent variable of interest (utilization rate on KCC) measured for farmer i at time (month) t. Utilization rate is defined as the KCC balance at the end of month t divided by the total sanctioned credit limit on KCC. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. Column (1) reports the estimate of β without any fixed effects. Columns (2), (3), and (4) report the estimate of β by sequentially adding fixed effects, to finally estimate key equation highlighted above in Column (5). The estimation sample comprises of farmers with valid KCCs in the states of Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 16: Effect of the Policy on Applications and Acceptance (Likelihood of Inquiry)

Panel A: Effect of the Policy on Credit Applications

Dep Var: Inquiry (=1)	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.0107**	0.0107**	0.0168***	0.0107**	0.0168***
	(0.0048)	(0.0048)	(0.0045)	(0.0048)	(0.0045)
Treatment	-0.0078***	-0.0078***	-0.0093***		
	(0.0023)	(0.0023)	(0.0022)		
Post	-0.0150***				
	(0.0049)				
Farmer FE				Yes	Yes
Month FE		Yes		Yes	
ZIP X Month FE			Yes		Yes
# Obs	779,592	779,592	779,592	779,592	779,592
R^2	0.0001	0.0108	0.1067	0.0179	0.1130
Sample Mean	0.0406	0.0406	0.0406	0.0406	0.0406
Sample SD	0.1974	0.1974	0.1974	0.1974	0.1974

Panel B: Effect of the Policy on Acceptance of Applications

Dep Var: Application Accepted (=1)	(1)	(2)	(3)	(4)	(5)
Treatment × Post	-0.0060	-0.0060	-0.0008	-0.0060	-0.0008
	(0.0045)	(0.0045)	(0.0048)	(0.0045)	(0.0048)
Treatment	-0.0065***	-0.0065***	-0.0078***		
	(0.0023)	(0.0023)	(0.0022)		
Post	0.0024				
	(0.0044)				
Farmer FE				Yes	Yes
Month FE		Yes		Yes	
ZIP X Month FE			Yes		Yes
# Obs	779,592	779,592	779,592	779,592	779,592
R^2	0.0001	0.0082	0.0942	0.0181	0.1032
Sample Mean	0.0378	0.0378	0.0378	0.0378	0.0378
Sample SD	0.1907	0.1907	0.1907	0.1907	0.1907

The table estimates the relative effect of cash transfers under PM-KISAN on credit inquiries in Panel A and acceptance of applications (inquiries) in Panel B for the treatment and control groups according to the following specification:

$$y_{i,t}(=1) = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}(=1)$ denotes the dependent variable of interest measured for farmer i at time (month) t. In Panel A, the dependent variable of interest is a binary variable taking a value of one if an inquiry occurred for a farmer i during month t. In Panel B, the dependent variable of interest is a binary variable taking a value of one if the inquiry for a farmer i during month t converted into a loan within 60 days of the inquiry. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 17: Guaranteed Income & Default: Evidence from Border District-pair Design

Dep Var: 1-Year Delinquency Rate	Panel A					
	(1)	(2)	(3)	(4)	(5)	(6)
Complier × Post	-0.0231***	-0.0301***	-0.0282***	-0.0266***	-0.0280***	
	(0.0031)	(0.0049)	(0.0049)	(0.0049)	(0.0048)	
Agricultural Loan × Complier × Post						-0.0187***
						(0.0052)
Month FE	Yes					
ZIP FE	Yes	Yes	Yes			
District Pair X Month FE		Yes	Yes	Yes		
Month X Lender Type FE			Yes	Yes		
ZIP X Lender Type FE				Yes	Yes	
District Pair X Month X Lender Type FE					Yes	
District Pair X Month X Lender Type X Loan Type FE						Yes
ZIP X Loan Type FE						Yes
ZIP X Month X Lender Type FE						Yes
# Obs	44,826	44,826	44,826	44,826	44,826	311,694
R^2	0.0802	0.1139	0.1212	0.1856	0.2083	0.3896
Adj. R^2	0.0644	0.0842	0.0906	0.1447	0.1562	0.2703
Sample	Agri loans	Agri loans	Agri loans	Agri loans	Agri loans	All loans
Dep Var: 3-Year Delinquency Rate	**Panel B**					
	(1)	(2)	(3)	(4)	(5)	(6)
Complier × Post	-0.0577***	-0.0866***	-0.0842***	-0.0821***	-0.0872***	
	(0.0054)	(0.0081)	(0.0079)	(0.0078)	(0.0078)	
Agricultural Loan × Complier × Post						-0.0659***
						(0.0087)
Month FE	Yes					
ZIP FE	Yes	Yes	Yes			
District Pair X Month FE		Yes	Yes	Yes		
Month X Lender Type FE			Yes	Yes		
ZIP X Lender Type FE				Yes	Yes	
District Pair X Month X Lender Type FE					Yes	
District Pair X Month X Lender Type X Loan Type FE						Yes
ZIP X Loan Type FE						Yes
ZIP X Month X Lender Type FE						Yes
# Obs	44,826	44,826	44,826	44,826	44,826	311,694
R^2	0.1003	0.1199	0.1710	0.2542	0.2798	0.4312
Adj. R^2	0.0848	0.0903	0.1422	0.2168	0.2324	0.3199
Sample	Agri loans	Agri loans	Agri loans	Agri loans	Agri loans	All loans

The table estimates the relative effect of PM-KISAN cash transfers on delinquency rate in ZIP codes located in complier and non-complier districts according to the following specification:

$$y_{z,l,t} = \beta \cdot Complier_{d(z\in d)} \times Post_t + \theta_{z,l} + \theta_{p(z\in p),l,t} + \varepsilon_{z,l,t}$$

$$y_{z,l,p,t} = \beta \cdot \text{Agricultural Loan}_p \times Complier_{d(z\in d)} \times Post_t + \theta_{z,l,t} + \theta_{z,p} + \theta_{p(z\in p),l,p,t} + \varepsilon_{z,t}$$

where $y_{z,l,p,t}$ denotes the dependent variable of interest, the delinquency rate, measured for ZIP code z by lender-type l and product-type or loan-type p for loans that were originated at time (month) t. Specifically, delinquency rate is calculated as the ratio of the number of loans issued in month t by lender-type l and product-type or loan-type p that are more than 90 days past due to the total number of loans issued in month t by lender-type l and product-type or loan-type p. The key dependent variable is the delinquency rate within one year and three years of loan issuance in Panel A and B, respectively. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. Agricultural Loan$_p$ takes a value of one for agricultural loans and zero for all other loan types. $\theta_{z,l}$ denotes ZIP code × lender-type fixed effects. $\theta_{p(z\in p),l,t}$ denotes district-pair × lender-type × month fixed effect. $\theta_{z,l,t}$ denotes ZIP code × lender-type × month fixed effects. $\theta_{z,p}$ denotes ZIP code × loan-type fixed effects. $\theta_{p(z\in p),l,p,t}$ denotes district-pair × lender-type × loan-type × month fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. The sample comes from the Transunion CIBIL credit bureau data from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure B.2. The specifications in Columns (1) through (5) restrict the analysis to agricultural loans only. Column (6) uses data for all loan types. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 18: How does guaranteed income increase credit demand?

Mechanism	Survey Question	Percentage of Respondents
Reduced consumption loss in case of default	*The money does not increase my ability to service debt during bad times, but it makes me more comfortable meeting basic needs in case I default*	38.80%
Increased comfort in repayment during bad times	*My concern before the policy was not default but meeting basic needs after repayment during bad times, the money reduced this concern*	21.88%
Reduced probability of default	*The money makes it possible for me to service debt during bad times*	20.78%
Reduced down-payment constraint	*The money helped me meet the down-payment requirements*	17.54%

The table presents the percentage of respondents associated with each mechanism. We directly ask respondents – *With regard to the money, which of the following channel was most significant in increasing your credit demand?* We presented respondents with the following four options to choose from as their primary reasoning for the question (with the exception of the *italics* part at the end of each sentence which is how we label the mechanisms internally). We randomized the order in which the options were presented across different respondents for the question. The options were – (a) My concern before the policy was not default but meeting basic needs after repayment during bad times, the money reduced this concern *(Increased comfort in repayment)*, (b) The money does not increase my ability to service debt during bad times, but it makes me more comfortable meeting basic needs in case I default *(Reduced consumption loss in case of default)*, (c) The money makes it possible for me to service debt during bad times *(Reduced probability of default)*, and (d) The money helped me meet the down-payment requirements *(Reduced down-payment constraint)*. The question was asked in the second wave of the survey over the telephone. Farmers who received PM-KISAN were asked to answer the questions as a result of the transfers. Farmers who did not receive PM-KISAN were asked to answer the question assuming they had got the transfers.

Table 19: Effect of the Policy on Credit: Heterogeneity by Risk & Incomplete Insurance Markets

Dep Var: $\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$	(1)	(2)	(3)	(4)
	Rainfall/Drought Risk		Basis Risk	
	Low Risk	High Risk	Low Risk	High Risk
Treatment X Post	0.1585	0.6130***	0.2792	0.8168***
	(0.1023)	(0.2162)	(0.1704)	(0.2960)
Farmer FE	Yes	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes	Yes
# Obs	1,021,016	412,479	576,612	139,341
R^2	0.0890	0.0861	0.0992	0.0909
Adj R^2	0.0286	0.0271	0.0364	0.0285

The table estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$\frac{\text{Loan Amt}_{i,t}}{Avg(\text{Loan Amt}_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where Loan $\text{Amt}_{i,t}$ denotes the dependent variable of interest (loan amount) measured for farmer i at time (month) t. $Avg(\text{Loan Amt}_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Columns (1) and (2) present the results on heterogeneity by risk measured using rainfall (drought) risk. We measure rainfall risk at the ZIP code level. For each month, we calculate average precipitation across all 0.25 degrees by 0.25 degrees latitude/longitude grid cell within the boundaries of the ZIP code. We translate ZIP code level precipitation measures into z-scores for the monsoon periods from 2014 through 2017. ZIP code-year observations with z-score values below the five percentile value refer to extreme low rainfall events and are defined as droughts. The average frequency of droughts over this period serves as our measure of the probability of drought for each ZIP code. ZIP codes above the median drought probability are defined as high-risk areas, while those below it are low-risk. Columns (3) and (4) present the results on heterogeneity by basis risk. We measure basis risk for each ZIP code by running the regression of monthly rainfall in the ZIP code on monthly rainfall at the nearest rainfall station during the monsoon season. We define ZIP code-level basis risk as one minus the regression R^2. Columns (1) and (2) present the results for farmers in regions with low and high rainfall risk, respectively. Columns (3) and (4) present the results for farmers in regions with low and high basis risk, respectively. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 20: Guaranteed Income & Risk-Taking: Evidence from Border District-pair Design

Dep.Var: Share of Cash Crops	(1)	(2)	(3)	(4)
Complier × Post	0.0308*	0.0350**	0.0365**	0.0372***
	(0.0170)	(0.0155)	(0.0165)	(0.0066)
Complier	-0.0477***	-0.0513***	-0.0542***	
	(0.0099)	(0.0094)	(0.0093)	
Post	0.0083	0.0074		
	(0.0179)	(0.0079)		
District Pair FE		Yes		
District Pair X Year FE			Yes	Yes
District FE				Yes
# Obs	331	331	298	298
R^2	0.0591	0.6792	0.7400	0.9609
Adj. R^2	0.0505	0.6494	0.4747	0.9064
Sample Mean	0.0986	0.0986	0.0986	0.0986
Sample SD	0.0955	0.0955	0.0955	0.0955

The table estimates the relative effect of PM-KISAN cash transfers on tractor sales in ZIP codes located in complier and non-complier districts according to the following specification:

$$y_{d,t} = \beta \cdot Complier_d \times Post_t + \theta_d + \theta_{p(d\in p),t} + \varepsilon_{d,t}$$

where $y_{d,t}$ denotes the dependent variable of interest measured for district d during year t. The key dependent variable is the share of cultivation area (gross sown area) under cash crops. We include gross sown area under sugarcane, cashew, oilseed, cotton, jute, mesta, sann hemp, spices, and tobacco to compute the gross sown area under cash crops. $Post_t$ takes a value of one for seasons after fiscal year 2019 and zero otherwise. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. θ_d denotes district fixed effects.$\theta_{p(d\in p),t}$ denotes district-pair × year fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. Each year refers to fiscal year starting in April of the calendar year and ending in the March of the next calendar year. The sample employed in the analysis is shown in Appendix Figure B.2. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Online Appendix for:

"Safety Nets, Credit, and Investment: Evidence from a Guaranteed Income Program"

Contents

Appendix A Institutional Details

A.1 Agriculture in India

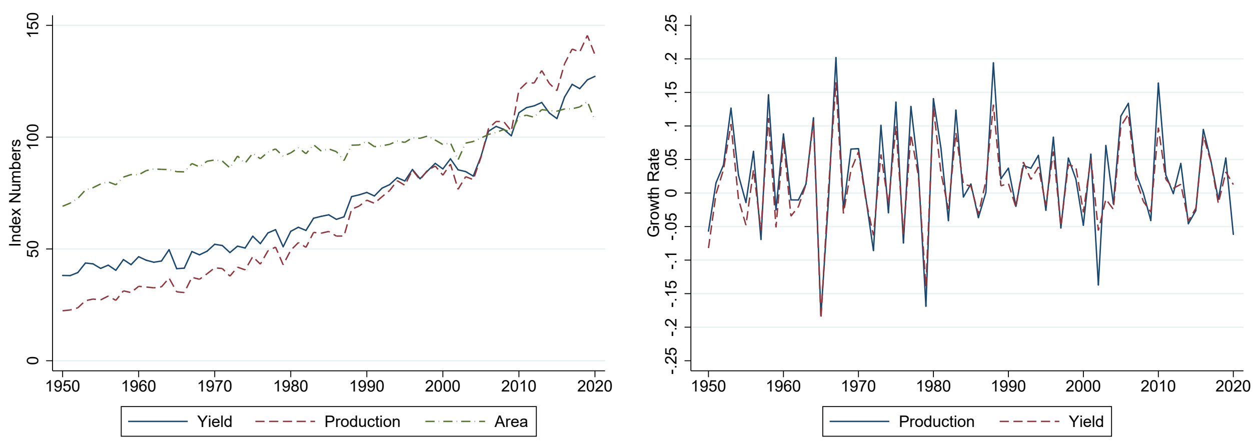
India has a particularly large agricultural sector, which is the primary source of livelihood for most Indians. There are five key noteworthy facts about Indian agriculture. First, as per the 2018 economic survey, more than 50% of the Indian workforce is employed in agriculture. However, agriculture accounts for only 17-18% of Indian GDP. Second, India has experienced a steady average nationwide annual increase of 2.5% in agricultural production and 1.8% in yields following the Green Revolution of the 1960s (see Appendix Figure A.1a). This increase in agricultural production boosted income and reduced poverty in rural areas (Bank, 2005). Third, despite the steady increase, agricultural production has been very volatile, indicating the high risk associated with the sector (see Appendix Figure A.1b). For example, agricultural production increased by 4.4% in 2013 but decreased by 4.6% in 2014 and by 2.6% in 2015. Growth in agricultural production and yield have experienced respective standard deviations of 7.9% and 6.2% since 1960. Fourth, given the low level of irrigation, rainfall is an important determinant of agricultural output in India (Cole, Healy, and Werker, 2012); therefore the risk to agriculture from erratic monsoons is high (Townsend, 1994). Fifth, there are two main cultivation seasons in India - *Kharif* and *Rabi*. The Kharif season starts in June and ends in October. Kharif crops are sown at the beginning of the southwest monsoon season (June) and are harvested at the end of the monsoon season (October–November). Rice, maize, and cotton are some of the major Kharif crops. The Rabi season starts with sowing around mid-November, and harvesting begins in April or May. The crops are grown either with rainwater that has percolated into the ground during monsoons or through irrigation. The major rabi crops include wheat, barley, and mustard.

