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 $10.12 increase in formal borrowing representing 59% 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 imply that uninsured income risk constrains 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 (Hoynes and Rothstein, 2019), 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 (Ramey, 2011, 2019). 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 entrepreneurs' financial constraints (Evans and Jovanovic, 1989) and their risk-aversion combined with uncertainty (Kihlstrom and Laffont, 1979) can result in under-investment. Proponents argue that guaranteed income will encourage investment by resolving constraints and increasing financial resilience. Moreover, as noted in Jappelli and Pistaferri (2010, 2017), positive permanent income shocks can increase spending on durables financed through credit. This is supported by empirical evidence from Aaronson, Agarwal, and French (2012); Agarwal and Qian (2014, 2017), and Agarwal et al. (2025) among others. Guaranteed income is also a permanent income shock and could increase investment through a similar channel. 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.

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.

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 (PMKSN), or the Prime Minister's Farmer's Tribute Fund, provides all landowning farmers with an annual, unconditional transfer of ₹6,000 (≈ $285 in PPP terms). Four features of this policy enable credible identification. First, although PMKSN 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) × 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN, 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 PMKSN 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, PMKSN 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 and credit card utilization by \$3.33. This implies a total increase in credit of \$10.12, which is equivalent to 58.68% 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, our upper-bound estimate suggests that the policy induced a total increase in capital of \$11.81, with \$8.48 attributable to term loans and the remainder to credit card financing. This investment response corresponds to roughly 68.52% of the perpetuity value of the transfer. Back-of-the-envelope calculations based on observed income gains imply a lower bound of the return to capital of about 14.90%.

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. The survey 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.

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 PMKSN. Our original survey of farmers supports this assumption.

We strengthen our evidence on the credit demand channel by taking a more direct approach of asking farmers in our survey 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. 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 PMKSN was the key driver of their increased borrowing. The lack of supply-side response is consistent with the prevalence of asset-based lending, instead of cash-flow based lending, in agriculture and other small businesses due to low contractility, small cash flow sizes, and the high cost of ex-post reorganization for lenders (Lian and Ma, 2021).

To further shed light on the underlying mechanism, we elicit the beliefs of PMKSN 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, PMKSN 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 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.

Lastly, 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.

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.[2] 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). While we view these channels as complementary and do not deny the presence of 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. This pattern is consistent with classical models, such as those discussed in Jappelli and Pistaferri (2010) and Jappelli and Pistaferri (2017), which predict higher credit-financed durable spending following a permanent increase in income. 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

[2] 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.

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.[3]

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.[4] 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.[5] The phenomenon has been dubbed the *Euler Equation Puzzle*, i.e., small-scale entrepreneurs in developing countries sometimes leave high expected-return investments 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

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

[4] 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).

[5] 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.

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. 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. 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.

2.1 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 (PMKSN, 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.[6] 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.

[6]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.

The policy is confined only to landowning farmers as the lack of systematic identifying data on landless farmers imposed legal restrictions on the GOI.[7] 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 PMKSN. 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 PMKSN 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 secretive process.[8] 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.

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

[8] 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.

3 Data

This section describes the various datasets employed in the paper.

3.1 Remote-sensing data on Agricultural Production

We use remote-sensing data to construct measures of unit-level (plot-level) agricultural production, as no such granular agricultural production data exists for India. This data comes from NASA's Earth Observation Satellite - Landsat 8. Specifically, we use Enhanced Vegetation Index (EVI) to construct our unit-level measures of agricultural production.

EVI is a chlorophyll-sensitive composite measure of plant matter generated by Landsat 8. The composites are created from all the scenes in each 8-day period beginning from the first day of the year and continuing to the 360th day of the year. Each pixel value is optimized considering cloud cover obstruction, the influence of background vegetation, image quality, and viewing geometry. We direct the readers to Huete et al. (2002) for details on the construction of an earlier version of EVI using 16-day EVI composites, and to Asher and Novosad (2020) for its usage in economics research.

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 construct unit-level measures of agricultural yields for the primary growing season of kharif that begins in June and ends in October of each year. We construct two measures using the 8-day composite based EVI values. Our first measure – maximum EVI – uses the maximum EVI value for the kharif season and our second measure is constructed by subtracting the average value of EVI during the initial weeks of kharif season from the maximum EVI value during the season. As noted in Asher and Novosad (2020), the two measures are highly correlated with each other and with real production measures.

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 $\times$ 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 $\times$ 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. 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 collects detailed data on all its retail and consumer banking customers working in the agricultural sector as farmers. Banks collect this data to comply with data requests on farmers from the Indian Parliament, to fulfill audit requirements under priority sector lending norms, and to meet other regulatory requirements related to financial inclusion under Pradhan Mantri Jan Dhan Yojana (PMJDY), crop insurance under Pradhan Mantri Fasal Bima Yojana (PMFBY), and the disbursal of kisan credit cards.

Our bank data is a sample of non-institutional farmers with active saving accounts.[9] The sample spans all farmers that have a savings account with our bank in one of the Indian states of Karnataka, Maharashtra and Punjab. Our analysis sample begins in March 2017, includes the policy change in March 2019, and ends in February 2020, just before the onset of COVID-19 pandemic. We require consumers to have at least one year of transaction records before March 2019 to be included in the sample. The final dataset is a sample of 64,761 farmers with 1.5 million farmer-by-month observations. The data contains a rich set of demographic and financial characteristics, such as age, gender, religion, ZIP code (and the corresponding city and state), account open date, credit scores, interest rates, and credit limits on their

[9]Following the World Bank standard, we define an account as active if it has at least one transaction per year.

kisan credit cards. The data also provides information on the landownership status of the farmers. This field is important for us to identify the treatment and control groups.

The data allows us to measure several farmer-level economic variables. The central variable of our analysis is the farmer's entrepreneurial income or simply income from work. We can observe several types of deposit inflows, including inflows due to loans, maturity of capital investments, and government cash transfers under PMKSN. We construct income from work as the sum of all cash inflows in the account after subtracting inflows due to disbursal of loans, maturity of financial markets investments, and transfers under PMKSN. Next, we verify that the majority of the transactions that we attribute as income from work are related to deposits made either physically or through the Unified Payments Interface (UPI).[10] We measure farmers' stock of savings as the average monthly balance in their savings account. We measure spending 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.

Table 1 presents the summary statistics of the key farmer-level variables in the bank data. In our dataset, the average farmer is approximately 50 years old and predominantly male. These farmers have maintained their accounts for an average duration of at least eight years by 2025. Their reported monthly income averages ₹9,300, with an average savings balance of ₹2,800 and monthly expenditures of about ₹9,200. The average credit score is 513 with at least 15% of farmers with a prior default tag as of March 2018.

A source of concern is whether the usage of bank data is appropriate in an emerging economy where several people in rural economies may be unbanked. We note that a focus on bank data likely includes a large share of the population of farmers in rural India. The 2018 Situation Assessment Survey (SAS) of farmers indicates that 98% of farmer households in rural India have at least one bank account (see Appendix Figure B.3). The extensive coverage of farmers by the banking sector can be attributed to the 2014 financial inclusion program (Pradhan Mantri Jan Dhan Yojana) and the 2016 demonetization episode. Moreover, in our original survey of farmers, all respondents reported having at least one actively used bank account.

Another source of concern is whether the usage of bank data can characterize the income of farmers, as a large part of their income may be given in cash and may not be reflected as deposits in their bank accounts. We view this as an important measurement error in our dependent variable and present some estimates of the extent of this issue as well as discuss its potential effects on the estimate. We begin by comparing the key metric of income in our bank data with the data reported by the 2018 Situation Assessment Survey (SAS) of farmers. Appendix Table B.2 reports the comparison. The average monthly income in the bank and the SAS data for the year 2018 are ₹9,297.50 and ₹15,330.98, respec-

[10] Unified Payments Interface (UPI) is an instant real-time payment system developed by the National Payments Corporation of India (NPCI), facilitating peer-to-peer and person-to-merchant transactions. UPI has been the primary mode of transaction for self-employed individuals in India since the demonetization in 2016. UPI is similar to Zelle in the United States. We direct readers to Dubey and Purnanandam (2023) for a detailed discussion on UPI.

tively. Specifically, the average value in bank data is 0.61 times the average value in the SAS survey. This difference can be attributed to the fact that our measure of banked income can only account for the proportion of income that is deposited in bank accounts, as well as the fact that we only observe accounts with one bank. Overall, the comparison indicates that our bank data can presumably characterize 61% of farmers' income in rural India.

To better characterize the extent of the measurement error, we directly ask farmers in a small second wave of our original survey about the percentage of their income deposited in bank accounts. Farmers report that, on average, they deposit 45.63% of their income in their bank accounts. Moreover, the distribution of the fraction of income deposited in bank accounts is similar across the recipients and non-recipients of PMKSN in our survey conducted three years after the treatment (see Appendix Figure B.4). Therefore, this error is likely to be systematically uncorrelated with the treatment status and thus exhibit properties similar to those of classical measurement error.[11]

There are two other caveats to be noted about our bank data. First, we can only observe the accounts of an individual with our bank. Our original survey of farmers indicates that 53.33% of farmers have only one bank account, whereas the rest have multiple accounts. As a result, there is likely to be another source of measurement error, and our bank data will underestimate key metrics. However, this measurement error is similar across the recipients and non-recipients of PMKSN three years after the treatment (see Appendix Table B.3 based on our original survey of farmers conducted in 2022). Therefore, the mis-measurement associated with capturing data from a single bank is likely to display properties similar to classical measurement error. Second, the access to credit is likely to be higher for our sample farmers relative to an average farmer. The bias in the access to credit is an artifact of our sample constructed using private bank data and the farmer identification methodology based on the disbursal of kisan credit cards, among others. We note that such a bias strengthens our empirical framework by providing an ideal setting to examine the effect of constrained credit demand on production activity for a sample of farmers with access to credit supply.[12]

3.4.1 Credit Bureau Data

We collect data on all loans disbursed to our sample farmers across all formal creditors. Specifically, we collect this data by inquiring about our sample farmers at TransUnion-CIBIL, India's largest consumer credit bureau. We collect all borrowing information for 43,619 ($\approx$ 50%) farmers in our bank sample. The data provides information on the date of loan disbursal, loan amount, the purpose of the loan, and the bank type of the disbursing loan. The data also provides the date of the inquiry for the farmers if a credit

[11]Note that unlike the classical measurement error in the independent variables that creates an attenuation bias, classical measurement error problem in the dependent variable does not bias the estimate. However, such an error does inflate the standard errors of the estimate, increasing the likelihood of Type II error.

[12]We do not argue that farmers in our bank data do not face borrowing constraints. We simply say that farmers in our sample are likely to face lower borrowing constraints relative to an average farmer.

inquiry was made. Credit cards and kisan credit cards are excluded from this data because the credit bureau reporting format for these products makes analysis difficult.[13]

The data captures all formal sector term loans, i.e., loans disbursed by banks (of any size), financial institutions (FI), self-help groups, etc. However, this dataset does not include loans from the informal sector, such as moneylenders or friends and family. This may be a serious concern if the predominant form of credit taken by farmers is from the informal sector, i.e., the measurement error is large, or if the measurement error systematically varies across PMKSN recipients and non-recipients. Appendix Table B.4 alleviates these concerns, with 60% of the farmers reporting using banks and other formal sources of credit as their biggest source of credit. Moreover, the reliance on formal sources of credit as the primary source is fairly similar for the treatment and the control group.

We analyze this data by collapsing at the farmer-by-month level and including zeros when no loan or inquiry was made. Our analysis of the borrowing data centers on four variables – the probability of getting a loan, the probability of inquiry, the number of loans, and 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 in India

We conduct an original large-scale survey of farmers in India. The survey was conducted between July and September 2022 in collaboration with Krishify, a social network for farmers that primarily operates through its Android-based application and farmer helpline.[14] The platform is the largest social network of Indian farmers spanning over 9.5 million users with a daily engagement time of 15 minutes. The application was only operated in Hindi at the time of the survey, the most widely spoken Indian language, with 43.6% of the Indian population, declaring it as their mother tongue.

Overall, the users of the application are a relatively good representation of a typical Indian farmer. We created a sample of respondents from application users to ensure representativeness across age groups, geographic location (state), and gender. Respondents were asked to participate in a short survey to understand their risk-taking and borrowing practices. The response rate was 21.7%. A representative random sample of 4,003 farmers was included in the final survey. Appendix Figure B.5 presents a comparison of our survey sample with all platform users. Of the 4,000 surveyed farmers, 53.44% of farmers reported receiving PMKSN transfers. Appendix Table B.5 provides other information on the characteristics of the surveyed farmers.

The survey was conducted in two parts. The first part was conducted online, through the Krishify application. In the online form, we collect socio-economic information and their general beliefs and perceptions related to risk-taking in agriculture, ability to meet basic needs, willingness to borrow, concerns about loan repayment, expected costs of default, and if they received PMKSN transfers. The second part

[13] We separately analyze the policy's effect on kisan credit cards using comprehensive data on credit limits, interest rates, and monthly credit utilization provided by our bank.

[14] The web-based platform of Krishify can be accessed here.

of the survey was a phone interview. In this interview, we inquired about the impact of PMKSN transfers on borrowing, investment, and risk-taking among farmers who received these transfers. We asked farmers who did not receive PMKSN transfers to assume that they received transfers identical to the policy and to respond to the identical set of questions in the telephonic survey. We use this set of counterfactual questions for the control group to evaluate their validity as a counterfactual to the treatment group and to examine the external validity of the estimate under the SANS framework of List (2020).

We follow the methodology of Colonnelli, Neto, and Teso (2025) to make respondents directly evaluate different hypothesized mechanisms (detailed discussion presented in section 5.4). Finally, we directly ask respondents whether the transfers improved their financial resilience, i.e., their ability to meet basic needs during bad times and if the policy improved their overall quality of life.

3.6 Other Data Sources

Additionally, we combine the above datasets with several other datasets that include monthly rainfall data at the ZIP code level from the Climate Data Service Portal, Geographic Information System (GIS) shapefiles for ZIP codes from the Indian Postal Services, gross sown area of different crops at district-level from the Ministry of Agriculture, data on fertilizer consumption at the district-level from the Ministry of Agriculture, village-level data on adoption of organic farming from Mission Antyodaya, and the 2019 Situation Assessment Survey (SAS) for farmers conducted by the National Sample Survey Office (NSSO). We present the summary statistics of the key variables alongside the corresponding regression results that utilize these variables.

4 Baseline Results

This section examines the impact of PM-KISAN (PMKSN) 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: PMKSN 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 PMKSN 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

This section employs a border discontinuity, or border district-pair, design across multiple outcome variables and datasets to document the effect of PMKSN implementation. We find that the transfers led to higher agricultural productivity, increased farm income, and greater investment and credit use among recipients after the transfers.

4.1.1 Effect on Agricultural Production

We begin our analysis by examining the effect of guaranteed income on agricultural productivity, leveraging a differences-in-discontinuity design that exploits the noncompliance of the PMKSN by the state of West Bengal. Specifically, we compare contiguous areas on either side of the state border, effectively comparing farmers that were and were not covered by the policy but exposed to similar cultural, geographic, climatic, or other economic conditions. The key identifying assumption of this test is that the variables influencing agricultural outcomes change smoothly across state boundaries, making boundary-adjacent plots a credible counterfactual.

We quantify agricultural productivity using remote-sensing EVI data, concentrating on narrow strips – that are 5-20 km long and 100 m wide – along the West Bengal border. These micro-units allow for precise comparisons between *complier* plots (outside West Bengal) and *non-complier* plots (inside West Bengal), which are similar in their environmental and geographic characteristics. The following empirical specification estimates the effect of the policy by comparing changes in EVI-based productivity before and after implementation across these neighbouring plots:

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

where, $ln(y_{i,t})$ is 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 plot level, controlling for time-invariant characteristics. 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 $\times$ year fixed effect, which ensures that the estimate β is identified using variation across two adjacent plots on either side of the border that share a common boundary.

Table 2 displays the estimation results for specification 1 across different bandwidths and plot lengths. Panels A, B, and C present results for plots measuring 5 km, 10 km, and 20 km in length, respectively. Columns (1) through (5) report findings using bandwidths of 1.0 km, 1.3 km, 1.5 km, 1.8 km, and 2 km, respectively, on either side of the border. Across all specifications, 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 PMKSN 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.