Despite the steady growth in agriculture production, Indian agriculture is ridden with poverty. Nearly one in four farmers in India live below the poverty line. The National Statistical Office's (NSO) Situation Assessment of Agricultural Households and Land and Livestock Holdings of Households in Rural India (SAS) 2019 survey estimates that an average farming household in 2018-19 had an income of ₹7,997 per month. Three key facts emerge from the 2019 SAS survey. First, Indian farmers tend to manage small farms. Specifically, nearly nine in ten farmer households were landless (tenant), marginal, or small, meaning they owned less than two hectares (about five acres) of land. Moreover, the marginal or small farmers are comparable to landless farmers in terms of income. Only 0.2% possessed land over ten hectares. Second, less than half of the farmer households use debt. The 2019 All India Debt and Investment Survey reports that the incidence of indebtedness among cultivator households was 40.3% as of June 2018, with an average outstanding debt of ₹74,460. Of the total loans, only 57.5% were taken for agricultural purposes. This indicates that despite the widespread nature of small and marginal farmers in India, debt is not extensively used. Moreover, the indebtedness of marginal farmers is very similar to landless farmers. Third, voluntary crop insurance uptake remains low despite crop losses. The low voluntary enrollment of farmers in crop insurance has been attributed to several reasons such as basis risk as well as a lack of trust, financial literacy, and access to insurance (Cole and Xiong, 2017; Platteau, De Bock, and Gelade, 2017).

Agriculture has been a vital aid area for the Indian government, given the large base engaged in the sector and the widespread poverty and inefficiencies. These policies have primarily aimed at creating downside risk protection and increasing access to credit. Besley and Burgess (2002) show that state governments in India are responsive to agricultural and weather-induced catastrophes but the degree of response depends on the sophistication of the voters. Given the low literacy rate among farmers and low media penetration in rural areas, these responses often fail to reach farmers. Similarly, several crop insurance programs have been launched to provide downside protection for farmers, but were subsequently withdrawn owing to institutional failures. Most recently, the Pradhan Mantri Fasal Bima

Yojana (PMFBY) was launched in 2016 to provide subsidized crop insurance to farmers in India. Under PMFBY, crop insurance was compulsory for loanee farmers availing themselves of crop loans or kisan (farmer) credit cards. However, insurance has been made voluntary since 2020 owing to severe implementation and payout failures. Another downside protection policy – Minimum Support Price (MSP) – aims to provide farmers with minimum crop prices. However, Bakshi and Munjal (2018) document that the prices received by farmers, particularly small farmers, were well below the MSP and that the MSP of crops often did not cover paid-out costs. Another set of policies aim to increase access to credit for farmers. Agriculture has been tagged as a priority sector, and the Reserve Bank of India guidelines require all commercial banks to lend at least 18% of their Adjusted Net Bank Credit to agriculture. Cole (2009) documents that the priority lending policy is often used as a tool to fix elections rather than fix market failures. Lastly, the Indian government directly intervenes in agricultural debt markets through debt waivers. Kanz (2016) and Giné and Kanz (2018) document that debt waiver-type interventions have failed to stimulate the savings, consumption, and investment decisions of farmers and have reduced the supply of credit to them.

Figure A.1: Agricultural Growth in India



(a) Index Numbers over time

(b) Growth over time

The figure presents the agricultural growth in India over time. Panel A.1a reports the index numbers of land area under cultivation, agricultural production and agricultural yields from 1950 until 2020. Panel A.1b reports the year-on-year growth in agricultural production and yield. The annual data used to create these figures comes from the Database on Indian Economy maintained by the Reserve Bank of India.

A.2 The Details of the Policy

This section describes a new policy launched by the Government of India (GOI) that provides unconditional and perpetual guaranteed income support to all landowning farmers – Pradhan Mantri Kisan Samman Nidhi (PM-KISAN, translation: Prime Minister's Farmer's Tribute Fund). To the best of our knowledge, we are the first to systematically evaluate the program's effects.

The program was announced by the interim Finance Minister, Piyush Goyal, during the 2019 Interim-Union budget in the lower house of the Indian Parliament on 1 February 2019. Under the program, all landowning farmers get ₹6,000 per year as guaranteed income support. The amount is disbursed in three equal installments of ₹2,000. The total income support is equivalent to $83 in 2020 nominal terms and $285 in purchasing power parity (PPP) terms. The policy covers all landowning farmers in India, representing 67% of all farmers and 27% of the total Indian population. On 24 February 2019, Prime Minister Narendra Modi launched the program by transferring the first installment of ₹2,000.

The amount is transferred directly into the primary bank account of the beneficiaries.[21] The list of landowning farmers and their bank accounts is provided by each state to the federal government based on land registration records, Aadhar cards, and soil health cards.

The policy is confined only to landowning farmers as the lack of systematic identifying data on landless farmers imposed legal restrictions on the GOI.[22] An important condition of the policy was that landownership for determining eligibility was fixed in December of 2018. Farmers who purchased land after December of 2018 are excluded but new farmers, who inherit land upon the death of a relative, are entitled to the benefits. Additionally, all landowning farmers who are also government employees were excluded to reduce instances of corruption. Using survey data from the state of Uttar Pradesh, Varshney et al. (2020) finds no evidence of selection bias based on farmers' social, economic, and agricultural characteristics.

The federal government transfers the amount using direct deposits following the verification of records by the state government. Appendix Figure A.2 presents the details of the transfer process under PM-KISAN. Cooperation by states was a key step in the implementation of the policy as land registration records are maintained by the state government. All Indian states agreed to cooperate with the federal government to implement the policy except the state of West Bengal. The policy was launched nationwide in March 2019 except in West Bengal.

The policy meets three essential criteria of our economic question – unconditionality, perpetuity, and initially unexpected. The cash transfers under PM-KISAN require no-means test for the well defined community of landowning farmers. Unconditionality of cash transfers implies orthogonality to income, wealth, and effort. Such a variation is necessary to isolate the effects of cash transfers holding other determinants of entrepreneurial activity, such as preferences and productivity, fixed. The cash transfers have no set end date and, given the large electoral bloc of farmers in India, the policy is unlikely to be rolled back. Perpetuity of transfers implies a shock to permanent income. The present value of the perpetual cash transfers is $\approx$ ₹103,448 or $4,926 in PPP terms, which is 28 times the average stock of savings of landowning farmers. Therefore, these cash transfers are economically significant for farmers. The program was completely unexpected since it was announced during the Union budget, a highly se-

[21]The majority of Indian farmers have at least one bank account due to Pradhan Mantri Jan Dhan Yojana (PMJDY, translation: Prime Minister's People's Wealth Scheme) and the subsequent demonetization. According to the 2019 All India Debt and Investment Survey, about 84% of the population of age 18 years and above had at least one deposit account in banks. The primary bank account refers to the primary account linked to an individual's Aadhar Card, analogous to a social security card in the United States. The primary account for farmers is usually the account opened for them under the PMJDY.

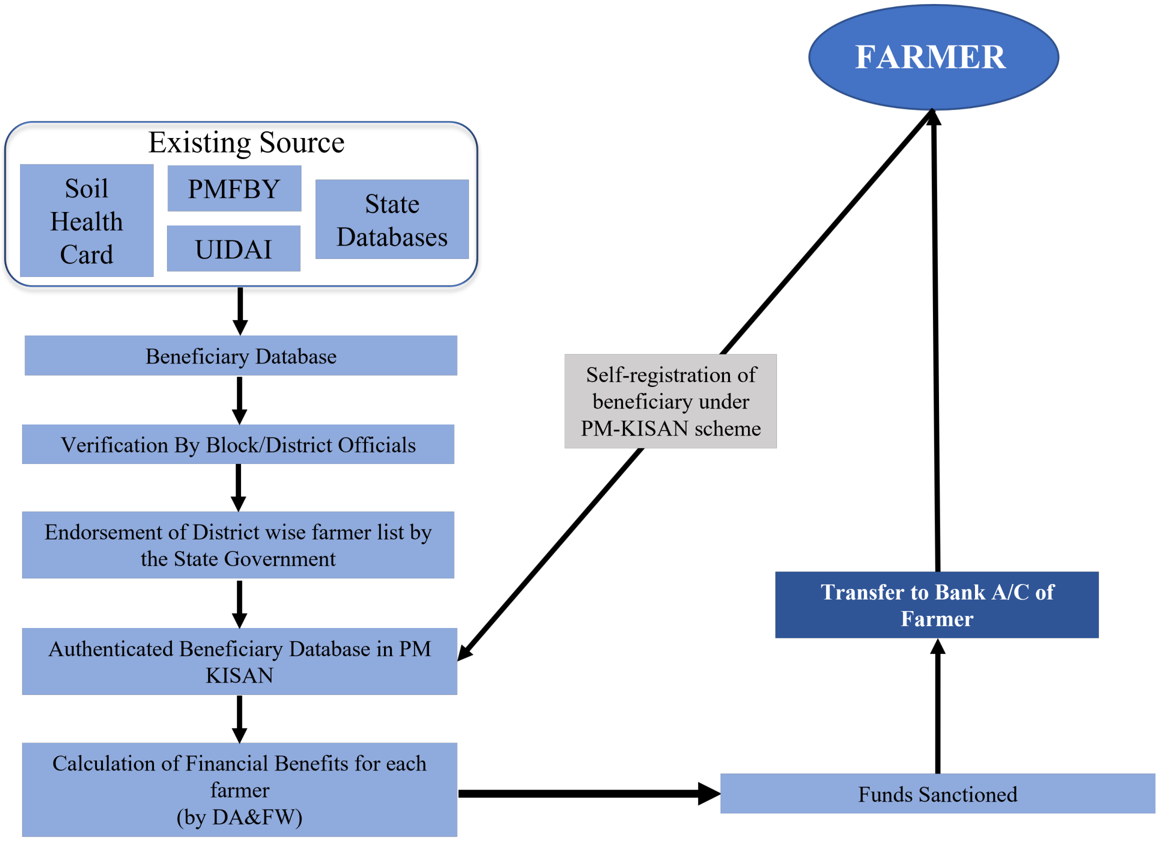
[22]Initially, the policy was confined to landowning farmers with less than two hectares of land. However, this provision was removed shortly after the announcement.

cretive process.[23] The unexpected nature of the announcement allows for credible identification using a methodology that exploits the timing of the policy.

Additionally, the cost of the policy is only 0.51% of Indian GDP, amounting to a total of 3.42% of government consumption expenditure. Therefore, the aggregate effects leading to changes in taxes, prices, and interest rates are likely to be of little concern given the small size of the $11 billion fiscal stimulus in a $2.87 trillion economy. Hence, this natural experiment provides an ideal setting to examine the partial equilibrium response of a class of self-employed individuals — farmers — to an unexpected and exogenous BI program.

[23] The secrecy of the Union budget is a well-preserved British legacy, and on budget day, the Parliament is informed of its contents. The process of creating and printing the budget is extremely confidential, including only a small number of officials, a complete shutdown of phones and internet, as well as the actual isolation of some individuals during the procedure. Moreover, the Official Secrets Act, 1923, India's anti-espionage law, makes it illegal to disclose budget documents. In India's history since independence, only one budget paper leak occurred in 1950.

Figure A.2: Data: Beneficiaries of PM-KISAN by ZIP code

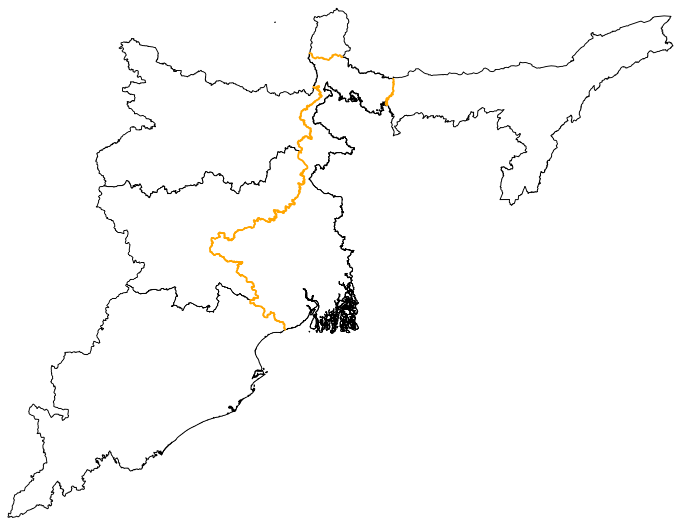


The figure plots the transfer process of benefits to eligible Indian farmers. The state government uses existing databases such as land registration records, Aadhar cards, and soil health cards to identify the list of beneficiaries. The list is then verified by the state government officials such as block or the district officer. The endorsed list is shared with the federal government who make the direct deposits. If a farmers feels that they have been wrongfully excluded from the list they can submit their information online through a portal. Apart from the possible grievances, farmers are passive in the process.

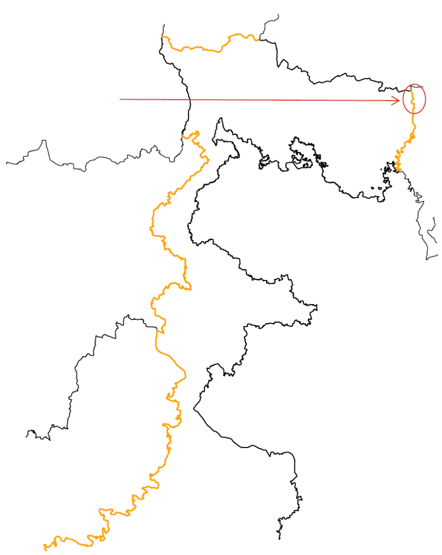
Appendix B Data

B.1 Sample & Spatial Geometry of Agricultural Production Data

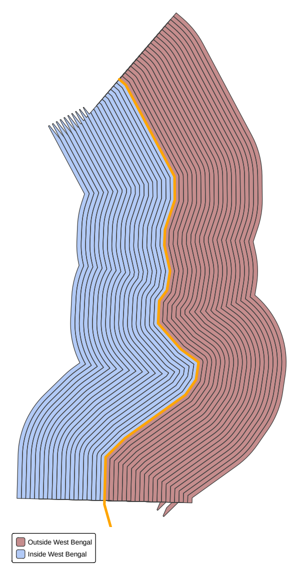
Figure B.1: Sample & Spatial Geometry of Agricultural Production Data



(a) Sample along the border of West Bengal



(b) Highlighted Border for blow Up

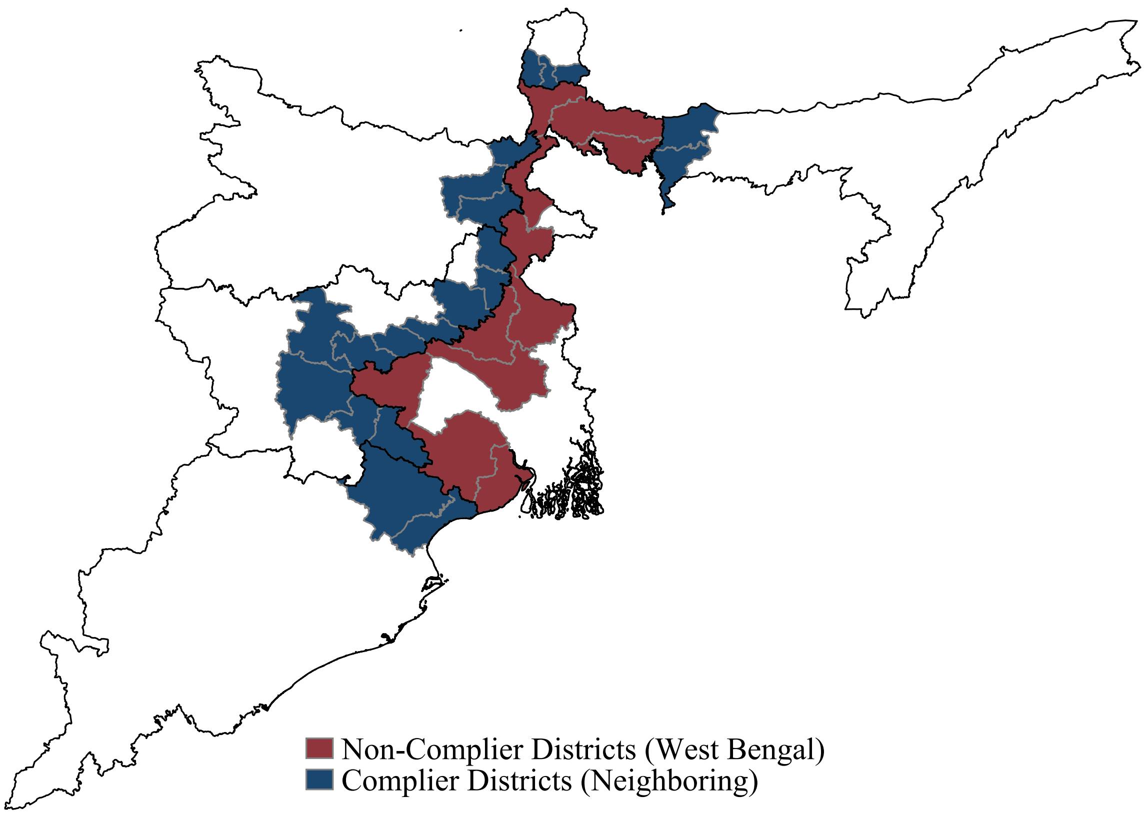


(c) Rectangular Micro-Regions

This figure illustrates the sample and spatial geometry of agricultural production data collected from rectangular micro-regions along the border of West Bengal. The yellow line in Figure B.1a marks the state boundary of West Bengal. Figure B.1c, which enlarges the red-circled area in Figure B.1b, shows the grid of rectangular micro-regions. The maroon strips indicate areas within West Bengal, while the blue strips represent areas just across the border. Each strip consists of multiple rectangles, each 100 metres wide. We define rectangular micro-regions of three lengths—5 km, 10 km, and 20 km to construct three sub-samples.

B.2 Sample of Bordering Districts Used in the Analysis

Figure B.2: Sample of Bordering Districts Used in the Analysis



The figure presents the sample of bordering districts used in the analysis. The blue-colored districts are located inside West Bengal along the state border. We refer to these districts as non-compliers as the state did not comply with the policy. The red-colored districts are districts in the bordering states of Assam, Bihar, Jharkhand, Odisha, and Sikkim. Moreover, the red colored districts are adjacent to the non-complier districts in the state of West Bengal. We refer to the red-colored districts as compliers since these states complied with the PM-KISAN policy.

B.3 Aggregate Credit Bureau Data

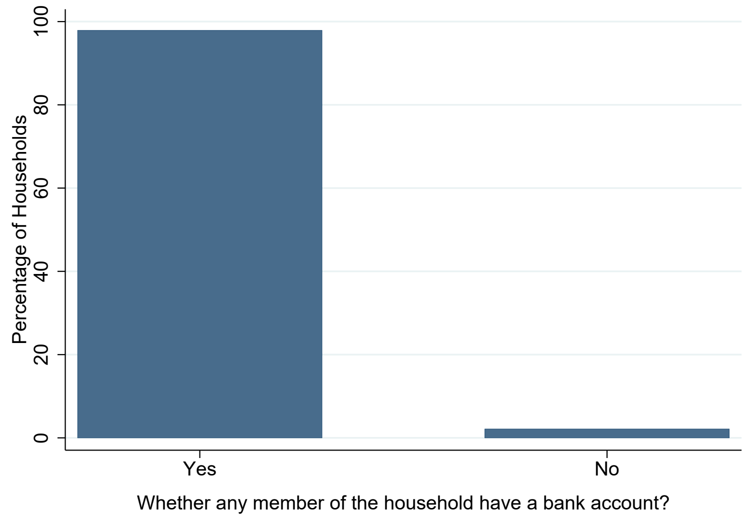
Table B.1: Summary Statistics for Aggregate Credit Bureau Data

Panel A: Full Sample		
	Mean	SD
LN(Loan Amount)	13.7105	1.7286
LN(# Loans)	1.6409	1.3171
1-year Delinquency Rate	0.027	0.1119
3-year Delinquency Rate	0.108	0.2131
Panel B: Agricultural Loans		
	Mean	SD
LN(Loan Amount)	13.7671	1.4819
LN(# Loans)	1.8322	1.4522
1-year Delinquency Rate	0.0344	0.1213
3-year Delinquency Rate	0.1544	0.2566
Panel C: Non-Agricultural Loans		
	Mean	SD
LN(Loan Amount)	13.7006	1.7679
LN(# Loans)	1.6076	1.2893
1-year Delinquency Rate	0.0257	0.1101
3-year Delinquency Rate	0.0999	0.2035

The table presents the summary statistics for the key variables from the aggregate credit bureau data that is obtained from India's oldest credit bureau - TransUnion CIBIL. The data is recorded at a granular level of month $\times$ ZIP code $\times$ lender type $\times$ product type. We obtain this data from March 2018, one year before the implementation of the policy, until February 2020, just before the onset of the COVID-19 pandemic, for all ZIP codes, approximately 19 thousand. We observe three outcomes: the number of loans issued, the total loan amount issued, and the number of defaulted loans that were issued in this month $\times$ ZIP code $\times$ lender $\times$ product. A loan is classified as defaulted once it reaches 90 days past due (DPD) within one year of being issued. We define the default rate as the fraction of loans issued each month that have surpassed the 90 DPD mark within one year of issuance.

B.4 Bank Data

Figure B.3: Fraction of Farmer Households with Bank Accounts



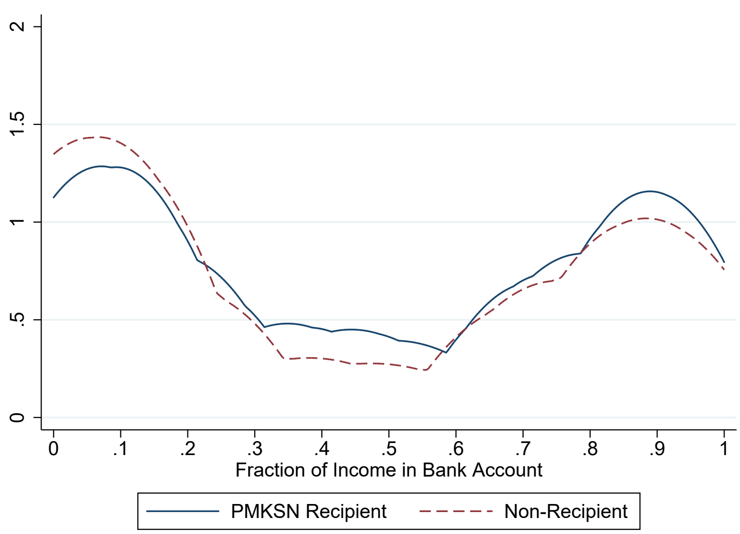
The figure plots the percentage of farmer households with at least one bank account. The data comes from the 2018 Situation Assessment Survey (SAS) conducted by the National Sample Survey Office (NSSO) during their 77^{th} round in the calendar year 2019. The survey records farmer responses as of 2018. The survey covers a stratified sample of all agricultural households in the rural areas of India. The precise survey question asks respondent to report *yes/no* to the question – *Whether any of the household member have bank account?*. This question is recorded as question number 13 of block 4 in visits 1 and 2. Detailed description of the survey as well as the data can be accessed at the Ministry of Statistics and Program Implementation (MOSPI) website.

Table B.2: Comparison of sample data with national data

	Bank Data	SAS Survey Data						
		Total	Farm	Animals	Sales	Non-farm	Pension	Rent
Income (in ₹)	8,334.00	15,330.98	7,996.89	2,467.78	1,799.61	2,414.92	1,308.66	53.37
Expenditure (in ₹)	11,578.78	11,858.00						
Age (in years)	45.23	48.91						
% with outstanding credit	–	40.3%						
% with some credit history	50.2%	–						

The table compares key metrics of income and spending in our sample data with the national data in the 2018 Situation Assessment Survey (SAS). The 2018 Situation Assessment Survey (SAS) was conducted by the National Sample Survey Office (NSSO) during their 77^{th} round in the calendar year 2019. The survey records detailed information on receipts and expenditure of the agricultural household members during 2018. Total survey income is constructed by adding the reported income from farming, animals, sales of assets and equipments, income from non-farm activities, pension, and rental income as reported in the SAS survey. Detailed description of the survey as well as the data can be accessed at the Ministry of Statistics and Program Implementation (MOSPI) website.

Figure B.4: Fraction of Income Deposited in Bank Account



The figure plots the fraction of income that is deposited by farmers in their bank accounts. The figure is plotted based on the second wave of our original survey of farmers. In this wave, we surveyed 1,000 farmers and asked them about the fraction of income that they deposit in their bank accounts. The sample consists of 609 farmers who are beneficiaries of PM-KISAN and 387 farmers who are not beneficiaries of PM-KISAN.

Table B.3: Number of bank accounts actively used by farmers

# Bank Accounts	All Respondents	PM-KISAN Recipients	
		Yes	No
1	52.44	49.88	55.37
2	24.31	26.35	21.97
3	9.82	10.53	8.97
More than 3	13.44	13.24	13.69
# Obs (Respondents)	4,003	2,137	1,862

The table presents the percentage of respondents choosing the number of actively managed bank accounts used by them. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey was – *"How many bank accounts do you use on a regular basis (an account is said to be used on a regular basis if there were at least ten transactions (withdrawal or deposit) in the last three months)?: a. 1, b. 2, c. 3, and d. More than 3."* Column (1) reports the percentage of respondents choosing each option. Columns (2) and (3) present the percentage of respondents choosing each option that received and did not receive PM-KISAN transfers, respectively.

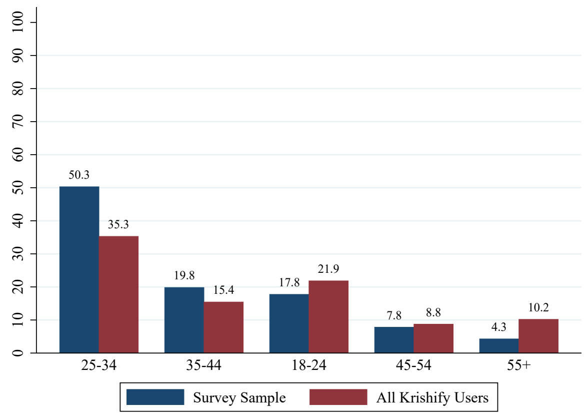
Table B.4: Biggest source of credit

Biggest Source of Credit	All Respondents	PM-KISAN Recipients	
		Yes	No
Banks & Other FI	61.07	67.06	53.75
Friends & Family	21.83	17.40	27.21
Moneylender	17.10	15.54	19.04
# Obs (Respondents)	2,643	1,454	1,187

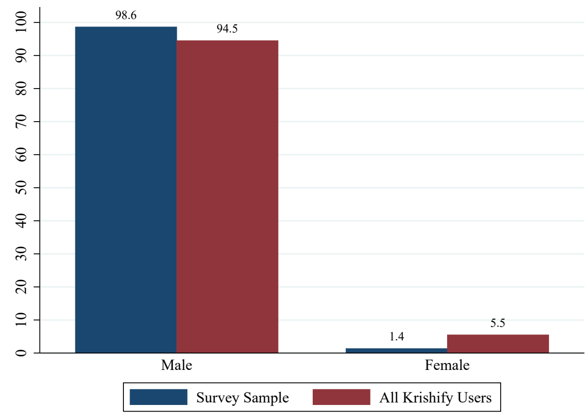
The table presents the percentage of respondents choosing their biggest source of credit. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey was – *"11. What is your biggest source of outstanding debt?: a. Banks or other financial institutions, b. Friends and family, and c. Moneylender."* This question was only asked to respondents who reported having some outstanding debt. Column (1) reports the percentage of respondents choosing each option. Columns (2) and (3) present the percentage of respondents choosing each option that received and did not receive PM-KISAN transfers, respectively.