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, we evaluate pre-trends to provide suggestive evidence supporting this assumption. Figure 1 shows the pre-trend analysis for the three subsamples with plot lengths of 5 km, 10 km, and 20 km. 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

Next, we investigate if the increase in agricultural production translates into higher income for farmers. To this end, we combine the household-level income data from Consumer Pyramids database maintained by the CMIE with a border district-pair design that compares outcomes across districts located on either side of the border of the state of West Bengal. This empirical strategy uses variation in compliance with PMKSN within contiguous district-pairs that straddle the state boundaries of West Bengal and the five neighboring states, as shown in Appendix Figure B.2. Specifically, we estimate the following regression specification:

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

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 $\times$ month fixed effects, where d refers to the district where farmer i operates. $\theta_{p(d \in p),T,t}$ denotes district-pair $\times$ treatment $\times$ 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.

This test effectively compares landowning farmers exposed to similar cultural, geographic, climatic, or economic conditions, which may affect the economic outcomes of interest. The key identifying assumption of this test is that the plausible confounding variables are likely to vary smoothly rather than discretely at jurisdictional boundaries. The key innovation of the test is to include district-pair $\times$ treatment $\times$ month fixed effects. This allows the estimate of the coefficient associated with the interaction term of treatment $\times$ complier $\times$ post to be estimated using variation across landowning farmers within a contiguous district-pair, such that one district is located in West Bengal (non-complier) and another in a bordering state (complier). Additionally, the test includes district $\times$ month fixed effects to partial out all time-varying district-level heterogeneity. Therefore, this design effectively constructs a counterfactual for landowning farmers who benefited from PMKSN using *similar* landowning farmers in West Bengal.

Table 3 reports the results from the border district-pair design.[15] We sequentially add fixed effects from Column (1) to estimate our preferred specification in Column (6). Across all these columns, the estimate of the triple interaction term is positive and statistically significant. Specifically, the magnitude of the coefficient remains stable despite a large increase in the model R^2 from 20% in Column (1) to 80% in Column (6), indicating that under the Oster (2019) framework the omitted variables are unlikely to drive our results. Lastly, Column (7) estimates a more stricter specification that ensures the estimate of interest is identified using variation across households that have similar education levels and gender ratio. Overall, our results remain robust.

In terms of economic magnitude we find that the income of landowning farmers increases by 15.8% after the introduction of guaranteed income relative to *similar* landowning farmers in bordering districts that did not receive the guaranteed income. This increase corresponds to an increase in income by ₹1,311.

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

[15] As noted earlier this test uses the Consumer pyramids database maintained by CMIE and the most granular geographic unit observable in this data is district.

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

Section 4.1.2 documents that farmers receiving cash transfers experienced significant increases in farm income. In this section, we investigate the underlying channels driving these gains. In particular, we examine whether treated farmers increased their reliance on capital-intensive production methods, reflected in greater adoption of technology and use of inputs such as tractors and fertilizers.

Effect on Tractors: This section examines the impact of cash transfers on tractor sales. We combine monthly, ZIP code–level tractor sales data from NITI Aayog with a border district-pair design that compares outcomes across districts located on either side of the West Bengal state border. The empirical specification includes district-pair × month fixed effects and exploits variation in PMKSN compliance across contiguous district pairs that straddle the boundary between West Bengal and its five neighboring states, as shown in Appendix Figure B.2.

Table 4 reports the results. Column (1) uses the total value of tractor sales (in INR) as the dependent variable, while Column (2) uses the number of tractors sold. The coefficient of interest is the interaction between Complier and Post, which captures the relative change in tractor sales for agricultural purposes in compliant districts relative to comparable bordering districts in West Bengal following the introduction of PMKSN transfers. The estimate is positive and statistically significant. The magnitude of the estimate indicates that following the treatment, tractor sales increased by 14% in value and 12% in quantity relative to the pre-treatment average. This corresponds to an average increase in investment of ₹74,171 per tractor purchase.

We further strengthen the identification by leveraging detailed information that distinguishes tractor sales for agricultural from non-agricultural purposes. This extended dataset allows the inclusion of ZIP code × month fixed effects. This allows us to control for all ZIP code level time-varying heterogeneity that may affect aggregate tractor sales. The key coefficient of interest is identified from a triple interaction between Complier, Post, and the indicator for agricultural use. Columns (3) and (4) present the corresponding estimates using the value and number of tractors sold, respectively. We additionally include ZIP code × agricultural-use fixed effects to control for persistent local sales patterns, and district-pair × agricultural-use × month fixed effects to isolate within-pair variation. The coefficient on the triple interaction remains positive and statistically significant, suggesting that the PM-KISAN transfers led to a pronounced increase in tractor purchases intended for agricultural production.

This result suggests that PMKSN cash transfers helped encourage greater capital investment in agriculture, potentially setting the stage for improvements in farm productivity and income.

Effect on Fertilizer Consumption: This section examines the impact of cash transfers on fertilizer consumption. We combine annual, season-wise district-level data on fertilizer use from the Government of

India with a border district-pair design that compares outcomes across districts located on either side of the West Bengal state border. The empirical specification includes district-pair × cultivation season (kharif/rabi) × year fixed effects and exploits variation in PMKSN compliance across contiguous district pairs that straddle the boundary between West Bengal and its five neighboring states, as shown in Appendix Figure B.2.

Table 5 presents the results. Columns (1) through (4) use the natural logarithm of total fertilizer consumption, nitrogen-based fertilizer use, phosphorus-based fertilizer use, and potash-based fertilizer use as dependent variables, respectively. The coefficient of interest is the interaction between Complier and Post, which captures the relative change in fertilizer consumption in compliant districts compared to similar bordering districts in West Bengal, following the introduction of PMKSN transfers. The estimates are positive and statistically significant, indicating a 32% increase in total fertilizer use after treatment, with particularly pronounced effects for nitrogen- and phosphorus-based fertilizers.

These findings align with the effect of PMKSN observed for tractor sales and suggest that these transfers may have encouraged greater investment in agricultural inputs. Together, the evidence points toward a shift toward more input- and capital-intensive farming practices, potentially paving the way for subsequent gains in agricultural productivity and, ultimately, farm income.

Effect on the Scale of Production (Gross Sown Area): This section examines the impact of cash transfers on the scale of production measured using gross sown area. To this end, we combine annual, season-wise district-level data on gross sown area from the Government of India with a border district-pair design that compares outcomes across districts located on either side of the West Bengal state border. The empirical specification includes district-pair × cultivation season (kharif/rabi) × year fixed effects and exploits variation in PMKSN compliance across contiguous district pairs that straddle the boundary between West Bengal and its five neighboring states, as shown in Appendix Figure B.2.

Table 6 reports the results. Columns (1) through (5) use the natural logarithm of total gross sown area, as well as sown area under food grains, cereals, pulses, and oilseeds, respectively, as dependent variables. The coefficient of interest is the interaction between Complier and Post, which captures the relative change in cultivated area in compliant districts compared with comparable bordering districts in West Bengal after the introduction of PM-KISAN transfers. The estimates are positive and statistically significant, implying a 48-55% increase in total gross sown area following treatment. The effect is broad-based, with similar increases observed across all major crop categories.

This result is consistent with the view that cash transfers may have facilitated an expansion in cultivated area, accompanied by greater use of agricultural machinery, such as tractors, and other complementary inputs such as fertilizers.

4.1.4 Effect on Credit

Thus far, we have documented substantial increases in investment and expansion of agricultural scale, that is, PMKSN cash transfers made recipients' farming practices more capital intensive. The magnitude of these investments is large relative to the annual transfer amount of ₹6,000, raising the question of how farmers finance these expenditures. We hypothesize that recipients may access new formal credit to fund their investments. This section provides evidence consistent with this argument by examining the effect of PMKSN cash transfers on formal credit.

To do so, we combine monthly, ZIP code–level data on lending—disaggregated by lender- and loan-type from TransUnion CIBIL with a border district-pair design that compares outcomes across districts situated on either side of the West Bengal state border, as shown in Appendix Figure B.2.

Table 7 presents the main results. Panel A reports estimates using the natural logarithm of new loan amounts as the dependent variable, while Panel B uses the natural logarithm of the number of new loans. Across Columns (1) through (5), we report the coefficient on the interaction between Complier and Post, which captures the effect of treatment for ZIP codes in compliant districts relative to comparable ZIP codes in contiguous West Bengal districts not subject to the policy. Moreover, these specification restrict the analysis to agricultural loans only. The specifications incrementally add fixed effects, with our preferred specification in Column (5) including ZIP code × lender-type fixed effects to account for all time-invariant heterogeneity at the lender-type level within each ZIP code. Notably, the specification in Column (5) also includes district-pair × lender-type × month fixed effects, ensuring that the estimate of interest is identified using variation in PMKSN compliance within contiguous district pairs straddling the West Bengal border.

Across all specifications, the estimated effect is positive and statistically significant. The magnitude of the coefficient remains stable even as the model R^2 increases by 20 percentage points moving from Column (1) to Column (5). In fact, the estimate in Column (5) is somewhat larger than in Column (1), suggesting that omitted variable bias would, if anything, attenuates the estimated effect under the Oster (2019) framework. Economically, the key specification indicates that the loan amount increases by 7.2% (Panel A), and the number of loans rises by 16.6% (Panel B).

Lastly, we leverage a distinguishing feature of our data, which enables us to analyze the effect of PMKSN 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.

Column (6) of Table 7 present the results for loan amount in Panel A and number in Panel B. The coefficient of interest is the triple interaction among the agricultural loan indicator, Complier, and Post. This estimate isolates the relative effect of PMKSN compliance on agricultural loan outcomes, over and above other loan-types and potential confounders. The coefficient is positive and statistically significant for both the natural logarithm of loan amounts (Panel A) and the number of loans (Panel B), reinforcing the results documented in Column (5). This result indicates that the expansion in credit following PMKSN transfers is especially pronounced in the agricultural loan segment.

Evidence from the largest State Owned Bank in India: To further substantiate our findings, we obtain branch-level monthly agricultural lending data from India's largest state-owned commercial bank, the State Bank of India (SBI). We use this data to replicate our primary analysis of the effect of PMKSN on agricultural credit. Specifically, we integrate the SBI branch-level data with the border district-pair framework, which compares outcomes across districts located on either side of the West Bengal state boundary.

Appendix Table C.2 reports these results. The coefficient of interest is the interaction term between the complier indicator and the post-treatment period, which captures the change in agricultural lending by branches in compliant districts relative to *comparable* branches in bordering districts in West Bengal following the rollout of PMKSN transfers. The coefficient is positive and statistically significant, reinforcing the findings presented in Table 7.

Evidence from Household-Level Data: We further substantiate our analysis of the effect of PMKSN on credit by examining outcomes at the household level. This test offers two main advantages. First, it enables us to present results using the CMIE Consumer Pyramids sample, for which we previously documented an increase in income in Section 4.1.2. Second, the CMIE data allow us to distinguish between formal and informal borrowings, enabling us to assess whether the observed increase in formal credit reflects an aggregate rise in total borrowing or a substitution between formal and informal credit.

Appendix Table C.3 presents these results using the specification outlined in equation 2. The dependent variable is an indicator for whether a household reports any borrowing for investment, business, or vehicle purchase purposes from any source in Columns (1) and (2), from formal banks in Columns (3) and (4), and from informal sources such as friends, relatives, moneylenders, or shops in Columns (5) and (6).

We include district-pair $\times$ treatment $\times$ month fixed effects, which allow the coefficient on the interaction of treatment, complier, and post to be estimated using variation across landowning farmers within contiguous district pairs, where one district is located in West Bengal (non-complier) and the adjacent district lies in a bordering state (complier). In addition, we include district $\times$ month fixed effects to absorb all time-varying district-level heterogeneity and household fixed effects to control for time-invariant household characteristics. This design thus constructs a credible counterfactual for landowning farmers who benefited from PMKSN using comparable landowning farmers in West Bengal.

Our results indicate that total borrowing increases for treated agricultural households in compliant districts following the rollout of PMKSN, with most of the increase driven by formal bank borrowings.

In contrast, there is no evidence of a rise in informal borrowing from friends, relatives, moneylenders, or shopkeepers. Overall, these findings suggest that PMKSN led to an overall increase in borrowing among treated agricultural households, primarily through formal credit channels rather than substitution away from informal sources.

Taken together, these results on credit are consistent with the view that farmers respond to these cash transfers by seeking additional formal credit, particularly for agricultural investments, thereby facilitating the observed increases in input use and cultivation scale.

4.2 Evidence Using Farmer Level Data

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 partly driven by a shift among treated households toward more capital-intensive production technologies, financed through expanded access to formal credit. However, with the exception of the analysis using CMIE survey data, our results thus far rely primarily on aggregate data. Consequently, 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 discussed in section 3.4.

The bank data offer a key advantage by allowing us to jointly observe income flows and credit utilization for the same set of farmers. Nonetheless, the data are 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, PMKSN transfers were extended only to landowning farmers, excluding tenant farmers.

4.2.1 Discussion of Bias

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.

Although our estimation strategy includes farmer fixed effects to mitigate these concerns, we complement this approach by using the data described in Section 4.1.2 to replicate the analysis within the bank sub-sample and to compare outcomes between landowning and tenant farmers. This exercise enables us to present some suggestive evidence towards both the potential direction and magnitude of sample selection and omitted variable biases.

Appendix Table C.4 reports the results. Column (1) uses the full India sample to compare outcomes for landowning farmers in the rest of India with those in West Bengal. Column (2) excludes West Bengal and compares outcomes between landowning and tenant farmers. Column (3) replicates the analysis in Column (1), restricting the sample to Karnataka, Maharashtra, and Punjab, the states included in the bank data, and the state of West Bengal. Finally, Column (4) compares outcomes between landowning and tenant farmers within these same bank-sample states after excluding West Bengal.

Comparing the estimates in Columns (1) and (2), as well as Columns (3) and (4), provides insight into the direction of omitted variable bias arising from systematic differences between landowning and tenant farmers. In contrast, the comparison between Columns (1) and (3) sheds light on the direction of sample selection bias related to the more restricted set of states included in the banking data. Notably, the estimated effect size reduces when shifting from the full sample in Column (1) to the bank sample in Column (3). Similarly, the effect size decreases when the identification strategy moves from comparing landowners across states to comparing landowners and landless farmers within the same state. Taken together, these 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.

4.2.2 Comparison of the Treatment & Control Groups in Bank Data

While it is unlikely that landowning and tenant farmers are identical across all observed and unobserved characteristics, we systematically examine their differences on a range of observable variables to assess the potential for omitted variable bias. The goal of this exercise is not to claim equivalence between the groups but rather to gauge how differences in observables may confound estimated effects and how to best account for those differences.

Table 1 presents sample means for key characteristics alongside both unconditional and within-ZIP code comparisons. While the unconditional differences between the two groups are statistically significant, the economic magnitude of these differences are modest relative to sample averages. Moreover, when comparisons are restricted to farmers within the same ZIP code, these differences shrink further, becoming both economically negligible and statistically insignificant in most cases. This suggests that while there are average differences between landowners and tenants, the two groups are comparable along many observable dimensions once geographic location is accounted for. These findings highlight the importance of incorporating farmer fixed effects and ZIP code $\times$ month fixed effects in our empirical strategy, which facilitates comparison among similar farmers within the same geographic locality while controlling for individual time-invariant traits that may differ across groups.

4.2.3 Effect on Income

This section presents three pieces of evidence and several robustness tests that together indicate an increase in income from work for the treated farmers after the implementation of the policy.

First, we examine the policy's effect on income from work for treatment and control farmers. Panel

A of Table 8 presents the farmer-level results. The estimated coefficient of interest is positive, statistically significant across all model specifications, and stable in magnitude. Notably, under the Oster (2019) framework, the presence of omitted variables is likely causing a downward bias in our estimate, as evidenced by the increasing magnitude of the coefficient from Column (1) through Column (4). Quantitatively, this coefficient implies a 12.74% increase in income for treated farmers, relative to the control farmers, following policy implementation.