B.5 Original Survey of Farmers

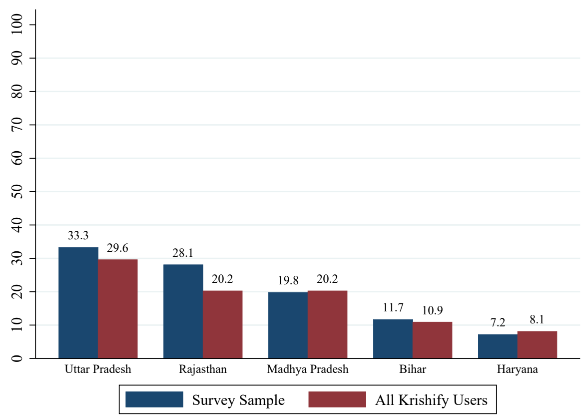
Figure B.5: Comparison of survey data with all Krishify application users



(a) Age



(b) Gender



(c) State

The figure presents the comparison of age, gender, and geographic location (state) for our survey sample with all application users.

Table B.5: Characteristics of Respondents in the Survey Data

Characteristic	# Obs	Options (Numbers - in percentage - reported under each option)					
Education		*Intermediate*	*Graduate*	*Less than Matric*	*Matric*	*Above Graduate*	*No Schooling*
	4,003	30.08	27.20	15.31	14.04	8.72	4.65
House Type		*Semi-Permanent*	*Temporary*	*Permanent*			
	4,003	42.97	30.23	26.80			
House Ownership		*Self-owned*	*Rented*				
	4,003	96.15	3.85				
Outstanding Debt		*Yes*	*No*				
	4,003	33.97	66.03				
Biggest Source of Debt		*Bank*	*Friends & Family*	*Moneylender*			
	2,643	61.07	21.83	17.10			
Got PM-KISAN		*Yes*	*No*				
	3,999	53.44	46.56				
Crop Insurance Usage		*Never*	*Always*	*Sometimes*	*Only with Loans*		
	3,986	50.20	22.18	19.82	7.80		
Number of Bank Accounts		*1*	*2*	*3*	*3+*		
	4,003	52.44	24.31	9.82	13.44		
Income per acre of land		*<INR 20,000*	*INR 20,001-40,000*	*INR 40,001-60,000*	*INR 60,001-80,000*	*INR 80,001-100,000*	*>INR 100,000*
	4,003	50.36	26.83	9.04	5.02	4.17	4.57

The table presents the key characteristics of the respondents in the survey sample. The survey data comes from the first wave (online form) filled by all respondents on the Krishify mobile application. All numbers are based on data self-reported by the farmers.

B.6 Classification of Loans into Productive & Consumption Loans

Table B.6: Classification of Loans

Loan Purpose	Loan Type
Category: Vehicles & Equipments	
Auto Loan (Personal)	Consumer Loan
Tractor Loan	Productive Loan
Commercial Vehicle Loan	Productive Loan
Two-Wheeler Loan	Consumer Loan
Used Car Loan	Consumer Loan
Commercial Equipment Loan	Productive Loan
Category: Business Loans	
Business Loan Priority Sector Agriculture	Productive Loan
Business Loan General	Productive Loan
Mudra Loans - Shishu / Kishor / Tarun	Productive Loan
Business Loan Priority Sector Small Business	Productive Loan
Business Loan - Secured	Productive Loan
Business Loan Priority Sector Others	Productive Loan
Business Loan Against Bank Deposits	Productive Loan
Business Loan Unsecured	Productive Loan
Category: Self-Help Groups & Joint Liability Groups	
SHG Individual	Productive Loan
SHG Group	Productive Loan
JLG Group	Productive Loan
JLG Individual	Productive Loan
Category: General Loans	
Gold Loan	Consumer Loan
Loan Against Bank Deposits	Consumer Loan
Housing Loan	Consumer Loan
Loan on Credit Card	Consumer Loan
Other	Consumer Loan
Personal Loan	Consumer Loan
Education Loan	Productive Loan
Consumer Loan	Consumer Loan
Individual	Consumer Loan
Property Loan	Consumer Loan
Loan Against Shares / Securities	Consumer Loan
Pradhan Mantri Awas Yojana - CLSS	Consumer Loan
Category: Microfinance Loans	
Microfinance Business Loan	Productive Loan
Microfinance Others	Consumer Loan
Microfinance Housing Loan	Consumer Loan
Microfinance Personal Loan	Consumer Loan
Category: Credit Facility	
Business Non-Funded Credit Facility-Priority Sector- Small Business	Productive Loan
Business Non-Funded Credit Facility General	Productive Loan
Business Non-Funded Credit Facility-Priority Sector-Others	Productive Loan
Business Non-Funded Credit Facility-Priority Sector-Agriculture	Productive Loan

The table presents the classification of different loan purposes into productive loans and consumption loans.

Appendix C Robustness

C.1 Effect of Guaranteed Income on Agricultural Production

Table C.1: Robustness Using EVI Implied Yield: Guaranteed Income & Agricultural Production

		Panel A: 5 km Boundary			
Dep. Var: LN(EVI Yield)	(1)	(2)	(3)	(4)	(5)
Complier × Post	0.0819***	0.0776***	0.0760***	0.0743***	0.0742***
	(0.0232)	(0.0211)	(0.0201)	(0.0193)	(0.0191)
Unit FE	Yes	Yes	Yes	Yes	Yes
Boundary X Year FE	Yes	Yes	Yes	Yes	Yes
Area Quantiles X Year FE	Yes	Yes	Yes	Yes	Yes
# Obs	38,390	49,919	57,604	69,141	73,000
R^2	0.7816	0.7677	0.7632	0.7582	0.7576
Adj. R^2	0.7104	0.698	0.6949	0.6914	0.6914
Bandwidth (in km)	≤ 1.0	≤ 1.3	≤ 1.5	≤ 1.8	≤ 2.0
		Panel B: 10 km Boundary			
Dep. Var: LN(EVI Yield)	(1)	(2)	(3)	(4)	(5)
Complier × Post	0.0769**	0.0834***	0.0790***	0.0805***	0.0809***
	(0.0307)	(0.0277)	(0.0264)	(0.0253)	(0.0251)
Unit FE	Yes	Yes	Yes	Yes	Yes
Boundary X Year FE	Yes	Yes	Yes	Yes	Yes
Area Quantiles X Year FE	Yes	Yes	Yes	Yes	Yes
# Obs	19,164	24,919	28,754	34,522	36,453
R^2	0.84	0.8201	0.8117	0.8038	0.8034
Adj. R^2	0.7834	0.7625	0.7541	0.7469	0.7471
Bandwidth (in km)	≤ 1.0	≤ 1.3	≤ 1.5	≤ 1.8	≤ 2.0
		Panel C: 20 km Boundary			
Dep. Var: LN(EVI Yield)	(1)	(2)	(3)	(4)	(5)
Complier × Post	0.1007**	0.1014***	0.0961***	0.0908***	0.0905***
	(0.0391)	(0.0349)	(0.0335)	(0.0320)	(0.0318)
Unit FE	Yes	Yes	Yes	Yes	Yes
Boundary X Year FE	Yes	Yes	Yes	Yes	Yes
Area Quantiles X Year FE	Yes	Yes	Yes	Yes	Yes
# Obs	9,521	12,387	14,304	17,170	18,124
R^2	0.8625	0.8493	0.8389	0.8348	0.8343
Adj. R^2	0.8062	0.7949	0.7841	0.7823	0.7826
Bandwidth (in km)	≤ 1.0	≤ 1.3	≤ 1.5	≤ 1.8	≤ 2.0

This table presents the results from the estimation of the following regression specification:

$$ln(y_{i,t}) = \beta \cdot Complier_i \times Post_t + \theta_i + \theta_{j,t} + \varepsilon_{i,t}$$

where, $ln(y_{i,t})$ is the natural logarithm of EVI-derived agricultural output for plot i at time t. The indicator Complier$_i$ equals one for plots outside West Bengal (treatment group) and zero for those inside (control group). Post$t$ is one for years after 2019, the policy implementation date. θ_i denotes fixed effects at the unit (or plot) level. Each plot measures between 5 and 20 km along the border and is 100 m wide, with EVI data collected within a 2 km bandwidth on either side of the border in 100 m increments. Finally, $\theta j, t$ denotes the boundary × year fixed effect. Panels A, B and C use the EVI-based measures for plots with lengths of 5 km, 10 km, and 20 km, respectively. The dependent variable is the natural logarithm of the EVi implied yield observed during the kharif season in year t for unit i. Columns (1)-(5) use bandwidths of 1.0 km, 1.3 km, 1.5 km, 1.8 km, and 2 km on either side of the border. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the unit level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

C.2 Effect of Guaranteed Income on Credit

C.2.1 Evidence Using Data from the Largest State Owned Bank in India

Table C.2: Guaranteed Income & Credit: Evidence Using Data from the Largest State Owned Bank in India

Dep Var: LN(Agricultural lending)	(1)	(2)	(3)	(4)	(5)
Complier × Post	0.1349*	0.1550**	0.1564**	0.2058***	0.2315***
	(0.0695)	(0.0722)	(0.0740)	(0.0710)	(0.0726)
Complier	-0.6654***	-0.6970***	-0.7051***		
	(0.1989)	(0.1973)	(0.1941)		
Post	0.2294***				
	(0.0330)				
District Pair FE	Yes	Yes			
Month FE		Yes			
District Pair X Month FE			Yes	Yes	Yes
ZIP FE				Yes	
Branch FE					Yes
# Obs	14,929	14,929	14,929	14,929	14,929
R^2	0.1533	0.1805	0.2192	0.4934	0.5481
Adj. R^2	0.1514	0.1774	0.1780	0.4532	0.5074
Sample Mean	12.9182	12.9182	12.9182	12.9182	12.9182
Sample SD	1,6262	1,6262	1,6262	1,6262	1,6262

The table estimates the relative effect of PM-KISAN cash transfers on agricultural credit by the largest state owned bank in India in ZIP codes located in complier and non-complier districts according to the following specification:

$$LN(y_{z,t}) = \beta \cdot Complier_d \times Post_t + \theta_b + \theta_{p(d\in p),t} + \varepsilon_{z,t}$$

where $LN(y_{z,t})$ denotes the natural logarithm of the agricultural credit extended by branch b located in ZIP code z at time (month) t. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. θ_b denotes bank branch fixed effect. $\theta_{p(z\in p),t}$ denotes district-pair × month fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. The sample comes from the largest state owned bank in India from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure B.2. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C.2.2 Evidence from Household-Level Data

Table C.3: Guaranteed Income & Credit: Evidence from Household-Level Data

	All Borrowing		Bank Borrowing		Informal Borrowing	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Complier × Post	0.0407	0.0415***	0.0658***	0.0208**	-0.0098	-0.0000
	(0.0409)	(0.0126)	(0.0328)	(0.0085)	(0.0112)	(0.0000)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
District X Month FE	Yes		Yes		Yes	
District Pair X Treatment X Month FE	Yes		Yes		Yes	
District X Month X Education X Gender FE		Yes		Yes		Yes
District Pair X Treatment X Month X Education X Gender FE		Yes		Yes		Yes
# Obs	4,979	3,924	4,979	3,924	4,979	3,924
R^2	0.6742	0.7734	0.6467	0.7844	0.6860	0.7826
Adj. R^2	0.6305	0.6209	0.5994	0.6394	0.6440	0.6363
Sample Mean	0.1086	0.1086	0.0552	0.0552	0.0061	0.0061
Sample SD	0.3111	0.3111	0.2285	0.2285	0.0781	0.0781

The table estimates the relative effect of PM-KISAN cash transfers on overall borrowing, borrowing from formal sources, and borrowing from informal sources for the treatment farmers in complier groups according to the following specification:

$$y_{i,t} = \beta \cdot \underbrace{Landowning_i}_{Treatment_i} \times \underbrace{\text{Outside WB}_d}_{Complier_d} \times Post + \theta_i + \theta_{d,t} + \theta_{p(d\in p),T,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for household i at time (month) t. In Columns (1) and (2), the dependent variable is a binary indicator that takes a value of one if there was any borrowing for business, investment or vehicle purchase purposes from any sources and zero otherwise. In Columns (3) and (4), the dependent variable is a binary indicator that takes a value of one if there was any borrowing for business, investment or vehicle purchase purposes from banks and zero otherwise. In Columns (5) and (6), the dependent variable is a binary indicator that takes a value of one if there was any borrowing for business, investment or vehicle purchase purposes from informal sources such as friends, family, shops and moneylenders and zero otherwise. $Treatment_i$ takes a value of one for treatment farmer households and a value of zero for control farmer households. Control households are defined as farmer households in the sample whose occupation is tagged as agricultural labourers. All other farmer households are landowning and are defined to be treatment households. $Complier_d$ takes a value of one for sample districts that are outside the state of West Bengal. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes household fixed effects. $\theta_{d,t}$ denotes district × month fixed effects, where d refers to the district where farmer i operates. $\theta_{p(d\in p),T,t}$ denotes district-pair × treatment × month fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. The sample comes from the consumer pyramids survey conducted by the CMIE from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure B.2. Gender group is a categorical variable that indicated if the household is gender balanced, female dominated, male dominated, only females and only males. Education group is another categorical variable that indicates if the household comprises of all graduates, all matriculates, graduated dominated, graduate minority, all literates, all illiterates, etc. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. respectively.

C.3 Farmer-Level Evidence using Bank Data

C.3.1 Sample Selection & Omitted Variable Bias

Table C.4: Sample Selection & Omitted Variable Bias using Bank Data

Dep Var: $\frac{y_{i,t}}{\mathbb{E}[y_{i,t}\|t=Pre]}$	(1)	(2)	(3)	(4)
Treatment × Complier × Post	0.0931**		0.0746***	
	(0.0365)		(0.0418)	
Treatment × Post		0.0919***		0.0464*
		(0.0185)		(0.0278)
Household FE	Yes	Yes	Yes	Yes
District X Month X Gender X Education FE	Yes	Yes	Yes	Yes
Treatment X Month FE	Yes		Yes	
# Obs	295,772	350,539	92,824	92,976
R^2	0.6285	0.6314	0.6646	0.6504
Adj. R^2	0.4283	0.4858	0.5308	0.5187
Sample	All India	All India w/o West Bengal	Bank sample + West Bengal	Bank sample w/o West Bengal

The table estimates the relative effect of PM-KISAN cash transfers on income from work for the treatment farmers in complier groups according to the following specification in Columns (1) and (3)

$$\frac{y_{i,t}}{\mathbb{E}[y_{i,t}|t = Pre]} = \beta \cdot \underbrace{Landowning_i}_{Treatment_i} \times \underbrace{\text{Outside WB}_d}_{Complier_d} \times Post + \theta_i + \theta_{d,t} + \underbrace{Landowning_i}_{Treatment_i} \times \theta_t + \varepsilon_{i,t}$$

Similarly, Columns (2) and (4) estimate the following regression specification comparing treated farmers with control farmers in the sample that excludes West Bengal:

$$\frac{y_{i,t}}{\mathbb{E}[y_{i,t}|t = Pre]} = \beta \cdot \underbrace{Landowning_i}_{Treatment_i} \times Post + \theta_i + \theta_{d,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for household i at time (month) t. $\mathbb{E}[y_{i,t}|t = Pre]$ denotes the sample average of the variable of interest during the pre-policy period. $Treatment_i$ takes a value of one for treatment farmer households and a value of zero for control farmer households. Control households are defined as farmer households in the sample whose occupation is tagged as agricultural labourers. All other farmer households are landowning and are defined to be treatment households. $Complier_d$ takes a value of one for households outside the state of West Bengal. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes household fixed effects. $\theta_{d,t}$ denotes district × month fixed effects, where d refers to the district where farmer i operates. The sample comes from the consumer pyramids survey conducted by the CMIE from March 2018 through February 2020. Column (1) sample for households all across India. Column (2) excludes all households living in West Bengal. Column (3) restricts the sample to households that are in states available in the bank data: Karnataka, West Bengal, Maharashtra, and Punjab. Column (4) restricts the sample to households that are in states available in the bank data after excluding the state of West Bengal: Karnataka, Maharashtra, and Punjab. The key dependent variable is the reported household income from work. Gender group is a categorical variable that indicated if the household is gender balanced, female dominated, male dominated, only females and only males. Education group is another categorical variable that indicates if the household comprises of all graduates, all matriculates, graduated dominated, graduate minority, all literates, all illiterates, etc. Standard errors clustered at the household level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C.3.2 Robustness: Estimation Using Poisson

Table C.5: Differences-in-Differences Using Bank Data: Estimation Using Poisson

Dep Var: Income	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.2373***	0.2326***	0.1396**	0.1227**	0.1238**
	(0.0573)	(0.0573)	(0.0586)	(0.0566)	(0.0581)
Treatment	-0.7938***	-0.7874***	-0.4188***		
	(0.0701)	(0.0703)	(0.0709)		
Post	0.0067				
	(0.0562)				
Farmer FE				Yes	Yes
Month FE		Yes		Yes	
ZIP X Month FE			Yes		Yes
# Obs	1,494,560	1,494,560	1,494,560	1,494,560	1,494,560
Pseudo R^2	0.0045	0.0402	0.2517	0.5310	0.5987

The table estimates the relative effect of cash transfers under PM-KISAN on income from work for the treatment and control groups according to the following specification:

$$y_{i,t} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. We estimate the above specification using Poisson pseudo-likelihood regression. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. Column (1) reports the estimate of β without any fixed effects. Columns (2), (3), and (4) report the estimate of β by sequentially adding fixed effects, to finally estimate key equation highlighted above in Column (5). The estimation sample is constructed from transaction-level administrative bank data covering farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Income from work is defined as the sum of all cash inflows into the farmer's account, net of inflows linked to loan disbursals, financial investment maturities, and PM-KISAN transfer receipts. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C.3.3 Robustness: Spillovers and the Treatment Effect

Table C.6: Robustness: Spillovers and the Treatment Effect

Dep Var: Income Growth	(1)	(2)	(3)	(4)	(5)
Treatment	0.1579**	0.1375**	0.1274**	0.1375**	0.1274**
	(0.0636)	(0.0636)	(0.0635)	(0.0637)	(0.0636)
Fraction of treated by district		0.0393***			
		(0.0141)			
Fraction of treated by ZIP			0.0053		0.0019
			(0.0044)		(0.0041)
State FE	Yes	Yes	Yes		
District FE				Yes	Yes
# Obs	67,966	67,966	67,966	67,966	67,966
R^2	0.0065	0.0067	0.0065	0.0133	0.0133
Adj. R^2	0.0065	0.0067	0.0065	0.0121	0.0121

This table reports estimates of the relative effect of cash transfers under the PM-KISAN program on income from work for treated and control households after accounting for potential spillovers according to the following specification:

$$LN\left(\frac{y_{i,Post}}{y_{i,Pre}}\right) = \beta \cdot Treatment_i + \beta_S \cdot \text{Frac. Treated}_d + \theta_s + \varepsilon_i$$

$$LN\left(\frac{y_{i,Post}}{y_{i,Pre}}\right) = \beta \cdot Treatment_i + \beta_S \cdot \text{Frac. Treated}_z + \theta_d + \varepsilon_i$$

Here, $y_{i,Pre}$ and $y_{i,Post}$ denote the sum of income from work for farmer i over the twelve months preceding and following the implementation of PM-KISAN, respectively. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. θ_s denotes state fixed effects and θ_d denotes farmer fixed effects. The empirical specification of the test is based on Berg, Reisinger, and Streitz (2021) and the unit of observation is at the farmer-level as in Panel A of Table 8. Columns (1) and (4) report the estimate of β with state and district fixed effects, respectively. Column (2) reports the estimate of β with state fixed effects after controlling for the fraction of treated farmers within the district d where the farmer operates. Column (3) reports the estimate of β with state fixed effects after controlling for the fraction of treated farmers within the ZIP code z where the farmer operates. Column (5) reports the estimate of β with district fixed effects after controlling for the fraction of treated farmers within the ZIP code z where the farmer operates. The estimation sample is constructed from transaction-level administrative bank data covering farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Income from work is defined as the sum of all cash inflows into the farmer's account, net of inflows linked to loan disbursals, financial investment maturities, and PM-KISAN transfer receipts. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C.3.4 Robustness: Controlling for observable farmer-level covariates

Table C.7: Robustness: Adding other farmer-level covariates measured before the policy

Dep Var: Income relative to average income	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment X Post	0.1494**	0.1479**	0.1499**	0.1583**	0.1505**	0.2610***	0.1470**	0.1498**	0.1227*	0.1129*	0.1279**	0.1474**	0.1450**	0.1499**	0.1748***	0.1723***
	(0.0675)	(0.0675)	(0.0673)	(0.0678)	(0.0675)	(0.0684)	(0.0678)	(0.0675)	(0.0638)	(0.0586)	(0.0593)	(0.0671)	(0.0675)	(0.0675)	(0.0674)	(0.0582)
LN(Age) X Post		-0.1513***														-0.1179***
		(0.0335)														(0.0306)
KCC Limit X Post			0.0237													0.2635***
			(0.0148)													(0.0157)
Default X Post				-0.1481***												-0.2271***
				(0.0154)												(0.0177)
Int Rate X Post					0.0584											0.0151
					(0.0600)											(0.0602)
Relationship X Post						0.6165***										0.2035**
						(0.0795)										(0.0862)
CC User X Post							0.7386***									1.1799***
							(0.2705)									(0.2440)
Other Inv X Post								0.1111								0.4291**
								(0.2154)								(0.2068)
Savings X Post									-0.1927***							-0.007
									(0.0095)							(0.0074)
Income X Post										-0.3998***						-0.7225***
										(0.0129)						(0.0268)
Consumption X Post											-0.3391***					0.1488***
											(0.0117)					(0.0240)
% Visits X Post												-0.0105***				0.1018***
												(0.0040)				(0.0045)
Credit Score X Post													0.0004***			0.0007***
													(0.0000)			(0.0001)
Female X Post														-0.0624**		-0.0750***
														(0.0288)		(0.0254)
Hindu X Post															-0.1271***	-0.0759***
															(0.0171)	(0.0227)
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682	1,462,682
R^2	0.3078	0.3079	0.3078	0.3079	0.3078	0.3079	0.3079	0.3078	0.3098	0.3150	0.3136	0.3079	0.3079	0.3078	0.3079	0.3184
Adj. R^2	0.2537	0.2537	0.2537	0.2538	0.2537	0.2538	0.2537	0.2537	0.2558	0.2614	0.2599	0.2537	0.2537	0.2537	0.2537	0.2651

The table estimates the relative effect of PM-KISAN transfers on income from work for the treatment and control groups according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \beta \cdot X_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. X_i refers to the vector of control variables measured as an average of farmer-level characteristics in the year prior to the policy. These characteristics include natural logarithm of age, the credit limit on Kisan credit cards scaled by sample average, default tag which takes a value of one for farmers with a prior default history and zero otherwise, interest rates on Kisan credit cards scaled by sample average, the natural logarithm of the age of relationship with the bank in years, CC user that takes a value of one for farmers with credit cards and zero otherwise, Other Inv which takes a value of one if the farmer has other investments such as investment in stock markets, fixed deposits, recurring deposits, and Public Provident Funds, Savings is measured as the average savings in liquid bank deposits during the twelve months before the policy implementation scaled by sample average, consumption is measured as the average total spending by farmers during the twelve months before the policy implementation scaled by sample average, % Visits refers to the percentage of days in a year farmer visited the bank branch, Credit Score refers to the TransUnion CIBIL score of the farmer, Female takes a value of one for female farmers and zero for male farmers, and Hindu takes a value of one for Hindu farmers and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The estimation sample is constructed from transaction-level administrative bank data covering farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Income from work is defined as the sum of all cash inflows into the farmer's account, net of inflows linked to loan disbursals, financial investment maturities, and PM-KISAN transfer receipts. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C.3.5 Placebo Test: Treatment Effect in prior years when policy was not launched

Table C.8: Placebo Test: Treatment Effect in prior years when policy was not launched

Dep Var: $\frac{y_{i,t}}{Avg(y_{Pre})}$	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.1390**				
	(0.0688)				
Treatment X Placebo Post-2015		-0.0222			
		(0.0770)			
Treatment X Placebo Post-2014			-0.1450		
			(0.1043)		
Treatment X Placebo Post-2013				-0.0574	
				(0.1135)	
Treatment X Placebo Post-2012					-0.1328
					(0.7970)
Farmer FE	Yes	Yes	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes	Yes	Yes
# Obs	1,532,700	209,027	99,043	49,494	25,397
R^2	0.3091	0.3256	0.4095	0.4430	0.4869
Adj. R^2	0.2535	0.1886	0.2554	0.2552	0.2695

The table estimates the relative effect of cash transfers under PM-KISAN on income from work for the treatment and control groups according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period here the pre-policy period is defined based on the timing of the actual policy in Column (1) and placebo policy timing in Columns (2) through (5). The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. In Column (1) $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. In Columns (2)-(5) $Post_t$ takes a value of one for months beginning March 2015, 2014, 2013, and 2012, respectively. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The estimation sample is constructed from transaction-level administrative bank data covering farmers in Punjab, Maharashtra, and Karnataka. The sample in Column (1) is from March 2018 through February 2020. The sample in Column (2) is from March 2014 through February 2016. The sample in Column (3) is from March 2013 through February 2015. The sample in Column (4) is from March 2012 through February 2013. The sample in Column (5) is from March 2011 through February 2013. Income from work is defined as the sum of all cash inflows into the farmer's account, net of inflows linked to loan disbursals, financial investment maturities, and PM-KISAN transfer receipts. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C.3.6 Robustness (Effect on Credit): Estimation Using Poisson

Table C.9: Robustness (Effect on Credit): Estimation Using Poisson

	(1)	(2)	(3)
	Loan (=1)	$\#Loan$	Loan Amt
Treatment X Post	0.0942***	0.1307***	0.2498**
	(0.0186)	(0.0234)	(0.0974)
Farmer FE	Yes	Yes	Yes
ZIP × Month FE	Yes	Yes	Yes
# Obs	1197488	1197488	1199836
Pseudo R^2	0.0367	0.0741	0.3353
Sample Mean	0.4783	0.6340	9,440.35
Sample SD	0.4995	0.8049	49,290.08

The table estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$y_{i,t} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. We estimate the above specification using Poisson pseudo-likelihood regression. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Column (1) uses a binary variable as the dependent variable taking a value of one if the farmer received at least one new loan during the period, and zero otherwise. Column (2) uses the number of new loans as the dependent variable. Column (3) uses the total loan amount as the dependent variable. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix D Mechanism

D.1 Effect of Credit: Heterogeneity by Credit Score

Table D.1: Effect of Credit: Heterogeneity by Credit Score

Dep Var: $\frac{\text{Loan Amt}_{i,t}}{Avg(\text{Loan Amt}_{Pre})}$	(1)	(2)	(3)
Treatment X Post	-0.0880	0.2959*	0.5203***
	(0.1487)	(0.1593)	(0.1309)
Farmer FE	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes
# Obs	382,032	416,640	537,048
R^2	0.1697	0.1467	0.1121
Adj R^2	0.0631	0.0362	0.0112
Sample	Bottom Tercile Credit Score	Middle Tercile Credit Score	Top Tercile Credit Score

The table estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable (loan amount) of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. We split the data into three equal parts based on the credit score of farmers before March of 2018. Column (1) reports the estimate for the farmers with the credit score in the bottom tercile. Column (2) reports the estimate for the sample of farmers with credit score in the middle tercile. Column (3) reports the estimate for the sample of farmers with credit score in the top tercile. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

D.2 Kisan Credit Cards

This section presents three illustrations from the 2017 RBI circular which provide guidance for bank managers when setting up credit limits.

D.2.1 Illustrations from the 2017 RBI Circular

Figure D.1: Illustration for Computing Kisan Credit Card Limit

Illustration I

A. Small farmer cultivating multiple crops in a year

1. **Assumptions**

   A. Land holding : 2 acres

   B. Cropping Pattern

   Paddy - 1 acre (Scale of finance plus crop insurance per acre : ₹.11000)

   Sugarcane - 1 acre (Scale of finance plus crop insurance per acre : ₹.22,000)

   C. Investment / Allied Activities

   i Establishment of 1+1 Dairy Unit in 1st Year () (Unit Cost : ₹ 20,000 per animal)

   ii Replacement of Pump set in 3rd year (Unit Cost : ₹.30,000)

2. (i) Crop loan Component

Cost of cultivation of 1 acre of Paddy and 1acre of Sugarcane (11,000+22,000)	:	₹.33,000
Add : 10% towards post-harvest / household expense / consumption	:	₹. 3,300
Add : 20% towards farm maintenance	:	₹. 6,600
Total Crop Loan limit for 1st year	:	**₹. 42,900**
Loan Limit for 2nd year		
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 42900 i.e 4300)	:	₹. 4,300
		₹. 47,200
Loan Limit for 3rd year	:	
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 47,200 i.e., 4,700)		₹. 4,700 **₹. 51,900**
	:	
Loan Limit for 4th year	:	
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 51,900 i.e 5,200)		₹. 5,200 **₹. 57,100**
	:	
Loan Limit for 5th year	:	
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 57100 i.e 5700)		₹. 5,700 **₹. 62,800**
Say ....(A)	:	**₹. 63,000**

(ii) **Term loan component :**

1st Year : Cost of 1+1 Dairy Unit	:	₹. 40,000
3rd Year : Replacement of Pumpset :	:	₹. 30,000
Total term loan amount **....(B)**	:	**₹. 70,000**
Maximum Permissible Limit /	:	**₹. 1,33,000**
Kisan Credit Card Limit (A) +(B)	:	**Rs. 1.33 lakh**

Note: Drawing Limit will be reduced every year based on repayment schedule of the term loan(s) availed and withdrawals will be allowed up to the drawing limit.