Second, we repeat the analysis using the farmer-period panel structure. Panel B of Table 8 reports results where each farmer contributes two observations, one measuring income from work during the twelve months prior to the program's implementation, and the other measuring income during the twelve months following it. This specification allows inclusion of farmer fixed effects, thereby controlling for all time-invariant heterogeneity at the individual level. Additionally, we can include ZIP code × post fixed effects ensure identification is derived from variation in PMKSN eligibility within the same ZIP code. These fixed effects allow us to control for any local shocks. The coefficient on the interaction of treatment and post indicators remains positive and statistically significant across all specifications (Columns (1)–(4)) as the model is progressively saturated with high-dimensional fixed effects. Our preferred specification, in Column (4), which includes both farmer and ZIP code × post fixed effects, indicates a 12.68% increase in income from work for treated farmers following the transfer.

Discussion on the Magnitude of the Effect: Economically, this effect corresponds to a relative rise in income of approximately ₹10,543–₹13,656 for the treatment group. Comparing this magnitude with the size of the cash transfers suggests that each \$1 of guaranteed annual transfer generates an additional \$1.76 of earned income over the following twelve months. Thus, the total average increase in income associated with the program amounts to \$2.76, composed of \$1 from direct transfers and \$1.76 from the induced growth in work-related income.

Differences-in-Differences Using Bank Data: Third, we extend the analysis using a differences-in-differences framework based on farmer-level monthly data. This specification incorporates both farmer and ZIP code × month fixed effects to estimate the coefficient on the interaction between treatment status and the post-policy indicator. The inclusion of ZIP code × month fixed effect allows for controlling high-frequency local shocks that may affect farmers within the same geographic area, providing finer temporal variation than the farmer-period analysis presented in Panel B of Table 8.

Table 9 presents the results. The coefficient of interest remains positive and statistically significant across all model specifications as we sequentially introduce additional fixed effects, progressing from Columns (1) to (5). Consistent with the improvement in model fit, the R^2 increases by 30.81 percentage points, while the coefficient of interest decreases in magnitude. Applying the Oster (2019) procedure to this variation in estimated coefficients and model fit between Columns (1) and (5) yields a positive lower bound, indicating that the identified set excludes zero. This allows us to reject the null that the observed effect is driven by omitted variables under standard Oster (2019) assumptions. Our preferred specification, which includes both farmer fixed effects and ZIP code × month fixed effects, suggests a 13.90% increase in income relative to the pre-policy period for treated farmers following the introduction of cash transfers.

Robustness to Alternative Estimation Methodology: Next, we demonstrate that our findings are robust to alternative econometric specifications. Our baseline specification follows the recommendation of Chen and Roth (2024), estimating treatment effects relative to the pre-period mean in the presence of zeros in the dependent variable. In addition, we implement the complementary approach of estimating a Poisson pseudo-maximum-likelihood model, also suggested by Cohn, Liu, and Wardlaw (2022). Appendix Table C.5 reports these results and confirms that the coefficient on the treatment-by-post interaction remains stable across specifications.

Spillovers: A key challenge in interpreting the estimated treatment effects is the potential violation of the Stable Unit Treatment Value Assumption (SUTVA) due to spillovers onto the control group. Such spillovers may arise through increased economic activity among treated farmers or from non-landowning farmers expecting to receive PMKSN transfers in the future. Positive spillovers to the control group do not compromise the economic interpretation of the treatment effect; rather, they bias the estimates downward. In this case, the coefficients reported in this paper can be interpreted as lower bounds of the true effects. In contrast, negative spillovers onto the control group would pose a more serious threat to the interpretation of the treatment effect.

Following Berg, Reisinger, and Streitz (2021), we formally test for the presence and direction of these spillovers and present the results in Appendix Table C.6. We assume that the cash transfers influence local agricultural input and output markets, thereby inducing potential spillover effects on both treated and control units.[16] Since farmers typically buy inputs and sell outputs within the same district or ZIP code, we define the spillover unit at the district level in Column (2) and at the ZIP code level in Columns (3) and (5). We further assume that spillovers depend on the treatment intensity within these local markets, measured as the fraction of treated farmers in the district or ZIP code. The estimates are remarkably stable: the specification that ignores spillovers (Column (1)) yields coefficients statistically indistinguishable from those incorporating potential spillovers (Columns (2), (3), and (5)). This pattern suggests that spillovers, if present, are minimal. This finding is consistent with the structure of Indian agricultural markets, where strict regulation limits the operation of competitive market forces that might otherwise generate substantial input–output spillovers across farmers.

Controlling for Covariates: Another potential concern is that the estimated treatment effect may be confounded by differences in covariates between treatment and control groups. To address this, we augment the baseline specification by including interactions of the post-policy indicator, $Post_t$, with a rich set of farmer-level covariates, X_i, measured prior to the policy implementation. Appendix Table C.7 reports these results. The covariates include average savings, income, spending, credit card usage,

[16] Cash transfers may increase demand for agricultural inputs, raising their prices. At the same time, higher agricultural productivity may lead to lower output prices.

investments in fixed deposits, recurring deposits, provident fund deposits, stock market holdings, daily number of banking transactions, credit score, interest rates, Kisan credit card limits, farmer age, account age, religion, and prior default status. The coefficient on the interaction term $Treatment_i \times Post_t$ remains robust to controlling for these variables, suggesting that the estimated treatment effect is unlikely to be driven by preexisting covariate differences. Notably, comparing the baseline estimate in Column (1) to that in Column (16), which incorporates the full vector of farmer-level characteristics interacted with post, we observe an increase in the magnitude of the treatment effect accompanied by a reduction in its standard error. This pattern suggests that omitted variables capturing differences between treatment and control groups may have biased the original estimate downward and reduced its precision.

Placebo Test: Lastly, we conduct a placebo test to address two concerns. First, the results are spurious and capture differential seasonality across the treatment and control groups. Second, the results are driven by the timing of the policy coinciding with the federal elections. We address these concerns by estimating the treatment effect in previous years when the policy was not implemented. Appendix Table C.8 presents the results from the estimation of baseline equation for the placebo years – 2015, 2014, 2013, and 2012.[17] The coefficients for all placebo years are statistically insignificant and, in most cases, economically negative, an opposite sign relative to the baseline estimate. These results suggest that our baseline results are unlikely to be spurious. Furthermore, the absence of a treatment effect in 2014, the year of the federal elections, indicates that the estimated effects are not driven by election-related shocks affecting treatment and control groups differently.

Homogeneity in the Intensity of Treatment: Saez (2002) and Hanna and Olken (2018) show that in the presence of a progressive tax schedule, basic income like cash transfers will not raise the after-tax income of all recipients by the same amount. Therefore, a concern with PMKSN cash transfers is that, after accounting for income taxes, the effective transfers are not identical across the income distribution. This is an important concern as such an effect would violate the assumption of homogeneity in the intensity of treatment across treatment units. However, this is likely to be of little concern due to an institutional feature of the Indian tax schedule. All farmers in India are exempt from income taxes, regardless of their income or wealth. Since we focus only on farmers in India, we can rule out any possible differences in effective transfers due to the tax schedule.

Stability of the Treatment and Control Group: Another concern is the stability of the treatment and the control groups over time. Specifically, buying and selling of agricultural land can allow individuals to select into or out of the treatment group, potentially threatening the assumption of the stability of the treatment and control groups. This assumption is likely to be satisfied due to an institutional feature of the policy. The policy was announced in February 2019 and fixed the list of beneficiaries based on agricultural landownership in December 2018. Farmers who bought agricultural land after December 2018

[17] We do not include 2016 and 2017 in the test since the sample required to conduct those tests overlap significantly with the episode of demonetization, which made 86% of cash in circulation illegal tender overnight. We direct readers to Chodorow-Reich et al. (2020) for a detailed discussion of this episode.

were ineligible for the benefits. Therefore, the policy design makes landownership status an immutable characteristic and ensures the stability of our treatment and control units over time.

4.2.4 Effect on Credit

This section examines the effect of the policy on credit using farmer-level data. Specifically, we document the role of credit in financing the increased investment, as documented in Section 4.1.3. To this end, we conduct an inquiry at the Indian credit bureau (TransUnion-CIBIL) for each farmer in our bank dataset and collect detailed loan-level information. We examine the policy's effect on credit access along both the extensive and intensive margins. The extensive margin captures whether a farmer obtained any new loan in a given month, while the intensive margin measures the number and total value of new loans. To analyze these outcomes, we construct a balanced panel at the farmer-month level, including one observation per farmer for each of the twelve months before and after the policy. Table 10 reports the results. For robustness, we repeat our analysis using Poisson pseudo-likelihood regression and find similar results (see Appendix Table C.9).

Columns (1) and (2) of Table 10 report the policy's effect on the extensive margin of credit outcome – the probability of a new loan and the number of new loans. The estimate of interest is positive and statistically significant. Results indicate that the probability of a new loan increases by 4.7% for the treatment group after the policy. The estimate represents a 10% increase over the pre-period sample mean of 48%. Column (2) reports the policy's effect on the number of new loans. The estimate of interest is positive and statistically significant. The number of new loans increases by 14.2% over the pre-period sample mean. Specifically, the treatment group gets 0.09 additional new loans each month relative to the control group after the policy.

Column (3) of Table 10 reports the policy's effect on the intensive margin – the loan amount, respectively. The monthly loan amount for the treatment group increases by 35.9%. On average, the loan amount increases by ₹40,703 for the treatment group during the twelve months following the policy. The policy's effect on credit is economically significant. Specifically, the effect is 6.8 times larger than the yearly cash transfer of ₹6,000 and is equal to 39.3% of the present discounted value of guaranteed income.[18].

Does the New Credit Finance Consumption or Productive Capacity?: Next, we document that the new credit finances productive capacity and not consumption. We hypothesize that for the increase in farmers' credit to generate greater investment in agriculture, it must be used to finance productive capacity. 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

[18]We obtain the value of 0.393 by comparing the increase in loan amount of ₹41,000 with the perpetuity value of guaranteed income (₹103,448). We compute the present value of a perpetuity that provides ₹6,000 annually discounted at the risk-free interest rate of 5.8%. The risk-free rate of 5.8% is computed by subtracting the average 10-year Indian Treasury rate of 7% during 2019 from the sovereign risk premium of 1.2%.

a *"bad"* credit boom (Mian, Sufi, and Verner, 2017; Mian and Sufi, 2018; Mian, Sufi, and Verner, 2020; Müller and Verner, 2021).

We classify loans as either being used for consumption or to enhance the productive capacity by exploiting the information on the purpose of the loan. Loans meant to purchase farm equipment or loans tagged as priority sector loans for business-related activities are classified as loans for enhancing productive capacity. All other loans are classified as loans for consumption. The complete classification of loans into productive and consumption loans is presented in Appendix Table B.6.

Table 11 reports the policy's effect on credit market outcomes for productive loans in Columns (1) through (3) and consumption loans in Columns (4) through (6). The results for productive loans are similar to the results reported in Table 10. Specifically, we document an increase in the probability of a new loan, the number of new loans and the loan amount for productive loans. Meanwhile, we do not find any economically or statistically significant effects for consumption loans. The result indicates that almost all new credit is used to finance the productive capacity of farmers.

We extend our analysis by employing a long-form dataset that includes the two loan categories for each farmer as separate rows. Our primary coefficient of interest corresponds to the triple interaction term of loan type, treatment status, and the post-policy indicator. A key advantage of this specification is that it allows us to incorporate farmer $\times$ month fixed effects, which control for all time-varying heterogeneity at the individual level. This approach ensures that identification relies on within-farmer variation, capturing how the policy affects productive loans relative to consumption loans for the same individual. In doing so, it mitigates potential systematic differences between landowning and tenant farmers. Columns (7) through (9) of Table 11 present the corresponding estimates. The results indicate a significant increase in the likelihood, number, and total amount of loans directed toward productive investment relative to consumption borrowing among treated farmers, compared with comparable control farmers, in the post-policy period.

Taken together, these findings imply that the expansion of credit observed among treated farmers following the policy primarily financed productive capacity rather than consumption expenditures.

4.3 Evidence from Original Survey of Farmers

We complement the quantitative analysis presented thus far with qualitative evidence drawn from our original survey of farmers. Specifically, the survey directly elicits farmers' self-reported responses to the PMKSN transfers in terms of their effort, investment, and borrowing behavior. Additionally, tenant farmers who did not receive PMKSN transfers were hypothetically asked how these outcomes would have changed had they been recipients.[19]

[19] To mitigate concerns that respondents' answers might be influenced by expectations that their responses could affect their eligibility for future PMKSN transfers, we implemented two key procedural safeguards. First, during the telephonic interviews, we framed the questions hypothetically by referring only to receiving an unconditional cash transfer of ₹6,000 per year, deliberately omitting any mention of the PMKSN program. Second, we explicitly reassured respondents both in the telephonic interviews and the online intake forms that the research team is independent of the government and that their responses would in no way influence their current or future access to transfers.

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 improves our understanding of external validity, which is critical when considering the broader applicability and scaling potential of this policy across other farmer populations. Specifically, our approach aligns with the SANS framework of external validity of List (2020), which emphasizes establishing credible generalizations beyond the initial treatment group.

Table 12 presents qualitative evidence on the effect of the PMKSN policy based on responses collected from farmers in our field survey. Panels A, B, and C respectively report the responses regarding the policy's impact on physical agricultural effort, investment in agriculture, and credit uptake. For each outcome, farmers were asked whether they expected the policy to increase, decrease, or have no effect on their behavior. Column 1 reports the overall percentage of respondents selecting each response category. Columns (2) and (3) disaggregate these responses by whether respondents received PMKSN transfers, allowing for a direct comparison between treated landowning farmers and untreated tenant farmers.

The results presented in Panel A indicate that farmers report an increase in their physical effort in agriculture following the transfers. Similarly, Panels B and C suggest that farmers are more likely to increase both their investment in agricultural inputs and their borrowing after receiving transfers. Specifically, 65% of respondents indicated an increase in physical effort, 70% reported increased investment, and 47% reported higher credit uptake. These effects are consistent across both recipients and non-recipients of PMKSN transfers.

There are three key takeaways from this analysis. First, the congruence between the quantitative effects documented earlier and the qualitative perceptions reported by farmers demonstrates the robustness of our key findings. Second, the qualitative survey responses substantiate the assumption that untreated tenant farmers provide a valid counterfactual to treated landowning farmers, as both groups describe similar expected effects of the transfers on effort, investment, and borrowing—thereby reinforcing the credibility of our identification strategy. Third, the similarity in responses between recipients and non-recipients improves our confidence that the estimated treatment effects possess external validity and can be generalized to other farmers populations beyond the treated sample. This aligns with the external validity framework of List (2020), which emphasizes the importance of assessing how treatment effects extend across contexts and populations.

5 Mechanism

This section discusses the underlying mechanism through which guaranteed income positively affects income from work. Specifically, this section documents the importance of credit markets and the salience of demand-side factors.

5.1 Importance of Credit Markets in Driving the Effect

This section evaluates the role of credit markets in driving the effect of guaranteed income on agricultural income. Specifically, we exploit the importance 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. In particular, we focus on farmers with prior default history. Garmaise and Natividad (2017) document that consumers are subjected to an extended period of reduced financial access following an adverse credit event. A negative credit event, such as a prior default tag, will cause a substantial and lasting drop in the debtor's credit score, leading to unfavourable interest rates or credit rationing. Hence, farmers with a prior default tag are severely limited in their ability to secure credit.

Therefore, we investigate the role of credit markets by estimating our baseline effect on income from work separately for two sub-groups of farmers – farmers with a default tag before March 2018 and farmers with no default tag through March 2018. Farmers with a default tag are likely to be cut off from credit markets and cannot finance lumpy investments with credit. Table 13 reports the results. Column (1) reports the estimate for the full sample. Columns (2) and (3) report the estimate for the sample of farmers without and with prior default, respectively. While the estimate of interest for the sample of farmers with no prior default is positive and statistically significant, it is economically negligible and statistically insignificant for the sample of farmers with a prior default tag.