The figure presents the illustration for computing the credit limit for kisan credit cards. This illustration is taken from the 2017 RBI circular and can be accessed at LINK The illustration provides the details for setting the credit limit for a two acre farm with one acre under paddy cultivation and one acre under sugarcane cultivation.

Figure D.2: Illustration for Computing Kisan Credit Card Limit

Illustration II

Assessment of KCC LIMIT

1. **Marginal farmer cultivating single crop in a year**
   1. ***Assumptions :***
      1. Land holding : 1 acre
      2. Crops grown : Paddy (Scale of finance plus crop insurance per acre : ₹ 11,000)
      3. There is no change in Cropping Pattern for 5 years
      4. Allied Activities to be financed - One Non-Descript Milch Animal (Unit Cost Rs : 15,000)
   2. ***Assessment of Card Limit :***

(i) **Crop loan Component**

(Cost of cultivation for 1 acre of Paddy)	:	₹ 11,000
Add : 10% towards post-harvest / household expense / consumption	:	₹ 1,100
Add : 20% towards farm maintenance	:	₹ 2,200
Total Crop Loan limit for 1st year ....(A1)	:	**₹ 14,300**

(ii) **Term Loan Component**

Cost of One Milch Animal ....(B)	:	₹ 15,000
1st Year Composite KCC Limit : (A1) + (B)	:	**₹ 29,300**
2nd Year :		
Crop loan component :		
A1 plus 10% of crop loan limit (A1) towards cost escalation / increase in scale of finance [14,300+(10% of 14300 = 1430)] **....(A2)**	:	₹ 15,730
2nd Year Composite KCC Limit : A2+B (15730 + 15000)	:	**₹ 30,730**
3rd Year :		
Crop loan component :		
A2 plus 10% of crop loan limit (A2) towards cost escalation / increase in scale of finance [15,730+(10% of 15730 = 1570)] **....(A3)**	:	₹ 17,300
3rd Year Composite KCC Limit : A3+B (17,300 + 15,000)	:	**₹ 32,300**
4th Year :		
Crop loan component :		
A3 plus 10% of crop loan limit (A3) towards cost escalation / increase in scale of finance [17,300+(10% of 17300 = 1730)] **....(A4)**	:	₹ 19,030
4th Year Composite KCC Limit : A4+B (19,030 **+ 15,000)**		**₹ 34,030**
5th Year :		
Crop loan component :		
A4 plus 10% of crop loan limit (A4) towards cost escalation / increase in scale of finance [19,030+(10% of 19,03 0 = 1,900)] **....(A5)**	:	₹ 20,930
5th Year Composite KCC Limit : A5+B (20,930 **+ 15,000)**		**₹35,930**

Maximum Permissible Limit /

Composite KCC Limi Say	**:**	**Rs.36,000**

Note: All the above costs estimated are illustrative in nature. The recommended scale of finance / unit costs may be taken into account while finalising the credit limit.

The figure presents the illustration for computing the credit limit for kisan credit cards. This illustration is taken from the 2017 RBI circular and can be accessed at LINK The illustration provides the details for setting the credit limit for a ten acre farm with five acre under paddy cultivation in one season followed by five acre under sugarcane cultivation and another five acre under groundnut cultivation.

Figure D.3: Illustration for Computing Kisan Credit Card Limit

B Other farmer cultivating multiple crops in a year

1. Assumptions :
2. Land Holding : 10 acres
3. Cropping Pattern :

   Paddy - 5 acres (Scale of finance plus crop insurance per acre ₹.11,000) Followed by

   Groundnut - 5 acres (Scale of finance plus crop insurance per acre ₹.10,000)

   Sugarcane - 5 acres (Scale of finance plus crop insurance per acre ₹.22,000)
4. Investment / Allied Activities :

   i. Establishment 1+1 Dairy Unit in 1st Year (Unit cost : ₹.50,000)

   ii. Purchase of Tractor in 1st Year (Unit Cost : ₹.6,00,000)

2. **Assessment of Card Limit**

   (i) ***Crop loan Component***

Cost of cultivation of 5 acres of Paddy, 5 Acres of Groundnut and 5 acres of Sugarcane	:	₹ 2,15,000
Add : 10% towards post-harvest / household expense / consumption	:	₹ 21,500
Add : 20% towards farm maintenance	:	₹ 43,000
Total Crop Loan limit for 1st year	:	**₹ 2,79,500**
Loan Limit for 2nd year		
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 2,79,500 i.e., 27,950)	:	₹ 27,950
	:	**₹ 3,07,450**
Loan Limit for 3rd year		
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 3,07,450 i.e., 30,750)	:	₹ 30,750
	:	**₹ 3,38,200**
Loan Limit for 4th year		
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 338200 i.e., 33,800)	:	₹ 33,800
	:	**₹ 3,72,000**
Loan Limit for 5th year		
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 3,72,000 i.e., 37,200)	:	₹ 37,200
	:	**₹ 4,09,200**
Say....	:	**₹ 4,09,000**
(A)		

   (ii) **Term loan component :**

1st Year : Cost of 1 +1 Dairy Unit	:	₹ 1,00,000
: Purchase of Tractor	:	₹ 6,00,000
Total term loan amount	**....(B)**	**₹ 7,00,000**

Maximum Permissible Limit /

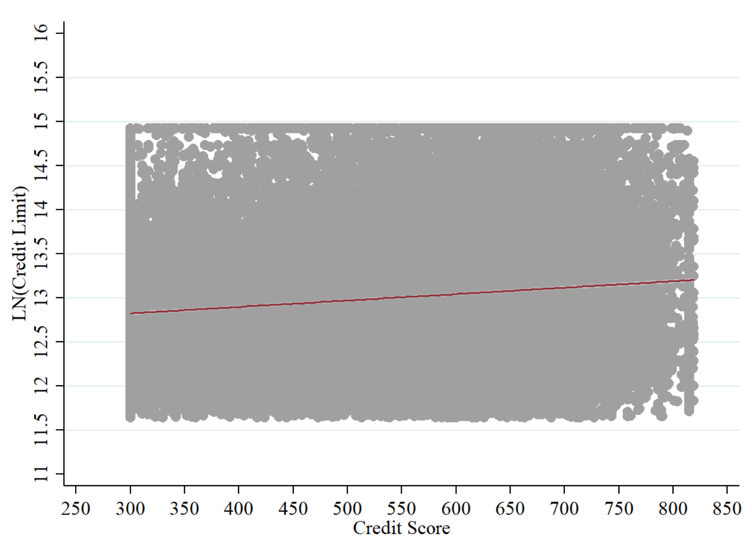
Kisan Credit Card Limit (A) +(B) : **₹ 11,09,000**

Drawing Limit will be reduced every year based on repayment schedule of the term loan(s) availed and withdrawals will be allowed up to the drawing limit.

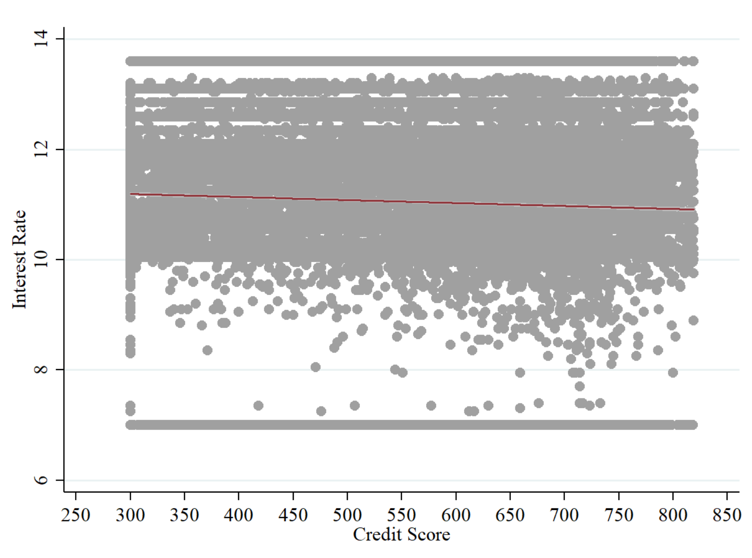
The figure presents the illustration for computing the credit limit for kisan credit cards. This illustration is taken from the 2017 RBI circular and can be accessed at LINK The illustration provides the details for setting the credit limit for a one acre farm with entire land under paddy cultivation.

D.2.2 Relationship between Creditworthiness, Credit Limit & Interest Rates on KCC

Figure D.4: Relationship between Credit Limits and Interest Rates on Kisan Credit Cards and credit worthiness



(a) Credit Limit



(b) Interest Rates

The figure presents the relationship between credit limits and interest rates on kisan credit cards (KCC) and the credit worthiness of the farmers. The sample includes farmers in the states of Punjab, Maharashtra and Karnataka before March of 2019. The data on credit limit and interest rates comes from the sample bank. The gray dots represents the scatter plot and the red line represents the best fit line

D.2.3 Effect of the Policy on KCC Credit Limit

Table D.2: Effect of the Policy on Credit Limit of Kisan Credit Cards

Dep Var: LN(KCC Credit Limit)	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.0591	0.0491	0.0327	0.0002	0.0004
	(0.0597)	(0.0618)	(0.0514)	(0.0002)	(0.0003)
Treatment	-0.1682	-0.1685	0.0124		
	(0.1424)	(0.1395)	(0.1203)		
Post	0.0372				
	(0.0572)				
Farmer FE				Yes	Yes
Month FE		Yes		Yes	
ZIP × Month FE			Yes		Yes
# Obs	28,839	28,839	28,021	28,839	28,017
R^2	0.0029	0.0423	0.6163	0.9996	0.9998

The table estimates the relative effect of cash transfers under PM-KISAN on the credit limit on kisan credit cards (KCC) for the treatment and control groups according to the following specification:

$$LN(\text{KCC Credit Limit}_{i,t}) = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $LN(\text{KCC Credit Limit}_{i,t})$ denotes the natural logarithm of the dependent variable of interest (credit limit on KCC) measured for farmer i at time (month) t. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. Column (1) reports the estimate of β without any fixed effects. Columns (2), (3), and (4) report the estimate of β by sequentially adding fixed effects, to finally estimate key equation highlighted above in Column (5). The estimation sample comprises of farmers with valid KCCs in the states of Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

D.3 Effect of PM-KISAN on Expected Lending Standards

Table D.3: Effect of PM-KISAN on (Expected) Lending Standards: Evidence from Field Survey

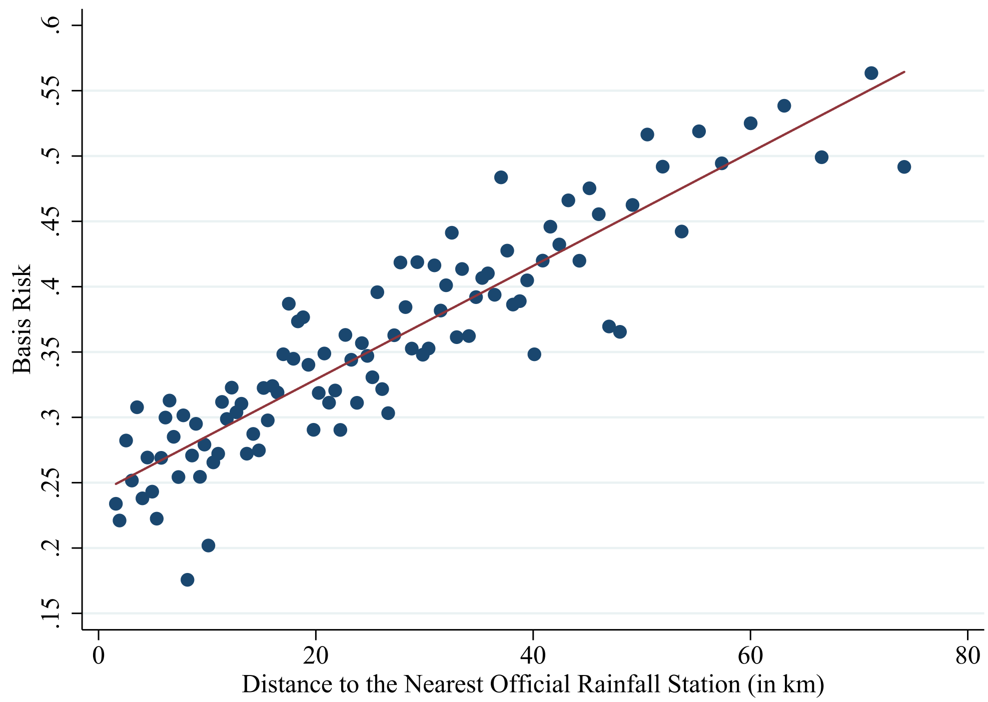
	All Respondents	PM-KISAN Recipients	
		Yes	No
Tighten	47.27	47.05	47.53
No Change	24.81	26.04	23.32
Loosen	27.92	26.91	29.14
# Obs (Respondents)	3,990	2,185	1,805

The table presents the percentage of respondents choosing their response to the effect of PM-KISAN transfers on (expected) lending standards. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey for PM-KISAN recipients was – *"With respect to additional loans, please indicate how banks will change their lending standards (loan application acceptance and interest rates) due to PM-KISAN: a. Tighten, b. Loosen, c. No Change"* The precise question of the survey for PM-KISAN non-recipients was – *"With respect to additional loans, please indicate how banks will change their lending standards (loan application acceptance and interest rates) due to you receiving a sum of ₹6,000 each year: a. Tighten, b. Loosen, c. No Change"* This question was asked to all respondents. Column (1) reports the percentage of respondents choosing each option. Columns (2) and (3) present the percentage of respondents choosing each option that received and did not receive PM-KISAN transfers, respectively.

D.4 Role of Downside Risk

D.4.1 Basis Risk and Distance to Nearest Rainfall Station

Figure D.5: Basis Risk and Distance to Nearest Rainfall Station



The figure presents the relationship between basis risk and the distance of the ZIP code from the nearest official rainfall station. We map the latitude and longitudes of the ZIP codes to the latitude and longitude of the nearest official rainfall station. We compute the model R^2 of the regression of total monthly rainfall in a ZIP code on the total monthly rainfall at the nearest official rainfall station. We define basis risk as one minus the model R^2. The data on locations and the monthly total rainfall for official rainfall stations comes from the Indian Meteorological Department.