We supplement the results on heterogeneity in income – documented in Table 13 – with the heterogeneity in credit market outcomes by prior default status. Table 14 presents the results documenting heterogeneity in credit outcome for farmers without and with a prior default default.We find the increased credit for the treatment group is driven by farmers with no prior default tag (Panel A). Meanwhile, we do not find any increase in credit for the treatment group with prior default (Panel B). The results indicate that credit markets play an important role in the documented positive income effect of guaranteed income transfers.

Furthermore, we validate the role of credit markets by focusing on the heterogeneity in the effect based on credit scores. The intuition behind this test is similar to our test on prior default, i.e., farmers with low credit scores are likely to face greater credit market frictions. Appendix Table D.1 reports the results on heterogeneity in credit outcomes based on credit scores before March of 2018. Consistent with the results on prior default status, we find that the effect of the policy on credit is concentrated among farmers with high credit score.

Overall, these results suggest the salience of credit markets in driving the effect on income among the treatment group following the PMKSN policy.

5.2 Are the Transfers Large Enough to Finance Investment?

Next, we discuss an alternative explanation, i.e., cash transfers increase investment directly by increasing the amount of cash-in-hand available for investment. The cash-in-hand channel of BI, is likely to be unimportant because the liquidity created by annual cash transfers of ₹6,000 is tiny. Specifically, the cash transfers account for only 7% of farmers' average annual income. Additionally, the transfer amount is small compared to the average size of lumpy investments required for shifting to a high capital-intensive mode of production. For example, a tractor costs around ₹700,000, a cow costs around ₹150,000, and a two-wheeler costs around ₹80,000. As another example, one of the several small ticket expenditures such as operating a small tractor would need a minimum of ₹6,700 worth of diesel during a cultivation season.[20] Therefore, the ability of such transfers to directly relax liquidity constraints is severely limited. Banerjee, Niehaus, and Suri (2019) echo a similar argument about the inability of small-sized transfers under UBI to ease liquidity constraints that impede lumpy investment.

5.3 Role of Demand for Credit

This section examines the policy's effect on the demand for credit. Specifically, we show that an increase in demand can potentially be an important factor that can explain the increase in credit to the treatment group documented in section 5.1. We begin by identifying the existence of the credit demand channel by examining changes in the utilization rate for kisan credit cards, a product whose credit limit and interest rates are invariant to the farmers' creditworthiness. Next, we establish the importance of the credit demand channel by examining the application data, acceptance rates, and the responses from the original survey. Additionally, we examine the effect on income and credit based on the heterogeneity of factors that determine credit demand – the ability of guaranteed income to protect against downside risk, salience of idiosyncratic risk, and incomplete insurance markets.

5.3.1 Existence of Credit Demand Effect: Evidence from Kisan Credit Cards

We begin our analysis by examining the policy's effect on the utilization rates for kisan credit cards (KCC), also known as farmers' credit cards.[21] The credit limit and the interest rates for KCCs are unrelated to farmers' creditworthiness. Therefore, this product provides an ideal laboratory to examine the effect that guaranteed income has on farmers' demand for credit.

The KCC program was introduced in 1998 by the Reserve Bank of India to issue a line of credit to farmers at a subsidized rate. Farmers can use this line of credit to purchase agricultural inputs such as seeds, fertilizers, pesticides, etc., and draw cash for their production needs. Farmers can repay their balances on KCC depending on the harvesting period of their crop for which the line of credit was given. KCCs have become an important source of credit for farmers constituting up to 40% of total agricultural credit in India (Bista, Kumar, and Mathur, 2012; Ghosh et al., 2025).

KCC are issued for a tenure of five years, with the initial year's credit limit determined by the

[20]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.

[21]The information on credit cards is not consistently reported at the credit bureau, and the key variable of utilization rate is difficult to construct using bureau data. However, banks maintain better internal data on credit limits, interest rates, and monthly utilization of credit cards. Therefore, we use the detailed information on KCC issued by our sample bank to conduct this analysis.

amount of land cultivated and the types of crops grown. Subsequent yearly credit limits increase by a fixed percentage, typically 10%, based on the previous year's limit. The 2017 RBI circular provides illustrations for the details of the calculations. Appendix Figures D.1, D.2, and D.3 present these illustrations.[22] Our conversations with the bank managers suggest that banks strictly adhere to these RBI guidelines when calculating credit limits. Crucially, the credit limit determination does not account for unanticipated changes in a farmer's income or creditworthiness after issuance. Instead, income is imputed solely on landholding and crop type, the latter fixed at the time of card issuance, and annual limit increases proceed mechanically via fixed percentage increments. This framework implies that KCC limits lack flexibility to adjust based on a farmer's evolving financial situation or any unexpected permanent income shocks within the five-year cycle.

The determination of the initial credit limit for the Kisan Credit Card is primarily based on historical data that imputes farmer income using two key parameters: the amount of land cultivated and the crop type grown. This calculation incorporates the scale of finance for the crop as decided by the District Level Technical Committee, multiplied by the extent of cultivated area. Additional components such as provisions for post-harvest and household expenses (typically 10% of the calculated amount), farm asset maintenance (20%), and crop or asset insurance costs are also added to arrive at the first-year credit limit. Notably, the crop type is fixed at the time of issuance and is assumed to remain constant over the five-year period, restricting adjustments in credit limits to fixed annual percentage increments rather than reflecting any real-time changes in farmer income or cropping patterns.

The illustrations, and subsequently the loan officers, do not account for farmers' creditworthiness or income. We validate this assumption by examining the pre-policy period relationship of credit limit and interest rates on KCC with the credit scores of farmers. Appendix Figure D.4 shows that the credit limits and interest rates are uniformly distributed across credit scores. This indicates a minimal relationship between credit limits or interest rates with credit quality. Additionally, we examine the changes in credit limit and interest rates for the treatment group after the policy. Appendix Table D.2 shows that the policy's effect on the KCC interest rates and credit limit for the treatment group was economically and statistically insignificant. Hence, any credit supply-side changes due to the increased creditworthiness of the treatment group are not reflected in this product. As a result, KCC provides an ideal environment where we can examine changes in demand following the policy, holding the credit supply fixed.

Table 15 presents the results from examining the utilization rates of KCC. The coefficient associated with the interaction term of treatment and post is positive and statistically significant across all columns. The results indicate that the utilization rate of KCC increases by 5.8 percentage points for the treatment group after the policy. The treatment effect is large relative to the average utilization rate of 19.6% and represents an average increased usage of ₹20,000.

[22] For example, a first-year limit of ₹100 would increase to ₹110 in the second year, followed by ₹121, ₹133.10, and ₹146.41 in the succeeding years, as detailed in the 2017 Reserve Bank of India (RBI) circular. So the schedule of the increase in credit limit is fixed at the time of issuance. The illustrations are taken for the 2017 RBI circular and can be accessed at this LINK

The increased credit usage of ₹20,000 on KCC combined with the increased credit of ₹41,000, documented in section 4.2.4, implies a total credit increase of ₹61,000, which is equal to 10.1 times the size of yearly cash transfer of ₹6,000. The total effect on credit is equivalent to 58.7% of the present discounted value of guaranteed income.

5.3.2 Effect on Credit Inquiries & Acceptance

We supplement the analysis by examining the policy's effect on a proxy for credit applications. Following Jiménez et al. (2014, 2017), we use the inquiry dataset obtained from the credit bureau as a proxy for credit applications. 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.

Panel A of Table 16 presents the results. We estimate a 1.7% increase in the monthly probability of inquiry. We interpret this increase in inquiries as an increase in the number of applications. The unconditional probability of application each month is 4.1% and the effect of the policy on applications corresponds to a 41% increase over the sample mean.

Panel B of Table 16 examines the effect of the policy on the probability of acceptance conditional on inquiry, i.e., the acceptance rate. The coefficient associated with the interaction term is statistically insignificant indicating that the acceptance rate was largely unchanged by the policy. Moreover, the magnitude of the effect is economically small when compared to the average monthly acceptance rate of 3.8%.

Overall, the results show that treated farmers submitted more credit applications following the policy, while their acceptance rates remained unchanged. We interpret this pattern as evidence of greater credit demand rather than a shift in credit supply. On the demand side, credit inquiries rise; on the supply side, lending standards appear stable. This interpretation relies on the assumption that farmers do not expect banks to relax lending criteria as a result of PMKSN. This assumption is crucial because if farmers expect lending standards to be looser after PMKSN then they are more likely to apply and the resulting inquiries no longer suggest demand but an equilibrium outcome wherein applications also respond to expected supply.

Our original survey of farmers supports this assumption. Contrary to the notion of looser credit standards, 47% of farmers report expecting banks to tighten lending requirements, and 25% anticipate no change (see Appendix Table D.3). These findings reinforce our view that the increase in applications captures higher demand for credit rather than changes in the supply environment.

5.3.3 Role of Credit Demand: Evidence from Original Survey of Farmers

To establish the role of increased credit demand among treated farmers following the policy, Section 5.3.1 documents a substantial rise in the utilization rate of Kisan Credit Cards, a product largely insulated from credit supply effects. This result provides a clean evidence in favor of increased credit demand, though it only establishes the existence of the credit demand channel as the evidence pertains to a specific product that accounts for roughly 40% of total agricultural lending in India. Moreover, the findings in Section 5.3.2, based on application and acceptance rate data, similarly point toward an important role for credit demand channel in driving the effect. However, this piece of evidence is suggestive rather than definitive.

This section seeks to strengthen that evidence by offering direct support for the credit demand channel. We take a more direct approach by asking farmers in our survey whether they believe the policy affected their borrowing primarily through changes in credit demand or credit supply. Directly eliciting farmers' perceptions serves two purposes. First, it helps overcome the empirical challenge of disentangling demand from supply in observational lending data, where shifts in applications and acceptance rates jointly reflect equilibrium outcomes of both sides of the credit market. For instance, an increase in applications could arise either because farmers are more willing to borrow (a demand-side response) or because they expect credit to be easier to obtain (a supply-side response). Second, survey responses provide insight into how farmers interpret policy-induced changes in credit conditions, complementing the more indirect evidence from administrative and bank-level data. Such a belief elicitation methodology using survey data to better understand the underlying mechanisms has previously been employed in Bursztyn et al. (2018, 2019); Breza, Kanz, and Klapper (2020); Galashin, Kanz, and Perez-Truglia (2020); Field et al. (2021), and Fiorin, Hall, and Kanz (2025) among others.

To directly assess the relative importance of the credit demand and supply channels, our survey asked farmers the following question: "In what way did this (PMKSN) money increase your borrowings?" Respondents could choose between two options: (a) It made me more comfortable to borrow, and (b) It made the bank more willing to accept my application and/or lend me money at a lower interest rate. We interpret option (a) as reflecting the credit demand channel and option (b) as capturing the credit supply channel.

Figure 3 shows the distribution of responses among farmers who received PMKSN 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 result indicates that the increased credit demand among the recipients of PMKSN was the key driver of their increased borrowing.

Why Do We See a Modest Supply Side Response?: The results so far suggest the credit supply response to the permanent income shock due to guaranteed income was not large. This result is surprising as the canonical works of Stiglitz and Weiss (1981) and Holmstrom and Tirole (1997) argue that a firm's borrowing capacity depends on its future cash flows. The lack of a large supply-side response can be attributed to three reasons. First, cash flow-based lending depends crucially on the contractibility of future cash flows. However, from a legal standpoint, future government transfers are rarely pledgable.[23] Moreover, garnishing a bank account to extract personal funds can be challenging when enforcement is weak. Second, 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). However, farmers are usually small. As a result, agricultural lending tends to be voluminous with low average ticket size making lending based on future cash flows unattractive.[24] Third, the institutional structure of agricultural lending in India complements the lack of a supply-side response. Loan officers typically use three data inputs to make decisions on agricultural loans –- expected agricultural yields to compute the debt-to-income ratio, availability of collateral, and credit scores. Expected yields, collateral availability, and credit scores are based on historical data. Changes in farmers' income are not reflected in either of the metrics, at least not in the short run. Therefore, the supply side is insensitive to such shocks in the short-run when the institutional structure relies on historical data to make lending decisions.

5.4 What Drives Credit Demand?: Evidence from Original Survey of Farmers

Next, we examine why the PMKSN cash transfer leads to higher credit demand. To shed light on the underlying mechanism, we elicit the beliefs of PMKSN recipients to understand the motivations driving their increased willingness to borrow.

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 4 presents a schematic representation of these concerns related to debt contracts during bad times. We argue that guaranteed income can reduce these costs by – (1) improving the ability to meet basic needs after loan repayment during bad times, (2) improving the ability to repay loan during bad times, and (3) can reduce the expected consumption loss associated with default.

We begin our analysis by validating our hypothesis related to the concern about the negative effects of debt contracts during bad times. Figure 5 reports these results. Three key takeaways emerge. First, farmers exhibit a large and constant amount of concern or worry about the effect of debt contracts during bad times (see panels 5a and 5b). Second, their worry about debt contracts during bad times is driven by the likelihood of default and ability to meet basic needs after loan repayment (see panels 5c). Third,

[23]The lack of pledgeability of assured future government transfers is not just an emerging market phenomenon, but even in the United States, households cannot pledge their social security checks or unemployment benefits.

[24]Moreover, 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.

the most prominent expected costs(s) of default are related to the loss in means of production and future exclusion from credit markets (see panels 5d).

In order to evaluate the most relevant drivers of credit demand we make respondents directly evaluate different hypothesized mechanisms à la Colonnelli, Neto, and Teso (2025). Specifically, we directly ask respondents – *Which of the following channels 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).[25]

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 17 reports the results from the survey. 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. Additionally, Table 17 is also informative about an alternative channel, i.e., guaranteed income increases credit demand by reducing down-payment constraints. 17.5% of respondents reported reduction in down-payment constraints as the primary driver indicating that while this channel is present it is small relative to the credit demand channels associated with repayment.

5.4.1 Effect of guaranteed income on ex-post default

Having established that the PMKSN cash transfer increases credit demand, we turn to the consequential question of how guaranteed income influences ex-post default behavior. Theoretically, the direction of this effect is ambiguous. On one hand, default could increase if higher credit uptake is primarily driven by a reduction in the expected consumption loss following default. This hypothesis is consistent with the findings of Field et al. (2013) who document an increase in default following a reduction in cost of default. On the other hand, if credit demand rises mainly because guaranteed income improves borrowers' ability to meet loan repayments during adverse shocks and improves their comfort in meeting basic needs post-repayment, then we would expect ex-post default to decrease or remain unchanged. Moreover, examining

[25]We randomized the order in which the options were presented across different respondents for the question.

the effect of the transfers on default behavior is not only crucial for identifying the underlying drivers of increased credit demand but also provides suggestive evidence regarding the long-run sustainability of the program's impact on credit access. Understanding how guaranteed income influences repayment outcomes informs the feasibility of scaling such interventions as durable solutions to credit constraints faced by farmers.

To investigate the effect of the PMKSN transfers on loan default, we leverage monthly, ZIP-code–level lending data disaggregated by lender and loan type from TransUnion CIBIL. We combine this rich dataset with a border district-pair research design that compares outcomes across districts situated on either side of the West Bengal state border. This data source, previously utilized in Section 4.1.4 to analyze the impact of the policy on credit access, now serves to examine default behavior on loans disbursed in complier areas after the policy implementation.

Table 18 presents the estimated effects of the PMKSN policy on delinquency rates within one and three years of loan issuance, reported in Panels A and B respectively. Given that most agricultural loans are short-term, typically with a one-year tenure, examining delinquency within one year provides a measure of the policy's short-term impact on default risk. In contrast, the three-year delinquency rate offers a longer-term perspective on the policy's effect on credit repayment behavior. Moreover, the three-year delinquency rate also allows us to circumvent issues related to the imposition of a loan moratorium in 2020 due to COVID-19 discussed in Fiorin, Hall, and Kanz (2023) and Indarte and Kanz (2024).

In Columns (1) through (5), the coefficient of interest is the interaction between Complier and Post, which captures the effect of treatment for ZIP codes in compliant districts relative to comparable ZIP codes in contiguous West Bengal districts not subject to the policy. Moreover, these columns restrict the analysis to agricultural loans only. The specifications incrementally add fixed effects, with our preferred specification in Column (5) including ZIP code $\times$ lender-type fixed effects to account for all time-invariant heterogeneity at the lender-type level within each ZIP code. Notably, the specification in Column (5) also includes district-pair $\times$ lender-type $\times$ month fixed effects, ensuring that the estimate of interest is identified using variation in PMKSN compliance within contiguous district pairs straddling the West Bengal border.

Across all specifications, the estimated effect is negative and statistically significant. The magnitude of the coefficient remains stable even as the model R^2 increases by 30 percentage points moving from Column (1) to Column (5). In fact, the estimate in Column (5) is somewhat larger than in Column (1), suggesting that omitted variable bias would, if anything, attenuates the estimated effect under the Oster (2019) framework. Economically, the key specification indicates that the one-year delinquency rate decreases by 2.8% (Panel A), and the three-year delinquency rate decreases by 8.7% (Panel B).

Lastly, we leverage a distinguishing feature of our data, which enables us to analyze the effect of PMKSN cash transfers on agricultural loans relative to other loan types. This approach offers a key advantage as it permits the inclusion of ZIP code $\times$ lender-type $\times$ 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.

Column (6) of Table 18 presents the results for the one- and three-year delinquency rate in Panels A and B, respectively. The coefficient of interest is the triple interaction among the agricultural loan indicator, Complier, and Post. This estimate isolates the relative effect of PMKSN compliance on delinquency rate in agricultural loans, over and above other loan types and potential confounders. The coefficient is negative and statistically significant, reinforcing the results documented in Column (5). This result indicates that the reduction in delinquency rate following PMKSN transfers is especially pronounced in the agricultural loan segment.

There are three key takeaways from this analysis examining the effect of the policy on ex-post default. First, 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. Second, by alleviating concerns about default risk, the evidence suggests the long-run sustainability of expanded credit access facilitated by guaranteed income programs. This insight carries important policy implications, highlighting the potential of scaled cash transfer interventions as durable, effective solutions to persistent credit constraints faced by smallholder farmers.

Third, these empirical findings substantiate the survey-based mechanisms underlying increased credit demand. 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.

5.5 Role of Downside Risk Protection

The results presented in Section 5.4 suggest that guaranteed income programs can heighten recipients' willingness to borrow by mitigating exposure to downside risk. Farmers frequently face large disaster shocks such as droughts and floods that create substantial income volatility. In such an environment, liquidity-constrained households may optimally restrain their credit demand, anticipating that adverse realizations of income could leave them unable to repay and force consumption into states of the world where its marginal utility is particularly high. We hypothesize that by providing a predictable income floor, guaranteed income reduces the probability that a farmer faces states of extremely low consumption during bad states of the world, where the marginal utility of consumption approaches infinity. By lowering the expected utility costs of adverse shocks, such transfers effectively relax liquidity and credit constraints, enabling households to participate more confidently in formal lending markets. This section provides evidence consistent with this hypothesis by showing that the effect is more pronounced among farmers exposed to greater ex-ante downside risk and operating in environments with incomplete insurance markets, which limit their ability to hedge against such shocks.

5.5.1 Role of Risk

This section examines the heterogeneity in the policy's effect on credit market outcomes based on the rainfall risk faced by farmers. We hypothesize that the policy's effect on credit demand is larger for farmers facing higher risk, as captured by the probability of experiencing extremely low rainfall or drought. The intuition behind this test is that when adverse shocks are more likely, the expected costs of debt repayment in bad years rise. As a result, farmers facing this downside risk may forgo otherwise profitable investment opportunities. Thus, the marginal benefit of an increased safety net is likely to be greater when farmers face higher risk, increasing their incentive to borrow and invest.

We focus on monsoon-related rainfall risk for two reasons. First, roughly 60% of India's agricultural land depends on rainfall, and between 80-90% of the annual rainfall occurs during the June–September monsoon season (Jayachandran, 2006). Second, rainfall shocks tend to affect all farmers within a village economy, limiting opportunities for informal risk-sharing (Townsend, 1994).

We measure rainfall risk at the ZIP code level. For each month, we calculate the 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 fifth percentile value refer to extremely 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. In our data, low-risk areas face a 2.8% probability of drought, compared to 13.2% probability of drought in high-risk areas.

Columns (1) and (2) of Table 19 present the heterogeneity in the treatment effect on credit market outcomes by rainfall risk. We estimate the main specification separately for ZIP codes categorized as high- and low-risk. The estimate presented in Column (1) indicates that the increase in credit among treated farmers is statistically insignificant in low-risk areas. In contrast, the estimate presented in Column (2) suggests that the treatment effect is both statistically significant and economically meaningful in high-risk areas, with an estimated magnitude roughly four times larger than that in low-risk areas. Moreover, the difference in coefficients across the two groups is statistically significant, with an F-statistic of 3.19. Overall, these results indicate that the policy's effect on borrowing is substantially larger in regions exposed to greater rainfall risk.

The results can be interpreted as being driven by greater credit demand. The key assumption required for this interpretation is that credit supply does not respond asymmetrically to the policy in areas with high or low rainfall risk. We validate this assumption using the data on acceptance rate. Panel A of Appendix Table D.4 presents the results from the DID analysis on acceptance rates of new loans. We find no statistically or economically significant variation in the treatment effect on acceptance rate by rainfall risk. The lack of heterogeneity in the supply response follows from the fact that rainfall risk is an idiosyncratic risk for geographically diversified banks.[26]

5.5.2 Role of Incomplete Insurance

This section examines the heterogeneity in the policy's effect on credit market outcomes by the extent of incompleteness in insurance markets. The intuition behind this test is that the marginal benefit of safety nets – such as guaranteed income for farmers – is likely to be higher when insurance contracts are incapable of providing a safety net against downside risk.

We exploit a feature of rainfall insurance contracts to identify regions where such contracts cannot provide a perfect hedge against rainfall risk. Rainfall insurance contracts are based on rainfall recorded at official stations rather than the rainfall on the field. This results in a basis risk if the rainfall stations are located further away from the field. Basis risk is an important determinant of insurance demand by farmers (Cole and Xiong, 2017; Robles et al., 2021). Hill, Robles, and Ceballos (2016) document that doubling the distance to a reference weather station increases basis risk and decreases insurance demand in India by 18%. Mobarak and Rosenzweig (2013) estimate that for every kilometer increase in the (perceived) distance of the weather station for a farmer without any informal risk protection, there is a drop-off in demand for formal index insurance of 6.4%. Using primary data from India, Cole, Giné, and Vickery (2017) document that farmers do view basis risk as a significant drawback of agricultural index insurance.

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. Appendix Figure D.5 shows that ZIP code-level basis risk increases with the distance to the nearest rainfall station. This positive association between distance to the nearest rainfall station and basis risk has previously been discussed in Mobarak and Rosenzweig (2012, 2013) and Cole, Giné, and Vickery (2017).

Columns (3) and (4) of Table 19 present the heterogeneity in the treatment effect on credit market outcomes by basis risk. We estimate the main specification separately for ZIP codes categorized as having low and high basis risk. The estimate presented in Column (3) indicates that the increase in credit among treated farmers is statistically insignificant in low basis risk areas. In contrast, the estimate presented in Column (4) suggests that the treatment effect is both statistically significant and economically meaningful in high basis risk areas, with an estimated magnitude roughly four times larger than that in low basis risk areas. Moreover, the difference in the estimates across the two groups is statistically significant, with an F-statistic of 2.49. Overall, these results indicate that the policy's effect on borrowing is substantially larger in regions exposed to greater basis risk—that is, areas where downside rainfall risk remains largely

[26]Rainfall risk is likely to be idiosyncratic for well-diversified large banks as the spatial correlation in rainfall falls sharply as distance increases Mobarak and Rosenzweig (2012, 2013).

uninsurable. This suggests that the impact of guaranteed income is greater for farmers who are ex-ante constrained due to uninsured risk.

We interpret the relatively larger increase in borrowing in high basis risk areas as being driven by demand. This interpretation relies on the assumption that credit supply does not respond differentially to the policy across areas with high and low basis risk. We provide suggestive evidence in support of this assumption using data on loan acceptance rates. Panel B of Appendix Table D.4 reports the DID estimates for the acceptance rate of new loans. We find no statistically or economically significant heterogeneity in the treatment effect on acceptance rates by basis risk. Taken together, the absence of changes in acceptance rate after the policy and the observed heterogeneity in credit outcomes suggest that safety nets such as guaranteed income can mitigate the dampening effect of uninsured risk on credit demand.

5.6 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.

5.7 Effect of the Policy on Hedging Activity & Risk Taking

This section examines the policy's effect on hedging activity in agriculture. Our previous results indicate that guaranteed income increases downside risk protection for farmers, which in turn raises their credit demand. A natural implication of this finding is that enhanced downside risk protection through social safety nets is likely to influence farmers' risk-taking decisions, specifically their engagement in hedging activities. Economically, in the presence of downside risk, social safety nets and agricultural practices that serve as natural hedges against such downside risk can act as substitutes. This substitution effect reflects the idea that when farmers have access to effective insurance or income guarantees, their incentive to engage in costly self-insurance strategies, such as diversification or alternative cropping, is reduced. This intuition aligns with the argument put forth by Karlan et al. (2014) in the context of agricultural insurance markets, where the presence of effective insurance mechanisms can reduce farmers' reliance on hedging practices.

Traditional agriculture employs several risk management strategies. One such hedging activity is cultivation of non-cash crops or subsistence crops. Subsistence crops are typically low-risk and low-return crops. By cultivating these crops, farmers ensure a basic level of food security irrespective of fluctuations in income or crop failure in more commercially-oriented activities, effectively hedging against income volatility. This practice acts as a self-insurance mechanism within traditional farming, providing a buffer that helps ensure basic survival even in adverse conditions. We hypothesize that guaranteed income can reduce incentives to self-insure using low-risk cultivation techniques. For instance, using a randomized controlled trial, Cole, Giné, and Vickery (2017) shows that rainfall insurance can induce farmers to shift production towards higher-return and higher-risk cash crops.

We collect detailed district-level data on crop cultivation to calculate the share of land dedicated to cash crops in each district. We combine this data with the border district-pair design that compares outcomes across districts located on either side of the West Bengal state border. The empirical specification includes district-pair × year fixed effects and exploits variation in PMKSN compliance across contiguous district pairs that straddle the boundary between West Bengal and its five neighboring states, as shown in Appendix Figure B.2.

Table 20 presents the results. Columns (1) through (4) sequentially add fixed effects to estimate our preferred specification with district fixed effects and district-pair × year fixed effects in Column (4). The coefficient of interest is the interaction between Complier and Post, which captures the relative change in area under cash crops in compliant districts compared to similar bordering districts in West Bengal following the introduction of PMKSN transfers. The estimates are positive and statistically significant across all specifications and the estimate of interest is stable in magnitude despite a substantial increase in model R^2 of 90 percentage points from the simplest specification in Columns (1) to the most saturated specification in (4). Economically, the results imply a 3.7% increase in the area under cash crops after treatment. This increase is economically significant and represents a 33% increase over the pre-period sample mean of 9.9%.

5.7.1 Effect on Adoption of New Farming Techniques

This section documents further evidence of changes in agricultural practices among treated farmers following the implementation of guaranteed income. Specifically, we use village-level survey data collected under Mission Antyodaya which provides details on the share of farmers engaged in organic farming to investigate the effect of guaranteed income on the adoption of a new farming technique: organic farming.

Organic farming is economically innovative for Indian farmers because it shifts production away from conventional practices. It offers the prospect of higher returns by enabling access to premium markets where consumers are willing to pay more for organic produce. However, organic farming also entails substantial risk: transitioning to organic methods often involves temporary yield declines, which can reduce short-term profitability and impose cash flow constraints on smallholders. These factors, combined with challenges in certification, market access, and knowledge-intensive management requirements, render organic farming a high-reward but uncertain investment strategy for resource-constrained farmers.

Appendix Table D.5 presents the results examining the effect of the policy on the adoption of organic farming by combining the village-level data with the border district-pair design. Our results indicate that villages in districts that complied with the policy exhibit an increase in the fraction of farmers adopting organic farming. These results are robust to the inclusion of village and district-pair × year fixed effects, indicating that the estimate is identified out of variation from villages in adjacent districts along the border of the state of West Bengal while controlling for all village-level time-invariant characteristics. The magnitude of the estimate suggests a 0.4 percentage point increase in the share of farmers engaging in organic farming after the implementation of the policy. This effect is economically equivalent to a 4.4% increase over the pre-period sample mean of 8.4%. This result further suggests that guaranteed income can transform agricultural practices and alter farmers' production decisions by enabling greater risk-taking.

5.7.2 Evidence from Original Survey of Farmers

This section provides qualitative evidence supporting increased risk-taking among farmers following the implementation of guaranteed income transfers through PMKSN. Using data from our original field survey, we directly elicit farmers' self-assessments of changes in their risk behaviors post-transfer. Appendix Table D.6 reports the results. 41% of surveyed farmers indicate an increase in risk-taking. Among those who actually received transfers, 38% confirm this increase, while 44% of non-recipients anticipate a similar shift in their risk-taking behavior were they to receive unconditional income of equivalent magnitude.

Do Farmers Build Buffer Stocks? An important channel through which guaranteed income insulates farmers from downside risk and affects their risk-taking behavior is by enabling the accumulation of buffer stocks. Specifically, we hypothesize that the transfers provide a predictable and stable source of income, which farmers can allocate to building tangible precautionary savings or reserves that serve as a self-insurance mechanism against future shocks, such as droughts or floods. This usage of money transfers to build buffer stock is an important intermediate step for the transfers to improve financial resilience of farmers and foster investment in productive assets financed by risky debt.

Qualitative evidence from our original field survey supports this hypothesis. Appendix Table D.7 shows that 53% of surveyed farmers report increases in their precautionary savings after receiving transfers. The same proportion of transfer recipients confirm this increase, while 53% of non-recipients anticipate similar behavior if they were to receive unconditional income of comparable magnitude. This suggests that guaranteed income does indeed increase resilience of farmers to adverse shocks by allowing them to build buffer stocks.

These qualitative findings align with quantitative results, collectively suggesting that social safety nets can reduce downside risk, thereby encouraging farmers to engage in higher-risk and potentially higher-return agricultural practices. This qualitative corroboration strengthens confidence in our interpretation of the results that social safety nets can alter risk preferences and investment behaviors in agricultural households.

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 term loans by $6.78 and credit card utilization by $3.33. This implies a total increase in credit of $10.12, which is equivalent to 58.68% of the perpetuity value of guaranteed income. Assuming a loan-to-value ratio of 0.8, our upper bound estimate of the policy's effect on capital is $11.81 wherein $8.48 is financed using term loans and the rest comes from credit card utilization. This increase in investment is equivalent to 68.52% of the perpetuity value of guaranteed income.

6.2 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 presence of financial constraints, the increased down-side risk associated with debt contracts can negatively affect credit demand and lead to under-investment.

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).

We rationalize our findings by estimating a version of the Herranz, Krasa, and Villamil (2015) dynamic partial-equilibrium model of investment, which features cost of default. Appendix section E presents this model. We add two new elements to this framework – (1) entrepreneurs, or farmers, with heterogeneous productivity, and (2) the presence of frequent disaster shocks, such as droughts. In this model, limited personal funds make credit necessary to finance investment, and periodic disaster shocks make downside risk prominent. The heightened downside risk is caused by – (1) limited funds which make loan repayment difficult after a disaster, and (2) the cost of default, which includes a permanent loss in consumption due to lost production capacity and future credit market exclusion. The model serves two purposes. First, the optimal investment balances between the potential returns and the higher downside risk entailed by the credit-financed investment. The model shows that high-risk-averse individuals deploy less credit and capital because of downside risk. Guaranteed income increases credit demand by lowering the downside risk associated with credit contracts. Second, the model successfully matches the untargeted moment for change in the capital due to guaranteed income with reasonable values of risk aversion, indicating that the hypothesized channel is quantitatively plausible.

6.3 Are Credit Supply Constraints Unimportant?

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.

6.4 External Validity

On external validity, we note that the objective of this paper is not to argue that guaranteed income programs such as UBI will always generate an identical effect regardless of context. This paper highlights a hitherto unexplored partial equilibrium mechanism through which such programs can spur credit demand, investment, and production through their effect on financial resilience. In other words, while do not aim to resolve the policy and academic debate around guaranteed income, we do seek to inform the discussion. We document the conditions under which the demand channel operates. Specifically, we argue that demand-side constraints arise due to high risk-aversion, binding consumption or liquidity constraints, and uninsured risk. Since these conditions are likely to be present in a variety of populations across contexts, our results may be informative on discussions around guaranteed income programs beyond farmers and India.