D.4.2 Effect of the Policy on Application Acceptance: Heterogeneity by Risk & Incomplete Insurance Markets

Table D.4: Effect of the Policy on Application Acceptance: Heterogeneity by Risk & Incomplete Insurance Markets

Panel A: Heterogeneity by Rainfall (Drought) Risk				
Dep Var: Application Accepted (=1)	(1)	(2)	(4)	(4)
	All Regions	Low Risk	High Risk	All Regions
Treatment × Post	-0.0008	-0.0049	0.0039	
	(0.0048)	(0.0063)	(0.0093)	
Treatment × Post × Low Risk				0.0049
				(0.0063)
Treatment × Post × High Risk				0.0039
				(.0093)
Farmer FE	Yes	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes	Yes
# Obs	779,592	452,084	192,984	779,592
R^2	0.1032	0.1038	0.0835	0.1032
Adj. R^2	0.0146	0.0177	0.0031	0.0146

Panel B: Heterogeneity by Basis Risk				
Dep Var: Application Accepted (=1)	(1)	(2)	(4)	(4)
	All Regions	Low Risk	High Risk	All Regions
Treatment × Post	-0.0008	-0.0090	-0.0183	
	(0.0048)	(0.0081)	(0.0165)	
Treatment × Post × Low Risk				-0.0090
				(0.0081)
Treatment × Post × Low Risk				-0.0183
				(.0165)
Farmer FE	Yes	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes	Yes
# Obs	779,592	251,438	63,448	779,592
R^2	0.1032	0.0976	0.1066	0.1032
Adj. R^2	0.0146	0.0070	0.0199	0.0146

The table estimates the relative effect of cash transfers under PM-KISAN on credit market outcomes for the treatment and control groups according to the following specification:

$$y_{i,t} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ (= 1) denotes the dependent variable of interest measured for farmer i at time (month) t. The dependent variable of interest is a binary variable taking a value of one if the inquiry for a farmer i during month t converted into a loan within 60 days of the inquiry. The variable $Treatment_i$ is an indicator equal to one for landowning farmers, who were eligible for the program, and zero for non-landowning farmers. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP code × month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The estimation sample includes farmers in Punjab, Maharashtra, and Karnataka from March 2018 through February 2020. Panel A presents the results on heterogeneity by risk measured using rainfall (drought) risk. We measure rainfall risk at the ZIP code level. For each month, we calculate average precipitation across all 0.25 degrees by 0.25 degrees latitude/longitude grid cell within the boundaries of the ZIP code. We translate ZIP code level precipitation measures into z-scores for the monsoon periods from 2014 through 2017. ZIP code-year observations with z-score values below the five percentile value refer to extreme low rainfall events and are defined as droughts. The average frequency of droughts over this period serves as our measure of the probability of drought for each ZIP code. ZIP codes above the median drought probability are defined as high-risk areas, while those below it are low-risk. Panel B presents the results on heterogeneity by basis risk. We measure basis risk for each ZIP code by running the regression of monthly rainfall in the ZIP code on monthly rainfall at the nearest rainfall station during the monsoon season. We define ZIP code-level basis risk as one minus the regression R^2. Columns (1), (2), and (3) uses the sample of all regions, farmers living in regions with low risk, and farmers living in regions with high risk, respectively. Column (4) uses the sample of all regions. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

D.5 Effect on Risk Taking

D.5.1 Adoption of New Farming Techniques: Organic Farming

Table D.5: Adoption of New Farming Techniques: Organic Farming

Dep Var: Adoption of Organic Farming	(1)	(2)	(3)	(4)
Complier × Post	0.0037***	0.0049***	0.0038***	0.0040***
	(0.0013)	(0.0011)	(0.0010)	(0.0010)
Village FE	Yes	Yes	Yes	Yes
District Pair X Year FE	Yes			
District Pair X Year X Cultivable Area Percentile FE		Yes		Yes
District Pair X Year X # Farmers Percentile FE			Yes	Yes
# Obs	182,871	182,871	182,871	182,871
R^2	0.9353	0.9419	0.9443	0.9494
Adj. R^2	0.9152	0.9205	0.9243	0.9281
Sample Mean	0.0840	0.0840	0.0840	0.0840
Sample SD	0.2172	0.2172	0.2172	0.2172

The table estimates the relative effect of PM-KISAN cash transfers on adoption of new farming techniques in villages located in complier and non-complier districts according to the following specification:

$$y_{v,t} = \beta \cdot Complier_v \times Post_t + \theta_v + \theta_{p(v \in p),t} + \varepsilon_{d,s,t}$$

where $y_{v,t}$ denotes the dependent variable of interest measured for village v in year t. The key dependent variable is the fraction of farmers engaging in organic farming. $Post_t$ takes a value of one for years after fiscal year 2019 and zero otherwise. $Complier_v$ takes a value of one for sample villages that are outside the state of West Bengal. θ_v denotes village fixed effects.$\theta_{p(v \in p),s,t}$ denotes district-pair × year fixed effect. Each district-pair (p) consists of two contiguous districts that lie on the opposite state of the state border of West Bengal, such that one of the districts in the pair lies inside West Bengal. Each year refers to fiscal year starting in April of the calendar year and ending in the March of the next calendar year. The sample employed in the analysis is shown in Appendix Figure B.2. The data for this analysis is village-level data and comes from the survey data collected under Mission Antyodaya for fiscal year 2019 starting in March of 2018 and fiscal year 2020 starting March of 2019. Standard errors clustered at the district-pair and month level are reported in parentheses. All continuous variables are winsorized at 1% level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

D.5.2 Effect on Risk Taking: Evidence from Field Survey

Table D.6: Effect on Risk Taking: Evidence from Field Survey

Effect of PM-KISAN on Risk Taking	All Respondents	PM-KISAN Recipients	
		Yes	No
Increase	40.70	37.85	44.16
Decrease	34.16	33.09	35.46
No Change	25.14	29.06	20.39
# Obs (Respondents)	3,990	2,185	1,805

The table presents the percentage of respondents choosing their response to the effect of PM-KISAN transfers on risk-taking. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey for PM-KISAN recipients was – *"An example of a high-risk and high-return strategy in agriculture is growing cash crops such as cotton or using tractors. Cash crops are risky because they are heavily dependent on rainfall but if the rainfall is normal, they give a very high return. How has the PM-KISAN money changed the amount of high-risk and high-return activity you are willing to take in agriculture? a. Increase, b. Decrease, c. No Change."* The precise question of the survey for PM-KISAN non-recipients was – *"An example of a high-risk and high-return strategy in agriculture is growing cash crops such as cotton or using tractors. Cash crops are risky because they are heavily dependent on rainfall but if the rainfall is normal, they give a very high return. How will the ₹6,000 annually change the amount of high-risk and high-return activity you are willing to take in agriculture? a. Increase, b. Decrease, c. No Change."* This question was asked to all respondents. Column (1) reports the percentage of respondents choosing each option. Columns (2) and (3) present the percentage of respondents choosing each option that received and did not receive PM-KISAN transfers, respectively.

D.5.3 Effect on Precautionary Savings: Evidence from Field Survey

Table D.7: Effect on Precautionary Savings: Evidence from Field Survey

Effect of PM-KISAN on Precautionary Savings	All Respondents	PM-KISAN Recipients	
		Yes	No
Increase	53.06	52.81	53.35
Decrease	23.86	26.68	27.92
No Change	23.08	20.50	18.73
# Obs (Respondents)	3,990	2,185	1,805

The table presents the percentage of respondents choosing their response to the effect of PM-KISAN transfers on risk-taking. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey for PM-KISAN recipients was – *"How did the following change for you after receiving ₹6,000 annual money under PM-KISAN? Please select either increase/decrease/no change for each question. Saving money for bad times such as drought/medical emergencies, etc."* The precise question of the survey for PM-KISAN non-recipients was – *"How would the following change for you after receiving ₹6,000 annual money? Please select either increase/decrease/no change for each question. Saving money for bad times such as drought/medical emergencies, etc."* This question was asked to all respondents. Column (1) reports the percentage of respondents choosing each option. Columns (2) and (3) present the percentage of respondents choosing each option that received and did not receive PM-KISAN transfers, respectively.

Appendix E Dynamic Model

We rationalize our findings by estimating a version of the dynamic partial-equilibrium model of investment, financed with credit, in Herranz, Krasa, and Villamil (2015), which features cost of default. We extend this framework by incorporating – (1) entrepreneurs, or farmers, with heterogeneous productivity or gross returns, and (2) the presence of frequent disaster shocks, such as droughts. Thus, in this model the optimal investment balances the returns on investment and the consumption loss incurred in case of default. We start with the description of model setup including the timeline and the farmer's problem. We then move on to the discussion of the importance of cost of default in determining the investment decision. Finally, we consider guaranteed income.

E.1 Model Setup

Consider an economy with discrete time periods, t=0,1,2,... We begin with the problem of infinitely-lived individuals, farmers hereafter, with the discount rate β, that maximize their lifetime utility denoted by $u(c_t)$ derived from consuming c_t in period t. All farmers have an initial endowment of personal funds w_o and a unit mass of land for cultivation. Farmer's gross returns per unit of capital (K_t) is given by random variable X that is independently and identically distributed across farmers with cumulative distribution function (cdf) $F(x)$ and probability density function (pdf) $f(x)$, which is strictly positive on support $[\underline{x}, \overline{x}]$ with $\underline{x} = 1$ and $\overline{x} > 1$.[24] Farmers experience disaster shock with a probability of p each period. The net return on capital is zero in case a disaster materializes.[25]

In all periods $t \geq 1$, the farmer's net worth w_t is derived from the return on capital from farming and an alternative investment opportunity with return r. Since w_t includes less liquid assets that are costly to use, we assume that $r > r_f$, where r_f is the risk-free rate and both r and r_f are exogenous. Net worth is known at the beginning of each period. The farmer invests capital $K > 0$. At any time t, the farmer chooses the fraction of self-financed capital (ϵ) and the fraction financed using debt $(1 - \epsilon)$. A risk-neutral competitive lender that makes one-period loans provides debt with an elastic supply of funds. The amount self-financed by the farmer is given by ϵK, and her opportunity cost of funds is $\epsilon K(1 + r)$. For the total amount of funds borrowed, $(1 - \epsilon)K$, the farmer owes $\bar{v}K$ at the end of the period. Thus, the loan rate is given by $r_L = \bar{v}/(1 - \epsilon) - 1$. The face value of debt $\bar{v}$, or equivalently r_L, is determined endogenously from the lenders' break-even condition, given the risk-free rate on the lenders' cost of funds r_f. We assume that $r_L > r$, i.e., the cost of debt is more relative to self-financing if a firm remains solvent. While self-financing offers a cost advantage relative to debt-financing, the latter provides protection against loss of personal funds in case of default.

After production, the farmer has assets xK and liabilities $\bar{v}K$, and she chooses whether to repay the loan or default. While the farmer can use her personal funds to avoid default, she cannot be forced to do so. When a default occurs, the lender captures $1 - \gamma$ fraction of farm assets, where γ is the deadweight loss. Moreover, the farmer is excluded from the credit markets for T periods as her act of default would be indicated in her credit record for a period of time, during which the creditors would be unwilling to lend to her.

E.2 Timeline

The timing of events for farmer's production is as follows:

1. Beginning of period t (ex ante) farmer's net worth is w. There are two cases:

[24] The random variable x, can be considered as farmers' productivity.

[25] In our setting, one can think of these disasters as frequent climate-based shocks farmers face, such as droughts.

(a) The farmer did not default in any of the previous T periods. Choose consumption C, firm assets K, self-finance ϵ (debt is $1-\epsilon$), and amount $\bar{v}K$ to repaid at the end of the period, subject to the lender receiving at least ex ante expected payoff $(1-\epsilon)K\left(1+r_f\right)$.

(b) The farmer defaulted m periods ago. The farmer cannot produce for the next $T-m$ periods. Hence, only current consumption is chosen.

2. At the end of period t (ex post) the return, x, is realized and total end-of-period income is xK. The farmer must decide whether or not to default.

(a) *If default:* Only capital assets are seized. The farmer is left with personal net worth $(1+r)(w-\epsilon K-C)$, invested at outside interest rate r.

(b) *If no default:* Farmer's net worth is $K(x-\bar{v})+(1+r)\ (w-\epsilon K-C)$, which includes both net income from the farm and the return on personal assets.

E.3 Farmers Problem

Consider the optimization problem of a farmer, with a given coefficient of risk aversion ρ and net worth w at the beginning of the period. We state the problem recursively. Our initial goal is to determine the structure of the value function. If default occurred in the previous T periods, then the state is given by (D,m,w), where m is the number of periods since default and D denotes default. Otherwise, the state is given by (P,w), where P denotes farmer continuing to produce. Denote the value functions by $V_{D,m}(w)$ and $V_P(w)$, respectively. After T periods the firm can restart; thus $V_{D,T}(w)=V_P(w)$. Let $\mathfrak{D}$ denote the set of asset return realizations x for which default occurs, with complement $\mathfrak{D}^c$. We specify the problem for each default state.

E.3.1 Case I:

If the firm did not default in the previous T periods, the individual solves the following problem.

$$\begin{aligned} V_P(w)=\max_{C\geq 0,K\geq 0,0\leq\epsilon\leq 1,\bar{v}} &\left\{u(C)+\beta\left[\int_{\mathfrak{D}} V_{D,1}((1+r)(w-\epsilon K-C))dF(x)\right.\right.\\ &\left.\left.+\int_{\mathfrak{D}^c} V_S(K(x-\bar{v})+(1+r)(w-\epsilon K-C))dF(x)\right]\right\} \end{aligned} \tag{E.1}$$

subject to

$$\int_{\mathfrak{D}}(1-\gamma)x dF(x)+\int_{\mathfrak{D}^c}\bar{v}dF(x)\geq(1-\epsilon)\left(1+r_f\right), \tag{E.2}$$

$$\mathfrak{D}\equiv\left\{x: V_{D,1}((1+r)(w-\epsilon K-C))>V_P(K(x-\bar{v})+(1+r)(w-\epsilon K-C))\right\}, \tag{E.3}$$

$$(1-\epsilon)K\leq bw \tag{E.4}$$

The objective of farmer's problem stated in equation E.1 is to maximize the utility of current consumption plus the discounted continuation value of end-of-period net worth. Constraint E.2 comes from the lender's break-even condition and ensures that the lender is willing to supply funds. Specifically, constraint E.2 ensures that the fraction, $1-\epsilon$, of funds the lender invests in the firm must earn at least reservation returns $1+r_f$. the first term in constraint E.2 indicates the fraction $(1-\gamma)$ seized or the bank's payoff in case of default and the second term is the fixed debt repayment when the firm is solvent. Constraint E.3 specifies the ex-post optimality of the default decision, i.e., a farmer defaults if and only if her expected continuation payoff after default exceeds her continuation payoff from solvency. Note that if $K = 0$, the farmer does not run the farm, inequality E.3 is never satisfied and the bankruptcy set is empty. Constraint E.4 is the borrowing constraint that limits loans to a fraction b of farmers' net worth.