More recently, evidence from a randomized guaranteed income program in the United States, which provided payments for up to three years, documents a decline in labor income among recipients (Vivalt et al., 2024). In contrast, we find that guaranteed income transfers increase income from work, primarily through greater investment. These findings are not contradictory but instead reflect differences in the underlying populations. Participants in Vivalt et al. (2024) are primarily wage earners facing a trade-off between leisure and labor supply, where unconditional transfers are expected to reduce labor supply as discussed in Hoynes and Rothstein (2019). By contrast, participants in our study are self-employed individuals who jointly determine capital and labor inputs (Ramey, 2011, 2019). In this setting, cash transfers can relax investment constraints and increase productive effort, particularly when self-employed individuals underinvest due to high downside risk. Moreover, a growing literature in development economics suggests that the labor supply distortions associated with social security programs in high-income settings may be less salient in developing economies (Baird, McKenzie, and Özler, 2018; Banerjee et al., 2024). For instance, Banerjee et al. (2017) re-analyze data from seven different experimental trials of large-scale, conditional cash transfer programs where earnings were explicitly not part of the conditionality and find no evidence of income effects on work. In fact, our findings are more closely related to Banerjee et al. (2020a, 2023), who find evidence of a shift from wage employment to self-employment following a universal basic income randomized control trial in Kenya.

Additionally, we note that the perpetual nature of these cash transfers plays an important role in driving the treatment effects. Using BJP vote share as the proxy of trust int he government commitment to continue these transfers, we find that the treatment effect is higher in areas where farmers have greater trust in the incumbent government that initiated these transfers. This result on the importance of the long-term nature of guaranteed income resonates with Bianchi and Bobba (2013) and Banerjee et al. (2024) who document that short-term transfers have a smaller effect relative to long-term transfers.

We compare our results with Egger et al. (2023) who examine the effects of a large randomized one-time cash transfer in rural Kenya. The perpetuity value ($ 1,400) of the guaranteed income program examined in this paper is comparable to the size ($ 1,000) of lump-sum cash transfers examined in Egger et al. (2023). This allows for a qualitative comparison of the economic effects of a wealth shocks when it is disbursed over time relative to when it is disbursed as a lump-sum. In a frictionless benchmark the two modes of transfers are isomorphic, however the results presented in the two studies differ. Cash transfer recipient households in Egger et al. (2023) spend most of the transfer on consumption and the purchase of durable assets, leading to higher local enterprise revenues. The durable assets purchased as a result of these transfers tend to be mostly non-productive assets and they do not find an increase in investment by enterprises owned by recipients. Moreover, they document a large spillover effect on non-recipient households and firms through the effect of the transfers on sales and wages of local enterprises.

In contrast, we find that when a large wealth shock is disbursed as a perpetuity, cash transfers increase financial resilience spurring credit demand and consequently increasing investment in productive assets and output. Moreover, we do not find evidence of the presence of large spillovers on the non-recipient group. These differences could be attributed to the greater ability of long-term transfers to protect against future risk.[27] Alternatively, behavioral frictions such as present bias, lack of self-control, etc., could also explain the differences. The quantification of the precise reasons for the differences in the effects of a long-term and a lump-sum transfer is beyond the scope and the ability of the natural experiment employed in this paper.[28]

6.5 Other Interventions to Reduce Downside Risk

We note that 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 increasing some sort of insurance. This is ana 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

[27] Market imperfections such as lack of savings technology, credit market frictions, etc. and behavioral biases such as lack of trust in the continuance of the perpetuity could prevent the costless conversion of a lump-sum payment into a perpetuity, and vice-versa.

[28] Banerjee et al. (2020a, 2023) already make some progress on this front and we seek to take up this question in future research.

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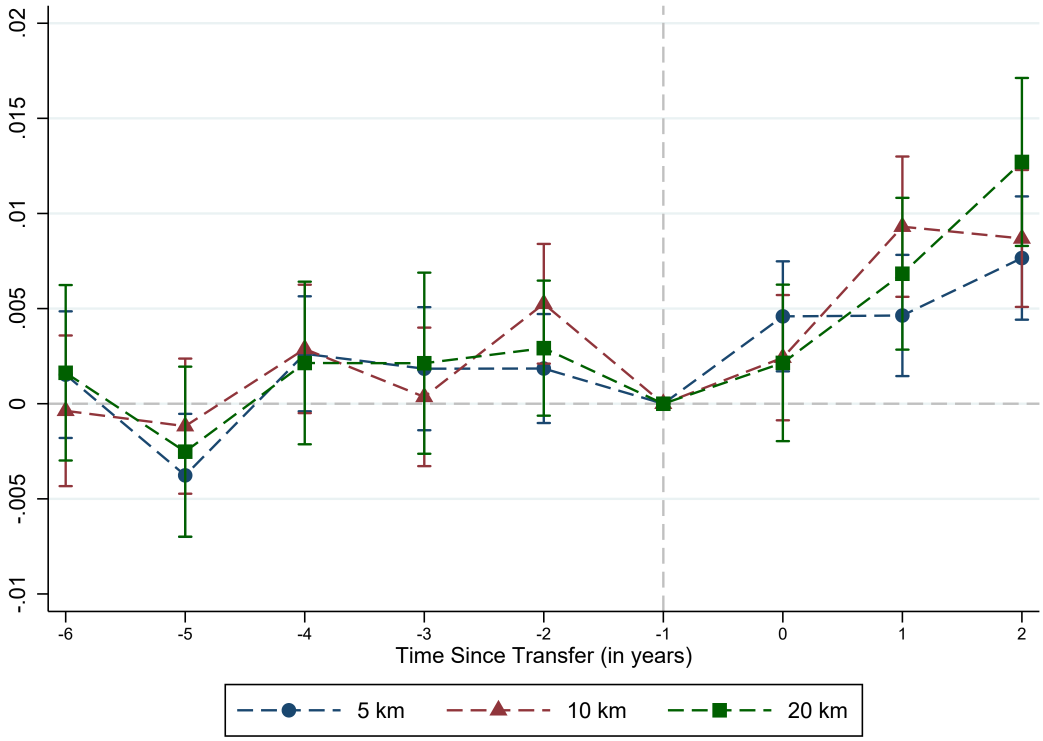
Figure 1: Assessment of Pre-Trends: Guaranteed Income & Agricultural Production

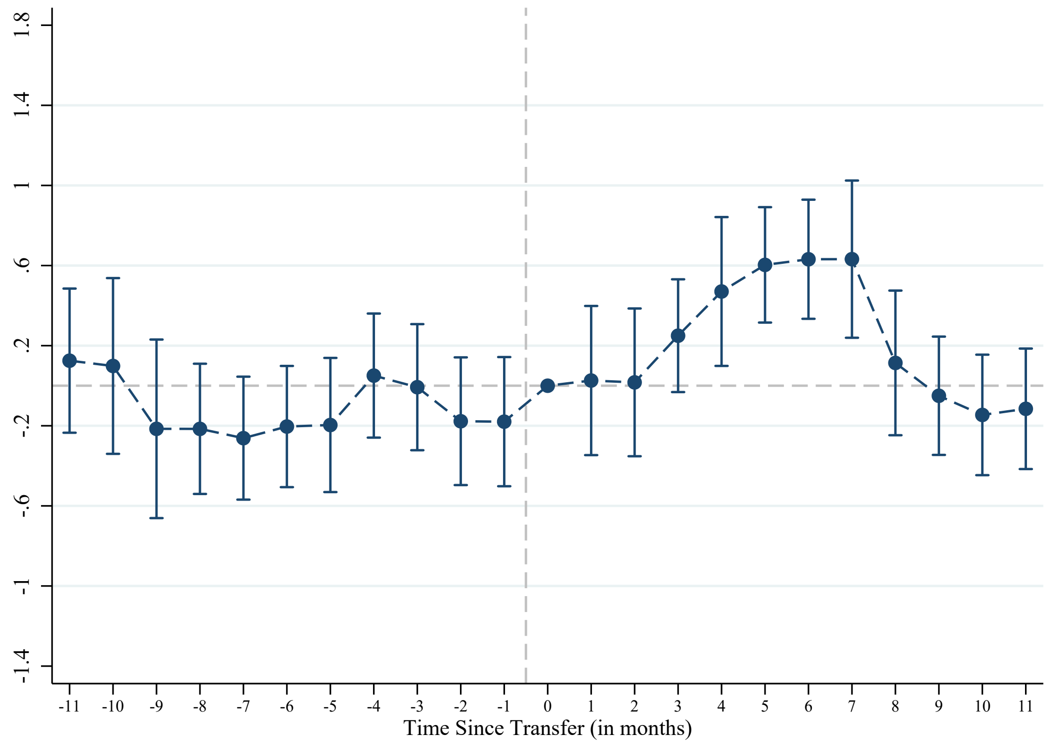


The figure plots the estimates of β_j and the 95% confidence intervals from the following regression equation:

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

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

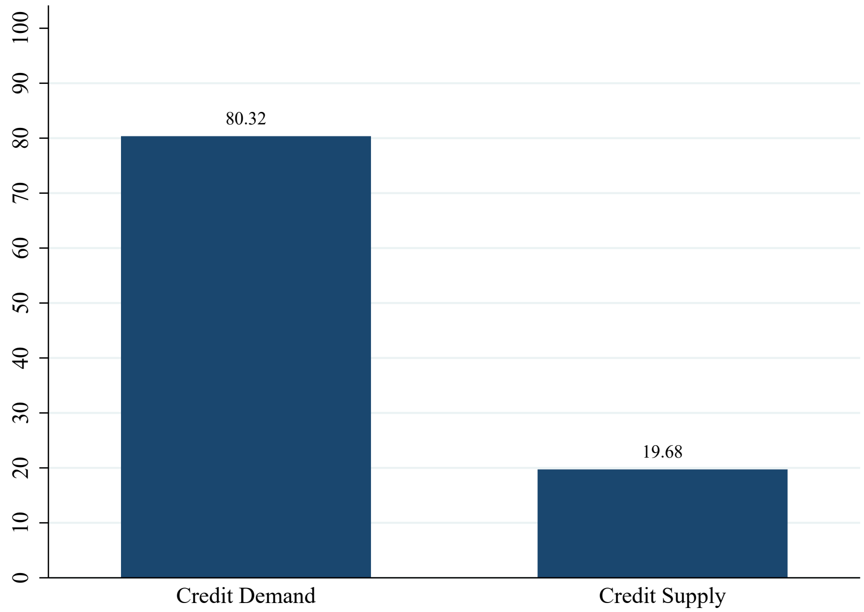


The figure plots the estimates of β_j and the 95% confidence intervals from the following regression equation:

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

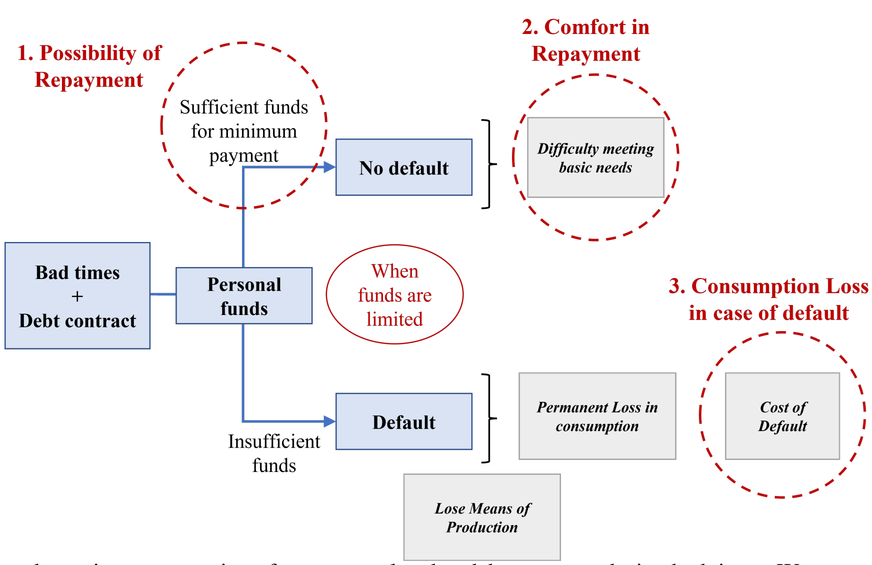
where $y_{i,t}$ denotes the dependent variable of interest measured for household i at time (month) t. $\mathbb{E}[y_{i,t}|t = Pre]$ denotes the sample average of the variable of interest during the pre-policy period. $Treatment_i$ takes a value of one for treatment farmer households and a value of zero 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



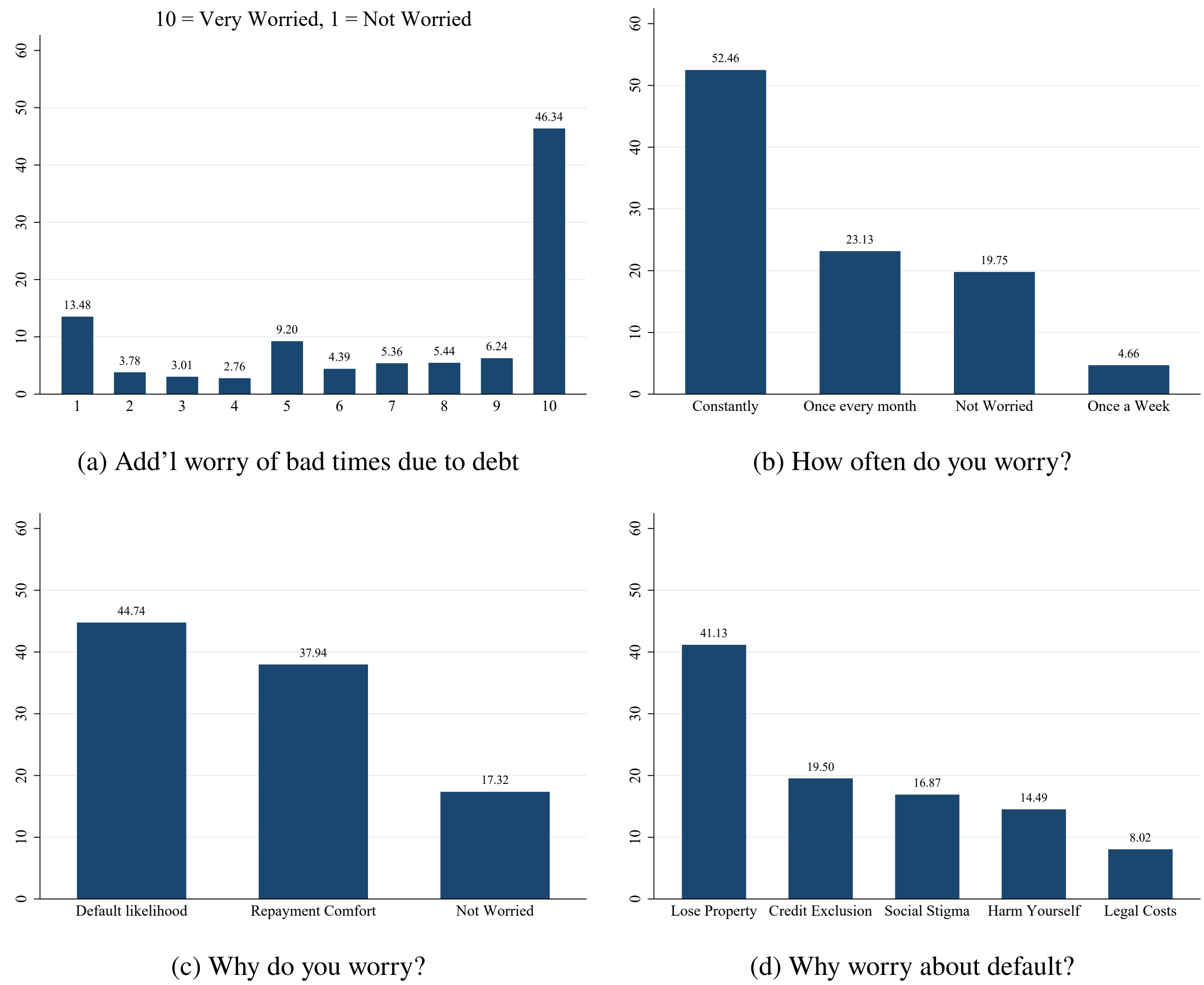
The figure presents the percentage of respondents choosing the primary reason for the increase in borrowings. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey was – *"In what way did this money increase your borrowings?: 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

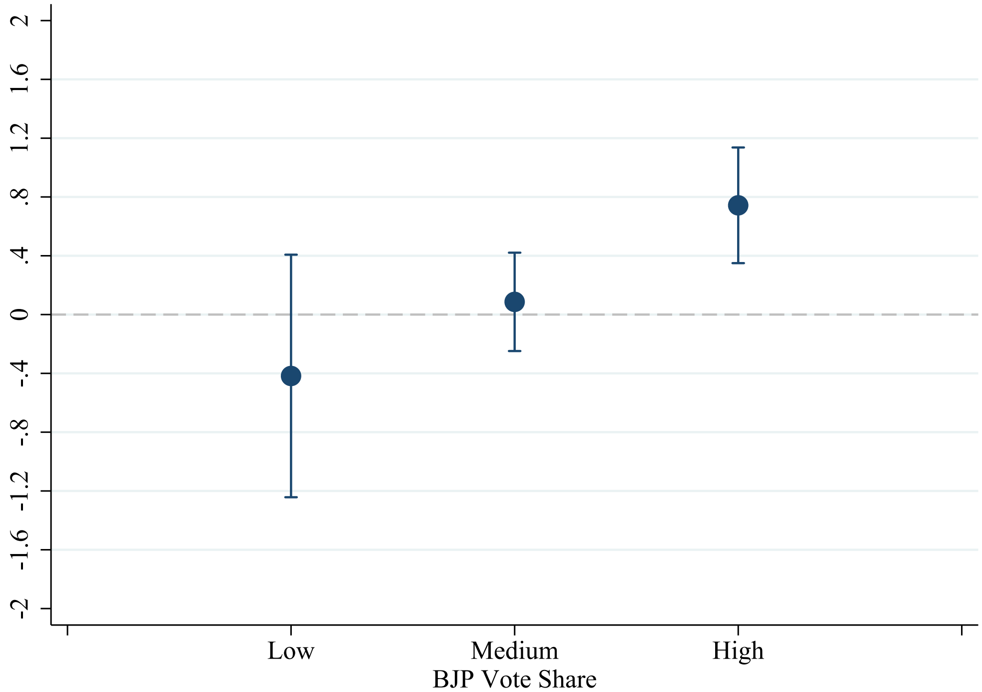
(b) How often do you worry?

(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. Specfcially, 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 PMKSN 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 Amt$_{i,t}$ denotes the dependent variable of interest (loan amount) measured for farmer i at time (month) t. Avg(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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN, 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 × 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 × 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 PMKSN 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 PMKSN 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 PMKSN 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 × 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 PMKSN 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. 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 PMKSN 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	PMKSN 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	PMKSN 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	PMKSN 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 PMKSN 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 PMKSN transfers, respectively. Panel A reports the effect of PMKSN on physical effort. The precise question of the survey for PMKSN 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 PMKSN 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 PMKSN on agricultural investment. The precise question of the survey for PMKSN 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 PMKSN 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 PMKSN on borrowing. The precise question of the survey for PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 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 PMKSN 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: 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 PMKSN were asked to answer the questions as a result of the transfers. Farmers who did not receive PMKSN were asked to answer the question assuming they had got the transfers.

Table 18: 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 PMKSN 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 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 PMKSN 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 PMKSN 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:

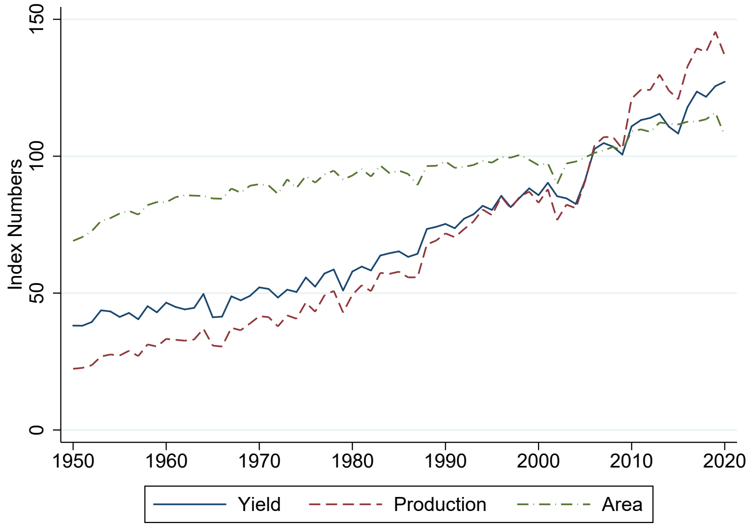
"Safety Nets, Credit, and Investment: Evidence from a Guaranteed Income Program"

Contents

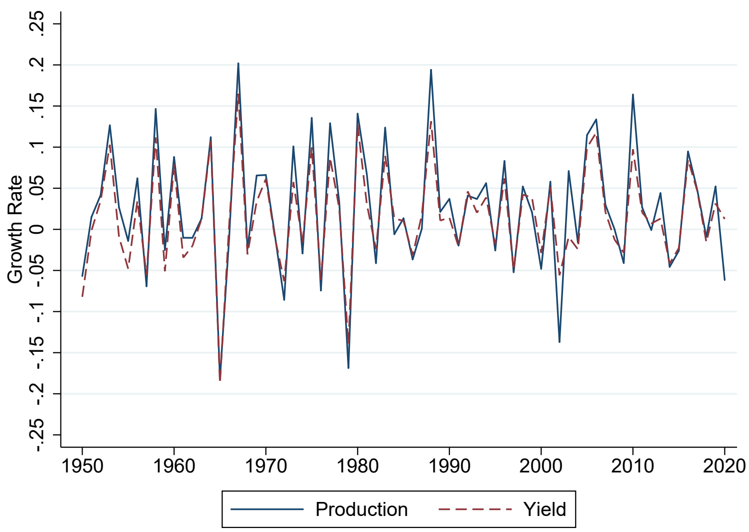
Appendix A Institutional Details

A.1 Agriculture in India

Figure A.1: Agricultural Growth in India



(a) Index Numbers over time

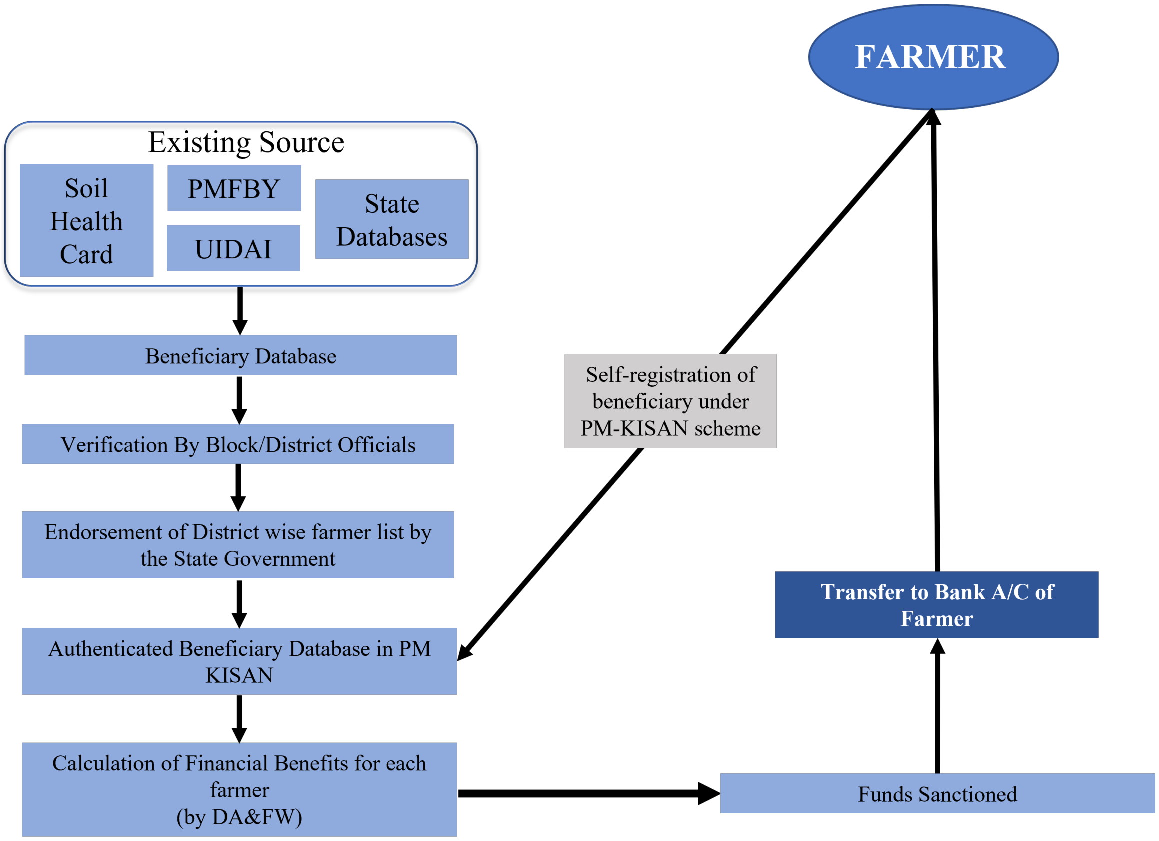


(b) Growth over time

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 Transfer process under PMKSN

Figure A.2: Data: Beneficiaries of PMKSNY by ZIP code

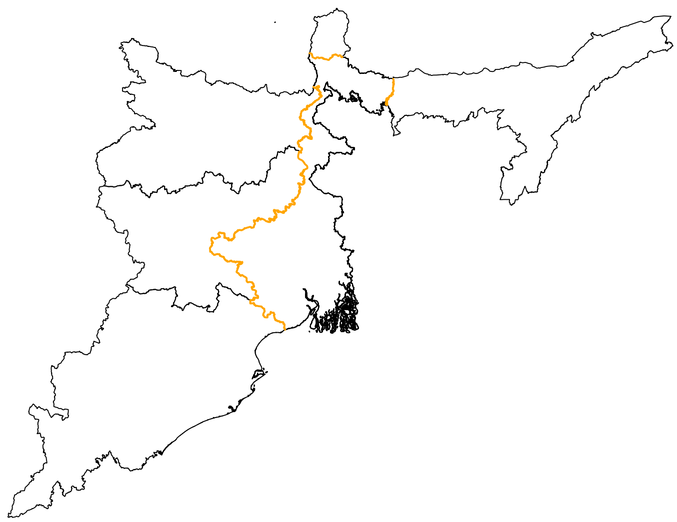


The figure plots the transfer process of benefits to eligible Indian farmers. The state government uses existing databases such as land registration records, Aadhar cards, and soil health cards to identify the list of beneficiaries. The list is then verified by the state government officials such as 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.

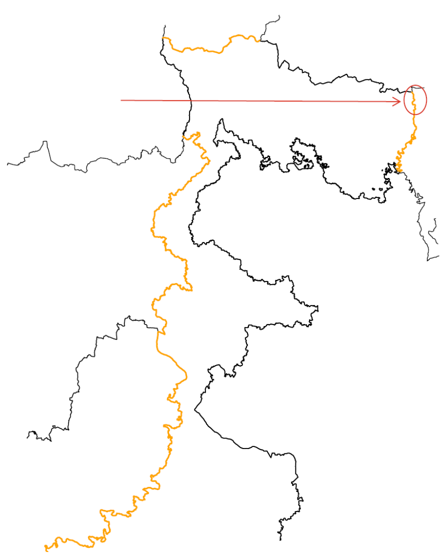
Appendix B Data

B.1 Sample & Spatial Geometry of Agricultural Production Data

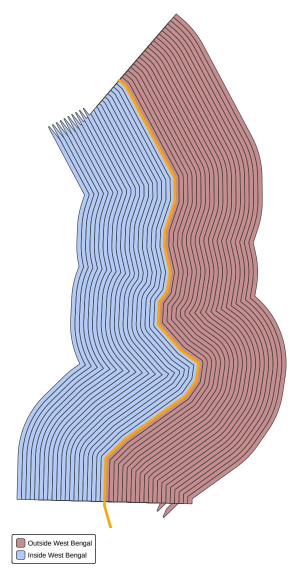
Figure B.1: Sample & Spatial Geometry of Agricultural Production Data



(a) Sample along the border of West Bengal



(b) Highlighted Border for blow Up

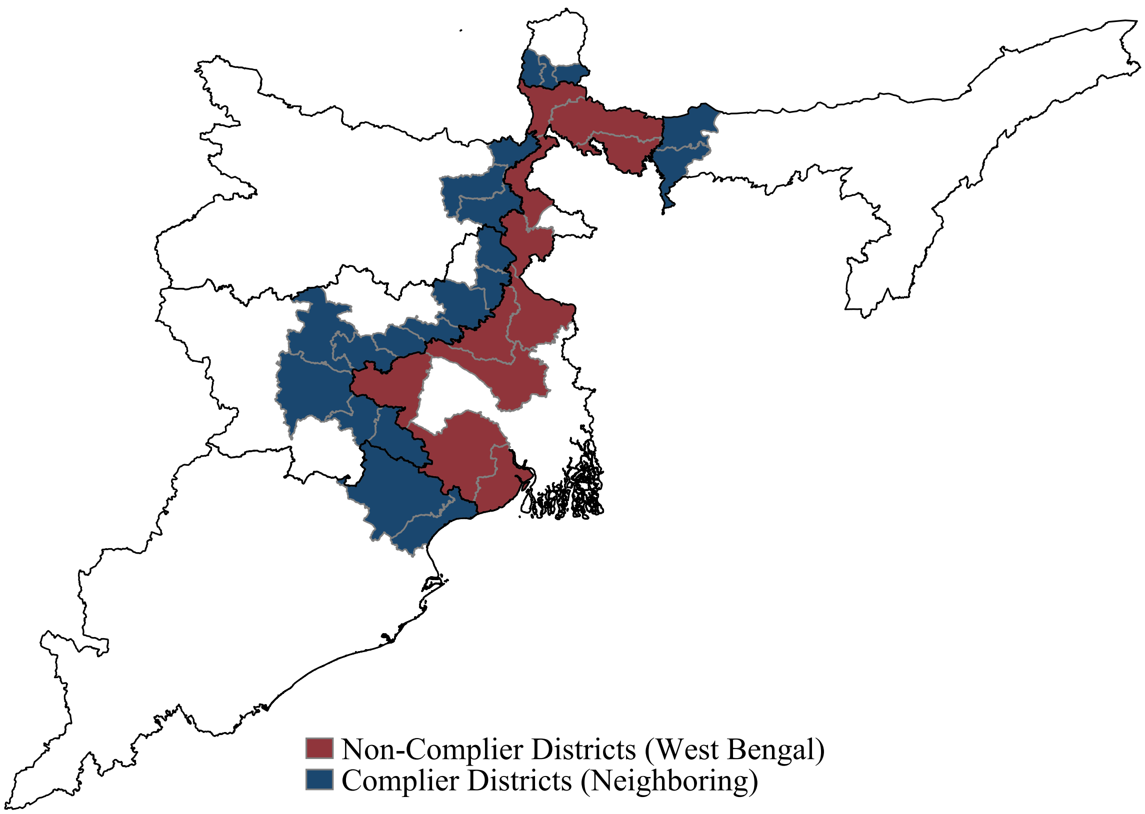


(c) Rectangular Micro-Regions

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 PMKSN policy.