E.3.2 Case II:

Now consider the problem of a firm that defaulted $m \leq T$ periods ago. After T periods the firm can operate again; thus $V_{D,T}(\cdot) = V_P(\cdot)$. Let w' denote net worth next period.

$$V_{D,m}(w) = \max_{w' \geq 0} \left\{ u\left(w - \frac{w'}{1+r}\right) + \beta V_{D,m+1}\left(w'\right) \right\} \tag{E.5}$$

The objective of farmer's problem stated in equation E.5 is to maximize expected ex-ante utility with budget constraint $C(1 + r)+ w' \leq w(1 + r)$ substituted in, satisfied at equality. If default occurred, the farmer cannot produce for T periods.

E.3.3 Solving farmer's problem

The farmer's problem outlined in case I and II is difficult to solve, directly. Therefore, we utilize the property that the constant relative risk aversion (CRRA) utility is scalable in net worth to determine the structure of the value function. This insight allows us to rewrite farmer's problem states in case I an II as a one-dimensional fixed-point problem.

Theorem E.1. *Suppose that the farmer has CRRA ρ.*

1. *Let $v_p = V_P(1)$ and $v_{d,m} = V_{D,m}(1)$. Then we get $V_P(w) = w^{1-\rho} v_p$ and $V_{D,m}(w) = w^{1-\rho} v_{d,m}$.*
2. *Let c, k, ϵ, and $\bar{v}$ be the optimal choices of consumption, production scale, equity structure, and debt face value starting with initial wealth $w = 1$ in a period. Then $C = cw, K = kw, \epsilon$, and $\bar{v}$ are the optimal values when starting with wealth w.*

Now, it is sufficient to determine v_p and $v_{d,m}$ in order to determine the entire value function. Using pcase II, it is straightforward to compute $v_{d,m}$ as a function of v_p. In problem 1 we need only $v_{d,1}$, the continuation utility given that default was just announced, and v_p. To simplify notation, write v_d for $v_{d,1}$. Thus, it remains to specify the recursive optimization problem when starting with an initial wealth of $w = 1$. Also, we can replace C and K by c and k, the values obtained when starting with one unit of wealth. Thus we can rewrite the problem as follows, such that all endogenous variables are now expressed as a fraction of net worth w.

$$\begin{aligned} v_p = \max_{c \geq 0, k \geq 0, 0 \leq \epsilon \leq 1, \bar{v}} & \left\{ \frac{c^{1-\rho}}{1-\rho} + \beta v_d \int_{\underline{x}}^{x^*} [(1+r)(1-\epsilon k - c)]^{1-\rho} dF(x) \right. \\ & \left. + \beta v_p \int_{x^*}^{\bar{x}} [k(x - \bar{v}) + (1+r)(1-\epsilon k - c)]^{1-\rho} dF(x) \right\} \end{aligned} \tag{E.6}$$

subject to constraint E.2 and

$$x^* = \max\left\{ \bar{v} - \left[1 - \left(\frac{v_d}{v_p}\right)^{1/(1-\rho)}\right] \frac{(1+r)(1-\epsilon k - c)}{k}, \underline{x} \right\}, \tag{E.7}$$

$$c + \epsilon k \leq 1, \tag{E.8}$$

$$(1-\epsilon)k \leq b. \tag{E.9}$$

The objective of the problem outlined in equation E.6 is to maximize the utility of current consumption and the discounted value of end-of-period net worth, with default set $[\underline{x}, x^*]$ and continuation set $[x^*, \bar{x}]$. Constraint E.2 is lender's individual rationality, which binds by lemma 1. Constraint E.7 is the optimal default cutoff and follows from lemma 2. The default cutoff equation is valid only if $k > 0$; if $k = 0$, the individual does not operate a firm. Constraints E.8 and E.9 denote the feasibility and the borrowing constraints, respectively. We direct the readers to Herranz, Krasa, and Villamil (2015) for discussion on the existence and uniqueness of the solution of the farmer's problem outlined in E.6 subject to constraints E.2, E.7, E.8, and E.9.

E.3.4 Guaranteed income in the model

The introduction of guaranteed income (GI) into the model increases the personal funds available at the end of each period (known at the beginning of each period). In the timeline, with the introduction of GI (denoted by τ), the farmer decision on whether or not to default changes as follows:

1. *If default:* Only capital assets are seized. The farmer is left with personal net worth invested at outside interest rate r and GI, i.e., $(1 + r)(w - \epsilon K - C) + \tau$.

2. *If no default:* Farmer's net worth is $K(x - \bar{v}) + (1 + r)(w - \epsilon K - C) + \tau$, which includes both net income from the farm, the return on personal assets and GI.

The farmer problem in E.6 can be leveraged to find the effects of GI on the farmers' decisions. Assuming that GI provides additional income of τ per period when starting with initial wealth of $w = 1$, the farmer's problem can be written as

$$v_p = \max_{c\geq 0, k\geq 0, 0\leq \epsilon\leq 1, \bar{v}} \left\{ \frac{c^{1-\rho}}{1-\rho} + \beta v_d \int_{\underline{x}}^{x^*} [(1+r)(1-\epsilon k - c) + \tau]^{1-\rho} dF(x) \right.$$
$$\left. + \beta v_p \int_{x^*}^{\bar{x}} [k(x-\bar{v}) + (1+r)(1-\epsilon k - c) + \tau]^{1-\rho} dF(x) \right\}$$

subject to constraint E.2 and

$$x^* = \max\left\{ \bar{v} - \left[1 - \left(\frac{v_d}{v_p}\right)^{1/(1-\rho)}\right] \frac{(1+r)(1-\epsilon k - c) + \tau}{k}, \underline{x} \right\},$$
$$c + \epsilon k \leq 1,$$
$$(1-\epsilon)k \leq b.$$

E.4 Mechanism – Characterizing Default

Following Herranz, Krasa, and Villamil (2015), we now derive the relationship between the default decision and farmer characteristics. The default cutoff x^* given by constraint E.7 can be decomposed into three distinct effects that we analyze individually. Let c_d and c_p be the constant consumption over time that would result in a utility of v_p or v_d, respectively. Then the ratio of consumptions c_d and c_p is given by

$$\frac{c_d}{c_p} = \left(\frac{v_d}{v_p}\right)^{1/(1-\rho)}.$$

Suppose that the default occurs with positive probability, that is, $x^* \geq \underline{x}$, then the constraint E.7 can be written as

$$x^* = \underbrace{\bar{v}}_{\textit{ex ante debt}} - \underbrace{\left(\frac{c_p - c_d}{c_p}\right)}_{\textit{consumption loss}} \times \underbrace{\left(\frac{(1+r)(1-\epsilon k - c)}{k}\right)}_{\textit{personal funds to production scale ratio}}$$

Consider the three forces that determine default cutoff x^*.

1. *Ex ante debt:* In static models, agents default if x is less than debt $\bar{v}$, and hence all firms with negative equity default (cf. Townsend 1979; Gale and Hellwig 1985).

2. *Consumption loss:* This term measures the percentage decline in consumption from losing the firm, where c_p and c_d are the constant consumption streams that yield the same utility as the entrepreneur's actual consumption in non-default and default states, respectively.

3. *Personal funds to production scale ratio:* To avoid default, the farmer can inject personal funds held outside the production to cover the debt $\bar{v}$. This term measures the farmer's ability to utilize the personal funds to avoid default.

E.5 Mapping the Model to Data

Table E.1 presents the list as well as the numerical values of parameters exogenously fixed in the calibration. The fixed parameters in the model are the discount factor $\beta = 0.97$, the borrowing constraint $b = 0.35$ i.e., farmer can take on a maximum debt of 35% of her net worth, the default exclusion parameter $T = 7$ (in India, default is removed from a credit record after 7 years) and the default dead weight loss $\gamma = 0.1$ (as in Boyd and Smith (1994)). The effective guaranteed income is taken to be 10% of initial wealth. We fix the lender's opportunity cost of short-term funds, denoted by r_f, as the average savings rate on one-year time-deposits. We fix farmer's opportunity cost of funds, denoted by r, using the average interest rates on public provident funds (PPF) over 2017-2020.

The value of return pdf $f(x)$ is computed from the data. Specifically, we use the estimated distribution of returns on capital by combining the natural experiment with the data. The distribution is shown in table E.2 for positive returns. Additionally, we fix probability of disaster as 0.22 based on the observed probability of drought in our data. Combining the probability of disaster $p = 0.22$ (in which case the net returns are zero) and the distribution of returns on capital, we compute the pdf $f(x)$. Specifically, $x = 1$ denotes returns on capital after a disaster, i.e., $f(1) = 0$.

The farmer's willingness to bear risk is crucial in determining the uptake of loans and the production scale conditional on the distribution of returns. Therefore, we extend the model specified for a certain risk aversion parameter to be heterogeneous with respect to risk aversion parameter (ρ), such that $\rho \sim \mathcal{N}(\mu, \sigma^2)$, where μ denotes the mean and σ denotes the standard deviation. We begin by constructing the effect of guaranteed income on debt for a given distribution of risk aversion parameter. We begin by assigning the mean μ to be equal to 1.7 following Mazzocco (2005). Then we estimate the standard deviation (σ) of the risk aversion distribution to match the average effect of guaranteed income on debt in the data conditional on the exogenous model parameters shown in Table E.1.[26] Table E.3 shows the values of the mean (μ) and standard deviation (σ) of the risk aversion distribution.

E.6 Risk Aversion & Heterogeneity in the Effect of Guaranteed Income

This section presents the results of the effect of guaranteed income on capital (shown in Figure E.1a) and debt (E.1a) by risk-aversion. The key takeaway from these figures is that the farmers with high risk-aversion tend to increase their capital and credit more relative to farmers with low risk-aversion.

[26]Additionally, we restrict the risk-aversion values to lie within 0 and 5.

Table E.1: Fixed Parameters

Parameter	Interpretation	Value	Comment
β	Discount factor	0.97	
b	Borrowing Constraint	0.35	
T	Default exclusion period	7	Indian Credit Bureau
γ	Default deadweight loss	0.10	Boyd and Smith (1994)
τ	Guaranteed Income (GI)	0.10	
p	Probability of diaster	0.22	Data
r_f	Lender's opportunity cost	5.50%	Average rate on 1-year time deposits
r	Farmer's opportunity cost	8.00%	Average interest rate on PPF
$f(x)$	Returns on capital	–	See Table E.2

The table presents the list as well as the fixed values of parameters exogenously fixed in the calibration.

Table E.2: Distribution of Returns on Capital

	Annualized Returns on Capital										
	p5	p10	p20	p30	p40	Average	p60	p70	p80	p90	p95
Data	0.38%	5.30%	11.53%	16.23%	20.39%	24.39%	28.52%	33.07%	38.60%	46.61%	53.56%

The table presents the distribution of the returns on capital estimated in the data.

Table E.3: Calibrated Parameters

Parameter	Interpretation	Model
μ	Mean of distribution of ρ (fixed)	1.7
σ	Standard deviation of distribution of ρ	0.96

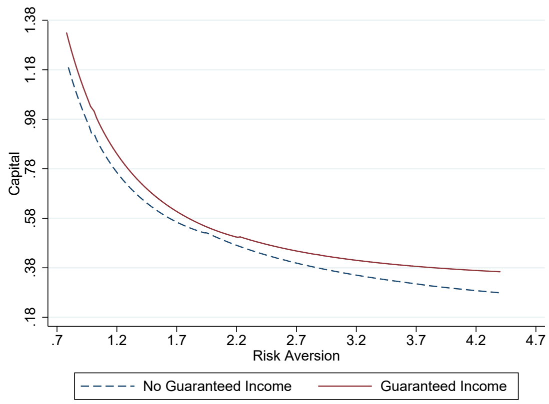
The table presents the mean and standard deviation for the risk aversion distribution.

Table E.4: Model Fit

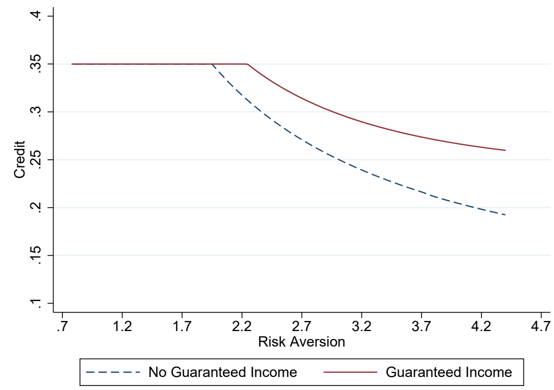
Note	Description	Model	Data
Targetted Moment	% Change in Debt	0.17	0.17
Untagretted Moment	% Change in Capital	0.11	0.10
	Change in Default Probability	-0.004	-0.013

Empirical targets in the calibration

Figure E.1: Risk Aversion and Effect on Capital and Credit



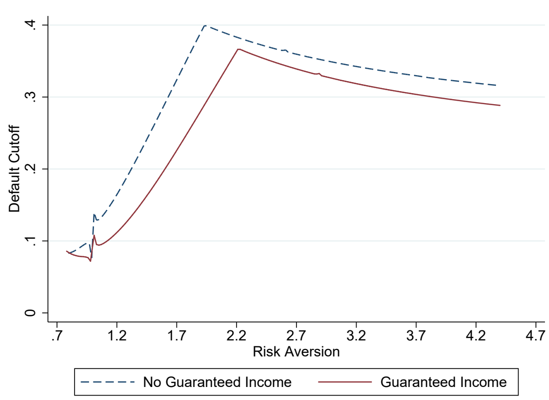
(a) Effect on Capital



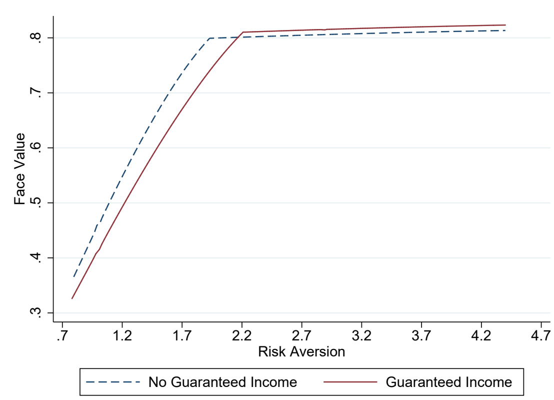
(b) Effect on Credit

The figure presents the estimates for capital and debt changes in the model due to the introduction of guaranteed income.

Figure E.2: Risk Aversion and Effect on Default Cutoff and Face Value



(a) Effect on Default Cutoff (x^*)



(b) Effect on Face Value ($\overline{v}$) of Credit

The figure presents the estimates for capital and debt changes in the model due to the introduction of guaranteed income.