B.3 Aggregate Credit Bureau Data

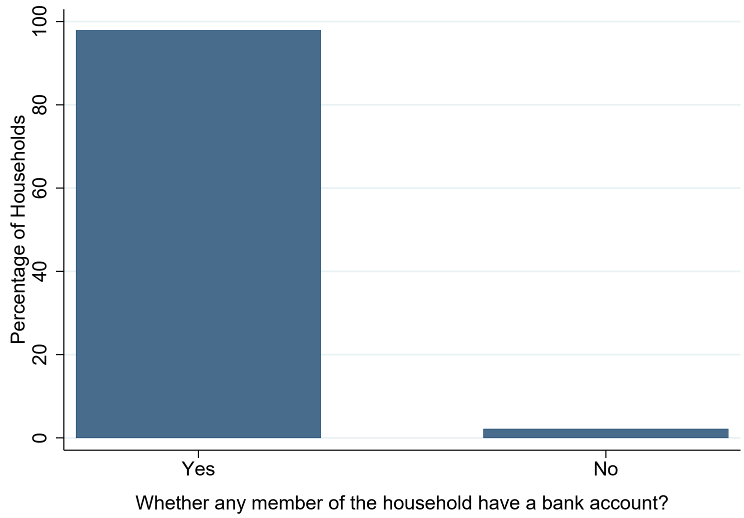
Table B.1: Summary Statistics for Aggregate Credit Bureau Data

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



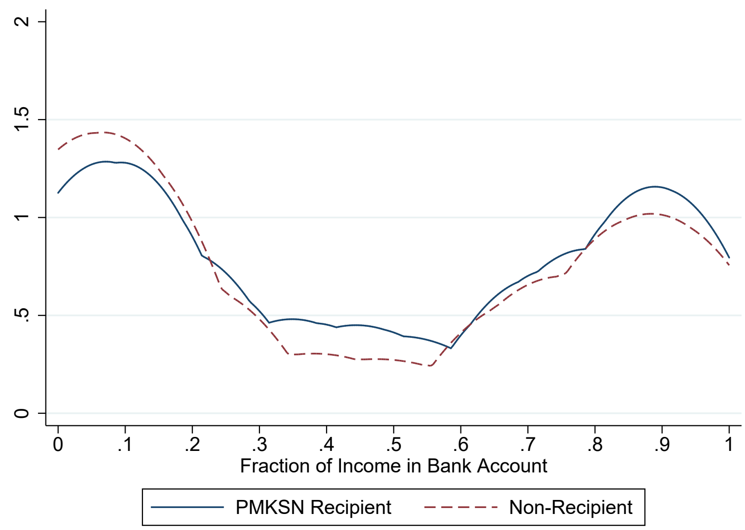
The figure plots the percentage of farmer households with at least one bank account. The data comes from the 2018 Situation Assessment Survey (SAS) conducted by the National Sample Survey Office (NSSO) during their 77^{th} round in the calendar year 2019. The survey records farmer responses as of 2018. 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 PMKSN and 387 farmers who are not beneficiaries of PMKSN.

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

# Bank Accounts	All Respondents	PMKSN 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 PMKSN transfers, respectively.

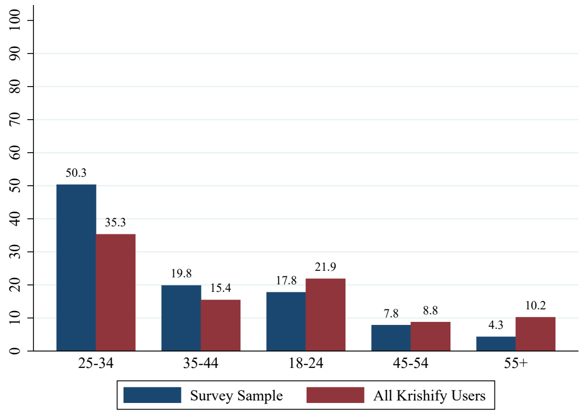
Table B.4: Biggest source of credit

Biggest Source of Credit	All Respondents	PMKSN 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

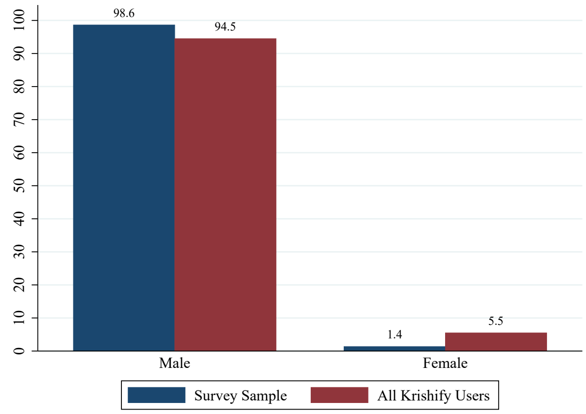
The table presents the percentage of respondents choosing their biggest source of credit. The data comes from the original survey of farmers designed by authors and conducted by Krishify. The precise question of the survey was – *"11. What is your biggest source of outstanding debt?: a. Banks or other 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 PMKSN transfers, respectively.

B.5 Original Survey of Farmers

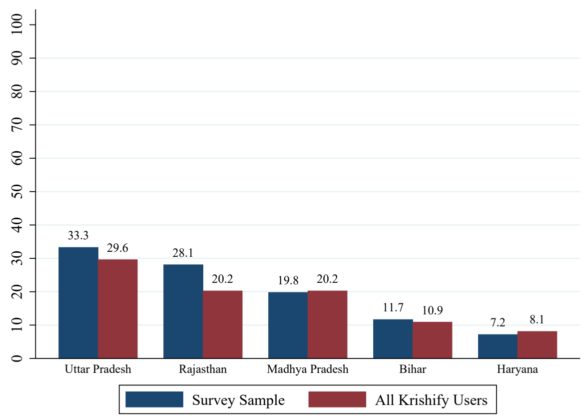
Figure B.5: Comparison of survey data with all Krishify application users



(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 PMKSN		*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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN program on income from work for treated and control households after accounting for potential spillovers according to the following specification:

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

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

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 PMKSN, 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN on credit market outcomes for the treatment and control groups according to the following specification:

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

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 /

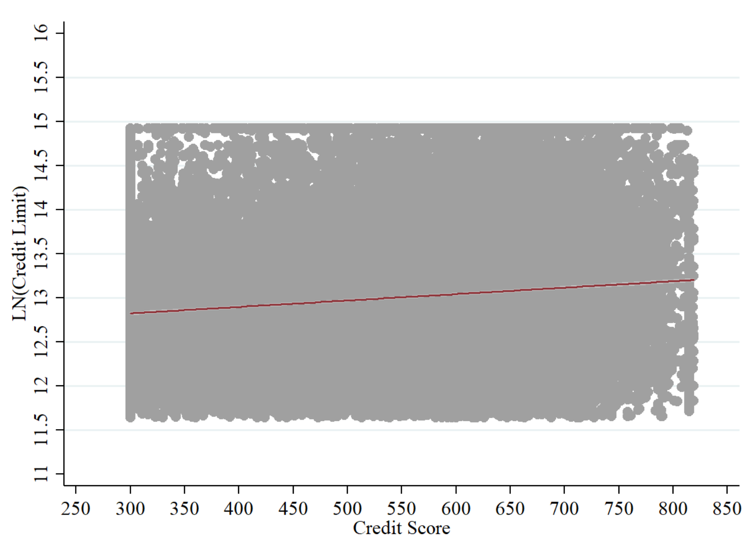
Kisan Credit Card Limit (A) +(B) : **₹ 11,09,000**

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.

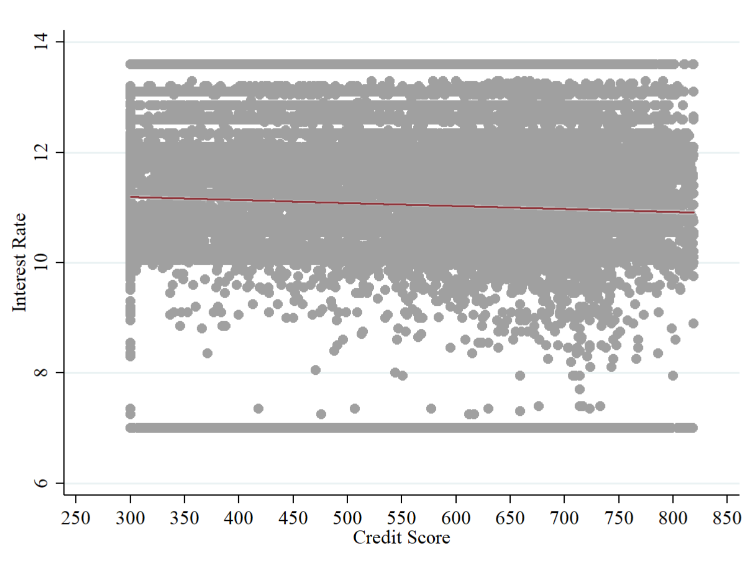
The figure presents the illustration for computing the credit limit for kisan credit cards. This illustration is taken from the 2017 RBI circular and can be accessed at LINK The illustration provides the details for setting the credit limit for a one acre farm with entire land under paddy cultivation.

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 PMKSN 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 PMKSN on Expected Lending Standards

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

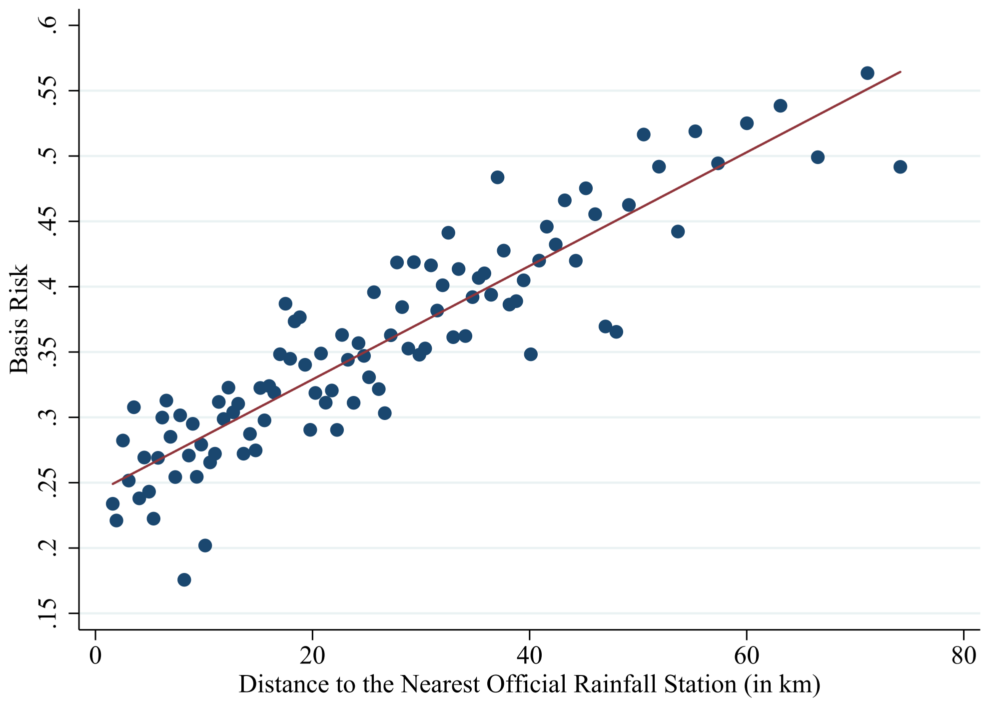
	All Respondents	PMKSN Recipients	
		Yes	No
Tighten	47.27	47.05	47.53
No Change	24.81	26.04	23.32
Loosen	27.92	26.91	29.14
# Obs (Respondents)	3,990	2,185	1,805

The table presents the percentage of respondents choosing their response to the effect of PMKSN 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 PMKSN recipients was – *"With respect to additional loans, please indicate how banks will change their lending standards (loan application acceptance and interest rates) due to PMKSN: a. Tighten, b. Loosen, c. No Change"* The precise question of the survey for PMKSN 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 PMKSN 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) All Regions	(2) Low Risk	(4) High Risk	(4) 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) All Regions	(2) Low Risk	(4) High Risk	(4) 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 PMKSN 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 PMKSN 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 PMKSN on Risk Taking	All Respondents	PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN 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 PMKSN on Precautionary Savings	All Respondents	PMKSN 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 PMKSN 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 PMKSN recipients was – *"How did the following change for you after receiving ₹6,000 annual money under PMKSN? 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 PMKSN 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 PMKSN 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 $\overline{x} > 1$.[29] Farmers experience disaster shock with a probability of p each period. The net return on capital is zero in case a disaster materializes.[30]

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:

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

[30] 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.

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

subject to

$$\int_{\mathfrak{D}}(1-\gamma)xdF(x)+\int_{\mathfrak{D}^c}\bar{v}dF(x)\geq(1-\epsilon)\left(1+r_f\right), \tag{E.2}$$
$$\mathfrak{D}\equiv\left\{x:V_{D,1}((1+r)(w-\epsilon K-C))>V_P(K(x-\bar{v})+(1+r)(w-\epsilon K-C))\right\}, \tag{E.3}$$
$$(1-\epsilon)K\leq bw \tag{E.4}$$

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.

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

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 $C = cw$, $K = kw$, ϵ, 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 $\left[\underline{x}, x^*\right]$ 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

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

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

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

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.[31] 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.2a) and debt (E.2a) 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.

[31] 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

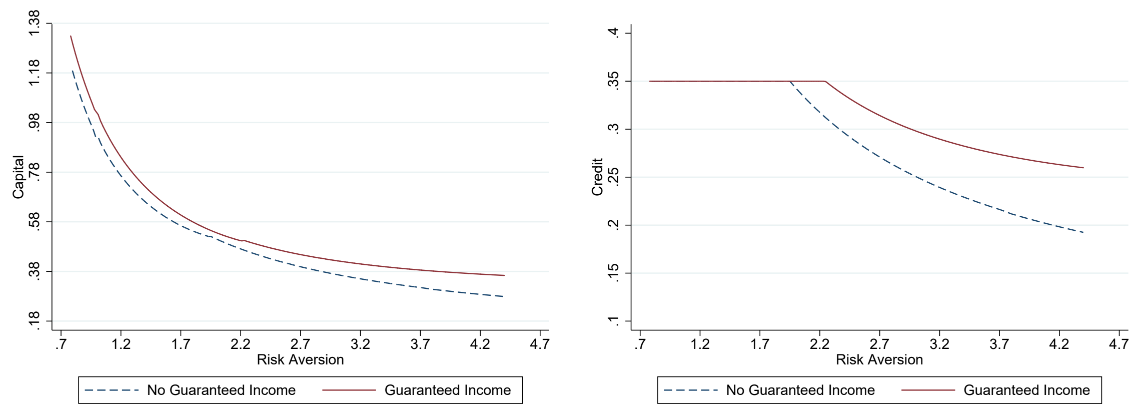
The table presents the mean and standard deviation for the risk aversion distribution.

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

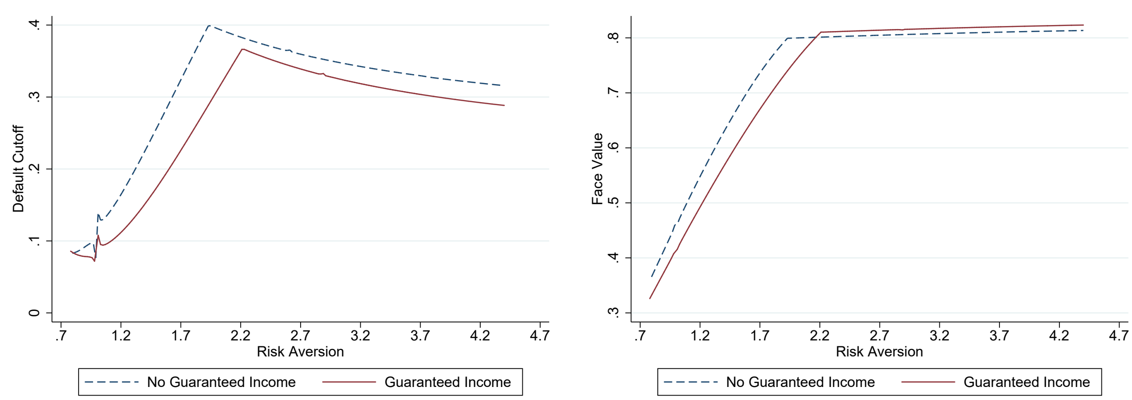
Figure E.1: Risk Aversion and Effect on Capital and Credit



(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.